Biomedical Signal Processing and Control 83 (2023) 104690

Contents lists available at ScienceDirect

Biomedical Signal Processing and Control

journal homepage: www.elsevier.com/locate/bspc

Restoration of missing or low-quality 12-lead ECG signals using ensemble deep-learning model with optimal combination

Hakje Yoo [a], Yunjin Yum [b], Yoojoong Kim [c], Jong-Ho Kim [a,d,*], Hyun-Joon Park [e], Hyung Joon Joo [a,d,f,*]

[a] Korea University Research Institute for Medical Bigdata Science, Korea University College of Medicine, Seongbuk-gu, Seoul, Republic of Korea
[b] Department of Biostatistics, Korea University College of Medicine, Seongbuk-gu, Seoul, Republic of Korea
[c] School of Computer Science and Information Engineering, The Catholic University of Korea, Bucheon-si, Gyeonggi-do, Republic of Korea
[d] Department of Cardiology, Cardiovascular Center, Korea University College of Medicine, Seongbuk-gu, Seoul, Republic of Korea
[e] Korea University Research Institute for Healthcare Service Innovation, Korea University College of Medicine, Seongbuk-gu, Seoul, Republic of Korea
[f] Department of Medical Informatics, Korea University College of Medicine, Seongbuk-gu, Seoul, Republic of Korea

A R T I C L E I N F O

Keywords:
12-lead Electrocardiogram
Missing signal
Restoration model
Linear regression
Ensemble model
Bidirectional long short-term memory
Convolution natural network

A B S T R A C T

Background and Objective: In a 12-lead electrocardiogram (ECG) examination, the ECG signals often have low-quality data problems due to high-frequency noise caused by muscles and low-frequency noise caused by body movement, breathing. These problems cause delays in examination results and increase medical costs. For this reason, solving low-quality data and missing ECG data problems can provide patients with improved medical services, reducing the work-loss and medical costs. The purpose of this study is to develop a signal restoration model for each of the 12 signals to solve the low-quality and missing data problems caused by mechanical and operator errors during 12-lead ECG examinations.
Methods: For this study, 13,862 high-quality 12-lead ECG recordings for multiple diseases were obtained from the 12-lead ECG database of a general hospital from 2016 to 2020. Two strategies were adopted to develop an accurate restoration model. First, to obtain the optimal input parameters for the ECG regeneration model for each ECG signal, linear regression (LR) models were developed for all 165 three-signal combinations of 11 signals. Second, the restoration models were constructed in a parallel architecture combining bidirectional long short-term memory (Bi-LSTM) with a convolutional neural network (CNN) to learn the temporal and spatial features of optimal combinations.
Results: The performances of the 165 candidate combinations for restoring missing signal were analyzed through the LR model to find the optimal input parameter for all ECG signals. The average root mean square error of the optimal combinations was 0.082 μV. The average RMSE of the signal restoration model made using the optimal combinations and deep-learning model (Bi-LSTM&CNN) was 0.037 μV, and the cosine simplicity was 0.991.
Conclusions: This ECG restoration technology obtained optimal input parameters through the LR model and developed ECG restoration model through the Bi-LSTM&CNN combined model to restore ECG signals for multiple diseases. The 12-lead ECG signal restoration model developed through this study offers high accuracy for the magnitude and direction components of all 12 signals. This technology can be used in emergency medical systems and remote ECG measurement situations, as well as in synthetic ECG generation technologies for constructing research datasets.

1. Introduction

Electrocardiogram (ECG), taken using 12-lead ECG equipment, is a representative medical technology used to diagnose cardiac disease [1,2]. A 12-lead ECG visualizes the activity of the heart muscle by attaching 10 electrodes to specific positions designated by the manual [3]. The 12 signals provided through the 10 electrodes are used by internal medicine doctors to gain clinical information about cardiac disease. To diagnose cardiac disease, the 12 ECG signals are analyzed both individually and together to gain comprehensive information [4].

* Corresponding authors.
E-mail addresses: mecey@naver.com (J.-H. Kim), drjoohj@gmail.com (H.J. Joo).

https://doi.org/10.1016/j.bspc.2023.104690
Received 16 September 2022; Received in revised form 27 January 2023; Accepted 11 February 2023
Available online 17 February 2023

The 12 signals can be divided into three categories: bipolar leads, augmented unipolar leads, and precordial leads. Lead I, II, III and aVR, aVL, and aVF are obtained using the voltage difference among four electrodes attached to the front plane, and leads V1 to V6 provide cardiac activity information on the side of the horizontal plane by using six electrodes attached around the heart [5]. Because the 12 signals obtained using the voltage difference between the electrodes contain information from both the frontal and horizontal planes, they provide effective information about heart function in three dimensions [6]. However, the 12-lead ECG requires that many electrodes to be accurately attached to the body, so it cannot be applied during daily activities [7,8]. In addition, for reasons such as poor electrode attachment, respiration, and mechanical errors, a signal missing problem along with a signal noise problem occurs [9,10] that can cause misleading health alerts in monitoring situations [11,12].

To improve the convenience of ECG examinations and solve the problem of missing signals, previous studies have described methods for restoring or acquiring ECG signals with a minimum number of leads [13–22]. In previous papers, the most widely used lead combination for reconstructing ECG signals is lead I, lead II, and V2 [13,21,22]. Because leads I and II reflect the electrode activity status in the vertical plane, and V2 reflects the electrode activity status in the horizontal plane, that combination can provide information on the three-dimensional activity of the heart [23]. Smith et al. developed an artificial intelligence model using six signals included lead I, lead II, and V2 as input parameters to restore precordial leads with a reduced lead set [15]. Atoui et al. restored the precordial leads using leads I, II, and V2 in a patient monitoring environment [13]. In addition, Zhang et al. rebuilt nine signals using only lead I, lead II, and V2 containing noise to reduce discomfort and noise problems caused by the large number of ECG electrodes [21]. Although those studies secured correlation coefficients of 0.9 or more on average, most of the previous studies used lead I, lead II, and V2 to restore the precordial leads. In other words, they all required that lead I, lead II, and V2 for restoring the precordial leads. However, none of them can provide suitable data if one of those input parameters is missing. It has been reported that three-axis information is required to restore ECG signals, but no results have been presented to analyze the accuracy of restorations according to the combination of signals used, and no optimal combination has been suggested to restore ECG signals for many diseases.

Previously, a statistical-based method, such as a linear regression (LR), was applied to regenerate signals, but more recently, deep-learning methods that can effectively learn nonlinear ECG signal features have emerged [13,15,16,19,21,22,24,25]. Restoring ECG signals through deep-learning is reported to improve accuracy compared with restoration methods that use regression equations, but LR is a traditional method for analyzing linear relationships between variables in polynomials and offers statistical access to those relationships [16,17,19,26]. LR has lower accuracy than deep-learning but has the advantage of being able to quickly learn the relationship between input parameters. If an optimal combination for restoring data from any missing signal could be ensured using the LR method and then used as input parameters for deep-learning, it would be possible to build a robust ECG restoration model suitable for restoring any missing ECG signal.

Therefore, the main purpose of this study was to obtain an optimal combination for restoring each signal in a 12-lead ECG and then develop an overall ECG restoration model using those optimal combinations. The optimal combination for each signal was found by analyzing the accuracy of all combinations of 11 signals (except for the missing signal) using an LR. In addition, to overcome the generality problem caused by the characteristics of ECG data that reflect the signal patterns indicative of different diseases, a 12-lead ECG dataset containing multiple diseases was used to develop the overall ECG restoration model.

