

Evaluation of a Wrist-Worn Device for ECG-Based Detection of Acute Myocardial Infarction

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Abstract—Objective: To determine whether a two-lead ECG (wECG), acquired using a self-applicable, wrist-worn device, provides diagnostic value in acute myocardial infarction (AMI) detection. **Methods:** Seventy-one patients with AMI, 26 with other cardiovascular diseases (CVDs), and 54 healthy controls were enrolled in the study. To acquire lead I, one electrode of the wrist-worn device was touched with the index finger of the opposite hand, while another lead was acquired by touching the electrode on the strap to a specific part of the body. The diagnostic value of the wECG is evaluated either directly or through synthesis of the standard 12-lead ECG using an echo state network. **Results:** Using the standard ECG, an AMI detector based on a convolutional neural network yields a sensitivity of 0.86 and a specificity of 0.71; the corresponding figures for blinded cardiologist diagnosis are 0.77/0.88. Using the synthesized ECG, the V3 electrode touch site yields the best performance, with a sensitivity/specificity of 0.84/0.71 for AMI detection and 0.67/0.86 for cardiologist diagnosis. Compared to the synthesized ECG across all touch sites, use of the wECG results in a substantially lower sensitivity, reduced by 0.12–0.13, while the specificity is comparable or slightly higher. Implementation of a two-stage approach, consisting of detector-based screening followed by cardiologist review of positive cases, results in correct decisions in 63% of the AMI cases using either the synthesized ECG or the wECG. **Conclusion:** The two-lead ECG acquired with a wrist-worn device offers diagnostic value and enables screening for AMI.

Clinical and Translational Impact Statement: This work enables AMI detection using a two-lead ECG acquired with a wrist-worn device, either directly or through synthesis of the 12-lead ECG, supporting cardiovascular diagnostics in remote and resource-limited environments. (Category: Clinical Research)

Keywords—Wearable device, screening, echo state network, individual-specific model, convolutional neural network

I. INTRODUCTION

TIMELY interventions in the population under 75 years of age could prevent two out of three deaths [1], with acute myocardial infarction (AMI) standing out as one of the primary causes. The life-threatening consequences of delayed treatment represent a serious social issue, as every delayed minute from symptom onset to intervention worsens the clinical outcome [2, 3, 4]. As AMI is becoming increasingly common, even among those without cardiovascular risk factors [5], this issue demands major efforts to raise the awareness among those experiencing AMI-related symptoms. Therefore, the availability of affordable, user-friendly technology capable of alerting individuals about a potential AMI plays an important role in preventing avoidable deaths [6].

Despite the growing interest in healthcare applications of smart devices [7], evidence supporting their use for AMI detection remains scarce. For instance, research on AMI detection using wrist-worn devices is still in its early stage and largely limited to case studies and manual interpretation [8, 9, 10]. This is mainly because smartwatches can acquire only a single-lead ECG, which is insufficient for accurately diagnosing complex conditions like AMI. To address this insufficiency, sequential 12-lead acquisition has

been explored [11, 8]. However, such an approach is time-consuming, requires knowledge of electrode placement, and introduces errors due to lead misplacement and asynchronous ECG [12].

With the availability of a self-applicable, wrist-worn device capable of acquiring a two-lead ECG (hereafter referred to as a wECG) with a single touch [13], new opportunities arise for cardiac disease screening. As lead I and an additional lead involving a specific touch site, such as a precordial, are acquired, the wECG can be used either directly for analysis [13] or to synthesize the standard 12-lead ECG [14]. An important question is to what extent the wECG can preserve features indicative of AMI.

The main challenge with wECG-based AMI detection is that two leads cannot reflect the infarct location as accurately as does the standard 12-lead ECG. Nonetheless, two leads provide richer information than does a single lead [14] because both a limb lead and a precordial lead can be acquired. The choice of touch site used to acquire the precordial lead plays a role in detection as certain AMI hallmarks may only be observed for certain sites. Another challenge is signal quality which tends to be lower than that of standard ECG leads acquired during rest with gel electrodes.

While the wECG cannot replace the standard 12-lead ECG, it can facilitate specific clinical tasks [15]. For example, AMI detection can be handled by a two-stage approach which first acquires the wECG at scheduled time intervals or when symptoms arise and performs detection based on machine learning [16]. Then, if abnormalities are detected, the wECG or, likely better, the synthesized ECG, is forwarded to a cardiologist for manual interpretation. To advance this

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approach, two key questions need to be addressed: Do features extracted from the wECG fall within acceptable error limits for automated analysis? Can the wECG provide diagnostic value comparable to that of the standard ECG?

The key contributions of this paper are as follows: (1) performance evaluation of an AMI detector based on a convolutional neural network (CNN) using the wECG, the synthesized 12-lead ECG, and the standard 12-lead ECG; (2) comparison of the detection performance to blinded diagnosis of cardiologists; and (3) evaluation of a two-stage approach combining CNN-based screening with cardiologist review. A tailored dataset comprising AMI patients, patients with other cardiovascular diseases (CVDs), and healthy controls is used.

The paper is structured as follows: Section 2 describes the dataset and Sec. 3 covers the machine learning models used to synthesize the 12-lead ECG and to detect AMI. Section 4 presents the results, including the discriminative power of AMI-related features, AMI detection performance, and the diagnostic evaluation of cardiologists. Section 5 concludes the paper with a discussion.

