Computer Assisted Methods in Engineering and Science
30(3): 291–304, 2023, doi: 10.24423/cames.644

This article belongs to the *Special Issue on Digital Twin Empowered Internet of Intelligent Things for Engineering Cyber-Physical Human Systems* edited by C. Venkatesan, Y.-D. Zhang, Q. Xin

Congestive Heart Failure Detection Based on Electrocardiomatrix Method with ECG Signal

B. Mohan RAO*, Aman KUMAR

Department of Electronics and Communication Engineering, NIT Hamirpur, Hamirpur, India

* *Corresponding Author e-mail: badavathmohan33@gmail.com*

Congestive heart failure (CHF) is a prevalent, expensive to treat, and dangerous disease in which the pumping capacity of the heart muscle is reduced due to injury or stress. It causes major medical problems in humans and contribute to many diseases, thus increasing the mortality rate. In a world with a growing population, there is a need for more precise and simpler approaches to detect such conditions, which can prevent many diseases and lead to a lower mortality rate. The main goal here is to use electrocardiomatrix (ECM) approach to perform the task of detecting CHF. It is detected quickly and accurately with this approach, as ECM converts 2D electrocardiogram (ECG) data into a 3D-colored matrix. The approach is tested using ECG readings from the Beth Israel Deaconess Medical Center (BIDMC) CHF Database on the Internet (Physionet.org). The ECM outcomes of are then compared to manual readings of ECG data. The ECM results achieved the accuracy of 96.89%, the sensitivity of 97.53%, the precision of 99.1%, the F1-score of 97.76%, and the specificity of 96.02% for CHF. This research shows that the ECM approach is a good way for machines and practitioners to interpret long-term ECG readings while maintaining accuracy.

Keywords: electrocardiomatrix, ECG signal, congestive heart failure.

1. Introduction

Cardiac arrest is a severe and challenging clinical condition caused by any physiological or pathological heart illness that impairs blood ventricular loading or blood discharge into the circulatory system to meet the demands of the human body [1]. CHF is caused by the heart ventricles not being able to transport enough blood to the body [2]. Blood and some other body fluids eventually collect in the lungs, liver, abdomen, and other inferior body organs, resulting in congestion [3]. ECG abnormalities that might induce CHF include "premature atrial contraction (PAC), supraventricular premature beats (SVPB), pre-

mature ventricular contraction (PVC), and R on T premature ventricular contraction (RTPVC)" [4, 5]. Manual annotations and machine algorithms make it difficult to identify all of these issues, and another issue is to accurately detect "PAC, SVPB, PVC, and RTPVC" [6]. Traditional approaches for quantifying various heart rate variability (HRV) signals using linear methods have shown that a reduction in variability is linked to an increase in heart disease mortality. However, there are several instances where HRV data cannot be analyzed using linear techniques [7].

The paper is organized as follows, Sec. 2 presents related work, and Sec. 3 provides ECG data descriptions. Section 4 describes the methodology and Sec. 5 presents the results and discussion. Section 6 provides the conclusion.

2. Related work

In recent decades, researchers have developed and used a variety of techniques to detect CHF, including the multiscale entropy metrics (MSE) and multiscale normalized corrected Shannon entropy (MNCSE) using inter-beat-interval (IBI) statistics extracted from ECG signals [8]. An IBI's dynamic symbol and a wavelet-based soft decision technique for classifying and detecting non-healthy subjects by combining classical HRV indicators with CHF was presented in [10].

Yu and Lee [11] presented a shared database that was primarily used to track heart disease symptoms. For the CHF test, Pecchia *et al.* [12] offered short-term HRV measures combined with a very simple threshold-based classification. Symbolic statistical detection has been studied by Aziz *et al.* [9] to distinguish normal patients from those with circulatory heart disease. Altan *et al.* [13] used the Hilbert–Huang transform (HHT) and a multilayer perceptron neural network (MLPNN) to capture symptoms from IBI statistics, and classify patients into healthy, CHF, and coronary artery disease (CAD) subjects. The latter ones were CAD and normal subjects among no-CHF subjects. Choudhary *et al.* [14] proposed a classified horizontal visibility entropy to distinguish healthy, CHF, and cardiac arrhythmia subjects.

Recently, Isler *et al.* [15] have applied a multi-stage classifier of CHF-based short-term heart rate variables. Narin *et al.* [16] concluded that short-term HRV approach predicts the onset of paroxysmal atrial fibrillation. The researchers [17] used irregularity in very short ECG signals to detect successful defibrillation in cardiac arrhythmia-ventricular fibrillation (VF) patients. The ranking of multimodal characteristics collected from CHF and normal sinus rhythm (NSR) patients was proposed by Hussian *et al.* [33].

Yoon *et al.* [18] looked at three statistical models for automatic detection of AF and CHF based on RRI time series. Empirical receiver operative characteristics (EROC) values were used to classify hierarchical features into one to

five groups. Instead of utilizing all multimodal characteristics, only high ranked features should be used to diagnose and distinguish CHF and NSR patients [33].