2. Materials and methods

2.1. Proposed algorithm

The 12-lead ECG signal restoration model proposed in this study uses three strategies to solve the missing signal problem and ensure both accuracy and generality. First, to secure the accuracy of the restoration result for each signal, the LR method was applied to find the optimal combinations for restoring missing signals. The second strategy minimized the effects of the disease on the model by securing a 12-lead ECG dataset that reflected various diseases, from general to rare diseases. The last strategy used an ensemble model suitable for the characteristics of signal data to develop a restoration model with high accuracy. The previous studies used a model combining a CNN effective for spatial feature extraction and a Bi-LSTM effective for temporal feature extraction to improve the prediction accuracy for nonlinear data [27–29]. According to a previous study, a deep-learning model that combines spatial–temporal features solves the problem of insufficient extraction and unknown spatial–temporal structure by extracting features of two aspects for data with a nonlinear and long time-series [29]. Therefore, in this study, a model combining CNN and Bi-LSTM was used to secure an ECG regeneration model using three optimal ECG lead combinations (Fig. 1).

2.2. Acquisition of 12-lead ECG data

Standard 12-lead ECG examinations were made at Korea University Anam Hospital using machines from two different vendors: GE Medical Systems (Milwaukee, WI, USA) and Philips Medical Systems (Andover, MA, USA). The ECG results were stored in the hospital's clinical information system (INFINITT Healthcare) in the eXxtensible Markup Language (XML) format. The waveform data in each cell were reconstructed by splitting the data based on commas, and a quantitative value for each waveform was obtained by multiplying the amplitude set in the ECG device by the waveform value. That process was applied to all waveform data to obtain full 12-lead ECG information from the database. This study protocol was approved by the Institutional Review Board of Korea University Anam Hospital (IRB NO. 2021AN0114). The requirement for written informed consent was waived because the retrospective study design held minimal risk to participants. The study also complied with the Declaration of Helsinki.

2.3. ECG dataset description

The dataset used in this study extracted about 700,000 data of high-quality ECG data from the 12-lead ECG database built at Korea University Anam Hospital from 2017 to 2020. The dataset was configured to include both normal and abnormal ECGs by applying 10 Minnesota classification categories to diagnosis information from the ECG machines. The Minnesota classification categories used in the dataset are shown in Table 1, where major diagnoses refers to the diagnoses most frequently included in that category [30]. Application of the Minnesota classification to the 147 diagnostic names extracted from the ECG machines was conducted by a circulatory physician and produced datasets for 10 diseases [31].

It is difficult to obtain uniform 12-lead ECG data for all 147 diagnostic names due to the scarcity of rare diagnoses. For this reason, among the diagnostic names included in each Minnesota classification, those with less than 100 data were necessarily included, and diagnostic names about general diseases were extracted uniformly. To prevent data duplication, only data from each patient's first ECG in the database were used in this study. However, when there were multiple diagnoses in one data, the data were included in all diagnoses. Through those processes, 2000 ECG recordings were extracted for each of the 10 Minnesota classes, and only one of the same ECG data included in multiple diagnoses was used. Furthermore, only electrocardiograms of 10 s using at

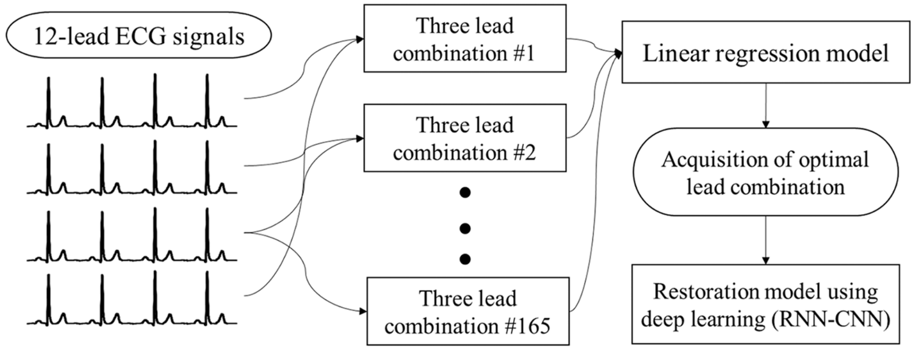

Fig. 1. Overall process for restoring ECG signals.

Table 1
Minnesota classification.

Minnesota classification category	Major diagnoses
Unclassified	Sinus rhythm, Sinus arrhythmia, QT interval (prolonged)
QRS axis deviation	Left axis deviation, Right axis deviation, Indeterminate axis
High amplitude R wave	LVH, RVH, Ventricular hypertrophy
Arrhythmia	Sinus rhythm (bradycardia), Atrial fibrillation, Sinus rhythm (tachycardia)
AV conduction defect	AV block, AV block (1st degree), PR interval (short)
Ventricular conduction defect	RBBB, RBBB (incomplete), rSr pattern in V1 and V2
Q and QS pattern	Myocardial infarction (inferior), Myocardial infarction (septal), Myocardial infarction (anterior)
ST junction and segment depression	Myocardial ischemia (lateral), ST-T abnormality (non-specific), Myocardial ischemia (anterior)
T wave items	T wave (abnormal), T wave (inverted), T wave (flattened)
Miscellaneous	ST segment elevation, P wave (abnormal), Voltage (decreased)

To reduce space, we used the highest three ECG diagnoses that make up each Minnesota classification. AV, atrioventricular; LAFB, left anterior fascicular block; LVH, left ventricular hypertrophy; RBBB, right bundle branch block; RVH, right ventricular hypertrophy; STEMI, ST segment elevation myocardial infarction.

the international standard of 500 Hz were used. ECG data of fewer than 10 s or missing were excluded to improve the quality of the dataset. Because the 12-lead ECGs used as input parameters were extracted directly from the xml format of the source data, various noises were included. Therefore, the quality of the waveforms was improved using a Butterworth filter (bandwidth: 0.05–150 Hz) and asymmetrically reweighted penalized least squares smoothing (arPLS) [16,32,33].

2.4. Selection of optimal alternative leads

The optimal input parameter for each missing signal was obtained by using an LR to improve the accuracy of the signal restoration model generated through deep-learning. Since the heart waveforms are obtained as 3D vector information, it is necessary to obtain vector information as the 3D-axis used as input to restore the waveform of a missing signal. The LR in this study is expressed as equation (1).

$$Y = X\beta + \varepsilon$$

$$\mathbf{Y} = \begin{pmatrix} y_1 \\ \vdots \\ y_m \end{pmatrix}, \mathbf{X} = \begin{pmatrix} 1 & x_{11} & \cdots & x_{13} \\ \vdots & & \ddots & \vdots \\ 1 & x_{m1} & \cdots & x_{m3} \end{pmatrix}, \beta = \begin{pmatrix} \beta_0 \\ \vdots \\ \beta_3 \end{pmatrix}, \text{and} \varepsilon = \begin{pmatrix} \varepsilon_1 \\ \vdots \\ \varepsilon_m \end{pmatrix} \tag{1}$$

Y is an $m \times 1$ target standard 12-lead ECG matrix which we want to restore, X is an $m \times 4$ matrix which is the subset for ECG restoration, β is an 4×1 matrix formed by linear coefficients, and ε is an $m \times 1$ error matrix. A subscript m indicates the number of frames in the ECG signal. We obtained β using the least squares estimator, $\widehat{\beta} = (X'X)^{-1}X'y$ [17]. For one restoration ECG, the remaining 11 signals can form 165 combinations, selecting three elements from a set of 11 elements. Therefore, an LR model was developed for all 165 combinations for each of the 12 signals of a 12-lead electrocardiogram, and the root mean square error (RMSE) was calculated for each model. As input parameter for the LR model, 80 % of the 13,862 patients were used as training information, and the remaining 20 % were used as a test set. All signals were subjected to min–max normalization, and the generalization of the model was improved by normalizing the range of signals to 0–1. The optimal combination for each signal selected the combination with the lowest RMSE value.

2.5. Restoration ECG model using deep-learning

For highly accurate ECG restoration, this study proposes an ensemble model for multiple diseases using the optimal combinations secured through the LR (Fig. 2). In this model, effective features were extracted by combining bidirectional long short-term memory (Bi-LSTM) and a CNN, and the combining the two-features were used as input parameters in Bi-LSTM for restoring of missing signal. Ensemble models are an effective method for improving prediction accuracy by using spatial–temporal features output from different models as input parameters [34–36].

