An Enhanced Premature Ventricular Contraction Pulse Detection and Classification Using Deep Convolutional Neural Network

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AN ENHANCED PREMATURE VENTRICULAR CONTRACTION PULSE DETECTION AND CLASSIFICATION USING DEEP CONVOLUTIONAL NEURAL NETWORK

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Abstract

Accurate and precise monitoring of cardiac arrhythmia's helps to avoid serious heart issues. The research concentrates on using Photoplethysmography (PPG) and Arterial Blood Pressure (ABP) with deep Convolutional Neural Networks (CNN) for the classification and detection of fetal cardiac arrhythmia or Premature Ventricular Contractions (PMVCs). The process starts with Icentia 11k, a public dataset of ECG signal which consist of different cardiac abnormalities. The process proceeds with the MIMIC dataset and test dataset available from the hospital which is the transferred weights obtained from Icentia 11k dataset. The fine tuning improves the accuracy of classification. The proposed method can be able to detect and classify PMVCs in to three types: Normal, P1 and P2 with an accuracy of 99.9%, 99.8% and 99.5%.

keywords: Premature Ventricular Contraction (PMVC), Photoplethysmography (PPG), Arterial Blood Pressure (ABP), Wavelet Transform, Convolutional Neural Network (CNN).

I. Introduction

Premature Ventricular Contractions (PMVCs) is considered to be the most common rhythmic irregularity of heart rate. PMVCs are the premature pulses occurs due to the secondary ectopic pacemakers located in the ventricles. This may occur in people with no significant cardiac health problems and it is often seen along with those suffering from structural heart diseases. Sometimes, this may trigger for future cardiac abnormalities [1,2,3] and the studies concluded that it could be non fatal in the absence of structural heart diseases [4]. However, recent research found that the increased frequency of PMVCs could be fatal and it results in cardiac failure. Multiple frequent PMVCs can be occurred as bigeminy and trigeminy where every second and third beats are premature respectively. This can cause inefficiency in blood circulation and that may lead to temporary loss of consciousness

[5,6,7]. PMVCs are the common type of cardiac rhythmic irregularity occurred in patients with chronic kidney disease [8].

Many methods were presented for the detection and classification of PMVC from ECG signals like Gaussian process Classifiers (GPC), Support Vector Machines (SVM) [9], Fuzzy neural network (FNN)[10],Wavelet transform and timing interval features[11],Wavelet transform and discreate cosine transform[12],SVM and particle swarm optimisation[13],Principal Component Analysis(PCA) and Feed Forward Artificial Neural Network(FNN)[14] and Quadratic spline wavelet and FNN[15]. However, the chest electrodes are generally used for acquiring ECG signal. But it may cause discomfort and limited movement for the patients [16]. The researchers suggested an alternative method for ECG which is known as Photoplethysmography (PPG) based devices. These devices are cheap, user friendly and can convenient for daily life screening [17]. Some studies have been dedicated to PMVCs detection and classification from PPG signal [18,19,20,21,22]. The studies were limited to few features in time and frequency domain and reduces the possibility of detecting premature pulses. In the current research, an automated detection and classification of PMVC from PPG and Arterial Blood Pressure (ABP) are proposed using wavelet based Convolutional Neural Network (CNN) algorithm. Wavelet transform helps to find multiscale frequency information. CNN extracts specific features of the signal and classified them into different category. These PPG and ABP signals increase the robustness of the algorithm.

II METHODOLOGY

Waveforms

PPG is a non-invasive method for monitoring blood volume changes in the cardiovascular system by illuminating tissue with certain wavelength of light [17]. Usually, PPG can be acquired from fingertip with a single sensor that is more comfortable to the patient than ECG electrodes. The ABP can be acquired using a tonometer attached to the radial artery of the patient [23]. The reduced ventricular filling during PMVC lessen the PPG and ABP pulse amplitude. Hence, the waveforms becomes very difficult to identify (P1) or showing very small amplitude(P2)[24].These premature pulses P1 and P2 in PPG and ABP along with reference ECG is given in fig.1.

