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Frequency Domain Feature Statistics for Cardiovascular Disease Diagnosis on Low-Computational Devices

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***Abstract*—Towards providing a low cost and readily available healthcare intervention system for rural India, we propose novel methods to analyze ECG on Android mobile devices for diagnostic purposes. In the proposed system, ECG is compressed to reduce the volume of input so as to enable processing on a low computational mobile device. Morphological, wavelet and statistical features are extracted directly from the compressed ECG. The subset of most discriminative features is extracted using information theoretic Dynamic Weighting based Feature Selection. Hybrid classification using majority voting-based classifier fusion is applied to enhance the classification performance. For the 14 MIT Arrhythmia classes, the proposed system achieved classification accuracy of 99.3% and a sensitivity of 100 % and a specificity of 98.9 %. Comparison with other existing methods shows better performance of the proposed method.**

***Index Terms*— Android App; ECG Analysis; Feature Extraction; Feature Selection; Hybrid Classifier; Mobile Telecardiology.**

I. INTRODUCTION

Cardiovascular diseases (CVDs) are the major cause for morbidity and mortality in developing nations as India. Cardiovascular disease encompasses all types of abnormalities affecting the Heart muscles, Valves and/or the blood vessels. These can be diagnosed using the Electrocardiogram (ECG), which is a device for recording the electrical impulses of the heart. The analysis if ECG demands expert knowledge which is not readily available in rural areas. In order to overcome this, mobile based healthcare intervention strategies were proposed. The two major challenges in mobile based ECG analysis systems include those inherent to mobile applications and ECG Classification.

Challenges inherent to mobile applications for analyzing ECG in a real-time environment are limitation in: storage, computational capacity, bandwidth and associated delays. Accordingly, general mobile based telecardiology architecture has evolved incorporating ECG Compression, low computation methods for feature extraction and classification and strategies to mitigate delays [1]. Despite the risks of losing of clinically significant data, lossy compression was used [2]. Features are generally extracted in time or frequency domain. In realization of the computational capacity of these devices, mobile based systems extract the key features in the time domain only and overlook frequency domain feature extraction methods. Time domain feature extraction methods adopted by many mobile based systems include the Pan Tompkins [3] algorithm for QRS detection and

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the ‘So and Chan’ algorithm [4] for QRS detection. Low computational methods compromise the accuracy of detection of CVDs due to limited storage and computational resources characterizing maximum accuracy of 96% in these systems. Low computational feature extraction methods proving higher accuracy are demanded.

The key challenge inherent to ECG Classification is the wide variety of ECG morphologies even among those samples that belong to the same class. We focus to address these challenges through the novel proposed framework. Challenges for real time CVD diagnosis on mobile devices drill down to: data loss due to compression, intricate feature extraction methods and efficient classification methods. The inherent diversity in morphology of ECG data belonging to the same class poses much challenge for extraction of discriminative features and efficient classification. We address these challenges in our proposed system with novel methods for compression, feature extraction and classification.

The first phase of the work involves a novel framework for classification of ECG on mobile devices and the second phase involves cross database evaluation of the developed classification model. In order to classify ECG on mobile devices, we propose a framework that compresses the ECG and extracts features from compressed ECG for detection of abnormality on the mobile phone. The framework was verified and validated using the MIT ADB and the cross-validation approach. On the validated framework, the second phase of work involves real-time validation of the developed ECG Classification model using the collected dataset using the cross-database evaluation approach. In this phase we aim to improve the performance of the classification model by training and testing on the real time dataset. Section 2 describes the material used, Section 3 elaborates the proposed framework and the methods proposed for compression, feature extraction and classification. Section 4 presents the methods for generalization of the developed classification model using the cross-database evaluation approach. Section 5 discusses the results and section 6 concludes the work.

II. MATERIALS USED

The Massachusetts Institute of Technology-Beth Israel Hospital Arrhythmia Database (MIT-BIH ADB) [5] is widely used in analyzing automated methods for cardiovascular diseases. In this work, we have adopted the same for training of our system. The MIT ADB contains 48 select two channel ECG recordings including 23 random recordings and 25 selected recordings having clinically significant arrhythmias. Arrhythmia is any abnormality in the cardiac rhythm and leads to Stroke and Myocardial Infarction (Heart Attack). Each recording is sampled at 360 Hz. The database is available for free download at the PhysioNet Repository (www.physionet.org). For our work we have purposefully omitted records 102 and 104 as they were measured in Lead II (V2) and not Modified Limb II (MLII) as the other records in the dataset and thus cannot be morphologically compared.