II. DATASET

Study population

A total of 151 participants were enrolled in the study, including 71 patients with AMI, 26 patients with other CVDs, and 54 healthy controls. Eligible participants were adults (≥ 18 years) without an implanted cardiac device or cognitive or/and linguistic deficits. The AMI group included patients diagnosed with ST elevation myocardial infarction (STEMI) or non-STEMI (NSTEMI) whose ECGs were acquired within 24 hours after percutaneous coronary intervention. The other CVDs group included patients with conditions causing infarction-like ECG deviations, such as acute pericarditis and bundle branch blocks. The healthy group had no history of CVDs. The participants were enrolled from the Cardiology Department at Vilnius University Hospital Santara Clinics in Lithuania. Informed written consent was obtained from all participants in accordance with the Declaration of Helsinki. The study was approved by Vilnius Regional Biomedical Research Ethics Committee under Application No. 158200-18/7-1052-557.

Wrist-worn device and lead configurations

A self-applicable, wrist-worn device, developed at the Biomedical Engineering Institute, Kaunas University of Technology, was used to acquire two leads via three embedded biopotential electrodes. The device was placed on the left wrist, with lead I obtained by touching an electrode with the right index finger and the other lead by touching a specific body site. The examined sites included the standard V3 and V5 positions, just below the biopotential electrodes, and the abdomen (A), 2 cm to the left of the umbilicus. In such a way, leads were obtained between the left arm (LA) and the aforementioned sites, labeled V3-LA, V5-LA, and A-LA, see

Fig. 1. All these recordings were acquired with the guidance of a cardiologist. After acquiring lead A-LA, the participants acquired by themselves the same lead without cardiologist assistance, denoted A-LA^w. Self-acquisition was evaluated only for the abdominal site (A-LA) because it can be located without identifying intercostal spaces. Each recording lasted about one minute, with at least a one-minute interval between recordings. For each touch site, the standard resting 12-lead ECG was acquired simultaneously.

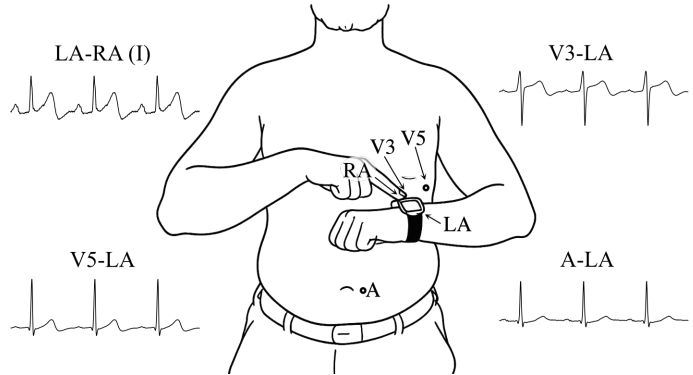


Fig. 1. wECG acquisition using a wrist-worn device equipped with three biopotential electrodes located at its base, at its upper end, and on the strap. Lead I is obtained by touching the upper electrode with the right index finger, while the strap electrode is placed at V3, V5, or 2 cm to the left of the umbilicus to obtain V3-LA, V5-LA, or A-LA, respectively.

III. METHODS

Both the wECG and the standard 12-lead ECG (12view Euroholter, Lumed, Italy), sampled at 500 Hz, were filtered using a forward-backward bandpass filter with cutoff frequencies at 0.5 Hz and 100 Hz to reduce the influence of baseline wander and muscle noise.

Some elderly participants struggled to maintain consistent pressure on the electrode, resulting in fewer wECGs of sufficient quality. Poor-quality ECGs were excluded using the *bsqi* index [17] together with an acceptance threshold of 0.65 [14]. The percentage of wECGs that met the signal quality criterion was lowest for the I and A-LA^w configuration in the AMI and other CVD groups, with 61% and 63% of the recordings retained, respectively. In contrast, more than 90% of the self-acquired recordings were retained in the healthy group. Participant demographics and data availability are detailed in Table I. The wECG dataset is available through the open-access portal Zenodo [18].

Individual-specific 12-lead ECG synthesis

Figure 2 illustrates the individual-specific synthesis of a 12-lead ECG using the echo state network (ESN)—a fixed, sparsely connected, recurrent neural network belonging to the reservoir computing family [19]. The ESN is particularly well-suited for physiological signal processing due to its ability to capture temporal dependencies and to provide a computationally efficient training process [20, 21, 22, 23].

The ESN consists of an input layer, a large reservoir of neurons, and an output layer, each represented by its weight

TABLE I
PARTICIPANT DEMOGRAPHICS AND DATASET COMPOSITION.