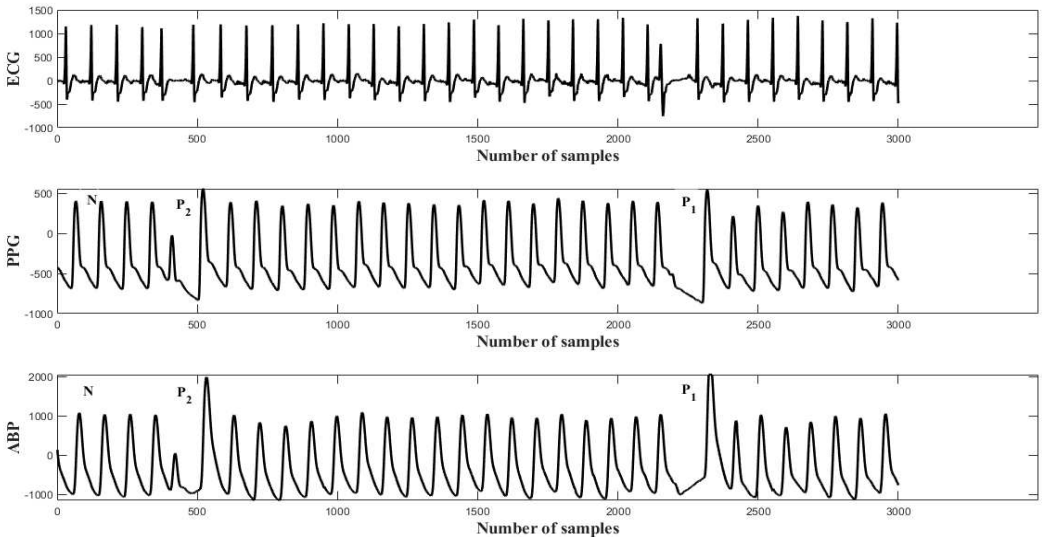


Figure 1: Example of PMVC pulse types in PPG and ABP signals with reference ECG signal, where N indicates Normal pulse and P1 and P2 indicates PMVC pulses respectively.

Datasets

Pretraining of the deep neural network was done on Icentia 11k dataset. Icentia 11k dataset was developed from the ECG signals provided by 11,000 patients in Ontario, Canada [25]. The ECG signals were recorded using CartioSTAT device. Automatic beat detection was performed on the extracted signal from CartioSTAT device and each beat were analysed by an Icentia technologist. They annotate the beat into different category of cardiac arrhythmias which included Premature Arterial Contraction, PMVC, Normal Sinus rhythm, Arterial Fibrillation and Arterial Flutteres. The PMVC pulses detected from Icentia dataset were 44,835.

The proposed method was developed on one hour duration of PPG and ABP signals from Physio net MIMIC database sampled at 250 Hz[26]. A total of 48 signals were taken for analysis. Out of that, 30 signals were taken as training signals from MIMIC database and 18 signals were taken as test signals. In addition to that, two records with PPG and ABP signals were collected from SRM medical college Hospital and Research Centre. Test signals and its respective PMVC pulses obtained from MIMIC database and from hospital were given in table 1.

Table 1: Test PPGs and ABPs from MIMIC database (No.1-18) and from hospital (No.19-20)

No.	Database	Record Name	P1	P2	No.	Record Name	P1	P2
1	MIMIC	039m	0	0	11	404m	9	2
2		041m	0	0	12	439m	12	3
3		055m	1	0	13	442m	1295	361

4		211m	0	0	14	444m	7	10
5		212m	161	30	15	449m	7	2
6		218m	0	0	16	471m	1	0
7		221m	11	0	17	474m	2	4
8		224m	0	0	18	485m	755	15
9		237m	41	13	19	SRMRC1	38	5
10		404m	1	265	20	SRMRC2	29	2

Proposed Framework

The proposed technique for PMVC detection and classification from PPG and ABP signals are shown in Figure 2. Prior to the process, signals were subjected to motion artifact reduction. The process is done by Low Rank Optimization algorithm. The denoised signal is subjected to wavelet transform at different scales. The result undergone the convolutional neural network process, detected the PMVC and classified into Normal,P1 and P2 pulses.