The Bi-LSTM was used to extract temporal features in the data that change over time [37], and the CNN was used to extract the overall spatial features of the data [38]. The restored ECG signal was secured through a fully connected layer between them. By combining the signal features extracted from the two deep learning methods through connected layers, the problem of insufficient features occurring in long term-series such as ECG can be minimized [34]. The ensemble model for ECG restoration consists of a structure using CNN and a structure using Bi-LSTM. In the temporal feature extraction step, four Bi-LSTM layers were used, and a batch normalization layer was placed before the fourth layer. The nodes of Bi-LSTM were set to 256, 128, 64, and 32, respectively. In the step of extracting spatial features, four 1-dimensional CNN layers were used, a batch normalization layer was added before the forth layer, and channels of the 1-D CNN were set to 256, 128, 64, and 32. In addition, temporal features and spatial features were combined and used as input information for two Bi-LSTM layers and one fully connected layer, and a batch normalization layer was used between each layer. The activation function used Relu, and the learning rate was set to 0.0001.

As for the input parameters of model, optimal combination obtained in the section of alternative lead selection was used, and one ECG signal out of 12 signals was used as the output parameter. Therefore, input parameters and output parameters were applied in the shape of 5000 by 3 and 5000 by 1, respectively. Normalization of all ECG signals from 0 to

10: 2,3,5
5: 1,2,3

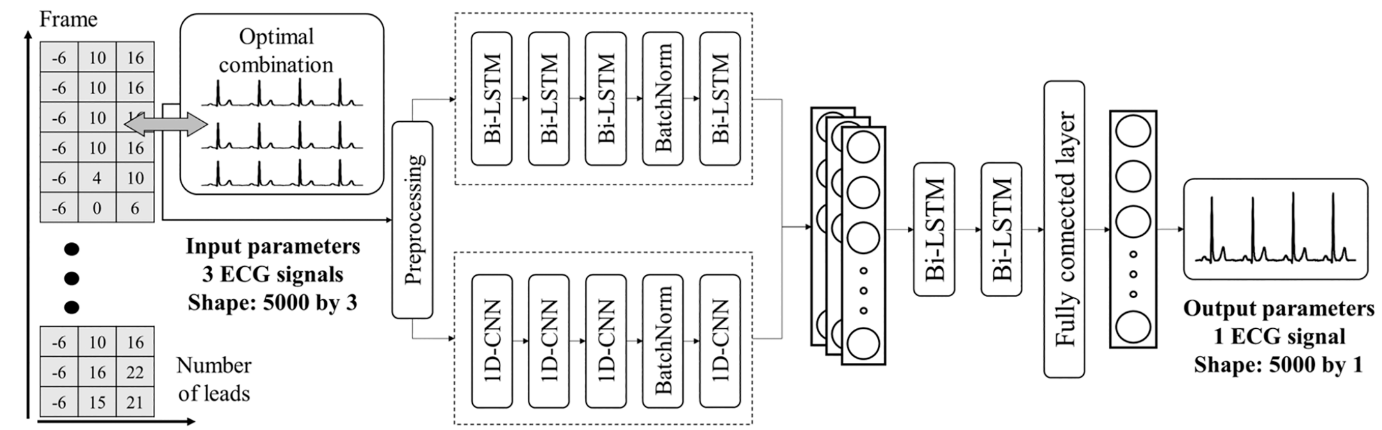

Fig. 2. Architecture of the ECG restoration model using three ECG signal.

1 was performed to overcome the problem of performance reduction that may occur due to differences in ECG ranges according to diseases. In addition, a 3-fold Monte Carlo cross-validation (MCCV) technique was applied to verify the robustness of the ECG restoration model. All result values of the model obtained through 3-fold MCCV were averaged and used for analysis of the accuracy [39,40]. In developing the environment for the deep-learning model, the operating system was Ubuntu 16.04 LTS, and the platform was TensorFlow 2.4 based on Python 3.8.

2.6. *Validation of the ECG restoration model*

The ECG regeneration model developed in this study was verified using 2,997 12-lead ECG recordings, which account for 20 % of the overall dataset. The overall model performance was analyzed based on the restoration results for all data, and the model performance by disease was analyzed using the data organized according to the Minnesota classification criteria. To analyze the absolute difference in waveform magnitude between the restored ECG signal and the original signal, the RMSE was used [41]. In Eq. (2), $PredictECG_i$ and $TestECG_i$ are the i-th frame of the restored ECG signal and the original ECG signal, respectively, and N equals 5000 frames, the total length of each signal.

$$RMSE = \sqrt{\sum_{i=1}^{N}(PredictECG_i - TestECG_i)^2 \Big/ N} \tag{2}$$

The change in the direction of the waveform between two signals was analyzed as a quantitative value using cosine similarity [42,43], a method for calculating the cosine angles of two vectors. After calculating the angles in each frame, the average value for 5000 frames was used. In terms of cosine similarity, similarity increases as the two signals become closer to 1 and decreases as the signals become closer to −1 (Eq. (3)).

$$Cosinesimilarity = PredictECG_i \bullet TestECG_i / |PredictECG_i|.|TestECG_i| \tag{3}$$

The difference in performance of the restoration ECG model by LR and deep learning was statistically analyzed by an independent t-test. The statistical significance level was set at 0.01. The software for statistics used SPSS 15.0 (SPSS Inc., Chicago, Illinois, USA). In addition, to examine the clinical applicability of the developed model, actual ECG with errors were selected and restored. The 12-lead ECG cases in which an error occurred were clinically examined by a specialist in cardiology, and the clinical usefulness was verified by restoring those signals with the model developed in this study.

3. Results

3.1. *12-lead ECG dataset*

To develop the restoration model for multiple diseases, the dataset was cleaned by removing ECG data of poor quality based on ECG machine information. The final sample contained 157,594 data were obtained. Based on the sampled data, the Minnesota classification system was applied to configure the dataset into 10 categories containing various diagnostic names. The completed ECG dataset contained 13,862 data. The average age of the patients was 58 years, and 24 % of the data were normal (Table 2).

Because all the extracted ECG data were high-quality, low-quality data containing information such as suspected arm lead reverse could be preemptively removed. In addition, a bandpass filter and the arPLS algorithm were applied to all signals to eliminate errors caused by mechanical problems and patient movements that can occur during ECG examinations. Fig. 3 shows the waveform changes according to the preprocessing of the V1 signals in the dataset. Fig. 3(a) is the original signal before preprocessing; Fig. 3(b) is the result from the bandpass filter at the frequency of bandwidth 0.05–150 Hz; Fig. 3(c) is the result from extracting the baseline to improve baseline wander; and Fig. 3(d) is the result of applying the arPLS to remove baseline wander noise in the waveform.

3.2. *Alternative lead combinations*

To ensure that the deep learning model had optimal input parameters to restore the missing ECG signals, the RMSE was calculated for the 165 candidate combinations for each lead through the LR model, and the optimal combination was selected as the one with the lowest RMSE. Fig. 4 shows the result of analyzing the changes in accuracy by aligning the combination with the lowest RMSE to the combination with the highest RMSE. The tendency of RMSE change in all signals was linear, and most signals had a threshold at which the RMSE changed rapidly. Most of the 12 signals showed the lowest RMSE value at 0.05–0.13 μV

Table 2
Characteristics of the ECG dataset.