To test the proposed methods on real-time data, we have collected 324 ECG samples in collaboration with the Government Rajaji Hospital, Madurai, India. The Ethical Committee at the institution approved the protocol of the study and each patient gave his or her informed consent to participate in this study. The acquisition device used was BPL CARDIART 9108. The device records 12 lead data simultaneously, each sampled at 1000Hz.In this work, we analyzed the ECG of 371 subjects (181 male and 190 female) who were referred for clinical suspicion of cardiovascular diseases. The patients were consecutively enlisted from the outpatient ward. Subjects ranged in age from 17 to 83 years, with an average of 53 years. The patients included normal subjects (15) and having cardiovascular abnormality (356). The rhythms were analyzed and classified into 15 classes as in the MIT BIH arrhythmia database as listed in Table I. The table also shows the distribution of subjects according to the cardiovascular pathology. Over 2000 data samples were collected and 371 samples were selected as for further analysis so that the number of samples for each MIT Class remains almost the same. This dataset is called MIT_RT_CC (MIT-Real time-Class-Compliant) The data was independently diagnosed by three cardiologists and conflicts were resolved by consensus. The diagnosis provided by the experts was used for validating the results of the proposed method.

Training of the system is performed using the MIT BIH ADB. In the training phase, the data is compressed and features are extracted from the compressed ECG, key features are identified using feature selection and classification model is deducted using a hybrid classifier. The deduced classification model is converted into set of decision rules and accumulated in the knowledge base. The knowledge base is directly used in the Android application in the testing phase. The system is tested using the collected real-time data. During the testing phase (executed on an Android Mobile device) data is compressed and only those features identified as discriminative in the training phase are extracted from the compressed ECG. The knowledge base is used to diagnose the cardiovascular disease in the test data. Each of these processes is detailed in the following sections.

TABLE I. DESCRIPTION OF REAL-TIME COLLECTED DATA USED FOR TESTING

S. No	MIT Class	Number of patients encountered		
		Male	Female	Total
1	Atrial bigeminy	13	12	25
2	Atrial fibrillation	15	14	29
3	Atrial flutter	13	16	29
4	Ventricular bigeminy	10	17	27
5	2° heart block	8	11	19
6	Idioventricular rhythm	16	7	23
7	Normal sinus rhythm	9	6	15
8	Nodal (A-V junctional) rhythm	11	16	27
9	Paced rhythm	12	10	22
10	Pre-excitation (WPW)	6	15	21
11	Sinus bradycardia	11	16	27
12	Supraventricular tachyarrhythmia	17	9	26
13	Ventricular trigeminy	14	12	26

III. PROPOSED METHODS FOR MOBILE BASED ECG CLASSIFICATION

In the initial stages, we developed a ECG classification model and developed novel feature extraction methods for extracting multi-domain features directly from the compressed ECG targeting on low computational methods for feature extraction and classification executable on mobile phones. The architecture of the proposed system is given in Figure 1. The process for diagnosis of cardiovascular diseases involves the steps shown in Figure 2. The steps include: lossless compression of ECG, novel methods for extraction of features from losslessly compressed ECG, selection of most discriminative features and a hybrid classifier for diagnosis of cardiovascular diseases. The development of the framework for ECG analysis is presented in section 4.

Training of the system is performed using the MIT BIH ADB. In the training phase, the data is compressed and features are extracted from the compressed ECG, key features are identified using feature selection and classification model is deducted using a hybrid classifier. The deduced classification model is converted into set of decision rules and accumulated in the knowledge base. The knowledge base is directly used in the Android application in the testing phase. The system is tested using the collected real-time data. During the testing phase (executed on an Android Mobile device) data is compressed and only those features identified as discriminative in the training phase are extracted from the compressed ECG. The knowledge base is used to diagnose the cardiovascular disease in the test data. Each of these processes is detailed in the following sections.