CHF has become one of the leading causes of hospitalization among the elderly [19]. In comparison to other heart illnesses, CHF patients (adults more than 65 years of age) were readmitted to the hospital roughly 50% of the time after discharge [20]. Masetic and Subasi divided their research into two phases: feature extraction and classification. During the feature extraction step, the autoregressive (AR) Burg approach was utilized [21]. CHF becomes more prevalent as people get older [21, 22] and with the use of an ECG, many computerized approaches have been employed to identify CHF. Tripathy *et al.* [22] proposed utilizing the Stockwell (S) – transform and frequency division to examine the time-frequency sub-band matrices using ECG data to build a classifier-based CHF automated detection system. Kumar *et al.* [23] suggested an automated technique for diagnosing CHF using heart rate variability (HRV) data. In their investigation, the flexible analytic wavelet transform was applied. Mahajan *et al.* [24] reported a probabilistic symbol pattern recognition (PSPR) approach for recognizing CHF patients based on their cardiac inter-beat intervals. A CHF detection ensemble technique based on deep neural networks and short-term HRV data was proposed by Wang *et al.* [25]. All of these solutions were either time-intensive or could be utilized for data that was only available for a short period. Acharya *et al.* [26] proposed a CNN-based CHF detection method that could classify the CHF using one raw heartbeat only, and the accuracy indicated in this method was 98,97%.

Recently, a new approach called ECM has been established for analyzing ECG signals [27]. ECM displays the same ECG data in a 3D matrix format, making it easier to see abnormalities such as atrial fibrillation (AF). Lee *et al.* [28] used the ECM method to diagnose atrial fibrillation (AFIB) and atrial flutter (AFL) in individuals. The online MIT-BIH AFIB database's ECG signals are evaluated using ECM (Physionet). This monitoring method does a one-sided examination of time-dependent heart rate changes and cardiac arrhythmia frequency, extracting all of the characteristics of cardiac electrical impulses consistently using raw ECG data. Then, the ECM-based results were compared with annotations produced by a doctor based on an ECG. According to data, labeled AF and AFL via PhysioNet and ECM are accepted in more than 99% of cases. Brown *et al.* [29] investigated the feasibility, reliability, and usefulness of unit telemetry data using ECM technology, and ECM shows telemetry data in a 3D matrix, making P-wave analysis more precise and efficient. ECG data is presented by ECM in a 3D graphical form, which makes it easier to spot irregularities. The 2 or 3 P-QRS-T pulses are shown on the y-axis in succession, while the x-axis shows heartbeat counts or lost time, and the z-axis shows the strength of the pulse signal. This monitoring system converts raw ECG data into a simplified

format that allows for easy study of time-dependent heart rate variations and the frequency of cardiac arrhythmias [29].

This study uses ECM technology to effectively examine the long duration of ECG signals. The ECG signal is displayed in a three-dimensional matrix format by ECM, making it easy to see irregularities. On the axis, 2 or 3 consecutive P-QRS-T-waves are shown for the heart rate numbers or laps at the cardiac signal amplitude on the x-axis and z-axis. By facilitating the evaluation of heart electrical impulses from raw ECG data, this monitoring system enables speedy evaluation of very short heart rate changes and the risk of cardiovascular illness. This study's objective is to test the proposed approach on the BIDMC-CHF dataset and demonstrate how to accurately evaluate huge amounts of data. There are four critical beats that CHF produces and they areas follows:

1. Premature atrial contractions (PACs) are extra heartbeats. The atria, or upper chambers of the heart, are impacted by this disease. PACs occur earlier than predicted, and the P-wave shape differs somewhat. In this situation, the P-R interval appears to be normal, but the QRS complex is narrow.
2. Supraventricular premature beats (SVPBs) are atrial contractions induced by ectopic beats rather than the sinoatrial node. Regressive conduction causes these contractions to happen inside the atria in the atrioventricular nucleus. Both in the II and V1-lead ECG measurements, the contrast between the topologies of the typical sinus P-wave and the ectopic P-wave is obvious. An ectopic P-wave is overlaid over a T-wave in the case of a V1 lead.
3. Premature ventricular contractions (PVCs) are abnormal heart rates that start in the lower pumping chambers of the heart, and the ventricles and disrupt the heart's regular rhythm. As shown, there is no P-wave before the PVC case. As a result, in this scenario, the P-R interval is unimportant. With a QRS of at least 0.12 s and frequentcy of 0.14 s or even more, PVC has a large and irregular QRS complex. Except where PVCs interfere, the beat is regular. If R-R durations are measured in this situation, there will be a compensating delay since there will be exactly two cycles between both the R peak before the PVC and the R peak after the PVC.
4. When an ectopic beat is placed over the T-wave of a preceding beat, the "R-on-T phenomenon" occurs. When the T-wave of the preceding beat reaches its peak. the R-wave begins [30].

