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***Abstract*—Myocardial Infarction (MI) is leading cause of growing global mortality rate. Existing methods currently in use are less accurate, expensive and difficult to operate. This works targets detection of MI through a novel Pulse Plethysmograph (PuPG) signal analysis. PuPG signal data for this study is collected from total 102 subjects which contains data from 30 persons who were positively identified as MI subjects by medical experts. PuPG signal is acquired through subject's index finger and preprocessed to remove noise. After comprehensive feature analysis, three features posing maximum intraclass difference were selected to classify MI and normal signals through Support Vector Machines (SVM), K-nearest neighbor (KNN) and Decision tree (DT) classification methods. SVM with Gaussian kernel achieves maximum average accuracy of 98.5%, sensitivity of 100% and specificity of 95.1% upon comprehensive experimentation. Proposed methodology is non-invasive, low cost and accurate as compared to the existing solutions and gives excellent insights towards alternate diagnosis techniques.**

Keywords—Myocardial Infarction, Feature extraction, Classification, Pulse Plethysmograph, Empirical mode decomposition

I. INTRODUCTION

Myocardial Infarction (MI) is one of the major causes of global mortality and responsible for 17.3 million death per year. It is expected that this death rate due to heart attack will become 23.6 million by year 2030. According to American Heart Association report in year 2016 that one out of three deaths is due to heart attack [1]. Worldwide stoke incidents occur almost 17 million times per year. This becomes one incident every two seconds [2]. It is claimed by World Health Organization (WHO) that Cardiovascular disease is the main cause of death of people above 35 years [3].

When blood flow stops to the heart MI occurs and its detriments the heart muscles. Oxygenated blood is supplied by coronary to the heart. Coronary arteries are blocked by formation of plaque. As a result, supply of blood to the heart decreases which causes heart attack also known as Myocardial Infarction (MI). MI is also known as silent heart attack because patients are unaware of their condition that they are suffering from MI [4].

MI has following different symptoms explained by [5].

- pain in the backbone or discomfort in jaw
- feeling weak
- having pain in chest
- discomfort in arms or shoulders
- shortness of breath

Accurate and timely diagnosis of MI is crucial to avoid sudden death. Existing methods involve use of ECG technique for condition monitoring of heart. Convolution neural network (CNN) and wavelet is implemented in [4] for classification of MI and normal ECG signals and achieved average classification accuracy of 95.22%. In another ECG based study, 12 electrocardiogram leads were used for detection of MI [3]. Twelve non-linear features and K-nearest neighbour (KNN) classifier was applied to achieve accuracy of about 98.7%. In [6] Coronary Artery Disease (CAD) and MI are classified through Discrete Cosine Transform (DCT), Discrete Wavelet Transform (DWT) and Empirical Mode Decomposition (EMD) . KNN classifier is employed to achieve 98% accuracy using seven features.

Shearlet and Contourlet transformations of the ECG signals were used in the [7] for classification of MI . Accuracy of 99.55% was attained through entropies, KNN classifier, decision tree (DT), and first and second order statistical features. In [8] DWT is implemented on the ECG waveforms to get accuracy of about 95%. In [9] 12 lead ECG signals with deep convolutional neural network (CNN) is employed for the detection of MI. Accuracy and sensitivity of 99% is achieved using this method. Particle Swarm Optimization (FFPSO) and Hybrid Firefly in [10] is employed on raw ECG signals and thus accuracy of 99.3% is attained. Local Configuration Pattern (LCP) and Curvelet Transform (CT) are used in [11] for the identification of MI. Accuracy of 98.99% is achieved through Support Vector Machines (SVM) classifier. In another research [12], 12 lead ECG signal is classified through SVM to achieve accuracy of 98%. 220 features are extracted from ECG signal. In [13] Flexible analytic wavelet transform (FAWT) is applied on ECG beats. J48 decision tree, Random forest (RF), back propagation neural network (BPNN) and SVM classifiers are trained to reach an accuracy of 99.3%.