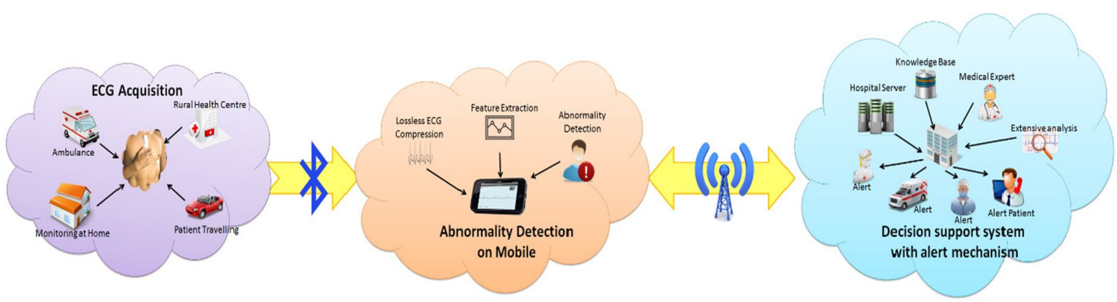

Figure 1. Proposed Mobile Telecardiology System Architecture

A. Lossless ECG Compression using Symbol substitution (LECS)

It is crucial to reduce the volume of the input to complete the analysis of ECG on a mobile device. Generally, lossy compression is adopted for this purpose. However, to avoid the loss of clinically significant data, it is very important to adopt a exclusive compression technology such as Lossless ECG Compression using Symbol substitution (LECS demonstrated in our earlier research in [6]). LECS compresses the ECG without any loss on mobile devices.

The main steps in LECS algorithm are Normalization, Differencing, Sign Epoch Marking and Compaction functions [6]. Demonstration of LECS for MIT ADB 100 is shown in figure 3. The algorithm uses preliminary mathematical computations without floating point data operations, and hence it was successfully deployed on a mobile device. The LECS Compression reduces the input size from 14.4KB (for 10 sec ECG recording) to nearly 2KB. This makes the extraction of multi-domain features on a low computational mobile device feasible.