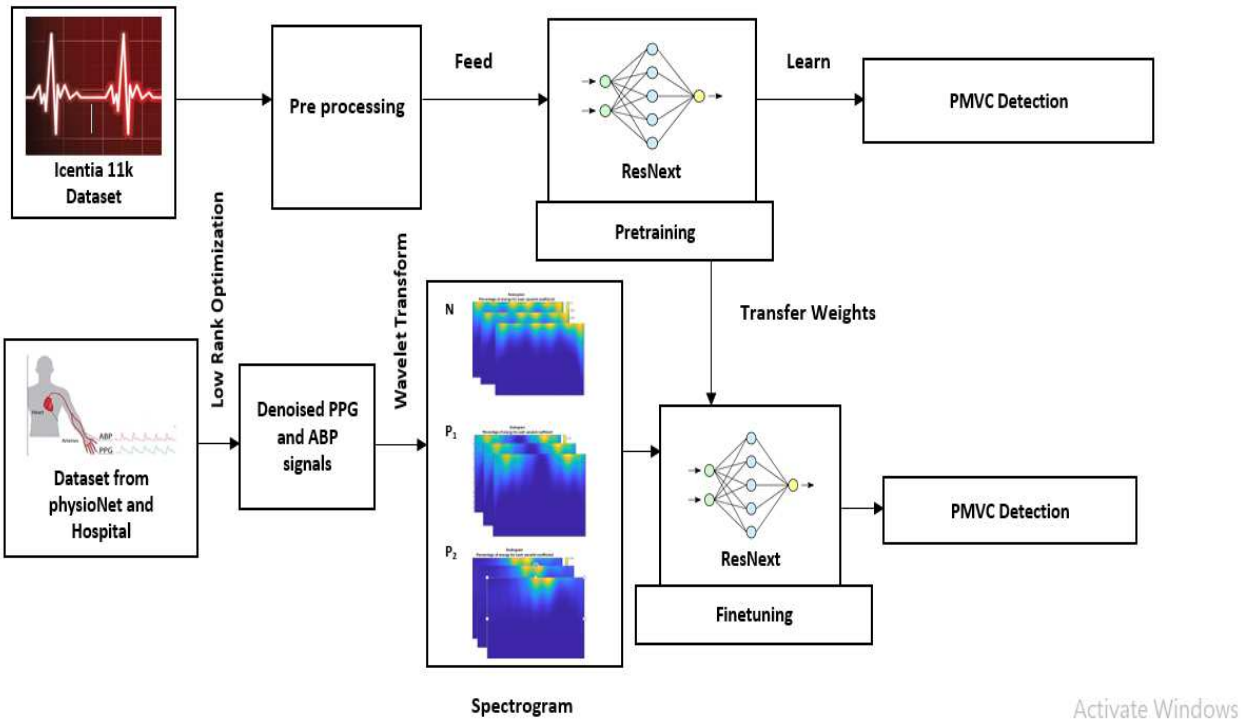


Figure 2: Block diagram of the proposed method

Motion Artifact Removal

Low rank optimization algorithm allows to model the same complexity of the PPG and ABP signals with smaller dimensions. This smaller dimension approximation of the original PPG and ABP signals are subject to constraint that the smaller dimension has lower rank. The rank constraint often imposes constraints on the deformities and outliers on the signal. This conceptualization can be mathematically proven by compacting full dimensional data into a smaller dimensional subspace while retaining the same information. The motion artifact signals can be mathematically modelled as

$$Y = Hx + n \tag{1}$$

where Y is the PPG/ABP signal corrupted with the motion artifact(H) and the additive noise(n). Using the equation (1), H and x is extracted from Y. This equation is known as an "ill- posed problem". It is called like this, because the number of unknown parameters is greater than the number of known parameters. When x and H are separated, the x will give us the motion artifact-free signal. For the Single Measurement Vector Model (SMV), Y is 1-D which consists only of the PPG sensor data or ABP sensor data.

Low rank approximation works well with signals affected by motion artefacts and is a major innovative contribution in the proposed approach. The equation (1) stands for Fourier frequency domain and the low rank approximation works well in this domain. Convolutive separation can be modelled as multiplicative separation of variables, and it also causes a distinct separation between motion artifact and PPG/ABP signal frequencies which is formerly occupied in the outer higher frequency bands. Alternatively, the optimization reduces additive noise and convolutive motion artefact. Both convolution and additive deterioration can be removed using the issue statement in equation (1). The low-rank algorithm turns this matrix into one with a significantly lower rank than the original by making the matrix have fewer independent rows but essentially same information content for a given Y.

Using low-rank approximation results in a smaller subspace structure, which can help in regularizing and solving an ill-posed problems by leveraging the amount of redundancy, which is proportional to rank. The number of observations in a low-rank matrix must be equal to or greater than the degree of freedom given by r (M+N-r), where M, N, and r denote the signal's rows, columns, and rank, respectively. The Augmented Lagrangian Method (ALM) is utilized to tackle the motion artefact problem. It is a linear, ill-posed, inverse problem, and the low-rank matrix is employed for efficient optimization approaches. Singular Value

Decomposition (SVD), a low-rank algorithm utilized in this paper, decomposes the signal into singular values. The low-rank algorithm used for Singular Value Decomposition (SVD), which decomposes the matrix into

$$[HX]_{MXN} = U_{MXD}\,\Sigma_{DXD}\mathrm{V}^{T}{}_{DXN} \tag{2}$$

and the rank of X is equal to the number of nonsingular values in the SVD. Where U, V represent the unitary square matrices of dimension [MxD, DxN] and $\sum$ represent the diagonal singular matrix of low rank which is equal to the number of nonsingular values in the SVD. When the signal is both sparse and low rank, the matrix decomposition into N atoms and all the atoms together form an atomic set A.

$$[\boldsymbol{HX}]_{\boldsymbol{MXN}} = \{\pm\,\boldsymbol{a_1}, \pm\,\boldsymbol{a_2}, \pm\,\boldsymbol{a_3}, \ldots, \pm\,\boldsymbol{a_N}\} \tag{3}$$

where

$$\pm\,\boldsymbol{a_N} = \left[\quad\right]_{\boldsymbol{1XN}}$$

The above process represents atomic set generation by concatenation of matrices.