Heart and respiratory rate estimation through photoplethysmography (PPG) is explained in [14]. For extracting cardiac and respiratory information from PPG signals, Fast Fourier transform (FFT) was applied. In [15], PPG signal analysis was performed for detection of Coronary Artery Disease through SVM. Another similar study targeted PPG and PCG are used for diagnosis of Coronary Artery Disease via combination of PPG and Phonocardiogram (PCG) signals [16]. These studies prove the vast cardiac health information carried by PPG signal.

TABLE I: SUMMARY OF EXISTING LITERATURE

Ref	Data/Signal Type	Methods	Results
[3]	Physiobank ECG Database	Entropy features, fractal dimension, Kolmogorov complexity, Lyapunov exponent K-Nearest Neighbor	Acc:98.74% Sen:99.5% Spec:99.16%
[4]	ECG database	Wavelet, CNN	Acc:95.22%
[6]	PTB Diagnostic ECG Database	DWT, EMD, DCT, K-NN	Acc:98.5% Sen:99.7% Spec:98.5%
[7]	Physiobank (PTB)	Statistical features, Decision tree (DT), KNN	Acc:99.5% Sen:99.93% Spec:99.24%
[8]	National Institute of Technology Calicut, India	DWT, Energy entropy	Acc:95%
[9]	Physiobank (PTB)		Acc:99% Sen:99%
[10]	PTB ECG Dataset	FFPSO, KNN, SVM, LMNN	Acc:99.3% Sen:99.97% Spec:98.7%
[11]	National Heart Centre (NHC), Singapore	CT, LCP, SVM	Acc:98.99% Sen:98.48% Spec:100%
[12]	PTB ECG Dataset	220 features, SVM	Acc:98.33% Sen:96.66% Spec:100%
[13]	PTB ECG Dataset	Wavelet, FAWT, BNN, LS-SVM	Acc:99.3%
[17]	National Heart Centre, Singapore ultrasound scanner (ProSound α 10, ALOKA Hitachi, Japan)	histogram equalization, DWT, GLCM, HOS, SVM	Acc: 99.5% Sen: 99.75% Spec: 99.2%

Other techniques like Phonocardiography (heart sounds), using 2D echocardiograms, ultrasound are also active research areas for detection of MI. Ultrasound images were used in [17] for categorization of MI. Support vector machine (SVM) classifier, DWT, Higher-Order Spectra (HOS) and Gray-Level Co-Occurrence Matrix (GLCM) were used to achieve accuracy of 99.5%.

Table I presents summary of existing works that targeted detection of MI. Most of the current research focus towards signal analysis using ECG signals. ECG signal acquisition is subjected to electromagnetic interference (EMI) due to electronic devices, moreover ECG machine is also very expensive. In contrast, this work presents a novel methodology of monitoring cardiac health through non-invasive and low-cost Pulse Plethysmograph (PuPG) signal analysis. PuPG signals are acquired through subject's index finger, which are further preprocessed with low pass filter. Comprehensive feature analysis is performed to select three features having best discriminative properties. SVM classifier is applied to perform detection of MI and Normal subjects. Proposed method is accurate, low cost and non-invasive as compared to existing methodologies. Rest of this article is structured as follows. In section II "Methods and Materials", details of proposed methodology and data acquisition protocols are explained. In section III "Results and Discussions" experimental details with comprehensive analysis of results with different feature extraction and classification methods is presented. Finally, section IV concludes this article giving insights into future directions.

II. MATERIALS AND METHODS

Figure 1 presents the proposed methodology for detection of MI through non-invasive and low-cost PuPG signal acquisition. PuPG signal is first preprocessed through a low pass filter in order to remove any high frequency noise or motion artifacts occurred during data acquisition. Next, feature extraction is performed which uses combination of mean frequency, Lyapunov Exponent and Spurious free dynamic range features. Features are selected on the base of thorough experimentation. Finally, extracted features are fed to SVM classifier to distinguish normal and MI classes.