	Dataset of 12-lead ECG
Signals (n)	13,862
Age (year)	58.81 ± 20.12
Proportion of normality (%)	24
Original frequency (Hz)	500
Recording time (s)	10
Leads (n)	12
Categories (n)	10

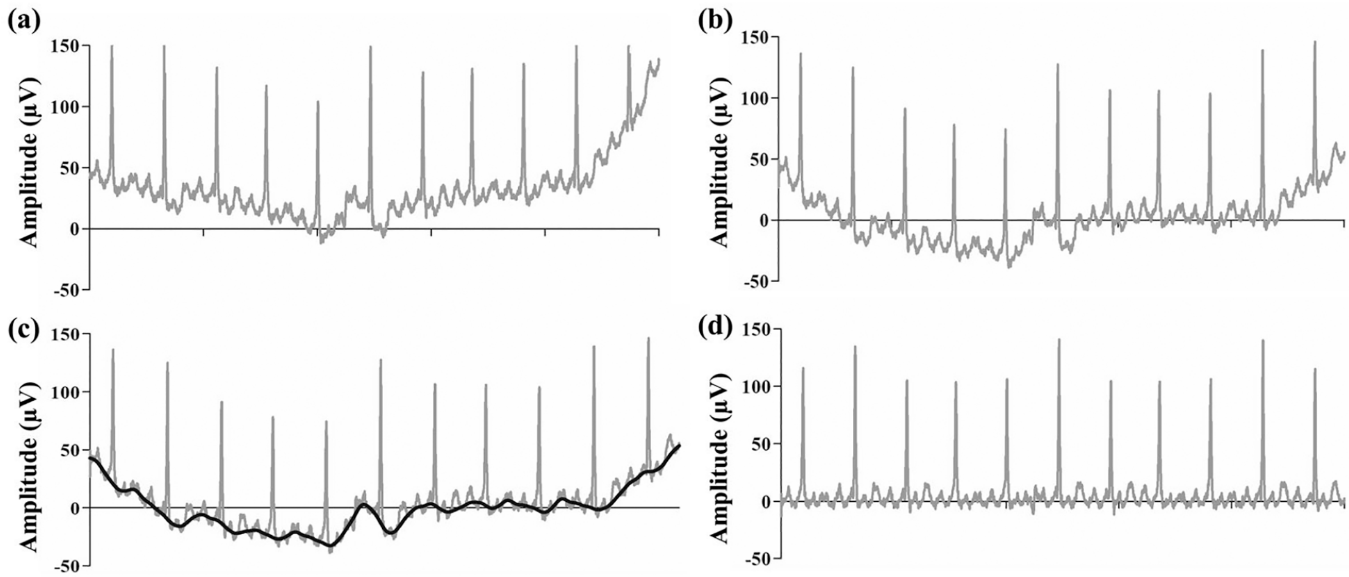

Fig. 3. Results from ECG signal preprocessing.

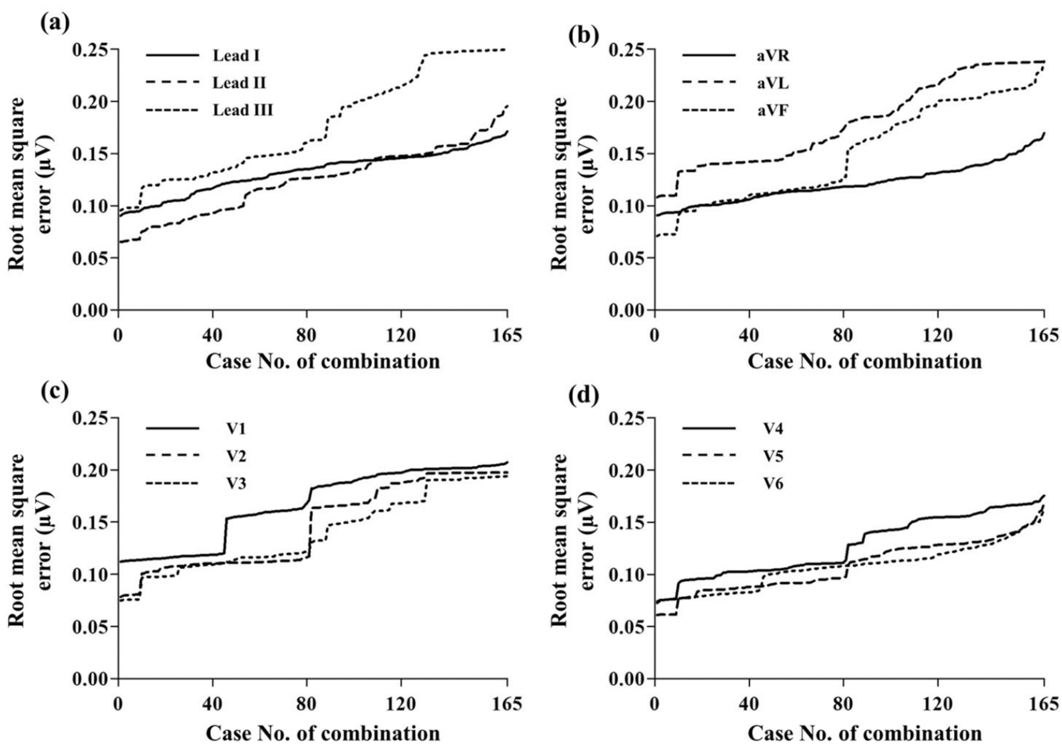

Fig. 4. RMSE results according to the 165 combinations for each signal through the linear regression.

and the highest RMSE value at 0.20–0.25 μV. The signals with the least change in RMSE were lead I, aVR, V4, V5, and V6, and the signal with the largest change was lead III.

Table 3 shows the leads and RMSE results for optimal combinations and threshold combinations each signal obtained through the LR. The average RMSE of the 12 optimal combinations was 0.083 μV, among which the lowest RMSE value was 0.061 μV, and the highest was 0.11 μV. The lead restored through the LR with the lowest RMSE value was V5, and the lead with the highest RMSE value was V1. In the selected optimal combinations, the leads with an RMSE value of 0.1 μV or more were aVL and V1. Most of the optimal combinations had an RMSE between 0.06 μV and 0.07 μV.

3.3. Restoration of 12-lead ECG using deep learning

To restore the 12-lead ECG, an optimal combination was obtained for each ECG signal, and a deep-learning model for the restored ECG signal was developed using those optimal combinations. The ECG regeneration model was analyzed for accuracy by dividing it into signal magnitudes through RMSE and directional components using cosine simplicity. Table 4 shows the results of the accuracy analysis through RMSE. In restoring the 12-lead ECG signals, the deep-learning model was statistically significantly decreased compared to the model using LR for all 12 signals ($p < 0.01$). Compared with the LR, the signal restoration using the deep-learning model decreased the RMSE by 0.045 μV on average,

Table 3
Optimal combinations for each signal and threshold combination.

	Optimal combination	RMSE (μV)	Threshold combination	RMSE (μV)
lead I	aVR, aVL, V6	0.090	aVL, aVR, V5	0.091
lead II	aVR, aVF, V6	0.065	aVR, aVF, V1	0.068
lead III	lead 2, aVL, aVF	0.096	aVL, aVF, V4	0.098
aVR	lead I, lead II, V6	0.091	lead I, lead II, aVF	0.091
aVL	lead I, lead III, aVR	0.108	lead I, lead III, V4	0.110
aVF	lead II, lead III, aVR	0.071	lead II, lead III, V4	0.073
V1	lead 1, aVR, V2	0.112	lead III, aVL, V2	0.120
V2	V1, V3, V4	0.078	lead I, V1, V3	0.081
V3	V2, V4, V5	0.075	aVR, V2, V4	0.076
V4	V2, V3, V5	0.074	aVR, V3, V5	0.076
V5	V3, V4, V6	0.061	aVR, V4, V6	0.061
V6	aVR, V4, V5	0.073	lead III, aVF, V5	0.084

Table 4
Analysis of 3-fold cross validation for RMSE and cosine similarity of 12-lead ECG restoration models through linear regression and deep-learning.