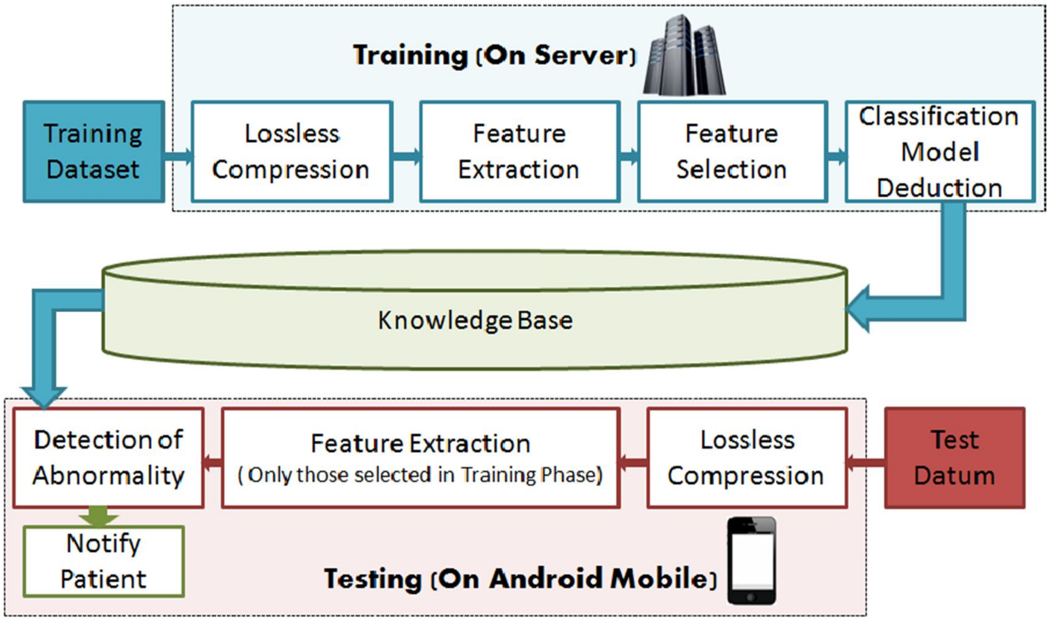

Figure 2. Process Flow of Proposed System

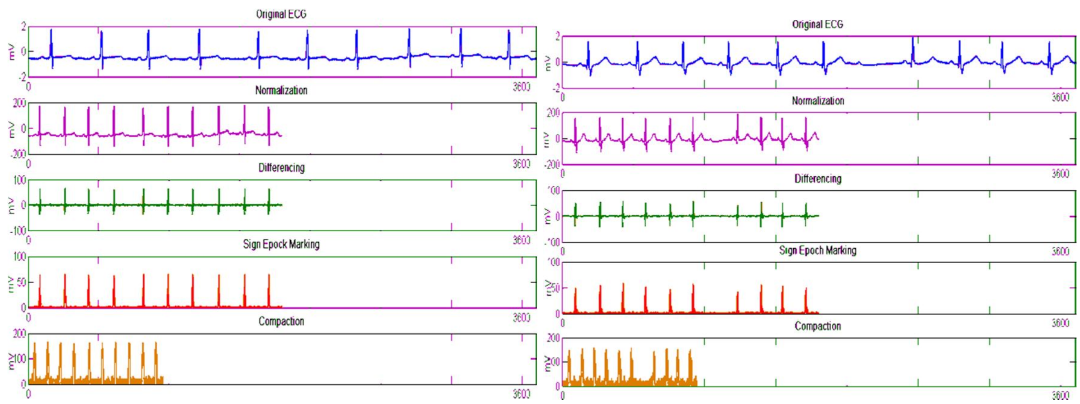

Figure 3. LECS Compression for (a) MIT ADB 115 (b) MIT ADB 231

B. Feature extraction from compressed ECG

Features were extracted in the time domain and frequency domain of the compressed ECG and statistics were computed for extracted features of both domains. The time domain features explore the morphology of the compressed ECG wave. The frequency distribution of the compressed ECG was analyzed using wavelet transformation methods. The Daubechies mother wavelet was chosen for fast numerical implementations. Most discriminative features were identified to reduce the dimensionality of the feature vector prior to classification. The statistics over the extracted features highlight the discrimination between ECG data belonging to different cardiovascular diseases during the classification.

C. Feature extraction in Time domain

The time domain analysis explores the structure of the ECG waveform and estimates the R Peaks, RR Interval, QRS Width and Heart Rate. Even though the exact values of the required features cannot be extracted from the compressed ECG, an illustrative representative of the feature can be extracted. For better comprehension, Figure 4 shows the original and compressed ECG of 4 samples.

The losslessly compressed ECG is first segmented into segments of 70 samples. The peak value in each segment is identified. The average of peaks of all segments is calculated. Those peaks with amplitude higher than the average of peaks are confirmed as R Peaks. The Q and S points are identified as the zero-crossings before and after each Confirmed R Peak of the compressed ECG. Furthermore, for each P-QRS-T sequence RR intervals and QRS width are also calculated. The Heart rate corresponds to the number of R peaks identified in a 10 second window.

D. Feature extraction in Frequency domain

Frequency domain methods analyze the signal mathematically against the frequency of its components rather than time. Analysis in different domains provides multiple representations of the signal and contributes insight and points out properties that are hard to discern in other representations. Most commonly used tool for frequency domain analysis is the Wavelet transform, which is used in many signal processing methods including ECG analysis.

The Daubechies wavelet was used to decompose the compressed ECG signal. The scaling function and the mother wavelet of the Daubechies 6(Db6) wavelet are shown in Figure 3. The sampling frequency of the collected test data (1000Hz) was first resampled to 360 Hz to become compatible with the MIT ADB test data. Hence the classification models deduced can be used without any adjustment and the classification performance analysis adopted for MIT ADB can be used directly. These coefficients of 4 ECG samples are shown in Figure 3. It can be seen from Figure 3 that the cd4 coefficients coincide with the compressed ECG and reveal maximum information about the waveform.

TABLE II. LIST OF ALL EXTRACTED FEATURES

Domain	Feature Name	Count
Time Domain	Number of R Peaks (N)	1
	Average R Peak (Avg_R_P)	1
	Average QRS Width (Avg_QRS_W)	1
	Average RR interval (Avg_RR_I)	1
	Heart Rate(HR)	1
Frequency Domain	DB6 Coefficients	128
Statistical Domain	Statistics of R Peak in Time Domain: Mean of R Peak (Mean_RP), Maximum of R Peak (Max_RP), Minimum of R Peak (Min_RP), Variance in R Peak (Var_RP), Standard Deviation of R Peak (SD_RP), Maximum 7 Deviation from Mean R Peak (Max_Dev_RP), Minimum Deviation from Mean R Peak (Min_Dev_RP)	7
	Statistics of RR Interval in Time Domain: (same as calculated for R Peak) 7	7
	Statistics of QRS Width in Time Domain: (same as calculated for R Peak) 7	7
	Statistics of absolute value of Db6 coefficients in each subbands cd1,cd2,cd3,cd4,ca4 (same as calculated for R Peak, 7 values for each subband)	35
Total No. of Extracted Features		189

E. Feature extraction using statistical analysis

Statistical analysis of features extracted in the time and frequency domains reveal more descriptive information about the ECG signal. The statistical features evaluated over the time domain explores the variations between consecutive wave cycles. The statistical features evaluated over frequency domain extracts the essence of the information in each subband.