A. Data Acquisition

In this study, we used PTN-104 Pulse Plethysmograph (PuPG) sensor for data accumulation. PTN-104 sensor is a portable and sensitive and low-cost. It uses piezoelectric material, which converts pulse activity signals from blood motion to electrical signals. Sensor is fastened on index finger to gather signals as It is small in size and can easily be attached on any finger. All the signals are recorded in digital computing

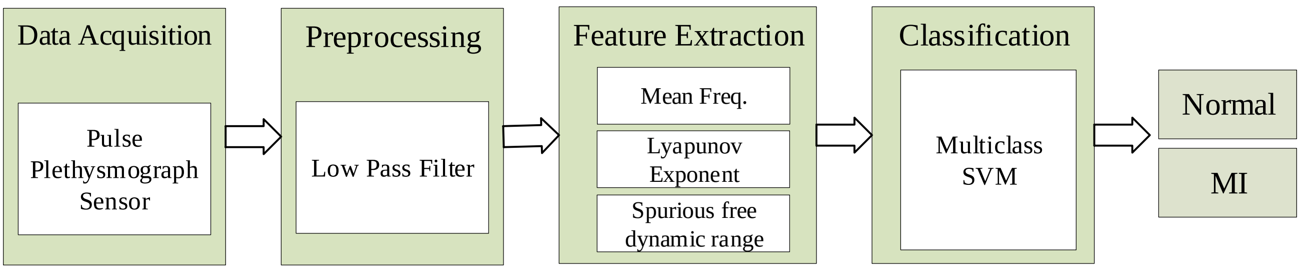

Figure 1: Block diagram of the proposed methodology for MI detection

Figure 2: PTN-104 Pulse Plethysmograph Sensor

device and stored as .mat files. Figure 2 shows PTN-104 PuPG sensor.

Total 102 signals were collected from normal persons and MI patients. PuPG signals acquired from MI patients were admitted at Armed Forces Institute of Cardiology, Islamabad, Pakistan and Pakistan Ordnance Factories hospital, Wah Cantt, Pakistan. Collection of normal PuPG data samples from 72 individuals were also carried out. Table II summarize all details about acquired dataset. Data was acquired in laying position as it is the most suitable condition . Figure 3 and 4 shows raw PUPG signals of normal and MI subjects.

TABLE II: DATASET DESCRIPTION

Classes	**Male**	**Female**	**samples**
Normal	36	36	72
MI	25	15	30
Total	120	-	-

B. *Preprocessing*

After data acquisition step the first step is to denoise the signals. For denoising of signals, we applied low pass filter of 35Hz on raw signals. Fig. 3 and 4 shows time and frequency domain representation of raw signal acquired from normal and MI subjects. It can be clearly observed from Fig. 3 that power line high frequency noise influences the original PuPG signal. Similar interferences are also induced due to motion artifacts. Fig. 4 and 5 depicts denoised time and frequency domain

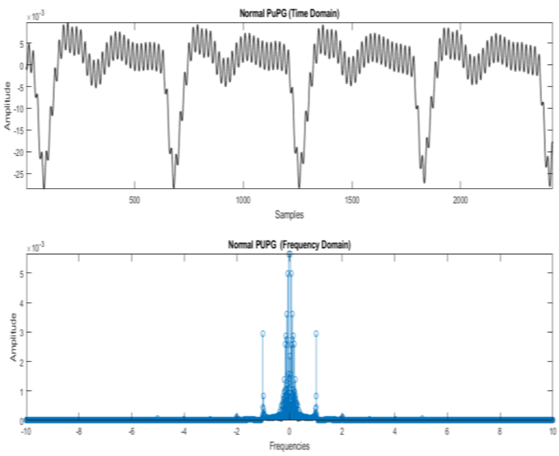

Figure 3: Raw PuPG signal of Normal subject with its Fourier Transform

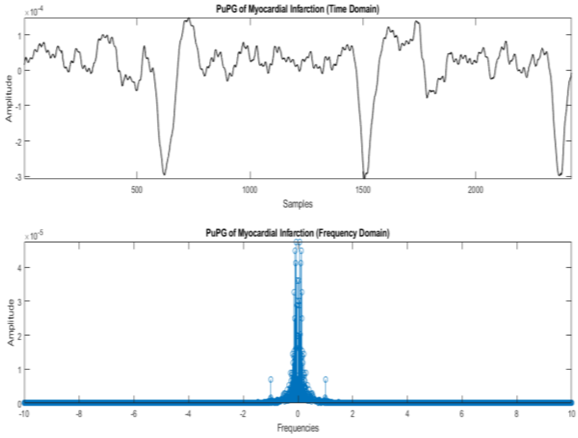

Figure 4: PuPG signal of MI subject with its Fourier Transform

representation of signal after preprocessing. It can be observed that power line interference is removed from the resultant signal.