	Root mean square error			Cosine similarity		
	Linear regression	Deep learning	p value	Linear regression	Deep learning	p value
lead I	0.092 ± 0.002	0.033 ± 0.002	< 0.01	0.951 ± 0.004	0.992 ± 0.001	< 0.01
lead II	0.065 ± 0.003	0.022 ± 0.003	< 0.01	0.880 ± 0.005	0.993 ± 0.001	< 0.01
lead III	0.093 ± 0.002	0.027 ± 0.002	< 0.01	0.958 ± 0.003	0.990 ± 0.002	< 0.01
aVR	0.090 ± 0.003	0.028 ± 0.002	< 0.01	0.971 ± 0.004	0.990 ± 0.003	< 0.01
aVL	0.101 ± 0.006	0.036 ± 0.001	< 0.01	0.952 ± 0.003	0.988 ± 0.002	< 0.01
aVF	0.075 ± 0.005	0.019 ± 0.002	< 0.01	0.964 ± 0.003	0.989 ± 0.002	< 0.01
V1	0.108 ± 0.003	0.074 ± 0.003	< 0.01	0.957 ± 0.002	0.995 ± 0.001	< 0.01
V2	0.081 ± 0.003	0.046 ± 0.002	< 0.01	0.963 ± 0.004	0.992 ± 0.002	< 0.01
V3	0.077 ± 0.002	0.045 ± 0.001	< 0.01	0.967 ± 0.003	0.989 ± 0.002	< 0.01
V4	0.076 ± 0.001	0.040 ± 0.002	< 0.01	0.958 ± 0.003	0.990 ± 0.002	< 0.01
V5	0.061 ± 0.002	0.035 ± 0.002	< 0.01	0.954 ± 0.004	0.991 ± 0.001	< 0.01
V6	0.069 ± 0.003	0.042 ± 0.002	< 0.01	0.955 ± 0.003	0.984 ± 0.001	< 0.01

and the largest decrease was 0.066 μV at lead III. As a result of analyzing the performance difference between LR and deep-learning in terms of the percentage, the average improvement rate of RMSE in deep-learning was 54.32 %.

The signal with the lowest cosine similarity was V6 with an average value of 0.984 in deep-learning model. The average similarity of all other signals was 0.991, indicating a high similarity between the restored signal and the original signal (Table 4). The ECG signal restored by deep-learning significantly improved the cosine similarity compared to LR ($p < 0.01$). As a result of comparing the difference in similarity in terms of the percentage, an average improvement rate of 4.10 % was achieved.

3.4. Restoration of 12-lead ECG using according to diagnosis

To verify the accuracy of the ECG restoration model, the results of the restored ECG for each diagnosis were analyzed using RMSE. Table 5 shows the results of calculating the RMSE between the restored signals and the original signals for each of the 10 Minnesota categories. The lead with the lowest RMSE was lead II; the lead with the highest RMSE was V1; and the average RMSE across all categories was 0.039 μV.

3.5. Restoration of 12-lead ECG in clinical case

To validate the restoration ECG model developed in this study, a clinical case in which a data problem occurred during a 12-lead ECG examination was obtained, and the problematic signal was restored using the restoration model developed herein. Fig. 5(a) presents the clinical case in which V6 was incorrectly measured during the 12-lead ECG examination. Fig. 5(b) is the total measurement signal of V6 (the last part of Fig. 5(a) is the same as the last part of Fig. 5(b)). It can be seen that the V6 signal has a large baseline wander and includes high-frequency noise. Fig. 5(c) is the signal restored using the V6 restoration model developed in this study, and it confirms that the inaccurate signal problems were solved by improving the baseline wander and high-frequency noise problems.

4. Discussion

Restoring an ECG signal is a base technology needed to diagnose heart disease through remote ECG and replace 12-lead ECG with protocols that use minimal electrodes. Therefore, research to develop accurate regenerative signals has been continually reported. In addition, ECG restoration technology can be used to impute missing ECG data caused by incorrect attachment locations or ECG equipment failures. This research found the optimal input data for each signal in a 12-lead ECG and developed an ECG restoration model using deep-learning to overcome the missing ECG problem caused for various reasons.

Previous studies that developed a regeneration ECG model using deep-learning presented models trained with 3 to 7 input parameters [13,15,21,22]. According to a study by Smith et al. results of ECG restoration model have been best when the combinations contain V2. For this reason, several studies have reported using a combination of lead I, lead II, and V2 in restoration ECG models that use neural networks and LR. However, 165 three-lead combinations of input parameters can be used in an electrocardiogram regeneration model when one signal is missing. In general, an ECG is an electrical signal generated by a 3D activation of the heart, so three-axis information is required to obtain an accurate ECG [7,20]. Therefore, this study always considered at least three signals, and the combination most related to the missing signal was selected through an LR. The optimal combinations were determined differently according to the signals, as shown in Table 3.

The most relevant combination of standard leads was chosen with two extremity lead signals derived from the electrode used to calculate the potential difference of standard lead and one signal from the other lead system. In other words, the electrode used to derive the missing signal has the most direct effect in selecting the input parameter that restores that signal. These results were similar to the optimal combination of extremity leads. The optimal combination to restore the extremity leads consisted of two standard leads and one signal from a different lead system. And the optimal combinations of precardiac leads consisted of a lead right next to the signal and one lead secured from the other lead system. For the optimal combination of all signals, two signals derived from nodes related to the missing signal and one signal from another derivation method with a relatively low correlation were selected. These results are also found in the threshold results. The threshold combinations, except for V1 and V6, mostly contain two signals included in the optimal combination. However, for V1 and V6, since the precordial lead uses a single node unlike other lead systems, it is judged that only the closest lead in the same lead system was selected. Most previous studies on restoring ECG signals used a combination of lead I, lead II, and V2 in their models [13,20–22,44]. That 3-lead subset was suggested to diagnose arrhythmias or ischemia by restoring precordial leads with only three leads for use in telemedicine [44]. However, the purpose in this study was to find the optimal combinations for restoring 12-lead ECG examination signals that are missing for various

Table 5
Analysis of 3-fold cross validation for RMSE between the restored ECG signals and original ECG signals according to the Minnesota categories.

	Unclassified	QRS axis deviation	High amplitude R wave	Arrhythmia	AV conduction defect	Ventricular conduction defect	Q and QS pattern	ST junction and segment depression	T wave item	Miscellaneous
Lead I	0.035 ±0.004	0.033 ±0.001	0.035 ±0.001	0.035 ±0.002	0.036 ±0.002	0.035 ±0.002	0.034 ±0.002	0.035 ±0.003	0.034 ±0.003	0.034 ±0.003
Lead II	0.021 ±0.002	0.022 ±0.003	0.022 ±0.003	0.023 ±0.003	0.021 ±0.003	0.022 ±0.003	0.022 ±0.003	0.023 ±0.001	0.022 ±0.002	0.021 ±0.002
Lead III	0.032 ±0.003	0.032 ±0.001	0.030 ±0.001	0.031 ±0.002	0.032 ±0.003	0.026 ±0.003	0.029 ±0.003	0.032 ±0.001	0.034 ±0.003	0.034 ±0.004
aVR	0.028 ±0.004	0.031 ±0.001	0.032 ±0.001	0.034 ±0.002	0.031 ±0.002	0.029 ±0.002	0.032 ±0.001	0.033 ±0.002	0.033 ±0.002	0.033 ±0.003
aVL	0.039 ±0.004	0.037 ±0.002	0.035 ±0.002	0.034 ±0.003	0.034 ±0.003	0.037 ±0.003	0.039 ±0.002	0.040 ±0.002	0.040 ±0.003	0.038 ±0.002
aVF	0.019 ±0.001	0.020 ±0.002	0.018 ±0.002	0.020 ±0.002	0.019 ±0.002	0.019 ±0.002	0.017 ±0.001	0.020 ±0.002	0.020 ±0.003	0.017 ±0.001
V1	0.068 ±0.007	0.072 ±0.002	0.074 ±0.002	0.074 ±0.001	0.072 ±0.001	0.070 ±0.001	0.076 ±0.002	0.078 ±0.001	0.076 ±0.002	0.075 ±0.003
V2	0.047 ±0.002	0.045 ±0.003	0.047 ±0.003	0.051 ±0.002	0.045 ±0.003	0.053 ±0.003	0.047 ±0.002	0.046 ±0.002	0.046 ±0.003	0.050 ±0.002
V3	0.045 ±0.002	0.043 ±0.002	0.047 ±0.002	0.046 ±0.003	0.045 ±0.003	0.048 ±0.003	0.045 ±0.003	0.044 ±0.001	0.044 ±0.002	0.045 ±0.002
V4	0.043 ±0.002	0.043 ±0.001	0.040 ±0.001	0.043 ±0.001	0.040 ±0.001	0.045 ±0.001	0.040 ±0.002	0.041 ±0.001	0.043 ±0.001	0.043 ±0.002
V5	0.035 ±0.002	0.035 ±0.002	0.035 ±0.002	0.035 ±0.001	0.035 ±0.002	0.035 ±0.002	0.032 ±0.003	0.035 ±0.001	0.036 ±0.002	0.033 ±0.002
V6	0.043 ±0.002	0.047 ±0.001	0.042 ±0.001	0.044 ±0.002	0.041 ±0.001	0.045 ±0.001	0.045 ±0.002	0.046 ±0.001	0.045 ±0.004	0.045 ±0.003
Mean	0.038 ±0.013	0.038 ±0.014	0.038 ±0.014	0.039 ±0.014	0.038 ±0.014	0.039 ±0.014	0.038 ±0.015	0.039 ±0.015	0.039 ±0.014	0.039 ±0.015