	AMI	Other CVDs	Healthy
Men	50	20	30
Women	21	6	24
Age, yrs	62.3 ± 12.4	58.7 ± 16.3	27.3 ± 7.8
Height, m	1.73 ± 0.09	1.75 ± 0.08	1.75 ± 0.11
Weight, kg	87.2 ± 15.1	90.4 ± 18.6	72.9 ± 13.2
BMI, kg/m ²	28.9 ± 4.3	29.7 ± 6.3	23.6 ± 3.0
AMI type			
NSTEMI	10		
STEMI	61		
AMI location			
Anterior	42		
Lateral	23		
Inferior	20		
Other CVDs			
Right bundle branch block	4	6	
Left bundle branch block	3	6	
Atrial fibrillation		2	
Myocarditis		4	
Pericarditis		2	
Conduction disorder		2	
Left ventricular hypertrophy		3	
Prior infarction	5	5	
Aortic stenosis		2	
Test dataset composition			
I & V3-LA	59 (83%)	23 (89%)	49 (91%)
I & V5-LA	57 (80%)	21 (81%)	48 (89%)
I & A-LA	46 (65%)	19 (73%)	50 (93%)
I & A-LA ^w	43 (61%)	16 (62%)	49 (91%)

Note: In some STEMI patients, infarction affected multiple heart regions, resulting in a larger number of locations. For each of the four lead configurations, the number and related percentage of recordings that met the signal quality criterion are presented for each of the three groups.

matrix. The input layer is defined by an $M \times 2$ matrix $\mathbf{W}_{in}$, where M is the number of neurons in the reservoir. The role of the input layer is to map the wECG to the reservoir, and, therefore, the identity activation function is used for the neurons. To control the degree of nonlinearity in the reservoir, $\mathbf{W}_{in}$ is scaled by the input factor a . If the scaled input samples are close to zero, the reservoir neurons, whose activation function is taken to be a hyperbolic tangent, will operate in regions that are mostly linear. Conversely, excessively large input samples can drive the activation function into saturation.

The reservoir layer, defined by an $M \times M$ weight matrix $\mathbf{W}$, acts as a nonlinear, excitable medium transforming the wECG into nonlinear “echoes”. The recurrent connections within the reservoir are randomly initialized and sparsely connected. It is important to ensure that the reservoir satisfies the echo state property [24], meaning that it responds primarily to the wECG rather than reflects its initial state. The echo state property depends on the characteristics of $\mathbf{W}$ and the hyperparameters, especially the spectral radius ρ .

The output layer, defined by an $8 \times (M+2)$ matrix $\mathbf{W}_{out}$, is the only trainable layer of the ESN. The matrix transforms the reservoir states and the wECG to the synthesized 12-lead ECG. The identity activation function is chosen for the output layer neurons. To determine $\mathbf{W}_{out}$, the 12-lead resting ECG and the wECG are simultaneously acquired in each participant.

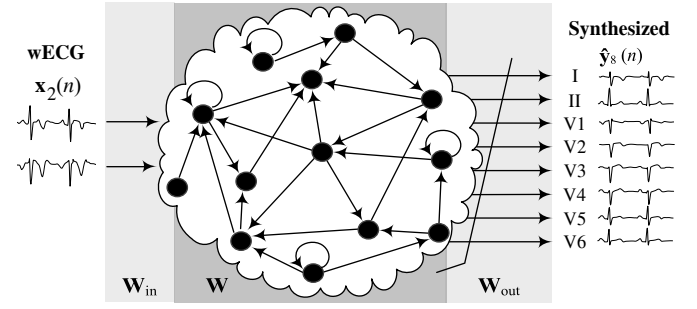


Fig. 2. Individual-specific ECG synthesis from two leads acquired with a single touch of a wrist-worn device. Synthesis of eight leads is based on an ESN acting as nonlinear, excitable medium to the wECG. The remaining leads III, aVR, aVL, and aVF are derived from leads I and II.

Details regarding the use of the ESN to synthesize the 12-lead ECG from the two-lead wECG, including hyperparameter selection, are provided in [14]. The reservoir size M , which plays a key role in determining memory capacity, is set to 1000 neurons. A larger M improves the learning of the transfer function between the wECG and the 12-lead ECG. However, an excessively large reservoir generally leads to overfitting. The echo state property is ensured by setting a to 0.6 and ρ to 1. The standard deviation σ_v is set to 0.001 to prevent overfitting.

A number of other hyperparameters also have to be set. Since the ECG synthesis does not benefit from feedback connections between the output and the reservoir, the feedback scaling factor is set to 0. The leakage rate of the reservoir neurons, which governs the memory decay, is set to 1. The reservoir sparsity, which has little or no impact on performance but speeds up the computations, is set to 10%. Each lead of the wECG is adjusted so that its mean is 0 before inputted to the ESN. Further information on the hyperparameter settings is found in [14].

A separate individual-specific ESN was determined for each wECG configuration. Accordingly, up to four 12-lead ECGs were synthesized for each participant using I and V3-LA, I and V5-LA, I and A-LA, and I and A-LA^w as input. The first 30 s of each recording were used to learn the ESN transfer function between the wECG and the standard 12-lead resting ECG, while the remaining 30 s were used to synthesize the 12-lead resting ECG for evaluation.

Extraction of clinical AMI features

The standard features used to characterize AMI, i.e., Q wave amplitude (A_Q) and duration (D_Q), R wave amplitude (A_R), QRS duration (D_{QRS}), ST deviation (Δ_{ST}), and T wave amplitude (A_T) [25] are extracted from the average beat of each lead [14]. Wave onset and end are determined using a validated wavelet-based delineator [26]. Wave amplitude is measured relative to the baseline in the PR segment.

To evaluate the discriminative power of each feature in detecting AMI, the sum of its absolute values across all leads is analyzed [27]. This definition of sum is preferred over the mean as it avoids that features prominent in only a few leads are averaged out. For both the standard and the synthesized

ECGs, the sum is computed from the eight leads, whereas for the wECG the sum is computed from the two leads. By varying the threshold applied to the sum, the receiver operating characteristic (ROC) can be computed, and the area under the curve (AUC) used as performance measure.