The SVD for the atomic set of sparse low-rank matrix A is given by

$$\boldsymbol{A} = [\boldsymbol{HX}]_{\boldsymbol{MXN}} = \boldsymbol{U_{MXD}\,\Sigma_{DXD}\mathrm{V}^{T}{}_{DXN}} \tag{4}$$

From the atomic set A, the low-rank matrix is retrieved and used in a convex optimization for motion artifact removal as

$$minimize\|X\|_{*}\ subject\ to\ Y = HX \tag{5}$$

where $\|X\|_{*}$ is the nuclear norm of the matrix.

Independent Component Analysis (ICA) has been used for motion artifact removal in the noisy signals, but it was shown only to be effective for small degradations. Like ICA, the low-rank approach also assumes that a motion artifact's high dimensional data can be modeled with much lower dimensional data without a motion artifact. The low-rank constrained optimization problem can be modeled as:

$$\min_{A,E} \|E\|_F, s.t. rank(A) \leq r, y = A + E \quad (6)$$

where $\| \ \|_F$ represent the Frobenius norm and E represents the error or the motion artifact. The above low-rank minimization uses SVD given by

$$A_{k+1} = U \sum_{\frac{1}{\mu_k}} V^T \quad (7)$$

$$E_{k+1} = \sum_{\frac{1}{\mu_k}} [D - A_{k-1} + E_{k+1}] \quad (8)$$

Where (U,∑,V) represent the SVD components and λ, μ_k represent the regularization and penalty variables. The low-rank decomposition with matrix recovery differs from other motion artifact reduction methods by using only rank-one matrix. This proposed algorithm is used for any low-rank obtained from an iterative minimization step given as

$$min\|Hx - y\| = \|A_k\| + \lambda\|E_k\| + \frac{1}{\mu_k}\|Y_{k+1} - Y_k\|_F^2 \quad (9)$$

where A_{k+1} represent the k+1 iteration atomic set is sparse domain. The atomic set is iteratively updated for optimal solution and recovered matrix after k+1 iterations. $\| \ \|_F$ represents the Frobenius norm. The low-rank matrix recovery is assisted with gradient priors to the preceding equation as

$$A_{k+1} = A_k - \gamma\nabla\|Hx\| \quad (10)$$

where $\boldsymbol{\gamma\nabla\|Hx\|}$ is the further regularized gradient prior and will be used to further rectify the motion artifact output without affecting the fundamental and harmonic frequencies.

Wavelet Transform

The motion artifact corrected signal was subjected to wavelet transform. This helps the signals to transform from time domain to a combination of time and frequency domain [28]. The Continuous Wavelet Transform(CWT) applied to the signal is given by

$$CWT_x^{\varphi}(\tau, s) = \frac{1}{\sqrt{s}} \int x(t)\varphi^* \left(\frac{t-\tau}{s}\right) dt \quad (11)$$

As seen in equation (11), the transformed signal is a function of two variables, translation (τ) and scale parameters (s) respectively. ψ(t) is the transforming function and is called mother wavelet. By applying the CWT, in each and every window(per second) of PPG and ABP yields a tensor of wavelet

coefficients as shown in Figure 2.The scalogram obtained from the CWT helps to distinguish morphological and structural variation at each time point of the raw signal.

Convolutional Neural Network

CNN is a newly introduced approach for artificial neural network which builds a network with several deep layers. The local connections and shared weights make CNN unique from other deep learning architectures. The architecture of deep CNN consists of several convolution layers and pooling layers. In convolution layer, a weight matrix or filter run across the input signal or image such that all elements are converted at least once to get a convoluted output [28]. ResNext is the deep CNN used in the proposed method. ResNeXt network is an integration of ResNet [29] and Inception [30]. A ResNeXt has repeated blocks of convolution layer with same topology and it also introduces a new dimension called cardinality(C). The Cardinality is also a necessary element along with width and depth. The ResNeXt used in this method has Cardinality, C=32. The structure of ResNeXt with C=32 is shown in Figure 3.