This study considers the detailed elements of the ECG short signals examined manually. Beat-by-beat assessment of ECG data has become a difficult task that requires more ECG signals to be increased. It is necessary to develop a novel method that simultaneously analyses ECG signals' micro and macro fea-

tures. The ECM methodology is required to enhance cardiac disease diagnosis since it offers improved specificity and sensitivity for cardiac disease detection compared to traditional and robotic arrhythmia identification techniques. Cardiac telemetry is used in the inpatient ischemic stroke/transient ischemic attack test to look for AF and CHF. However, there are certain methods available to assist doctors in analyzing large amounts of telemetry data. Brown *et al.* [29] have developed ECM, a new approach to assess tested electrocardiographic signals for their feasibility, authenticity, and usability on stroke unit telemetry data. ECM delivers a 3-dimensional matrix of telemetry data, improving accuracy and speeding up P-wave processing. One of the most commonly used techniques for the non-invasive diagnosis of cardiovascular disorders and fundamental cardiac research is the electrocardiogram (ECG). A new technology called ECM uses cutting-edge signal processing techniques to thoroughly evaluate ECG data and aid in illness detection. Long cardiac impulses may be compactly shown via ECM. Real-time monitoring of cardiac problems is aided by ECM. In comparison to manual identification and automatic arrhythmia detection, the ECM technique offers higher responsiveness and precision for diagnosing a cardiac arrhythmia. It is anticipated that it improves the diagnosis of heart diseases.

Machine learning (ML) and deep learning (DL) models can be used to detect CHF. But training the model will cost money and take up a lot of memory. The primary problem with ML and DL models is that they take a long time to train and need a graphics processing unit (GPU). It takes skill to read the ECG signal pattern abnormalities between succeeding R-R intervals, making a human evaluation of the ECG data challenging.

3. ECG data descriptions

The BIDMC CHF Database [31] has long-term ECG recordings of 15 people with severe congestive heart failure (11 men aged 22 to 71 and 4 women aged 54 to 63). The patient records, which are one hour long, contain ECG signals captured at 250 Hz over a spectrum of 10 millivolts with 12-bit resolution. The five hand annotations types that are shown on each record are SVPB, PVCs, PAC, R-on-T PVC, and Normal.

4. Methodology

The proposed ECM method is shown in Fig. 1 as the flow chart of the ECM technique. The chart illustrates the step-by-step procedure for the preprocessing of the ECG signals. The following are the steps for the preprocessing of the ECG signal.

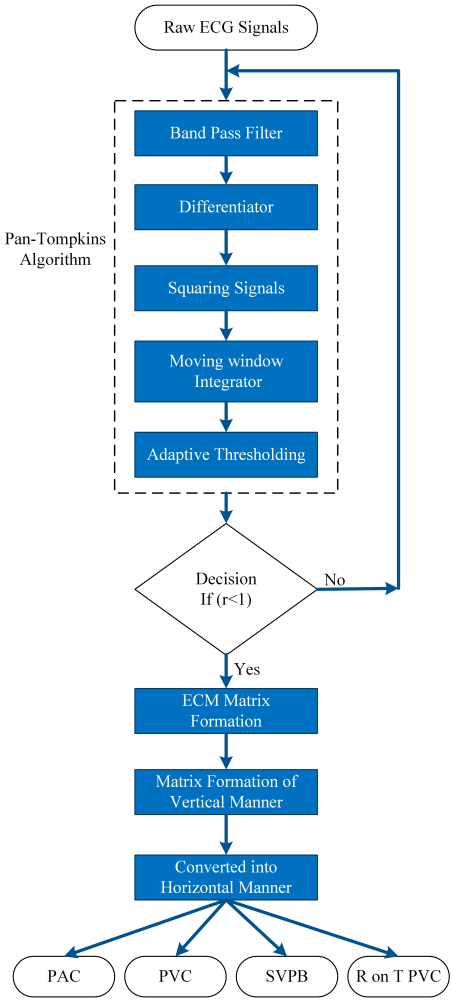

Fig. 1. Flow chart for the proposed method.

Step 1: Preprocessing with Pan–Tompkins algorithms [32].

Step 2: After that, determine if the adaptive threshold condition in the decision box is fulfilled or not. If it is, go to the next stage; otherwise, return to step 1.

Step 3: Go to ECM matrix formation when finished with step 2, and the ECM matrix divides the ECG signal into equal-length short segments.

Step 4: After segmentation, the smaller segments are turned into a colored matrix with the amplitude [mV] and intervals (PR, QT, ST) of each ECG wave (P, QRS, T) color-coded. A higher voltage equals a warmer color (red), whereas a lower voltage equals a cooler hue (blue). Each line's RRIs shows the time interval between two consecutive R peaks.

Step 5: Previously, RRIs (such as the intervals between the 1st and 2nd R peaks (RRI 1–2) and the 2nd and 3rd R peaks (RRI 2–3) heartbeats) were displayed on the ECG monitor's x-axis. However, on the ECM display, they are now presented on the y-axis, indicating that the vertical method has been switched to a horizontal method, enabling simple identification of the needed parameters.

Step 6: In step 5, manual interpretations of four specific parameters for the observation of congestive heart failure are required.

5. Results and discussion

In Figs. 2–6, ECM analysis tracks four different types of beats to demonstrate their potential use. Figure 2 shows the horizontal ECM matrices (a) for #chf02 and (b) for #chf02 (BIDMC CHF Database). In columns 1:250, 500:1200, 1300:2100, at around 2750, 3300:3350, and 3800:3850, in 4600:4700, and then at 5700, PVC can be observed. As shown in Fig. 2b the extensive PVC beat QRS complex is recognizable as a complex with an oblong width, modified colors (indicating changes in amplitude), and expanded periods between consecutive beats. The sample data showing PVC in ECG annotations is chosen, and as a result, it is noticed that these are characteristic for the extensive PVC beat QRS complex.