reasons and then develop an ECG restoration model using those optimal combinations. As a result of obtaining the optimal combination for each lead, an ECG restoration model with high accuracy was obtained in this study compared to previous studies. Table 6 shows the results of analyzing the differences between this study and previous studies in terms of the dataset characteristics, method, and correlation coefficients (CC) [13–16,18–22]. The average CC of the model presented in this study was 0.983, which is similar to or higher than those in previous studies. The source ECG data in this study used 500 Hz signals obtained from 12-lead ECG devices, unlike the data conditions in previous studies that reported high CC. Nevertheless, this study shows results that correspond to or improve upon those of previous studies.

In addition, by improving the structure of the restoration model, it was possible to obtain a robust model. In most previous ECG studies using deep-learning methods, the restoration ECG model was based on LSTM, which is an effective model for extracting signal characteristics [16,21]. LSTM is an effective for extracting features continuous time series data but in general, deep-learning performs poorly with comprehensive datasets, compared with single-label datasets [45–47]. Therefore, previous studies attempted to improve the training performance through ensemble models [28,29,34–36,48]. Xiao et al. used a model combining CNN and LSTM that can extract spatio-temporal features to improve the prediction performance of multivariate time series such as ECG signals. In the combined model, the RMSE was significantly improved compared to the single model. This means that extracting spatiotemporally relevant features is important for performance improvement of the deep-learning model that use data with a long time period [28,29]. Bae et al. combined CNN with LSTM to improve the feature extraction from long signals and compared and analyzed that model against the two components individually [34]. The learning performance of their combined model improved by 2–4 % compared with the single models because LSTM and CNN extract features from the time series and spatial aspects, respectively, and so work in a complementary the missing feature in each method. Zegers and Hamme also used LSTM, CNN, and a combined LSTM-CNN to extract a specific signal from a dataset containing various signals and compared their performances [35]. They reported that the combined LSTM-CNN performed better than the LSTM or CNN alone, and the best performance was secured when the LSTM was made bi-directional in the hyperparameter settings. Therefore, in this study, the reason that the ECG signal was able to be restored with high accuracy despite the data set composed of various diseases in this study is considered to be because it can learn by combining the spatial–temporal features extracted from the two models.

The results of the Bi-LSTM&CNN model is also confirmed by the cosine similarity analysis, which analyzed the morphological similarity of the signals. The vector direction component showed an average similarity of 0.991 between the restored and original ECG signals. Thus, most of the restored and original ECG signals have the same vector direction, which indicates that an accurate regeneration model has been developed. The results from analyzing restored 12-lead ECG according to the 10 Minnesota classification categories also showed high accuracy (Table 5), with an average RMSE of 0.039 μV and a standard deviation of 0.014 μV. This reason is considered to be the result of the characteristics of the model combining LSTM and CNN, as well as data set quality constructed in this study. The dataset used in this study contains 13,862 data, each of which has multiple Minnesota diagnostic names because the data contain all the diagnoses determined by the ECG equipment [31]. Therefore, because each ECG data is composed of several Minnesota diagnoses, at least 2000 data could be secured for each diagnosis. Thus, high accuracy in the regenerated ECGs was obtained for all diagnoses because sufficient data were available for each one.

In the results of this study, the RMSE and cosine similarity values indicated high accuracy for most signals, but relatively low accuracy for V1. There are two reasons for this result. First, in the cosine similarity results, the overall direction was the same. Therefore, this problem could be eliminated by adding a smoothing step to the signal preprocessing step or changing the bandwidth of the bandpass filter, but this study attempted to develop an ECG restoration model that maintains the original signal as much as possible. In a future study, additional preprocessing and model modification should be attempted to improve the performance in the high-frequency range. Second, signals with intermittently low restoration accuracy were generated in the precardiac leads because the dataset contained recordings with extremely abnormal patterns. Because all the diagnostic names provided by the