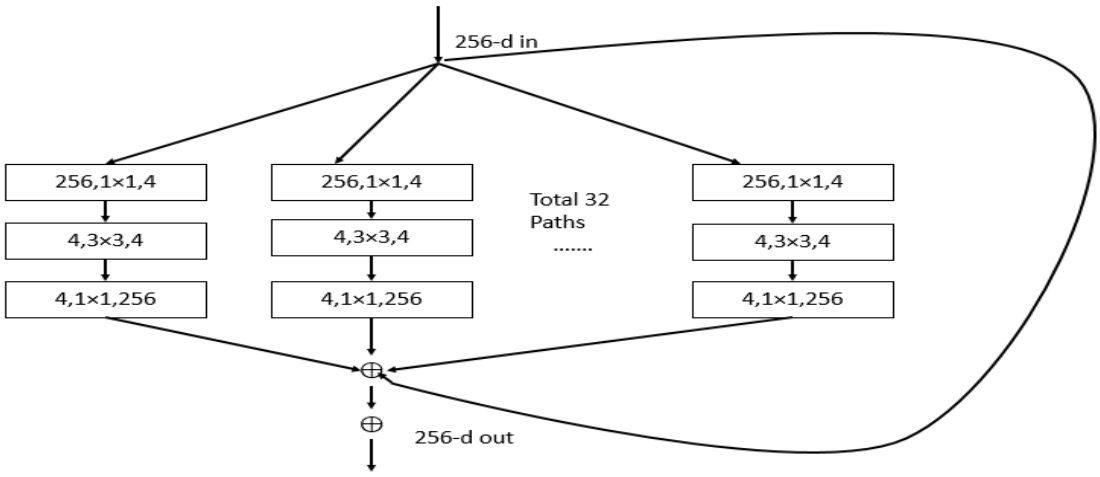


Figure 3: ResNeXt Structure

The output layer of ResNeXt consist of three neurons with a softmax activation that gives the probabilistic distribution of three classes: Normal, P1 and P2. The architecture of ResNeXt network used in this paper is shown in Figure 4. The ResNeXt network is pretrained using the Icentia 11k dataset to detect the PMVC pulses. After that, the network was finetuned using the pretrained weights obtained from Icentia dataset for input MIMIC and test dataset from hospital.