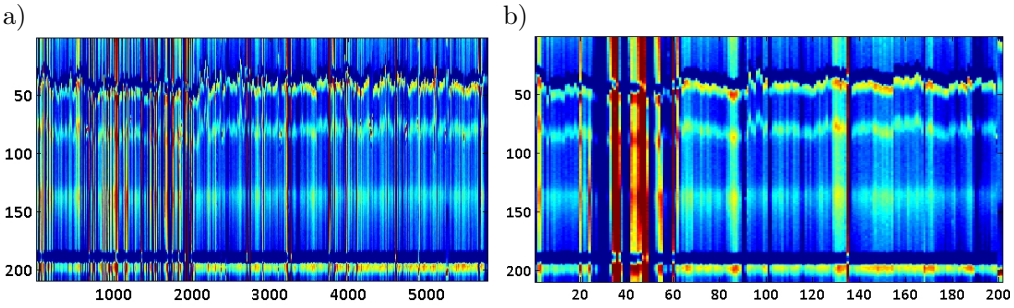

Fig. 2. a) Horizontal matrix of #chf02 ECG; b) horizontal matrix of PVC #chf02 ECG signal.

The horizontal ECM matrix for #chf05 (BIDMC CHF Database) is then shown in Fig. 3a. SVPB is visible in column 500:600, PVC is visible in column 100:500, and RTPVC is visible in columns 800:900, 1700:2000, approximately in column 2600, 2900:4000, and 6000:6400. A separate matrix is created to demonstrate the nature of SVPB in Fig. 3b, in which samples with SVPB in the ECG annotations are included, and it is found that longer RR cycles are frequently predicted by relatively short RR periods with premature beats, with no variation in premature R peak demonstration. There is a distinct break in the ECM's

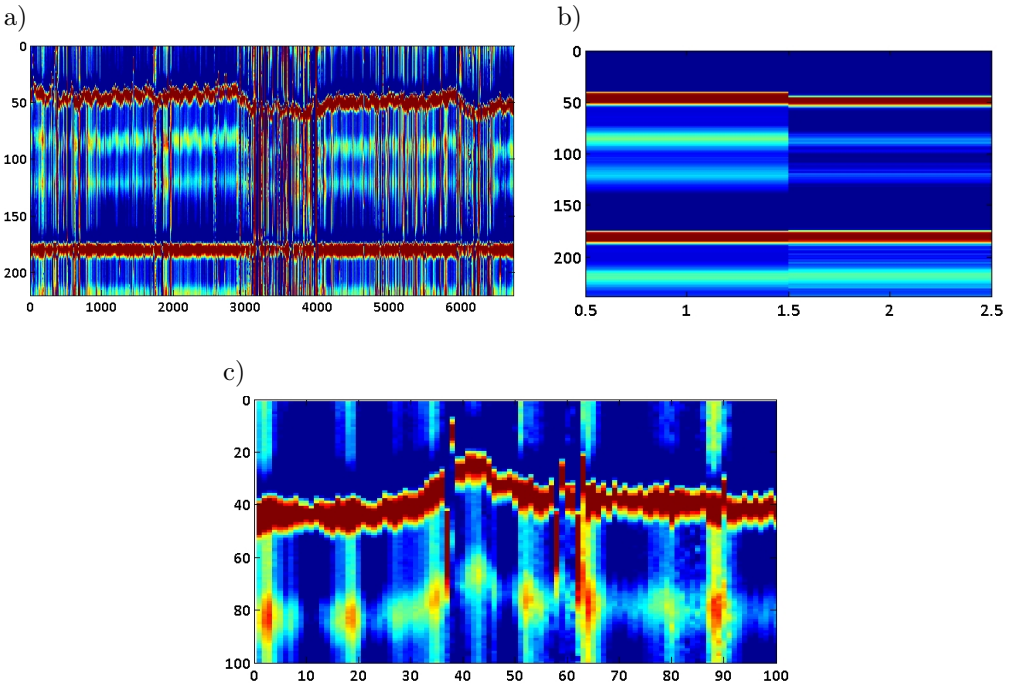

Fig. 3. a) Horizontal matrix of #chf05 ECG; b) matrix of SVPB ECG signal; c) matrix of PVC and RTPVC section I #chf05.

regularity when it comes to these PACs. The rhythms are not in sync here. In Fig. 3c, a distinct matrix is created to demonstrate the condition of PVC and RTPVC, demonstrating that the extensive PVC and RTPVC beat QRS intricate may be recognized as a composite with an oblong width, changed colors (showing amplitude variations), and increased intervals between succeeding beats. PVC in column 87:93 is observed, and in column 62:68, RTPVC is observed.