AMI detection using a convolutional neural network

The AMI detector uses a 1D CNN consisting of three convolutional blocks. Each block contains eight filters with a 1×15 kernel and a stride of 1, followed by a 1×2 average pooling layer with a stride of 2. The rectified linear unit activation function is used for nonlinearity throughout the network. A dropout rate of 0.1 is applied after each layer to reduce overfitting. The output of the final convolutional block is flattened and passed through a fully connected layer with 128 neurons, followed by another dropout layer. A second fully connected layer outputs class scores (AMI vs. non-AMI), with a softmax activation applied to produce probability distributions. The model is trained using the Adam optimizer [28] with a learning rate of 0.001. The detection threshold, determined as the point on the ROC curve closest to the upper-left corner, is 0.03.

Three detectors are evaluated, using as input either a two-lead average beat obtained from a single-touch, represented by a 500×2 matrix, or a 12-lead average beat of the standard or the synthesized ECG, represented by 500×12 matrices; for details on beat averaging, see [14, 16].

The detector is trained on a subset of the Physikalisch-Technische Bundesanstalt PTB-XL dataset (v1.0.3) [29], comprising 238 10-s, standard 12-lead ECGs sampled at 500 Hz from AMI patients (100 women, 138 men; age: 68.5 ± 12.2 yrs). Only ECGs labeled “stadium I”, “stadium I-II”, and “stadium II” (acute/subacute infarction) were included. The subset also contains 685 ECGs (392 women, 293 men; age: 52.3 ± 16.6 yrs) labeled as normal. The detector using the wECG is trained on the same database, however, because the lead between LA and a specific site is nonstandard, ECGs from the PTB-XL dataset were converted to match the wECG [16]. One average beat was computed from each recording, resulting in 238 AMI average beats and 685 normal average beats. The ECGs were randomly split into training and validation sets with an 80:20 ratio.

Evaluation by cardiologist

Three cardiologists were asked to diagnose AMI, adhering to well-established rule-based criteria. The cardiologists were blinded to whether the 12-lead ECG was standard or synthesized. For STEMI, the cardiologists had to specify the infarct location by choosing from anterior, septal, lateral, inferior, and posterior. Since ST depression does not localize the ischemic area, the location in patients with NSTEMI was not determined.

The feasibility to diagnose AMI using the wECG was also evaluated.

Performance evaluation

Bland–Altman plots are used to assess the amplitude- and duration-based features extracted from the standard and the synthesized ECGs. The relation is expressed using Pearson's correlation coefficient.

Both detection and diagnostic performance are expressed in terms of sensitivity, defined as the number of correctly identified infarcts divided by the total number of infarcts, and specificity, defined as the number of correctly identified non-infarcts divided by the total number of non-infarcts. These two measures serve as the basis for judging the diagnostic value of lead synthesis.

To assess the stability of the training process, each CNN was independently initialized and trained 100 times. The sensitivity and specificity were computed on the test dataset for each run. The results are presented as the mean and 95% confidence interval.

To assess the level of agreement among the three cardiologists when evaluating the same ECG, as well as the agreement between the standard and the synthesized ECGs for each cardiologist, Fleiss's κ is computed.

IV. RESULTS

Synthesis examples

Figure 3 illustrates the standard and the synthesized ECGs for a patient with AMI and a patient with right bundle branch block. The synthesis is accurate in terms of wave morphology, and, importantly, Q waves, ST segments, and T waves are well-reproduced. A slight reduction in T wave amplitude is observed in lead V1 for the patient with right bundle branch block.

Feature agreement

Figure 4 illustrates the agreement between AMI features determined from the standard and the synthesized ECGs. All features are extracted with negligible difference; the occasional outliers primarily result from problems associated with the wave delineation. Such problems occur regardless of whether the ECG is standard or synthesized.

For A_Q , outliers occur in 1.7% (26/1572) of all beats, typically due to when a small Q wave is missed or a low-amplitude R wave is incorrectly identified as a Q wave. For A_R , outliers are observed in 2.7% (42/1572) of all beats, often due to when the R and S waves have similar amplitudes leading to misidentification of the S wave. For A_T , outliers occur in 3.4% (54/1572) of all beats, often due to a flattened T wave.

Feature discriminative power

AUCs for AMI detection, based on the sum of absolute feature values across all leads of the standard ECG, the synthesized ECG, and the wECG indicate that the features extracted from the synthesized ECG show a discriminative power comparable to that of the standard ECG, see Fig. 5. When analyzing individual features computed from the synthesized ECG, A_R and A_T exhibit the greatest discriminative power,