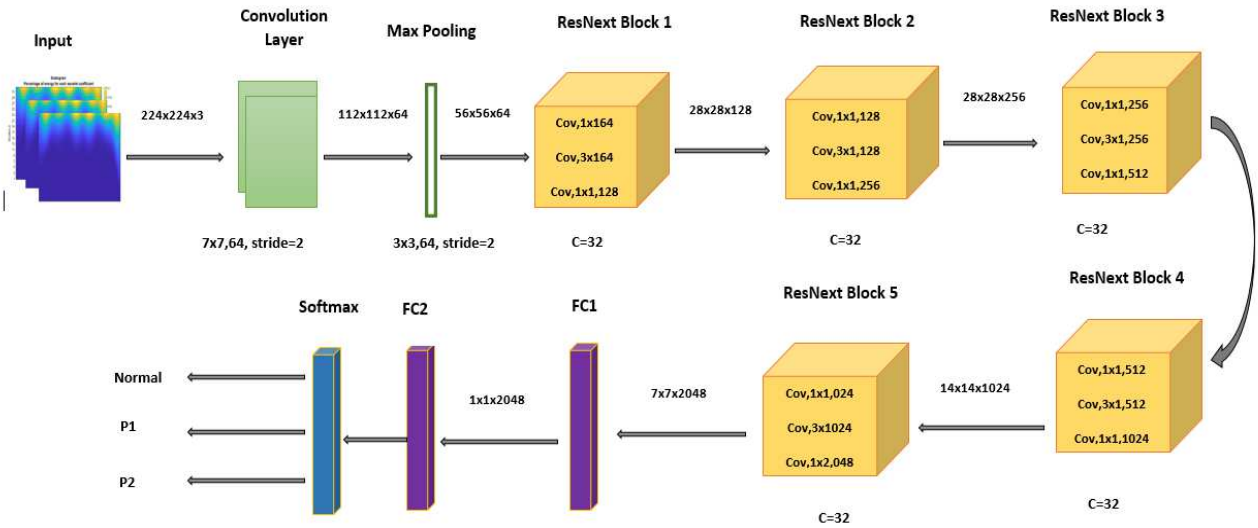


Figure.4: ResNeXt architecture for the proposed method

Fine tuning of CNN

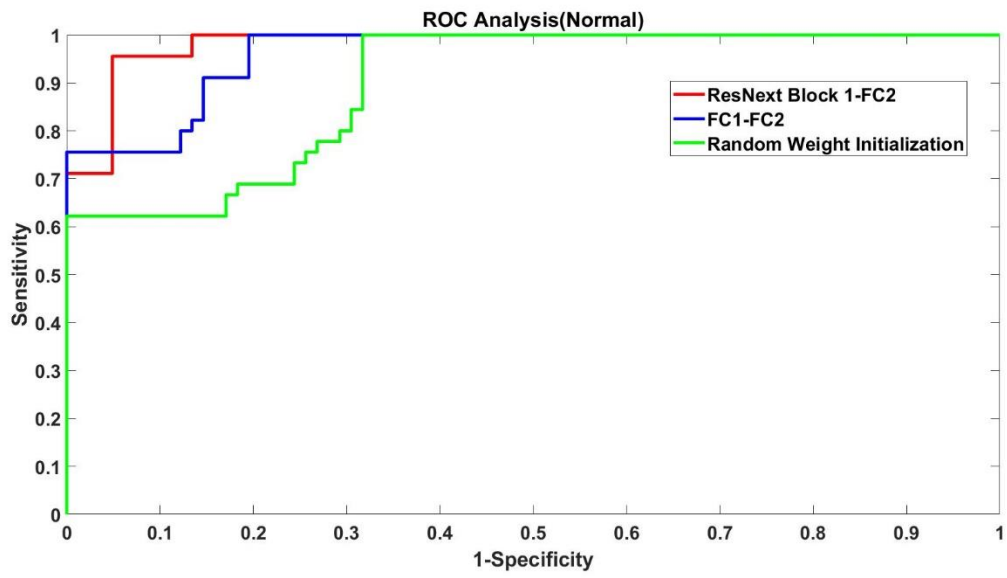
Fine tuning a network begins with transferring all weights from a pretrained network to currently used network. A common practice of fine tuning is to replace the last fully connected layers with the number of classes available for our application. This can be applied, if the distance between source and the target is somewhat similar. Otherwise, the effective way of fine tuning starts from last layer and incrementally include layer by layer until the desired performance is reached. In the proposed work, the network shown in Figure 3 is used for fine tuning. PPG is the change of intensity in blood volume occurred during each cardiac cycle. It is obtained from the fingertip and any changes in the ECG rhythmic activity or minute changes will reflect on the PPG signal. This results in obtaining good fine-tuning accuracy. The fine tuning of CNN was done on the MIMIC dataset. The dataset consists of labelled normal, P1 and P2 pulses. Before fine tuning the pre-processing, the down sampling and normalization should be completed. The dataset was down sampled to a frequency of 250-300 Hz to match it with the signal frequency of Icentia dataset. Also, zero padding to be done with the signal to make the duration of signals to a second. The dataset was divided into validation set, train set and test set. Test set also includes the signal acquired from hospital. The fine tuning starts with replacing the output layer of ResNext with fully connected layer. Here, the output indicates the PMVC and its classes. The network was fine tuned in a block wise manner, starting with tuning from last block and then continue to all other blocks. The number of epochs used for training is 200 and the macro F1 score generated after each epoch should be saved.