In addition, Fig. 4a shows the horizontal ECM matrix for #chf06 (BIDMC CHF Database). SVPB is observed in columns 1:500, 600:900, 1050:2200, 2600:3300, 3800:4800, and 5300:6300, and RTPVC is observed in 500:600, near 1000, and 2200:2600, 3300:3400, 3600:3700, 4800:4900, and 5100:5300. As a result, the broad RTPVC beat QRS complex is distinguishable as a complex with an oblong width, changed colors (showing amplitude variations), and increased intervals between subsequent beats in Fig. 4b, where a distinct matrix is generated to highlight the nature of RTPVC. Although the amplitudes are small, the beats are synchronized (light blue). In Fig. 4c, a separate matrix that only includes samples with NSR in the ECG annotations is produced to illustrate the nature of NSR. The beats are on time here and the distinct matrix is developed in Fig. 4d to emphasize the characteristics of SVPB and RTPVC.

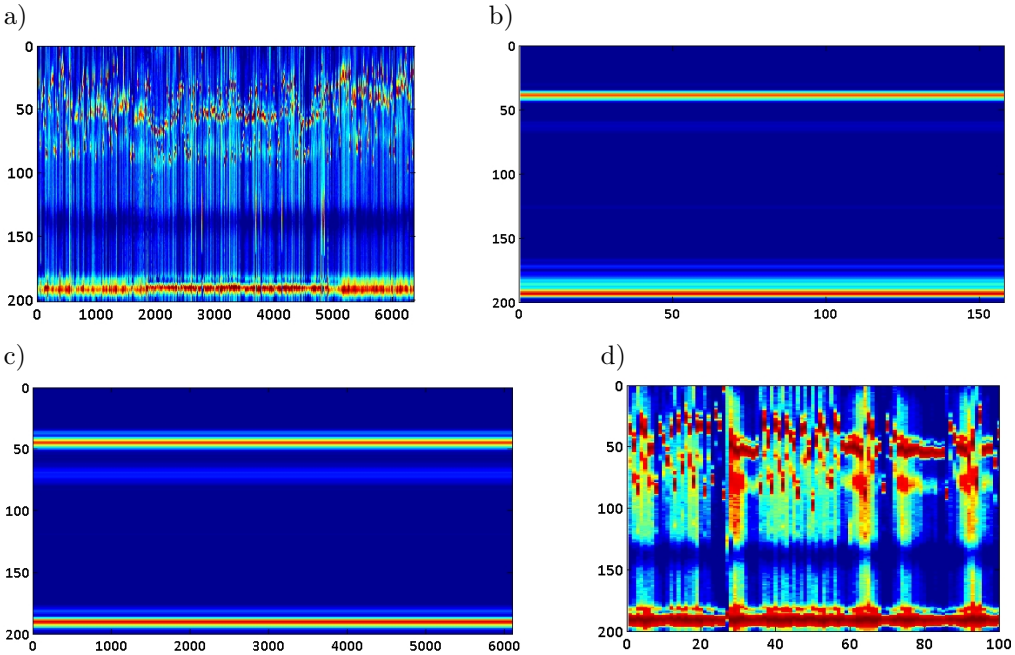

Fig. 4. a) #chf06 horizontal ECG signal; b) RTPVC matrix of #chf06 ECG signal; c) NSR matrix of #chf06 ECG signal; d) horizontal matrix of RTPVC and SVPB for #chf06 section I signal.

The horizontal ECM matrix is displayed in Fig. 5a for #chf07 (BIDMC CHF Database). In columns 4000:4500, one observes PAC. In Fig. 5b, a separate matrix is generated to demonstrate the nature of PAC, in which only samples with PAC in ECG annotations are taken, and it is discovered that longer RR cycles are frequently preceded by shorter (vertically aligned) RR cycles with premature beats, with no variation in premature R peak demonstration. The beats are in tune here.

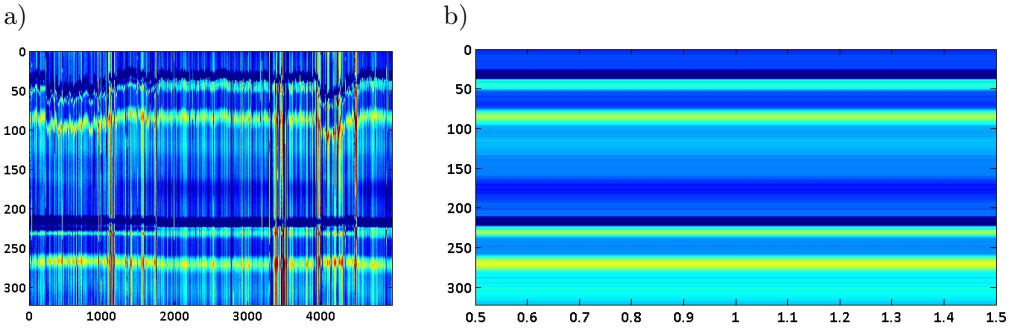

Fig. 5. a) #chf07 horizontal matrix of ECG signal; b) #chf07 horizontal matrix of PVC ECG signal.