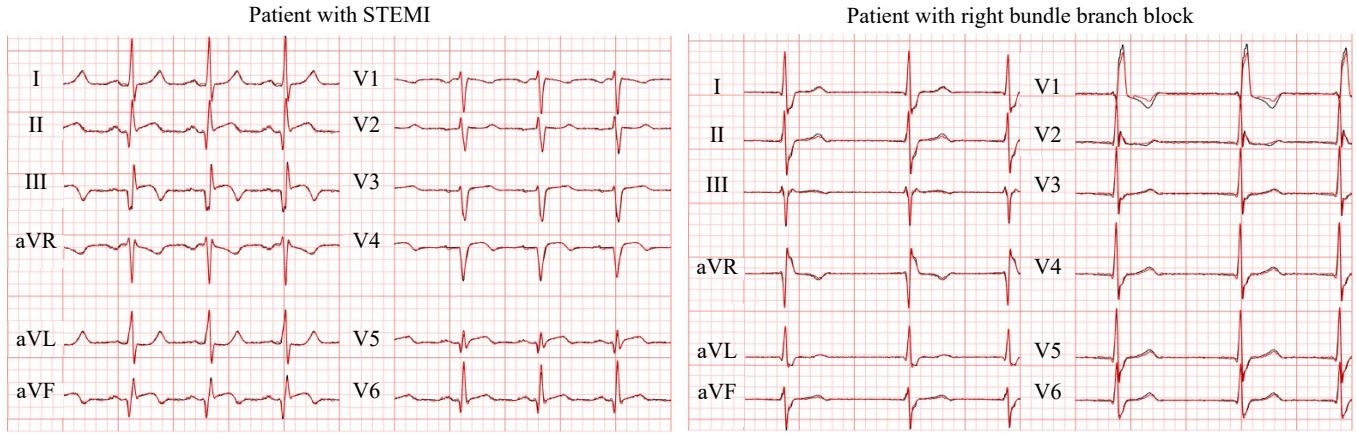


Fig. 3. Examples of the standard and the synthesized 12-lead ECGs, displayed in black and red, respectively.

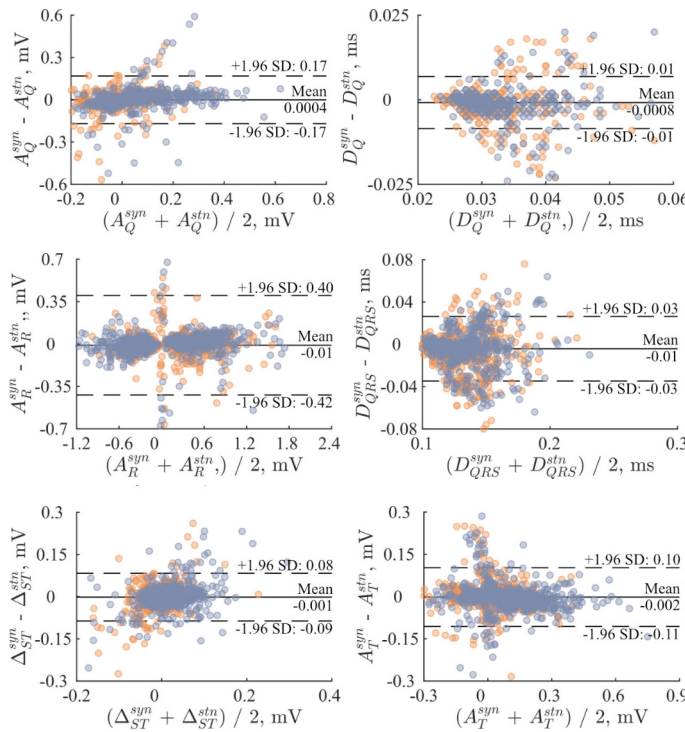


Fig. 4. Bland-Altman plots for AMI features extracted from the standard ECG (superscript “stn”) and the synthesized ECG (superscript “syn”) from leads I and V3-LA. Data from all leads are pooled. Blue and orange dots indicate limb and precordial leads, respectively.

with AUCs ranging from 0.77 to 0.83 and from 0.78 to 0.79, respectively. Across all lead configurations, the discriminative power of the features extracted from the wECG is lower than that of the features extracted from the standard and the synthesized ECGs.

AMI detection/diagnosis performance

Figure 6 shows the detection performance when the CNN-based detector was initialized and trained 100 times for each participant followed by averaging of the resulting sensitivity and specificity. The best performance is obtained for the

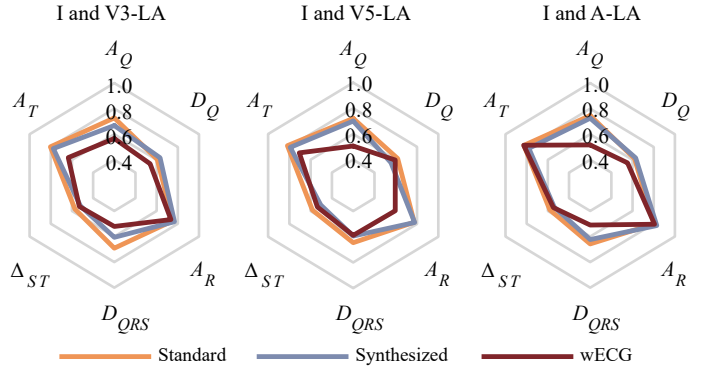


Fig. 5. AUCs for AMI detection based on the sum of absolute feature values presented for the three different lead configurations used for synthesis.

standard 12-lead ECG, yielding a sensitivity of 0.86 (95% CI: 0.85–0.87) and a specificity of 0.71 (95% CI: 0.70–0.72). However, almost identical performance is obtained for the synthesized ECG using I and V3-LA, resulting in a sensitivity of 0.84 (95% CI: 0.83–0.86) and a specificity of 0.71 (95% CI: 0.70–0.73). Notably, when patients with other CVDs are excluded, the specificity for both the standard and the synthesized ECGs increases to 0.96.

Compared to the synthesized 12-lead ECG across all touch sites, detection using the wECG has a substantially lower sensitivity of 0.12–0.13; while the specificity is comparable or slightly higher. When the wECG is acquired with and without cardiologist assistance, the performance is similar, with sensitivity/specificity of 0.70/0.73 and 0.73/0.76, respectively. The slightly better performance obtained without assistance can be attributed to inaccurate touch sites, which to some extent alter the obtained morphology of the wECG.