The time domain features were extracted for each wave cycle are R Peak, QRS Width and RR Interval. The statistics of each feature over multiple wave cycles derived for R Peak are: 1) Mean of R peak, 2) Maximum of R Peak, 3) Minimum of R Peak, 4) Variance in R Peak, 5) Standard Deviation of R Peak, 6) Maximum Deviation from Mean R Peak, 7) Minimum Deviation from Mean R Peak. These 7 statistical features were calculated for QRS Width and RR Interval over multiple wave cycles. The same statistical features were calculated for the absolute values of coefficients in each subband. The list of all the features collected from the time, frequency and statistical domains is given in Table 2.

F. Feature selection

Feature selection identifies a subset of the extracted features in the training feature set which when used alone in testing yield the same or higher performance. The main purposes of feature selection include: reduction in dimensionality, development of more robust classifier by eliminating over-fitting and improvement in classification performance due to elimination of noisy data. Reduction in dimensionality implies that the number of features extracted during the test phase is minimal. Consequently the testing system is computationally light

and deployable on mobile devices. Generally feature selection methods identify the correlation and redundancy among the extracted features and discard those that are highly correlated and assume that the interdependence between features is nil or negligible. However, in CVD diagnosis, the features are highly interdependent.
Traditional methods discard such feature reducing the discrimination in the resulting feature set. To overcome this issue, we have adopted the information theoretic, Dynamic Weighting based Feature Selection (DWFS) proposed by Sun et al [7]. The DWFS iteratively selects and dynamically updates the weight of each feature based on its correlation with the class feature and the interdependence between the selected features. This ensures that inherent feature groups with high discrimination power as a groups selects features by iteratively ranking each feature.

G. Classification

Classification is a data mining task that builds a classification model using a given training input to predict the outcome of a test data. The performance of classification quantified by Accuracy (Acc) is the number of test samples correctly classified. Towards improving the accuracy of classification, many approaches for the combination of classifiers have been proposed where multiple classifiers are trained and the results combined to provide a final classification output. Generally, a hybrid classifier performs better than individual classifiers when each classification model hits different errors. Specifically, classifiers that build model using different strategies hit different errors on test samples. Consequently, when results of individual classifiers are combined the model hits the correct classification.
In the proposed work, five different classifiers: J48, RandomTree, Random Forest, LAD Tree and REP. These are decision tree-based classifiers, which is why we have chosen them. The classification models built by these classifiers are converted into a set of diagnostic rules. These simple 'If-Then' diagnostic rules are incorporated in the Android Application Code in the testing phase. The Hybrid classifier derives a decision out of the 15 MIT ADB classes. The decision is based on the classification of each of the five individual classifiers combined using majority voting-based classifier fusion. The performance of the different classifiers and the integrated classifier for the selected feature set using the MIT ADB and NSRDB databases for training and testing is shown in Table 3. The integrated classifier performs better than individual classifiers (as shown in Table 3) and is optimized for the given set of features.

TABLE III. PERFORMANCE OF DIFFERENT CLASSIFIERS

Classifier	**Train**	**Test**	
		MIT ADB	**Real-Time DB**
REPTree	MIT ADB	97.5	93.3
	Real-Time DB	98.4	99.9
Random Forest	MIT ADB	94.3	89.4
	Real-Time DB	93.8	94.7
J48	MIT ADB	98.1	92.3
	Real-Time DB	99.2	98.6
LAD Tree	MIT ADB	94.3	92.8
	Real-Time DB	98.6	94.7
NB Tree	MIT ADB	96.2	87.9
	Real-Time DB	97.5	97.2
Integrated Classifier	MIT ADB	98.7	96.3
	Real-Time DB	100	99.8

IV. PROPOSED METHODS FOR GENERALIZATION OF CLASSIFICATION MODEL USING CROSS-DATABASE EVALUATION

Generalization is the process of deriving general classification models by abstracting common rules across multiple instances. We aim to find ECG classification model with reduced dimension, efficient and generalized model in multi-database scenario. As most of the systems in literature use overlapping training and testing data, the performance of the system is highly projected. Therefore, for a system to be usable practically, data used to train the classifier must not overlap with the test data.