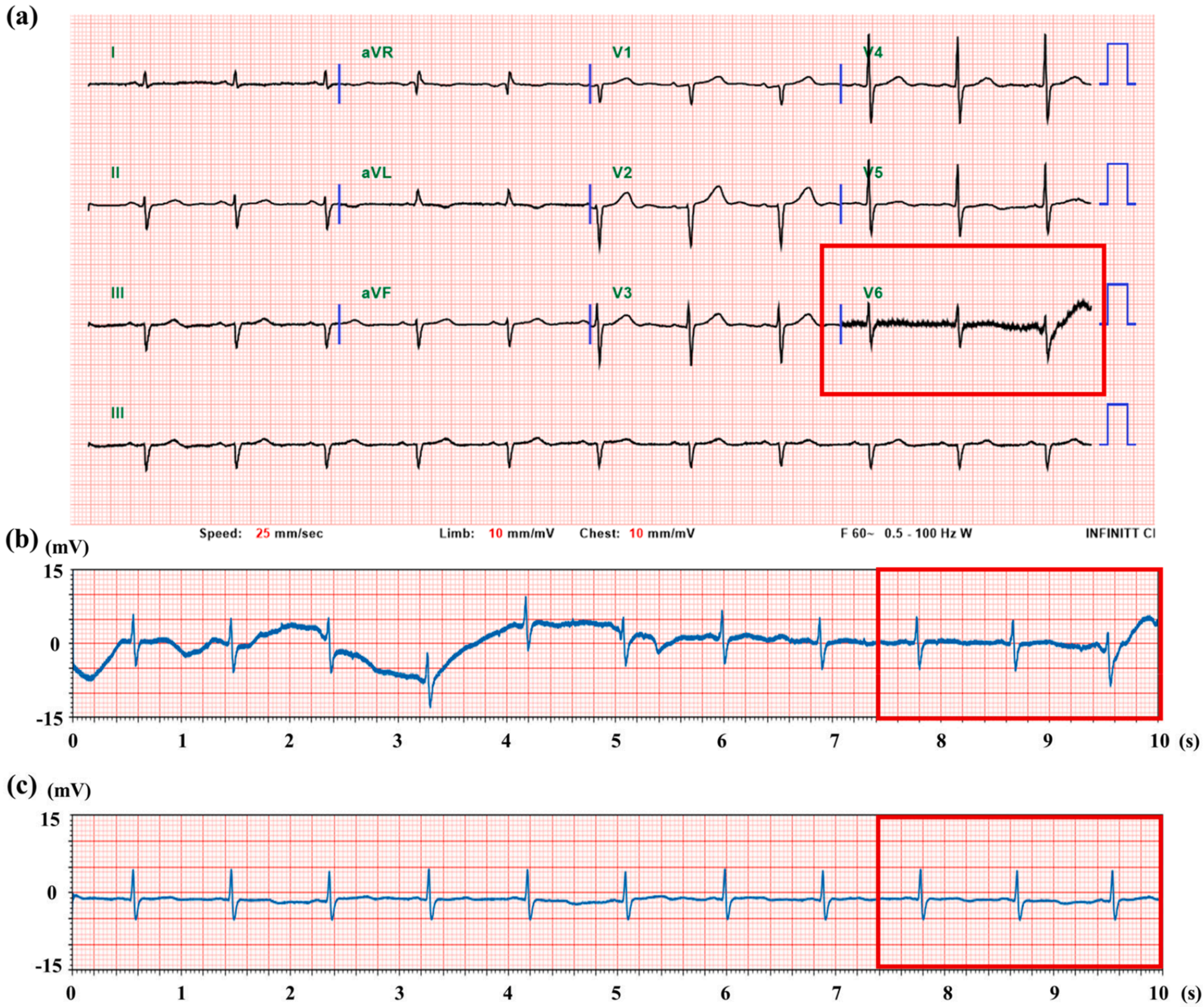

Fig. 5. Clinical case of 12-lead ECG with baseline wander and high-frequency noise and the signal restoration of V6 through the restoration model.

ECG equipment were collected into a single dataset in this study, ECGs of rare diseases with unusual patterns were included. To solve that problem, data sampling for rare diseases with a low probability of occurrence is needed. In addition, although all 12 ECGs showed high overall accuracy, there is a limit that the accuracy may decrease when two or more missing signals. In this study, not only the optimal combinations but also the combinations before the threshold with a small RMSE difference (Fig. 4) can be applied to the ECG restoration model. However, a combination with a low RMSE means a low correlation with the waveform that needs to be restored, resulting in lower accuracy compared to the optimal combination. Therefore, future studies are required to develop a model that ensures accuracy in conditions of low correlation combinations to overcome current limitations.

5. Conclusion

To overcome the problem of low-quality signals and missing signals from 12-lead ECG examinations, an ECG restoration model was developed for each signal. The restoration model for each signal was trained through a Bi-LSTM&CNN ensemble model after the optimal input parameters for each signal were found using an LR. In the 12 models trained using the optimal combinations, the RMSE value between the original and restored signals averaged 0.037 μV, and the cosine simplicity averaged 0.991. Thus, the magnitude and direction of the signal vector restored through the model shows a similar pattern to that of the original signal. The model presented in this study can be used to overcome the low-quality of ECG and missing ECG problem caused by various errors. Furthermore, an ability to restore ECG signals could contribute to the establishment of a synthetic medical dataset for research promotion of medical data that will have no identification problems. Although it was possible to obtain a signal regeneration model with high accuracy through the optimal combination and ensemble model presented in this study, intermittent deterioration of restoration performance occurred in the precordial leads. In future studies, high-frequency restoration performance improvement and additional data sampling should be performed.

6. Ethics approval and consent to participate

This study protocol was approved by the Institutional Review Board of Korea University Anam Hospital (IRB NO. 2021AN0114).

Table 6
Comparison with previous studies of ECG restoration models.

	ECG dataset (Normal: Abnormal)	Source ECG style	Frequency (Hz)	Restoration method	Average CC
Zijan et al.	72 (19:81)	Three bipolar lead	1000	Neural network	0.892
Lee et al.	280 (100:0)	Three bipolar lead	250	Neural network	0.920
Trobec et al.	99 (30:69)	Three bipolar lead	1000	Linear regression	0.959
Tomasic et al.	27 (0:100)	Three bipolar lead	100	Regression trees	0.985
Sohn et al.	60 (50:50)	Three bipolar lead	250	Deep learning	0.950
Atoui et al.	157 (71:29)	Subset of 12-lead ECG	500	Neural network Linear regression	0.948
Smith et al.	319 (0:100)	Subset of 12-lead ECG	1000	Deep learning	0.921
Zhang et al.	549 (19:81)	Subset of 12-lead ECG	1000, 360	Deep learning	0.820
Zhu et al.	39 (20:80)	Subset of 12-lead ECG	250	Linear regression	0.947
Our study	13,862 (24:76)	Subset of 12-lead ECG	500	Deep learning	0.983

Funding

No Funding.

CRediT authorship contribution statement

Hakje Yoo: Conceptualization, Methodology, Software, Validation, Writing – original draft, Writing – review & editing, Visualization, Funding acquisition. **Yunjin Yum:** Data curation, Formal analysis. **Yoojoong Kim:** Methodology, Software. **Jong-Ho Kim:** Conceptualization, Supervision, Project administration. **Hyun-Joon Park:** Supervision, Resources, Data curation. **Hyung Joon Joo:** Conceptualization, Resources, Supervision, Project administration.

Declaration of Competing Interest

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

Data availability

The authors do not have permission to share data.

Acknowledgements

This research was supported by a Digital Healthcare Research Grant through the Seokchun Caritas Foundation (SCY2204P) and by the Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education (No. 2021R1I1A1A01059747).