C. *Feature Extraction*

Feature extraction is significant processing stage in biomedical signal analysis. Objective of feature extraction stage is to characterize signal data with accurate and minimum possible parameters. To figure out features having highest discriminative ability between normal and MI class, comprehensive features analysis is performed on preprocessed PuPG signals. We employed statistical features (signal mean, standard deviation, and variance), frequency domain features (mean frequency) and time domain features (energy, total jitter, log energy, Spurious free dynamic range, Lyapunov exponent) for thorough feature analysis.

Maximum average classification accuracy is achieved through mean frequency, Lyapunov exponent and Spurious free dynamic range features. Details of these features is explained next.

i. *Lyapunov Exponent (LE)*

The Lyapunov exponent is defined by the average growth rate λi of the initial distance [18]. Lyapunov exponents are the functions of dynamic system [19]. Eq. 1 defines

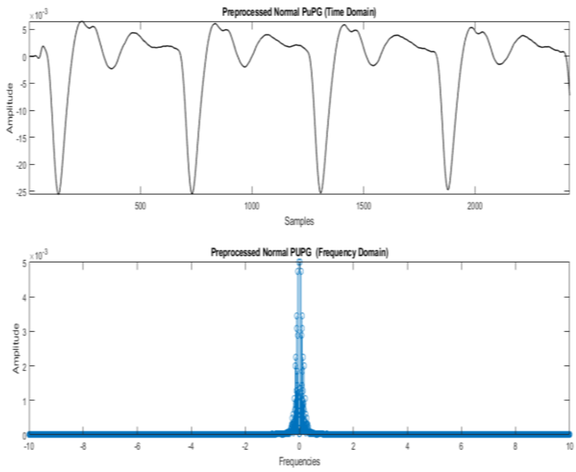

Figure 5: Time and frequency domain representation of PuPG of Normal person

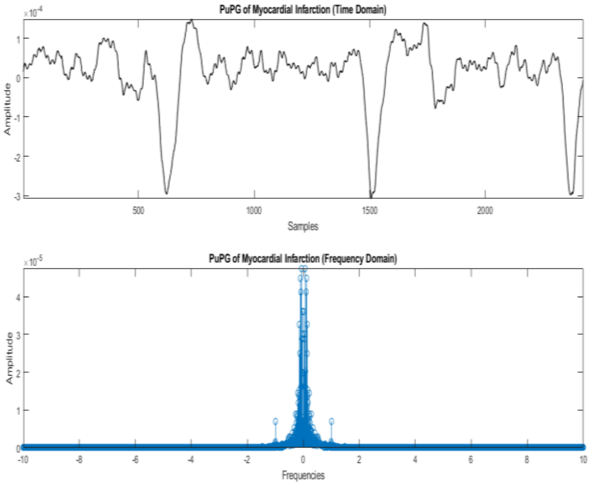

Figure 6: Time and frequency domain representation of PuPG signal of MI subject

$$\frac{\| \delta x_i(t) \|}{\| \delta x_i(0) \|} = 2^{\lambda_i t} (t \rightarrow \infty) or\ \lambda_i = \lim_{t \rightarrow \infty} \frac{1}{t} \log_2 \frac{\| \delta x_i(t) \|}{\| \delta x_i(0) \|} \quad (1)$$

To explain Lyapunov exponent consider two nearest points in the phase space at a time 0 and time t ,distances of the points in the ith direction being $\| \delta x_i(0) \|$ and $\| \delta x_i(t) \|$ [18].