More over when the number of training samples is far higher than the number of test data used, almost all methods yield very high accuracy in classifying the different classes. But these systems fail miserably when tested with real-time data due to the fact that data belonging to the same class have various morphologies that often are very similar to other classes as well. The model without generalization was presented in [17]. To ensure the credibility of using of our proposed system in real-time, the developed classification model should be generalized.

Generalization is achieved in three steps. Prior to generalization, MIT ADB is processed in the proposed framework described in Section 3 and classification model is optimized using the integrated classifier approach. The first step in generalization is the cross-database evaluation of the developed classification model. The second step is to identify those features that are discriminative across multiple databases. The final step is to evolve a generalized classification model using those features that are most discriminative across multiple databases. The selection of features that are discriminative across multiple databases ensures that the features that are robust to multiple types of noises, artifacts and errors are taken into account for development of the classification model. Thus, the developed classification model is robust across multiple acquisition scenarios and is suitable for use in real-time environment. The process for these steps is explained as follows.

Step 1: Evaluation of Classification model.

The ECG classification model was developed using the integrated classifier approach. The first step in generalization then tests the proposed classification model developed using MIT ADB and the framework using real-time data. The results of classification using MIT ADB for training and Real-time data for testing using different classifiers are presented in Table 2. It can be seen from table 2 that use of overlapping data for training and testing (i.e use of same dataset for training and testing) always projects the performance of the system. When using non-overlapping train-test data, the true performance of the system is revealed. It can also be seen that, when the classification model is trained using MIT ADB and tested using the real-time data the classification performance is reduced. This is due to the fact the classification model built using MIT ADB with limited training samples

Step 2: Selection of most discriminative features across multiple databases

The second step is the selection of best features across different databases. To accomplish this step, we have trained the system using the benchmarked MIT ADB database (taking 46 records as mentioned above) and tested the system using 324 samples collected from Madurai Rajaji Hospital (the details of which are presented in Table 1). This ensures that the performance of the proposed system is consistent and robust when applied for real time data besides those in the training data. The list of features selected in this scenario result in a more robust development of a classification model that is generalized across multiple databases. The Robust feature subset thus determined by this cross-database evaluation strategy is listed in the Table 4.

Step 3: Building a Classification Model with the Robust Feature Subset

The integrated classification scheme is used to develop the classification model using only the robust feature subset. The classification performance of the different classifiers and the integrated classifier is shown in Table 5.

V. Results and Discussions

In this work we have developed and evaluated a cardiovascular disease diagnosis system and deployed as an Android Application. The Massachusetts Institute of Technology-Beth Israel Hospital Arrhythmia Database (MIT- BIH ADB) [5] was used in the training and the collected data described in Section II was used for testing. During training, we have purposefully omitted records 102 and 104 as they were measured in Lead II and not in Modified Limb II (MLII) as the other records in the dataset.

We adopt two approaches to estimate the performance of ECG classification. In the first approach, we use the MITADB as the training dataset and the Real-time data for testing.

In the training phase, ECG was losslessly compressed using LECS. The LECS achieved a high Compression Ratio of 7.04 in spite of its lossless nature. The Percentage-Root-mean-squared-Distortion (PRD) was as low as 0.0221. The LECS compression scheme guarantees untrimmed transmission of data through SMS on mobile devices upon detection of abnormality. Features are extracted in three domains from the compressed ECG including the time domain, frequency domain and statistical features. The list of all features extracted from the compressed ECG is given in Table 2. The selection of features was successfully done using Dynamic Weighting based Feature Selection (DWFS). A hybrid classifier was engaged for CVD diagnosis. The use of hybrid classifier improved the accuracy of the CVD diagnosis abnormality detection by mitigating the misclassifications errors.

TABLE IV. LIST OF FEATURES SELECTED AS THE ROBUST FEATURE SUBSET

Domain	Feature Name	Count
Time Domain	Number of R Peaks (N)	1
	Average R Peak (Avg_R_P)	1
	Average QRS Width (Avg_QRS_W)	1
	Average RR interval (Avg_RR_I)	1
	Heart Rate(HR)	1
Frequency Domain	DB6 Coefficients	9
Statistical Domain	Statistics of R Peak in Time Domain: Mean of R Peak (Mean_RP), Maximum of R Peak (Max_RP), Minimum of R Peak (Min_RP), Variance in R Peak (Var_RP), Standard Deviation of R Peak (SD_RP), Maximum 3 Deviation from Mean R Peak (Max_Dev_RP), Minimum Deviation from Mean R Peak (Min_Dev_RP)	3
	Statistics of RR Interval in Time Domain: (same as calculated for R Peak) 7	3
	Statistics of QRS Width in Time Domain: (same as calculated for R Peak) 7	3
	Statistics of absolute value of Db6 coefficients in each subbands cd1,cd2,cd3,cd4,ca4 (same as calculated for R Peak, 7 values for each subband)	8
Total No. of Selected Features		31