Figure 6a shows the horizontal ECM matrix for #chf08 (BIDMC CHF Database). SVPB may be seen in columns 480:1000. In Fig. 6b, a separate matrix is built, highlighting the nature of SVPB in columns 42:62 and 82:88 by utilizing section 1000:1100.

a) b)

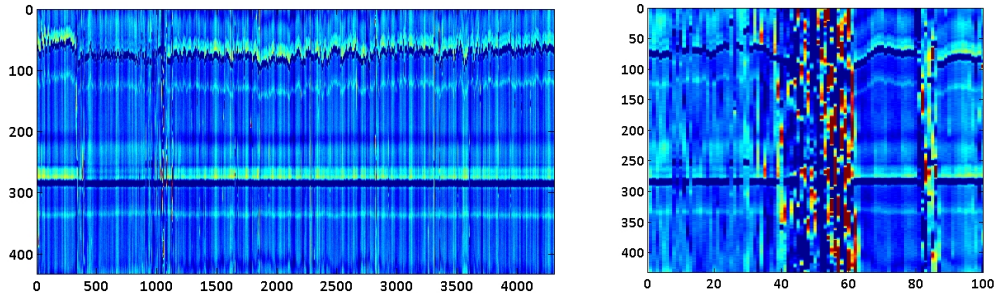

Fig. 6. a) #chf08 horizontal matrix of ECG signal; b) #chf08 horizontal matrix of SVPB section I.

Altogether, the ECM approach proved successful in detecting all of the different types of conditions found in the BIDMC CHF database. The suggested approach performance measurements are presented in the last line of Table 1. This data demonstrates that the ECM approach may be used to visually identify differences in ECG peak representation, amplitude, and durations between various peaks.

Table 1. Comparison of existing methods and the proposed method.

Algorithm	Year	Sensitivity [%]	Specificity [%]	Precision [%]	Accuracy [%]	F1-score	PPV [%]
Pecchia *et al.* [12] (ST-HRV)	2010	89.70	100	–	96.40	–	–
Altan *et al.* [13] (MLPNN)	2016	97.13	98.18	–	97.53	–	–
Acharya *et al.* [26] (CNN)	2017	98.8	99.01	–	98.97	–	–
Choudhary *et al.* [14] (SVM, KNN RT)	2019	–	–	71	–	0.81	–
Brown *et al.* [29] (ECM)	2019	–	–	90	–	0.90	86
Proposed algorithm (ECM)	**2022**	**97.53**	**96.02**	**99.1**	**96.89**	**97.76**	–

The main contributions of this research are:

- In this work, an ECM matrix was utilized for the detection of CHF. Until now, no study wasconducted on detecting CHF using ECM. Therefore, this

work proposes the detection of CHF using ECM, which is easy to analyze and less time-consuming.

- The proposed method was applied to the standard database, i.e., MIT-BIH CHF, for authenticity.
- It was found that the proposed method had an accuracy of 96.6%, a sensitivity of 97.53%, a specificity of 96.02%, and a precision of 99.1%.

This research looked into four main problems: "(1) For the BIDMC CHF Dataset durations, both ECG and ECM annotations identified CHF, (2) ECM annotations but not ECG annotations identified CHF, (3) ECM annotations but not ECG annotations identified CHF, and (4) ECM and ECG annotations did not indicate CHF" [31]. When the ECG and ECM annotations concurred, these durations of time were utilized to compute the time in CHF. In addition, the proportion of time with ECM and ECG annotations that are inconsistent was calculated. The events were either absent (false negative) or incorrectly categorized when annotations between ECG and ECM annotations did not follow (false positive). On the premise that ECG annotations (the standard measure) provide 100 percent specificity and sensitivity, the relative specificity and sensitivity of the ECM annotation were calculated. "True positives (TP) were defined as aspects in which both ECG and ECM annotations identified CHF, false positives (FP) were defined as aspects in which ECM identified CHF, but ECG annotations did not, and false-negatives (FN) were defined as aspects in which ECM did not identify CHF, but ECG annotations did, and true negatives (TN) were defined as aspects in which both ECG and ECM annotations did not identify CHF" [34]. The CHF signals (TP, FP, FN, TN) were tagged using these four ECM annotations, and five key parameters were determined, as shown in Table 1. A comparison of existing methods is shown in Table 1. The following restrictions apply to the ECM method's ability to identify CHF: the suggested solution requires manual ECM interpretation. A crucial challenge is to recognize R-on-T PVCs and other premature ventricular contractions. Excellent observational abilities are also required to distinguish between PAC and SVPB.

Only about 200 KB of memory is needed to keep each colored ECM matrix of an ECG signal with a sampling frequency of 250 Hz and a length of 1 hour. There are just 15 recordings in the MIT-BIH CHF database, and their ECM matrices only require about 2.929 MB of capacity. Because of this, the ECM uses far less storage space than other methods that are already in use.

The formation of an ECM matrix is a very simple process. An ECM matrix is formed as follows:

- Equally sized, short segments of the ECG signal are separated. The rising short segment consists of two subsequent heartbeats and starts at a position in each section that is between the T-wave of the preceding heartbeat

and the P-wave of the current pulse. After that, each segment's shorter segments are all vertically aligned to the first of the two R peaks.