III RESULTS

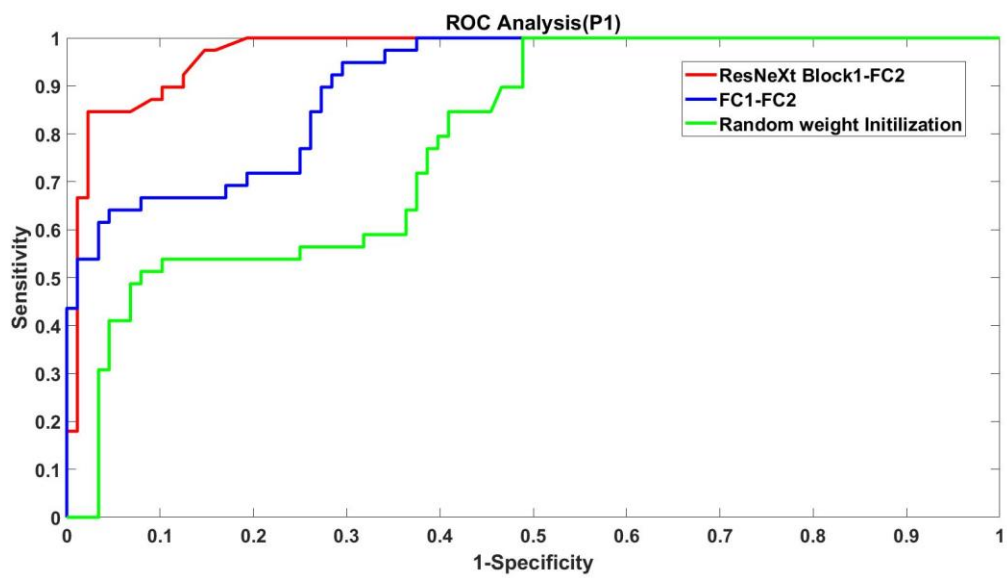
ROC Analysis

The 18 test signal collected from MIMIC dataset and 2 test signal obtained from hospital were analyzed to get the classification accuracy. Figure 5 compares the Receiver Operating Characteristics (ROC) curve for fine-tuned CNN for Normal, P1 and P2 classes. During fine tuning, the least performance was obtained when random weight was initialized to the CNN. However, fine tuning the last two layers (FC1 – FC2) gives better results when compared to random weight initialization. The performance was improved with the fine tuning of ResNext from block 1 to FC2 layer for all classes.

(a)



(b)



(c)

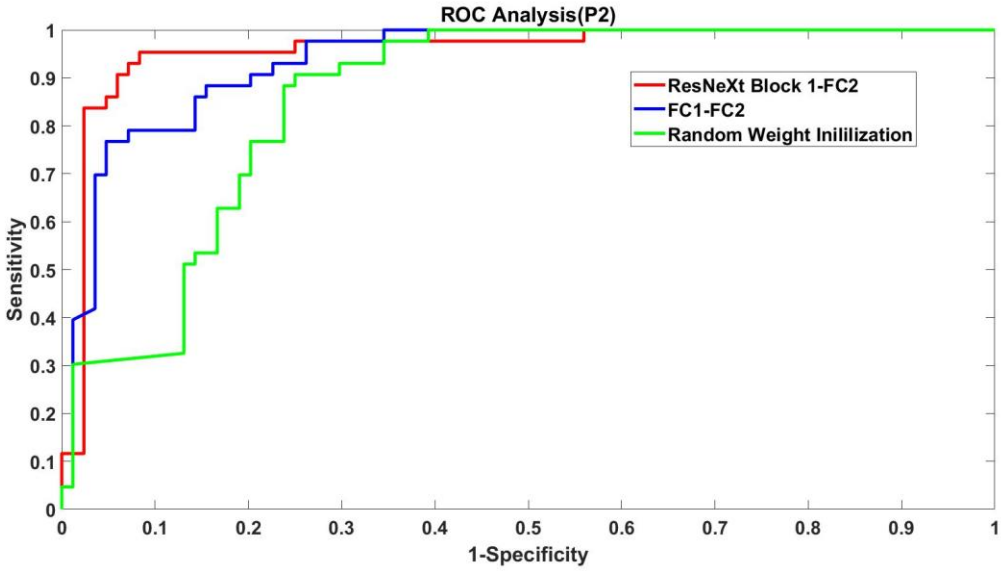


Figure 5: Comparison of different fine-tuning layers with respect to ROC curve

(a)ROC of Normal pulses, (b) ROC of P1 pulse and (c) ROC of P2 pulse

Figure 6. compares the ROC curve for Normal, P1 and P2 obtained from fine-tuned ResNext block 1 to FC2 layer. The network could classify normal signal with an Area under the Curve (AUC) of 0.9821 and P1 and P2 with an AUC of 0.971 and 0.9565 respectively. The classification accuracy of P2 pulse got reduced because of the misclassification with some smaller pulses occurred due to severe motion artifacts.

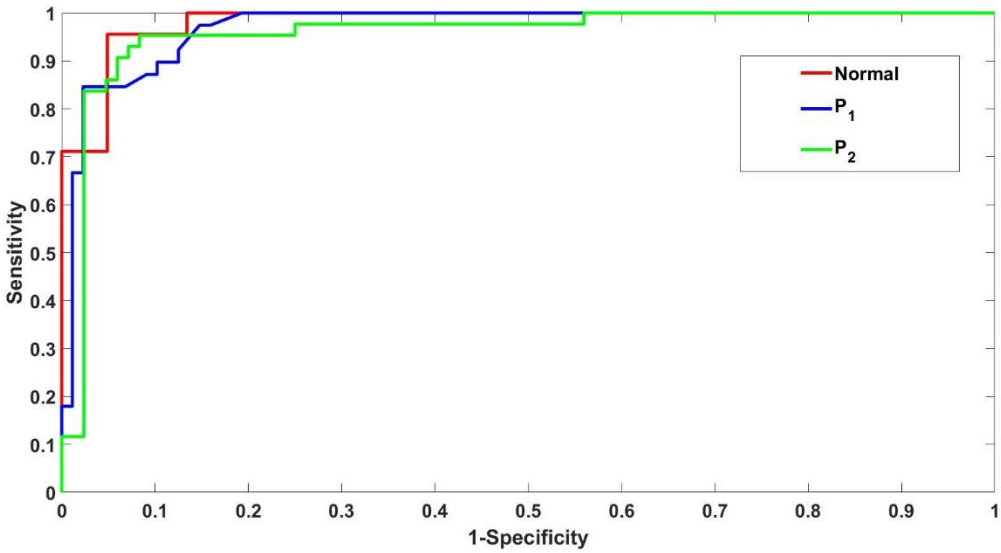


Figure 6: ROC analysis of Normal, P1 and P2 pulses for the fine-tuning Convolutional layer 1 to fully connected layer 8