In the testing phase, the acquired ECG was transmitted to the Android device using Bluetooth communication. The ECG was losslessly compressed using LECS on the Android device. The features selected using DWFS during the training phase were extracted from the compressed ECG and used for classification. All these methods were developed using the Android Software Development Kit (version) and deployed and tested on three different mobile phones: Sony Ericsson ST25i (Android OS, v2.3 Gingerbread, Dual-core 1 GHz Cortex-A9, 512 MB RAM), Micromax Bolt A62(Android OS, v2.3.5 Gingerbread, 1GHZ Dual Core, Spreadtrum SC6820 Processor, 256 MB RAM), Samsung Galaxy Star 2 (Android OS, v4.4.2 KitKat, 1 GHz, SC6815A Processor, 512 MB RAM). The Android App is shown in figure 8.

TABLE V. PERFORMANCE OF DIFFERENT CLASSIFIERS USING ROBUST FEATURE SUBSET

Classifier	Train	Test	
		MIT ADB	Real-Time DB
REPTree	MIT ADB	98.5	96.7
	Real-Time DB	98.4	99.9
Random Forest	MIT ADB	93.2	93.9
	Real-Time DB	94.1	94.7
J48	MIT ADB	98.1	97.6
	Real-Time DB	99.3	98.7
LAD Tree	MIT ADB	94.3	94.8
	Real-Time DB	96.1	95.3
NB Tree	MIT ADB	97.2	97.6
	Real-Time DB	97.5	98.1
Integrated Classifier	MIT ADB	98.8	99.4
	Real-Time DB	100	99.8

The use of non-overlapping data samples in training and testing aids in validation of the developed classification model. Moreover, the use of real-time data aids in development of a robust classifier effective in real-time scenarios.

The comparison of the proposed method with some of the existing methods is presented in Table 6. We observed that our proposed approach achieved improvements in the classification accuracy. The improved performance indicates that the proposed feature extraction methods and the combination of morphological, wavelet and statistical features exhibits higher classification accuracy for discriminating different cardiovascular diseases. In addition, the proposed hybrid classifier-based CVD diagnosis strategy enhances the classification accuracy and

TABLE VI. COMPARISON OF PERFORMANCE OF PROPOSED GENERALIZED CLASSIFIER WITH OTHER TELECARDIOLOGY SYSTEMS

Literature	**Data**	**Features**	**Classifier**	**Classes**	**Target Device/ Technologyy**	**Accurac yy (%)**
Osowski & Linh 2001[1]	MIT ADB	Higher Order Spectra	Hybrid Fuzzy Classifier	7	Server/Wor kstation	96.06
Martis et al 2013[2]	MIT ADB and EuropeanST-T Ischemia	Morphology, Wavelettransform *Selected using PCA*	PNN	5	Server/Works tation	99.28
Pecchia et al 2011[8]	Real-time	Heart Rate VariabilityAnalysis, Power Spectral Density	CART	2	Server/Works tation	96.4
Park & Kang 2014[9]	MIT ADB	Pan-Tompkins[3]	J4.8	20	Server/Works tation	90
Oresko et al 2010[10]	MIT ADB, Real-time	Pan-Tompkins[3]	MLP	5	Mobile	99
Chen et al 2013[11]	MIT ADB	So & Chan[4]	Hybrid Classifier	6	Mobile-GSM/3G/LT E	79.4-100
Wen et al 2008[12]	MIT ADB, Real-time	Morphology analysis	Adaptive Resonance Theory NN	4	Mobile-GSM	98.98
Shih et al 20101[13]	MIT ADB, Real-time	Morphology analysis	Fuzzy Petri Nets	11	Mobile-GPRS	94.74
Rodriguez et al 2005[14]	MIT ADB with 4 other standard ECG Databases	ECGPUWAVE tool	Decision Treebased	15	Mobile-GSM/GPR S/UMTS	96.12
Dong et al 2012 [15]	MIT ADB	Morphology analysis	SVM	2	Mobile-GSM/GPR S/3G	98.74
Lee et al 2007[16]	MIT ADB	HRV analysis	Rule based Classifier	4	Mobile-GSM	--
Proposed Generalized ECG Classifier	MIT ADB, NSRDB, Real-time	Morphology, Wavelet,Statistical features from compressed ECG selected using DWFS	Hybrid Classifier	15	Mobile-GSM/GPRS/3G	100

thus the credibility of using this system. Based on the observed results, we can conclude that the proposed method offers improved performance over existing approaches.