- Following segmentation, these smaller segments are converted into a colored matrix, where each ECG wave's amplitude [mV] and intervals (PR, QT, ST) are denoted by a different hue. A greater voltage is shown by the warmer red color, whereas a lower voltage is denoted by the cooler blue color. The RR intervals show how long each line's two adjacent R peaks are separated from one another.

6. Conclusion

Congestive heart failure is a life-threatening condition that contributes significantly to global death rates. This situation could only be avoided if it could be diagnosed more precisely and in a shorter amount of time. By assessing a vast quantity of data in a single glance, the ECM plays a critical role in achieving this goal. The accuracy of the presented approach was evaluated using the BIDMC CHF dataset, which yielded a 96.89% accuracy, with sensitivity and specificity values of 97.53% and 96.02%, a precision of 99.1%, and an F1-score of 97.76%. Although this study may not be able to distinguish between PVCs and R-on-T PVCs or PACs and SVPBs, separate matrices derived from their hand annotations may be able to do so. This method might be used to examine the effects of various arrhythmias. With more computing power, a larger amount of data may be examined, resulting in improved results for the same approach. By combining the ECM approach with deep learning algorithms, the outcomes of the ECM technique might be studied more easily.

References

1. Premature Ventricular Contractions (PVCs) and Premature Atrial Contractions (PACs), Frankel Cardiovascular Center, University of Michigan Health, https://www.umcvc.org/conditions-treatments/premature-ventricular-contractions-pvcs-and-premature.
2. What Are Premature Atrial Contractions?, WebMD, https://www.webmd.com/heart-disease/atrial-fibrillation/premature-atrial-contractions.
3. Supraventricular premature beats, *Knowledge for medical students and physicians*, AMBOSS, 2022, https://www.amboss.com/us/knowledge/Supraventricular_premature_beats.
4. B. Surawicz, R. Childers, B.J. Deal, L.S. Gettes, AHA/ACCF/HRS Recommendations for the standardization and interpretation of the electrocardiogram, *Circulation*, **119**(10): e235–e240, 2009, doi: 10.1161/circulationaha.108.191095.
5. ECG Basics Tutorial – Complete 12-lead ECG Review, LearntheHeart.com, Healio https://www.healio.com/cardiology/learn-the-heart/ecg-review/ecg-interpretation-tutorial.
6. T.R. Engel, S.G. Meister, W.S. Frankl, The "R-on-T" phenomenon: An update and critical review, *Annals of Internal Medicine*, **88**(2): 221–225, 1978, doi: 10.7326/0003-4819-88-2-221.

7. Y. İşler, M. Kuntalp, Combining classical HRV indices with wavelet entropy measures improves to performance in diagnosing congestive heart failure, *Computers in Biology and Medicine*, **37**(10): 1502–1510, 2007, doi: 10.1016/j.compbiomed.2007.01.012.
8. I. Awan *et al.*, Studying the dynamics of inter-beat interval time series of healthy and congestive heart failure subjects using scale based symbolic entropy analysis, *PLoS One*, **13**: e0196823, 2018, doi: 10.1371/journal.pone.0196823.
9. W. Aziz, M. Rafique, I. Ahmad, M. Arif, N. Habib, M. Nadeem, Classification of heart rate signals of healthy and pathological subjects using threshold-based symbolic entropy, *Acta Biologica Hungarica*, **65**(3): 252–264, 2014, doi: 10.1556/ABiol.65.2014.3.2.
10. A. Hossen, B. Al-Ghunaimi, A wavelet-based soft decision technique for screening of patients with congestive heart failure, *Biomedical Signal Processing and Control*, **2**(2): 135–143, 2007, doi: 10.1016/j.bspc.2007.05.008.
11. S.N. Yu, M.Y. Lee, Conditional mutual information-based feature selection for congestive heart failure recognition using heart rate variability, *Computer Methods and Programs in Biomedicine*, **108**(1): 299–309, 2012, doi: 10.1016/j.cmpb.2011.12.015.
12. L. Pecchia, P. Melillo, M. Sansone, M. Bracale, Discrimination power of short-term heart rate variability measures for CHF assessment, *IEEE Transactions on Information Technology in Biomedicine*, **15**(1): 40–46, 2011, doi: 10.1109/TITB.2010.2091647.
13. G. Altan, Y. Kutlu, N. Allahverdi, A new approach to early diagnosis of congestive heart failure disease by using Hilbert–Huang transform, *Computer Methods and Programs in Biomedicine*, **137**: 23–34, 2016, doi: 10.1016/j.cmpb.2016.09.003.
14. G.I. Choudhary, W. Aziz, I.R. Khan, S. Rahardja, P. Fränti, Analysing the dynamics of interbeat interval time series using grouped horizontal visibility graph, *IEEE Access*, **7**: 9926–9934, 2019, doi: 10.1109/ACCESS.2018.2890542.
15. Y. Isler, A. Narin, M. Ozer, M. Perc, Multi-stage classification of congestive heart failure based on short-term heart rate variability, *Chaos Solitons and Fractals*, **118**: 145–151, 2019, doi: 10.1016/j.chaos.2018.11.020.
16. A. Narin, Y. Isler, M. Ozer, M. Perc, Early prediction of paroxysmal atrial fibrillation based on short-term heart rate variability, *Physica A: Statistical Mechanics and its Applications*, **509**: 56–65, 2018, doi: 10.1016/j.physa.2018.06.022.
17. T. Jagrič *et al.*, Irregularity test for very short electrocardiogram (ECG) signals as a method for predicting a successful defibrillation in patients with ventricular fibrillation, *Translational Research*, **149**(3): 145–151, 2007, doi: 10.1016/j.trsl.2006.09.004.
18. K.H. Yoon *et al.*, Analysis of statistical methods for automatic detection of congestive heart failure and atrial fibrillation with short RR interval time series, [in:] *2015 9th International Conference on Innovative Mobile and Internet Services in Ubiquitous Computing*, Santa Catarina, Brazil, pp. 452–457, 2015, doi: 10.1109/imis.2015.88.
19. J.B. O'Connell, The economic burden of heart failure, *Clinical Cardiology*, **23**(Suppl 3): III6–III10, 2000, doi: 10.1002/clc.4960231503.
20. M.W. Rich, Epidemiology, pathophysiology, and etiology of congestive heart failure in older adults, *Journal of the American Geriatrics Society*, **45**(8): 968–974, 1997, doi: 10.1111/j.1532-5415.1997.tb02968.x.
21. Z. Masetic, A. Subasi, Congestive heart failure detection using random forest classifier, *Computer Methods and Programs in Biomedicine*, **130**: 54–64, 2016, doi: 10.1016/j.cmpb.2016.03.020.