D. Mean frequency

Mean frequency is calculated using the periodic -mean frequency estimate [20].

$$M_i = \frac{f_s}{4\pi} \{ \arg [\sum_{k=0}^{N/2-1} | X_i(k) |^2 \ e^{j2\pi k/N}] \bmod 2\pi \} \qquad (2)$$

E. Spurious free dynamic range (SFDR):

In SFDR is defined as the ratio of desired frequency component to the largest undesired FREQUENCY component at the output of DDFS. Its unit is decibel.

$$SFDR = 20 \log_{10} (\frac{A_p}{A_s}) \qquad (3)$$

Where A_P is the amplitude of desired frequency component and A_s is the amplitude of the largest undesired frequency component [21].

III. CLASSIFICATION

SVM is a powerful and widely applied classifier in the domain of medical signal analysis [22, 23]. SVM employs hyperplane that performs separation between two classes. Linear SVM is given as:

$$y = W^T X + b \qquad (4)$$

where X is the feature vector, y represents class label, W is the weight vector, b is the classifier bias. W and b are optimized through training, while X is extracted features from signal. Non separable data is classified by SVM through mapping low dimensional features to higher dimensions where separation become possible using kernel trick.

In this study, MI and normal class of PuPG signals is distinguished through SVM with different kernels. SVM-linear (SVM-L), SVM-Quadratic (SVM-Q), SVM-Cubic (SVM-C) and SVM-Gaussian (SVM-G) were employed to test the classification performance.

IV. RESULTS AND DISCUSSIONS

Pulse Plethysmograph (PuPG) based signal analysis framework is proposed for classification of normal and MI class. After preprocessing with low pass filter, a detailed feature analysis is performed to figure out features having powerful discriminative properties. Table III presents summary of comprehensive feature analysis using SVM-G classification method. It is observed that combination of Lyapunov Exponent, SFDR and mean frequency features yields 98.5% classification accuracy. So, we select these best performing features for our feature extraction block. All other experiments are performed with this feature combination.

Evaluation of classifier is performed through 10-fold cross validation. K-fold cross validation techniques is reliable way to analyze performance of classification model. In 10-fold cross validation (CV), dataset is split into ten random subsets. In first iteration, one subset is utilized as test data while other nine are combined to form training dataset. 10 iterations are performed in a similar manner and results are averaged over all iterations. In this research, classification model is tested 100 times and average results of these experiments are presented. All results are presented in terms

TABLE III. PERFORMANCE EVALUATION OVER COMBINATION OF MULTIPLE FEATURES

Mean	**Standard deviation**	**Total Jitter**	**Energy**	**Lyapunov Exponent**	**SFDR**	**Mean frequency**	**Log Energy**	**Variance**	**Accuracy**
●	●		●	●				●	78.4%
	●							●	67.6%
		●	●	●			●		71.6%
	●	●			●		●	●	79.4%
				●	●	●			**98.5%**
		●					●	●	68.6%
●				●	●	●			94.1%
	●	●	●			●	●		81.4%

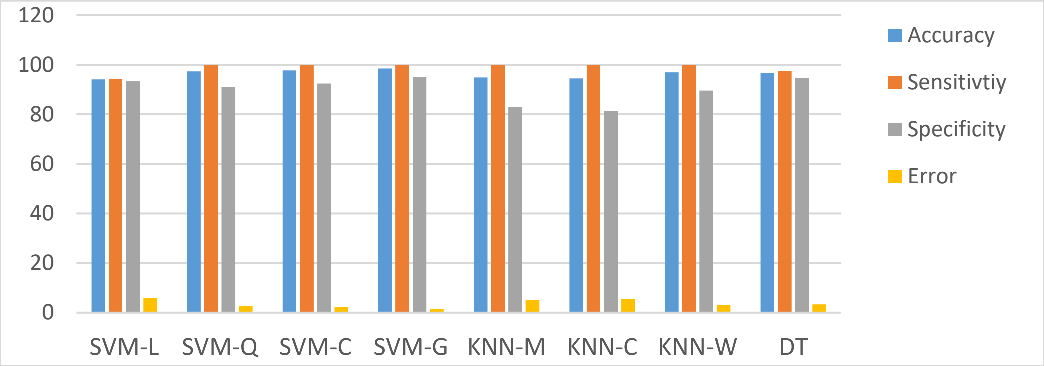

Figure 7: Performance comparison with different classifiers

of standard performance evaluation metrices such as accuracy, sensitivity, specificity and error rate.