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REFERENCES

[1] Osowski, S , Linh, TH 2001, ECG beat recognition using fuzzy hybridneural network, IEEE Transactions on Biomedical Engineering, Vol.48,no.11, pp.1265-1271.

[2] Martis, RJ, Acharya, UR, Prasad, H, Chua, CK, Lim, CM & Suri, JS 2013, Application of higher order statistics for atrial arrhythmia classification,Biomedical Signal Processing and Control, Vol. 8, pp. 888– 900.

[3] So, HH & Chan, KL 1997, Development of QRS detection method for realtime ambulatory cardiac monitor: Proceedings of the 19th AnnualInternational Conference of the IEEE, pp. 289-292

[4] Pan, J & Tompkins, WJ 1985, A real-time QRS detection algorithm, IEEE Transactions on Biomedical Engineering, Vol. 3, pp. 230-236.

[5] Mark, RG, Schluter, PS, Moody, G, Devlin, P & Chernoff, D 1982, An annotated ECG database for evaluating arrhythmia detectors, IEEETransactions on Biomedical Engineering, Vol. 29, no. 8, pp. 600-602.

[6] Diana, M & Deisy, C 2015, Lossless Compression for Transmitting ECGin SMS with High Quality for Mobile Telecardiology Systems, International Journal of Ad Hoc and Ubiquitous Computing, Vol. 26, no. 3, pp. 157-166

[7] Sun, X, Liu, Y, Xu, M, Chen, H, Han, J & Wanga, K 2013, Featureselection using dynamic weights for classification, Knowledge- BasedSystems, Vol. 37, pp. 541 –549.

[8] Pecchia, L, Melillo, P & Bracale, M 2011, Remote health monitoring ofheart failure with data mining via CART method on HRV features, IEEETransactions Biomedical Engineering, Vol. 58, no. 3, pp. 800-804.
[9] Park, J & Kang, K 2014, PcHD: Personalized classification of heartbeat types using a decision, Computers in biology and medicine, Vol. 54, pp.79-88.
[10] Oresko, JJ, Jin, Z, Cheng, J, Huang, S, Sun, Y, Duschl, H & Cheng, AC 2010, A wearable smartphone-based platform for real-time cardiovasculardisease detection via electrocardiogram processing, IEEE Transactions onInformation Technology in Biomedicine, Vol. 14, no. 3, pp. 734-740.
[11] Chen, T, Mazomenos, EB, Maharatna, K, Dasmahapatra, S & Niranjan, M 2013, Design of a Low-Power On-Body ECG Classifier for RemoteCardiovascular Monitoring Systems, IEEE Journa-l of Emerging SelectedTopics in Circuits and Systems, Vol. 3, no. 1, pp. 75-85.
[12] Wen, C, Yeh, MF, Chang, KC & Lee, RG 2008, Real-time ECGtelemonitoring system design with mobile phone platform, Measurement,Vol. 41, no. 4, pp. 463-470.
[13] Shih, DH, Chiang, HS, Lin, B & Lin, SB 2010, An Embedded MobileECG Reasoning System for Elderly Patients, IEEE Transactions onInformation Technology Biomedicine, Vol. 14, no. 3, pp. 854-865.
[14] Rodriguez, J, Goni, A & Illarramendi, A 2005, Real-time classification of ECGs on a PDA, IEEE Transactions on Information Technology inBiomedicine, Vol. 9, no. 1, pp. 23-34.
[15] Dong, J, Zhang, J, Zhu, H, Wang, L, Liu, X & Li, Z 2012, A RemoteDiagnosis Service Platform for Wearable ECG Monitors, IEEE IntelligentSystems, Vol. 27, no. 6, pp. 36-43.
[16] Lee, RG, Chen, KC, Hsiao, CC & Tseng, CL 2007, A mobile care system with alert mechanism, IEEE Transactions on Information Technology inBiomedicine, Vol. 11, no. 5, pp. 507-517.
[17] Moses, Diana, and C. Deisy, 2016, m-CADE: A mobile based cardiovascular abnormality detection engine using efficient multi-domain feature combinations, Intelligent Data Analysis, Vol. 20, No. 3, pp. 575-596.