References

[1] P. Hao, X. Gao, Z. Li, J. Zhang, F. Wu, C. Bai, Multi-branch fusion network for Myocardial infarction screening from 12-lead ECG images, Comput. Methods Programs Biomed. 184 (2020), 105286.
[2] B.J. Maron, R.A. Friedman, P. Kligfield, B.D. Levine, S. Viskin, B.R. Chaitman, P. M. Okin, J.P. Saul, L. Salberg, G.F. Van Hare, Assessment of the 12-lead ECG as a screening test for detection of cardiovascular disease in healthy general populations of young people (12–25 years of age) a scientific statement from the American Heart Association and the American College of Cardiology, Circulation 130 (2014) 1303–1334.
[3] S. McStay, Recording a 12-lead electrocardiogram (ECG), Br. J. Nurs. 28 (2019) 756–760.
[4] A.K. Dohare, V. Kumar, R. Kumar, Detection of myocardial infarction in 12 lead ECG using support vector machine, Appl. Soft Comput. 64 (2018) 138–147.
[5] T.B. Garcia, 12-lead ECG: The art of interpretation, Jones & Bartlett Publishers, 2013.
[6] M. Vafaie, M. Ataei, H.R. Koofigar, Heart diseases prediction based on ECG signals' classification using a genetic-fuzzy system and dynamical model of ECG signals, Biomed. Signal Process. Control 14 (2014) 291–296.
[7] J.R. Hampton, J. Hampton, The ECG made easy e-book, Elsevier Health Sciences, 2019.
[8] M. Matyschik, H. Mauranen, P. Bonizzi, J. Karel, Feasibility of ECG reconstruction from minimal lead sets using convolutional neural networks, 2020 Computing in Cardiology, IEEE, 2020, pp. 1–4.
[9] N. Meziane, S. Yang, M. Shokoueinejad, J. Webster, M. Attari, H. Eren, Simultaneous comparison of 1 gel with 4 dry electrode types for electrocardiography, Physiol. Meas. 36 (2015) 513.
[10] A. Soroudi, N. Hernández, L. Berglin, V. Nierstrasz, Electrode placement in electrocardiography smart garments: A review, J. Electrocardiol. 57 (2019) 27–30.
[11] S.S. Al-Zaiti, Z. Faramand, K. Rjoob, D. Finlay, R. Bond, The role of automated 12-lead ECG interpretation in the diagnosis and risk stratification of cardiovascular disease, in: Cardiovascular and Coronary Artery Imaging, Elsevier, 2022, pp. 45–87.
[12] V. Krasteva, I. Jekova, R. Schmid, Simulating arbitrary electrode reversals in standard 12-lead ECG, Sensors 19 (2019) 2920.
[13] H. Atoui, J. Fayn, P. Rubel, A novel neural-network model for deriving standard 12-lead ECGs from serial three-lead ECGs: application to self-care, IEEE Trans. Inf Technol. Biomed. 14 (2010) 883–890.
[14] D. Lee, H. Kwon, H. Lee, C. Seo, K. Park, Optimal lead position in patch-type monitoring sensors for reconstructing 12-lead ECG signals with universal transformation coefficient, Sensors 20 (2020) 963.
[15] G.H. Smith, D.J. Van den Heever, W. Swart, The reconstruction of a 12-Lead electrocardiogram from a reduced lead set using a focus time-delay neural network, Acta Cardiologica Sinica 37 (2021) 47.
[16] J. Sohn, S. Yang, J. Lee, Y. Ku, H.C. Kim, Reconstruction of 12-lead electrocardiogram from a three-lead patch-type device using a LSTM network, Sensors 20 (2020) 3278.
[17] I. Tomašić, R. Trobec, Electrocardiographic systems with reduced numbers of leads—synthesis of the 12-lead ECG, IEEE Rev. Biomed. Eng. 7 (2013) 126–142.
[18] I. Tomasic, R. Trobec, M. Lindén, Can the regression trees be used to model relation between ECG leads?, International Internet of Things Summit, Springer, 2015, pp. 467–472.
[19] R. Trobec, I. Tomašić, Synthesis of the 12-lead electrocardiogram from differential leads, IEEE Trans. Inf Technol. Biomed. 15 (2011) 615–621.
[20] Z. Xu, R. Zhou, Y. Cao, B. Yong, X. Wang, Q. Zhou, Reconstruction of 12-Lead Electrocardiogram Based on GVM, in: 2018 Sixth International Conference on Advanced Cloud and Big Data (CBD), IEEE, 2018, pp. 275–280.
[21] Q. Zhang, K. Frick, All-ECG: A least-number of leads ECG monitor for standard 12-lead ECG tracking during motion, 2019 IEEE healthcare innovations and point of care technologies,(HI-POCT), IEEE, 2019, pp. 103–106.
[22] H. Zhu, Y. Pan, K.-T. Cheng, R. Huan, A lightweight piecewise linear synthesis method for standard 12-lead ECG signals based on adaptive region segmentation, PLoS One 13 (2018) e0206170.
[23] S. Meek, F. Morris, Introduction. I—Leads, rate, rhythm, and cardiac axis, BMJ 324 (2002) 415–418.
[24] S.P. Nelwan, S.W. Crater, S.H. Meij, T.B. van Dam, Simultaneous comparison of three derived 12-lead ECGs with standard ECG at rest and during percutaneous coronary occlusion, J. Electrocardiol. 37 (2004) 171.
[25] S.P. Nelwan, J.A. Kors, S.H. Meij, J.H. van Bemmel, M.L. Simoons, Reconstruction of the 12-lead electrocardiogram from reduced lead sets, J. Electrocardiol. 37 (2004) 11–18.
[26] I. Tomašić, S. Frljak, R. Trobec, Estimating the universal positions of wireless body electrodes for measuring cardiac electrical activity, IEEE Trans. Biomed. Eng. 60 (2013) 3368–3374.
[27] Q. Cheng, Y. Chen, Y. Xiao, H. Yin, W. Liu, A dual-stage attention-based Bi-LSTM network for multivariate time series prediction, J. Supercomput. (2022) 1–22.
[28] Y. Xiao, K. Xia, H. Yin, Y.-D. Zhang, Z. Qian, Z. Liu, Y. Liang, X. Li, AFSTGCN: Prediction for multivariate time series using an adaptive fused spatial-temporal graph convolutional network, Digital Commun. Networks (2022).
[29] Y. Xiao, H. Yin, Y. Zhang, H. Qi, Y. Zhang, Z. Liu, A dual-stage attention-based Conv-LSTM network for spatio-temporal correlation and multivariate time series prediction, Int. J. Intell. Syst. 36 (2021) 2036–2057.

[30] R.J. Prineas, R.S. Crow, Z.-M. Zhang, The Minnesota code manual of electrocardiographic findings, Springer Science & Business Media, 2009.
[31] H. Yoo, Y. Yum, S. Park, J.M. Lee, M. Jang, Y. Kim, J.H. Kim, H.J. Park, K.S. Han, J. H. Park, H.J. Joo, KURIAS-ECG: A 12-lead electrocardiogram database with standardized diagnosis ontology, J. PhysioNet (2021).
[32] Y. Altay, A. Kremlev, K. Zimenko, A. Margun, The effect of filter parameters on the accuracy of ECG signal measurement, Biomed. Eng. 53 (2019) 176–180.
[33] S.J. Baek, A. Park, Y.J. Ahn, J. Choo, Baseline correction using asymmetrically reweighted penalized least squares smoothing, Analyst 140 (2015) 250–257.
[34] S.H. Bae, I. Choi, N.S. Kim, Acoustic scene classification using parallel combination of LSTM and CNN, Proceedings of the Detection and Classification of Acoustic Scenes and Events 2016 Workshop (DCASE2016), 2016, pp. 11–15.
[35] J. Zegers, Cnn-lstm models for multi-speaker source separation using bayesian hyper parameter optimization, arXiv preprint arXiv:1912.09254, 2019.
[36] R. Zhao, R. Yan, J. Wang, K. Mao, Learning to monitor machine health with convolutional bi-directional LSTM networks, Sensors 17 (2017) 273.
[37] Y. Zhou, H. Zhang, Y. Li, G. Ning, ECG heartbeat classification based on ResNet and Bi-LSTM, in: IOP Conference Series: Earth and Environmental Science, IOP Publishing, 2020, p. 012014.
[38] F. Liu, X. Zhou, T. Wang, J. Cao, Z. Wang, H. Wang, Y. Zhang, An attention-based hybrid LSTM-CNN model for arrhythmias classification, in: 2019, International Joint Conference on Neural Networks (IJCNN), IEEE, 2019, pp. 1–8.
[39] S. Yousefi, H. Sokooti, M.S. Elmahdy, I.M. Lips, M.T.M. Shalmani, R.T. Zinkstok, F. J. Dankers, M. Staring, Esophageal tumor segmentation in CT images using a dilated dense attention Unet (DDAUnet), IEEE Access 9 (2021) 99235–99248.
[40] Q.-S. Xu, Y.-Z. Liang, Monte Carlo cross validation, Chemom. Intel. Lab. Syst. 56 (2001) 1–11.
[41] T. Chai, R.R. Draxler, Root mean square error (RMSE) or mean absolute error (MAE)?–Arguments against avoiding RMSE in the literature, Geosci. Model Dev. 7 (2014) 1247–1250.
[42] T. Apaydin, H. Ferhatosmanoglu, Access structures for angular similarity queries, IEEE Trans. Knowl. Data Eng. 18 (2006) 1512–1525.
[43] M.G. Kim, S.B. Pan, A study on user recognition using the generated synthetic electrocardiogram signal, Sensors 21 (2021) 1887.
[44] H. Atoui, J. Fayn, P. Rubel, A neural network approach for patient-specific 12-lead ECG synthesis in patient monitoring environments, in: Computers in Cardiology, 2004, IEEE, 2004, pp. 161–164.
[45] J. Brownlee, Feature selection to improve accuracy and decrease training time, Machine Learning Mastery (2014).
[46] D. Chen, S. Liu, P. Kingsbury, S. Sohn, C.B. Storlie, E.B. Habermann, J.M. Naessens, D.W. Larson, H. Liu, Deep learning and alternative learning strategies for retrospective real-world clinical data, NPJ Digital Med. 2 (2019) 1–5.
[47] X. Yuan, L. Xie, M. Abouelenien, A regularized ensemble framework of deep learning for cancer detection from multi-class, imbalanced training data, Pattern Recogn. 77 (2018) 160–172.
[48] L. Guo, D. Zhang, L. Wang, H. Wang, B. Cui, CRAN: A hybrid CNN-RNN attention-based model for text classification, in: International Conference on Conceptual Modeling, Springer, 2018, pp. 571–585.