The cardiologists' diagnosis of AMI was found to favor specificity over sensitivity for all three types of ECG. Using the standard ECG, a sensitivity/specificity of 0.77/0.88 is achieved, whereas the corresponding numbers for the synthesized ECG are 0.67/0.86. Using the wECG, the highest sensitivity (0.74) is achieved using leads I and V3-LA, compared with 0.66–0.67 for other lead configurations. The opposite tendency is observed for specificity: 0.66 for I and

V3-LA versus 0.76 for other configurations. The substantial decrease in specificity compared to those of the standard and the synthesized 12-lead ECGs is likely explained by the cardiologists' unfamiliarity to the non-standard lead, whose wave morphology was likely interpreted as AMI.

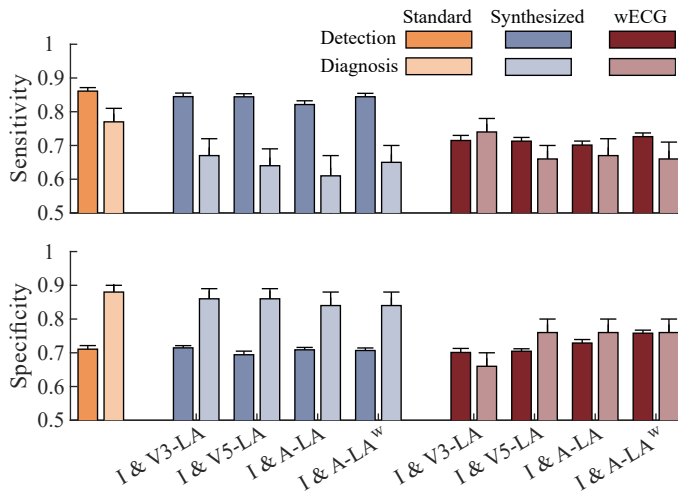


Fig. 6. Performance of the CNN-based AMI detector, using the standard ECG, the synthesized ECG, and the wECG, compared with the cardiologists' diagnosis. Results are presented as the mean and 95% confidence interval.

Decision agreement

Inter-cardiologist agreement, reflecting consistency among the cardiologists when evaluating the same ECG, is highest for the standard ECG, with a Fleiss' κ of 0.62, see Table II. Moderate inter-cardiologist agreement is observed for the synthesized ECG and the wECG, with κ ranging from 0.45 to 0.55 and from 0.48 to 0.56, respectively.

Intra-cardiologist agreement, reflecting consistency between diagnoses based on the standard and the synthesized ECGs for each cardiologist, is substantial for leads I and V3-LA, with a κ of 0.75. The ECG synthesized from the self-acquired wECG is associated with the lowest inter- and intra-cardiologist agreement, 0.37 and 0.59, respectively.

When evaluating the wECG, the intra-cardiologist agreement is lower, with κ ranging from 0.50 to 0.59.

TABLE II
INTER- AND INTRA-CARDIOLOGIST AGREEMENT FOR AMI DIAGNOSIS.

	Inter-cardiologist agreement		Intra-cardiologist agreement	
	Synthesized	wECG	Synthesized	wECG
I & V3-LA	0.55	0.56	0.75	0.50
I & V5-LA	0.54	0.55	0.69	0.59
I & A-LA	0.45	0.48	0.71	0.55
I & A-LA ^w	0.37	0.49	0.59	0.52

Figure 7 shows the overlap between CNN-based AMI detection and cardiologist diagnosis across the standard ECGs, the synthesized ECGs, and the wECGs for correct and incorrect decisions.

For correct decisions, the highest pairwise overlap among detectors is between the standard and the synthesized ECGs

(92%), followed by the standard ECG and the wECG (82%) and the synthesized and the wECG (80%). For cardiologist diagnosis, the overlap between the standard and the synthesized ECG is 87%, between the standard and the wECG 78%, and between the synthesized and the wECG 82%. The cross-overlap between detection and diagnosis is similar: 81% for the standard ECG, 85% for the synthesized ECG, and 79% for the wECG.

For incorrect decisions, the overlap is much lower. Among detectors, the overlap is 73% for the standard vs. the synthesized ECG, 40% for the standard vs. the wECG, and 37% for the synthesized vs. the wECG. For cardiologist diagnosis, the overlap is 48% for the standard vs. the synthesized ECGs, 32% for the standard vs. the wECG, and 51% for the synthesized vs. the wECG. The cross-overlap ranges from 20% for the standard ECG to 47% for the wECG.

Two-stage approach to AMI diagnosis

Figure 8 shows the results from using a two-stage approach combining screening using a CNN-based detector and a subsequent cardiologist's review of AMI-positive cases for diagnostic confirmation. Since screening is more sensitive than the cardiologist's diagnosis, a greater number of positive AMI decisions is passed for review: 73 for the standard ECG, 70 for the synthesized ECG, and 63 for the wECG. Of these positive decisions, 43 (73% of all AMI cases), 37 (63%), and 37 (63%), respectively, are correctly confirmed.