22. R.K. Tripathy, M.R.A. Paternina, J.G. Arrieta, A. Zamora-Méndez, G.R. Naik, Automated detection of congestive heart failure from electrocardiogram signal using Stockwell transform and hybrid classification scheme, *Computer Methods and Programs in Biomedicine*, **173**: 53–65, 2019, doi: 10.1016/j.cmpb.2019.03.008.

23. M. Kumar, R.B. Pachori, U.R. Acharya, Use of accumulated entropies for automated detection of congestive heart failure in flexible analytic wavelet transform framework based on short-term HRV signals, *Entropy*, **19**(3): 92, 2017, doi: 10.3390/e19030092.

24. R. Mahajan, T. Viangteeravat, O. Akbilgic, Improved detection of congestive heart failure via probabilistic symbolic pattern recognition and heart rate variability metrics, *International Journal of Medical Informatics*, **108**: 55–63, 2017, doi: 10.1016/j.ijmedinf.2017.09.006.

25. L. Wang, W. Zhou, Q. Chang, J. Chen, X. Zhou, Deep ensemble detection of congestive heart failure using short-term RR intervals, *IEEE Access*, **7**: 69559–69574, 2019, doi: 10.1109/access.2019.2912226.

26. U.R. Acharya *et al.*, Deep convolutional neural network for the automated diagnosis of congestive heart failure using ECG signals, *Applied Intelligence*, **49**(1): 16–27, 2019, doi: 10.1007/s10489-018-1179-1.

27. D. Li, F. Tian, S. Rengifo, G. Xu, M.M. Wang, J. Borjigin, Electrocardiomatrix: A new method for beat-by-beat visualization and inspection of cardiac signals, *Journal of Integrative Cardiology*, **1**(5): 124–128, 2015, doi: 10.15761/jic.1000133.

28. V. Lee, G. Xu, P. Farrehi, J. Borjigin, Accurate detection of atrial fibrillation and atrial flutter using the electrocardiomatrix technique, *Journal of Electrocardiology*, **51**(6): S121–S125, 2019, doi: 10.1016/j.jelectrocard.2018.08.011.

29. D.L. Brown *et al.*, Electrocardiomatrix facilitates accurate detection of atrial fibrillation in stroke patients, *Stroke*, **50**(7): 1676–1681, 2019, doi: 10.1161/strokeaha.119.025361.

30. H.F. Jelinek, D.J. Cornforth, A.H. Khandoker [Eds.], *ECG Time Series Variability Analysis: Engineering and Medicine*, CRC Press, Boca Raton, 2017, doi: 10.4324/9781315372921.

31. *The BIDMC Congestive Heart Failure Database*, PhysioBank ATM, PhysioNet, https://archive.physionet.org/cgi-bin/atm/ATM, doi: 10.13026/C29G60.

32. J. Pan, W.J. Tompkins, A real-time QRS detection algorithm, *IEEE Transactions on Biomedical Engineering*, **32**(3): 230–236, 1985, doi: 10.1109/TBME.1985.325532.

33. L. Hussain, W. Aziz, I.R. Khan, M.H. Alkinani, J.S. Alowibdi, Machine learning based congestive heart failure detection using feature importance ranking of multimodal features, *Mathematical Biosciences and Engineering*, **18**(1): 69–91, 2021, doi: 10.3934/mbe.2021004.

34. K. Sharma, B.M. Rao, P. Marwaha, A. Kumar, Accurate detection of congestive heart failure using electrocardiomatrix technique, *Multimedia Tools and Applications*, **81**(21): 30007–30023, 2022, doi: 10.1007/s11042-022-12773-8.

Received June 7, 2022; revised version July 23, 2022;
accepted August 10, 2022.