Table IV presents classification performance of proposed features over several classifiers. We evaluated proposed methodology with eight different classification methods namely Decision tree (DT), K-nearest neighbor (KNN) with K=5, KNN with weighted distance (KNN-W), KNN with cubic distance metric (KNN-C), SVM-L, SVM-Q, SVM-C and SVM-G. Experimental analysis reveals that SVM-G achieved best performance in terms of accuracy (98.5%), sensitivity (100%) and specificity (95.1%). It can be observed that classification performance with all classification methods is well above 90%. This proves the discriminative robustness of extracted features. Figure 7 presents graphical comparison of evaluation of different classifiers.

TABLE IV: PERFORMANCE EVALUATION OVER DIFFERENT CLASSIFIERS

Classifier	Acc.	Sen.	Spec.	Error
SVM-L	94.12	94.44	93.33	5.88
SVM-Q	97.35	100.00	91.00	2.65
SVM-C	97.79	100.00	92.50	2.21
SVM-G	**98.58**	**100.00**	**95.17**	**1.42**
KNN-M	94.95	100.00	82.83	5.05
KNN-C	94.51	100.00	81.33	5.49
KNN-W	96.96	100.00	89.67	3.04
DT	96.67	97.50	94.67	3.33

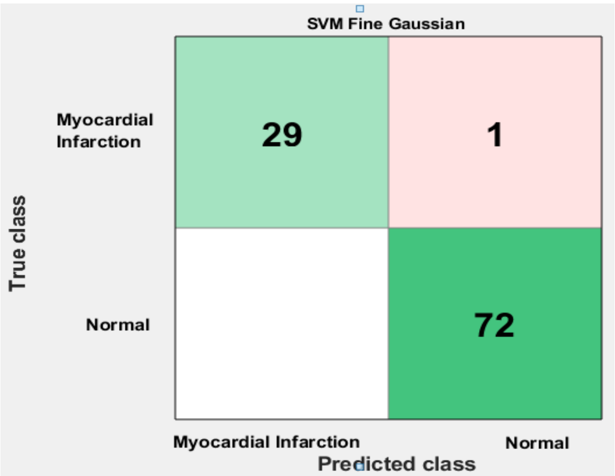

Figure 8: Confusion matrix with SVM-G

Figure 8 and 9 presents class-wise achieved with proposed methodology. 29 out of total 30 signals from MI class were correctly detection as MI by classifier, while all normal signals were correctly classified as normal with 10-fold cross validation. Normal class achieved 100% accuracy, while 97% accuracy is achieved by MI class.

In comparison to the other existing approaches summarized earlier in table I, it is pertinent to mention that one-to-one comparison is not possible due to the difference in data acquisition methodology. Proposed method in this research is highly accurate and performance of MI detection is comparable to the existing mature techniques.

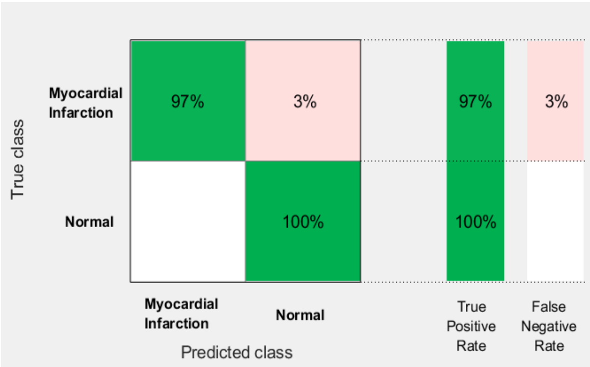

Figure 9: Class-wise accuracy in the form of confusion matrix

V. CONCLUSIONS

In this research, a novel methodology for detection of MI for cardiac health monitoring is proposed. Our proposed framework relies on strong signal analysis and classification performed on Pulse Plethysmograph (PuPG) signals acquired through low-cost and non-invasive sensor. Proposed method is reliable in terms of detecting MI and gives insights towards new paradigm for cardiac health monitoring using PuPG signals. In future, we aim to collect more signals from MI subjects, in order to train classifier with more data.

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