V. DISCUSSION

The main finding of this study is that the 12-lead ECG, synthesized from the two-lead wECG, shows considerable promise for AMI detection, irrespective of whether a cardiologist or a CNN makes the final decision. The AMI detector emphasized sensitivity over specificity, whereas the cardiologists emphasized specificity as more AMI cases were missed in exchange for fewer false positives. The emphasis on specificity is consistent with findings from previous studies on STEMI diagnosis using the standard ECG. For example, a sensitivity/specificity of 0.65/0.79 were reported in [30].

A. AMI detection/diagnosis

When AMI was diagnosed by the cardiologists using the synthesized ECG, the specificity decreased by only 0.02–0.04 relative to that of the standard 12-lead ECG. However, a more substantial drop was observed in sensitivity, which decreased by 0.10–0.16 depending on touch site. When AMI was diagnosed using only the wECG, the sensitivity was comparable to that of the synthesized ECG while the specificity decreased. This suggests that relying on just two wECG leads, of which one is non-standard, complicates ECG interpretation and increases the likelihood of false positives, thereby supporting the need for 12-lead synthesis.

The CNN-based AMI detector, bypassing traditional feature engineering using average beats as input, was chosen over a detector relying on clinical features due to its slightly better performance when analyzing wECGs [16]. Using the same

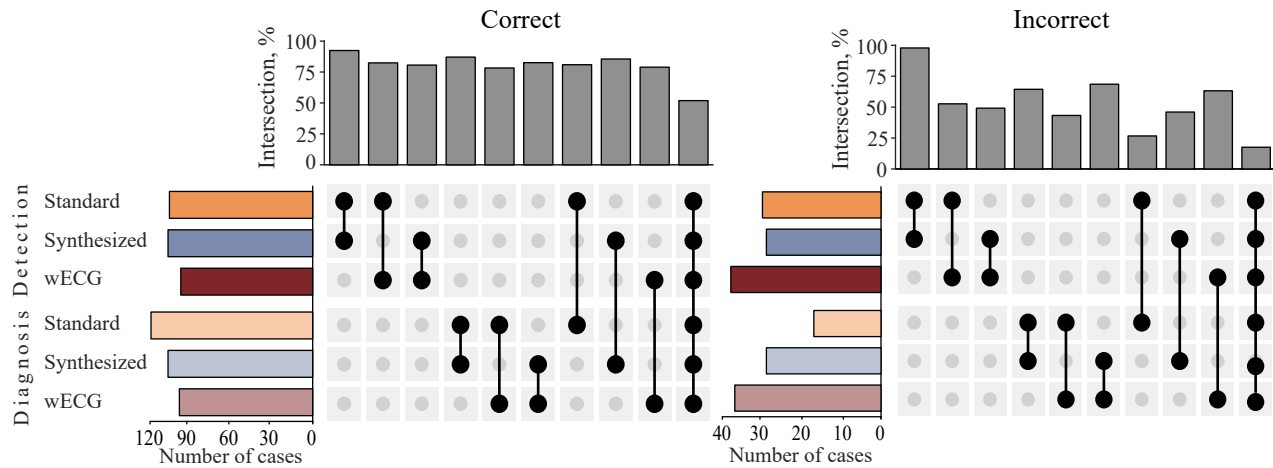


Fig. 7. UpSet plot illustrating the overlap between CNN-based AMI detection and cardiologist diagnosis for the standard ECG, the synthesized ECG, and the wECG. The title 'correct' includes both correctly identified AMI and correctly identified non-AMI cases. Rows represent the total number of correct and incorrect cases. Black circles connected by vertical lines show the modalities included in a given intersection, while top bars show the number of ECGs belonging to each intersection. The final decision of the cardiologist diagnosis is determined by majority voting.

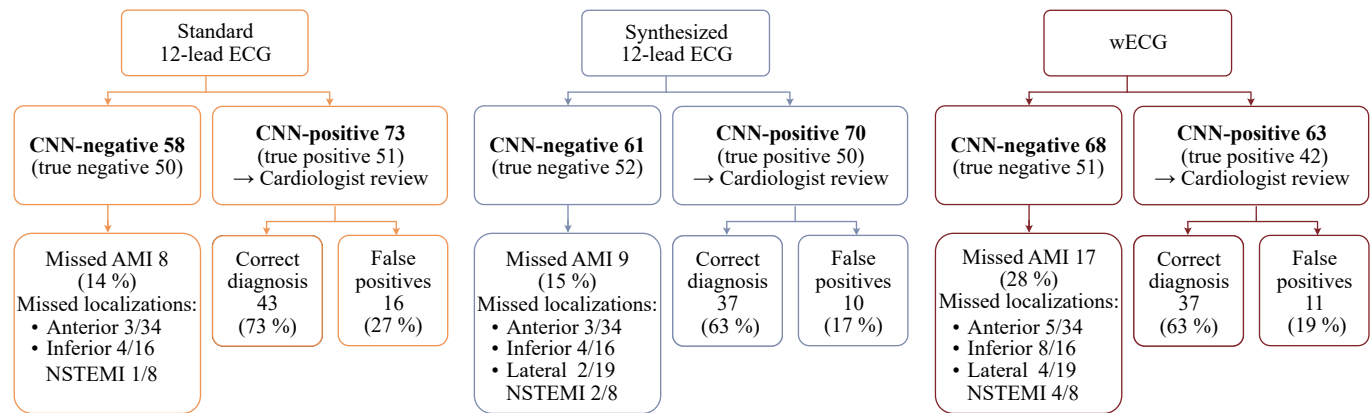


Fig. 8. Two-stage approach to early diagnosis combining CNN-based screening and cardiologist review. The final diagnosis is determined by majority voting.

detector architecture as in [16] but with 12 leads synthesized from I and V3-LA instead of just two leads, the sensitivity increased by 0.13, while the specificity decreased by 0.01. It should be noted that both the sensitivity and the specificity were much higher on the validation dataset, being 0.93 and 0.97, respectively. This can be attributed to the fact that the training and validation datasets did not include ECGs from patients with other CVDs.

The sum of absolute ST-segment deviations has previously been considered for AMI detection using the ECG synthesized from the EASI electrode placement [27]. In that study, the AUC was 0.64 for the synthesized ECG, which is superior to the AUCs in our study, yielding 0.51–0.53 depending on the lead configuration used for synthesis. The poorer discriminative power obtained in our study is likely due to the fact that the EASI system provides three ECG leads, and therefore contains more information. Another contributing factor is likely the better signal quality, as standard electrodes were used in [27].

B. Wrist-worn device

The diagnostic value of the wrist-worn device has previously been explored in the context of atrial fibrillation diagnosis [13], however, that work did not involve ECG synthesis. Instead, atrial fibrillation was diagnosed using six leads, of which four were derived from the two-lead wECG. Although no additional information was obtained beyond the two leads, the familiarity of the cardiologists with the conventional ECG format contributed to improved diagnostic accuracy [13].

For wrist-worn devices the challenge lies not only in the number of leads but, as already noted, the lower signal quality. Simultaneous ECG acquisition, as considered in [11, 8], increases the risk of obtaining leads of poor quality, which ultimately can lead to ECG loss. The approach explored in this study, where one electrode is touched with a finger while the other makes contact with a specific body site, is also susceptible to ECG loss due to noisy leads. We observed that the wECG obtained by touching the electrode on the body, i.e., V3-LA, V5-LA, A-LA, have generally a signal quality comparable to that of lead I, which is acquired via finger contact. This finding does not support the assumption that finger contact provides better signal quality due to lower

impedance associated with thinner skin and higher moisture at the fingertips.

The present study was restricted to examining three body touch sites, however, other touch sites, such as V2, might enhance the accuracy of synthesizing precordial leads. Prior research has identified V2, V3, and V4 as the most informative leads for synthesis [31]. Our decision to focus on V3, V5, and the abdomen was primarily influenced by the limited range of motion often observed in elderly individuals. As a result, we excluded the V1 and V2 touch sites due to the difficulties some patients faced in reaching these sites. Based on the performance results, the V3 touch site was found preferable; however, caution is needed in certain cases. For example, accurately locating precordial leads can be challenging in women and obese individuals [32]. Therefore, the abdominal touch site may be the most practical option for individuals without proper training.

C. 12-lead ECG synthesis

Numerous efforts have been made to synthesize the 12-lead ECG from a reduced subset of leads often part of the standard 12-lead ECG [33]. The resulting synthesized ECG has shown value in diagnosing cardiac abnormalities [27, 34], particularly when at least one precordial lead is included next to the limb leads. For example, lead configurations I, II, V1, and V6 [35], and I, II, V1, and V5 [36], resulted in diagnostic performance comparable to that of the standard 12-lead ECG in distinguishing between normal and abnormal cardiac conditions. Research has demonstrated that three leads are often sufficient for identifying acute coronary syndromes [37, 34].

Most studies have used universal models for ECG synthesis, however, individual-specific models have consistently demonstrated superior performance [38, 39, 33]. Although universal models have the advantage of not requiring individual-specific training, such models do not account for inter-individual differences, e.g., sex, thoracic anatomy, and heart orientation. In contrast, individual-specific synthesis offers better performance thanks to its indirect account of these factors, however, this comes at the cost of simultaneous acquisition of the standard 12-lead ECG and the wECG.

A key advantage of the ESN over other neural networks designed for time series analysis is its highly efficient training process. Unlike recurrent neural networks, which require an iterative weight adjustment, the ESN only requires tuning of the output weights [24, 19]. The ESN has been found superior to linear regression, especially in synthesizing precordial leads [14]. Also, our preliminary evaluation of machine learning-based models, such as a deep learning encoder-decoder U-Net architecture [40] and a long short-term memory network [41], demonstrated less favorable synthesis performance when trained solely on individual-specific ECGs without prior pretraining on a large dataset.

D. Limitations

The study has a number of limitations which should be considered when interpreting the results. The study included patients who already had cardiac conditions. Therefore, the

lack of ECGs during non-infarction states for AMI patients raises the question whether the transfer function learned by the ESN using non-infarction ECGs is applicable to AMI. Answering this question is most challenging as it would require complex procedures such as temporarily occluding a coronary artery to induce myocardial ischemia [34]. The study participants self-acquired the wECG following initial acquisition with cardiologist assistance. Therefore, larger misplacements in electrode touch sites can be expected when ECGs are self-acquired in an uncontrolled environment.

Another limitation is the demographic mismatch between the AMI and non-AMI groups. Because the CNN can estimate age from the ECG [42], age-related differences, including a reduction in QRS amplitude [43], may have acted as confounding factors.

VI. CONCLUSION

This study demonstrates that a two-lead ECG, acquired using a self-applicable, wrist-worn device, is a promising approach to detecting AMI. The approach has the potential to enhance cardiovascular diagnostics, particularly in resource-limited or remote settings.

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