F1 score Analysis

The comparison of F1 score of different pre training objectives on test dataset were given in Table 2. The pre training objectives includes heart rate classification, Arterial fibrillation, PMVC and sinus rhythm. The transferred weights from Icentia dataset which corresponds to PMVC were given as initial weights to MIMIC dataset. The F1 score of both normal and noisy signal and its average was illustrated in the table. The MIMIC test dataset has good F1 score for PMVC events when compared with other pre training objectives. The average F1 score obtained for PMVC was 0.959 ± 0.52. The ResNeXt shown best F1 score of 0.934± 0.12 for noisy PMVC pulses also.

Table.2: Comparison of F1 score of different pre training objectives

Pre training Methods	Average F1 Score	F1(Normal)	F1((Noisy)
Heart Rate Classification	0.714±0.26	0.784±0.24	0.692±0.28
Arterial Fibrillation	0.802±0.265	0.812±0.92	0.792±0.32
PMVC	0.959±0.52	0.984±0.92	0.934±0.12
Sinus Rhythm	0.787±0.18	0.732±0.14	0.842±0.23

Table 3 shows the comparison of F1 score of pre training objectives on different CNN architectures. Here, compared ResNeXt with different layers of ResNet and DenseNet. Out of all ResNet architectures, the maximum F1 score was obtained for ResNet 50 with an F1 score of 0.892±0.72 for PMVC pulses. When compared with ResNet and DenseNet, ResNeXt outperformed with an F1 score of 0.959±0.52 for detecting PMVC pulses.

Table.3: Comparison of F1 score on different CNN architectures

Pretraining Methods	ResNet 18	ResNet 34	ResNet 50	ResNext	DenseNet
Heart Rate Classification	0.632±0.13	0.743±0.16	0.784±0.12	0.826±0.52	0.852±0.32
Arterial Fibrillation	0.642±0.17	0.752±0.28	0.832±0.18	0.854±0.85	0.785±0.08
PMVC	0.699±0.52	0.783±0.45	0.892±0.720	0.959±0.52	0.895±0.23
Sinus Rhythm	0.642±0.28	0.714±0.13	0.793±0.82	0.796±0.66	0.845±0.55

Classification Results

Table 4 presents the classification results using CNN alone with PPG and ABP signals. It obtained an accuracy of 93.8%, 92.3% and 89.4% for Normal, P1 and P2 pulses respectively. The results obtained using wavelet based CNN with PPG signal alone is given in Table 5.The performance of wavelet based CNN with PPG signal gives better classification results than CNN with PPG and ABP

signals with an accuracy of 95.9 %,93.4 % and 90.08 % for Normal,P1 and P2 pulses respectively. The proposed method of wavelet based CNN using PPG and ABP signals were given in Table 6.The classification results of the proposed method outperformed above two methods with an accuracy of 99.9 % ,99.8 % and 99.5 % for Normal, P1 and P2 pulses respectively.

Table 4: The Classification results obtained using CNN with PPG and ABP signals

Pulses	Accuracy(%)	Specificity(%)	Sensitivity(%)
Normal	93.8	92.4	89.3
P1	92.3	93.9	90.4
P2	89.4	92.1	85.3

Table 5: The Classification results obtained using wavelet-based CNN with PPG signal

Pulses	Accuracy (%)	Specificity (%)	Sensitivity (%)
Normal	95.9	96.5	94.5
P1	93.4	95.9	93.4
P2	90.08	94.4	88.3

Table 6: The Classification results obtained using wavelet based CNN with PPG and ABP signals

Pulses	Accuracy (%)	Specificity (%)	Sensitivity (%)
Normal	99.9	95.4	99.9
P1	99.8	95.2	99.3
P2	99.5	99.6	94.3

IV DISCUSSION

The goal of this proposed work was to develop a method for the detection and classification of PMVC from simultaneous PPG and ABP signals. The use of wavelet transforms and CNN allowed to achieve better performance than other machine learning based method,[21],[22] which are discussed in the literature. With wavelet transform, the multiscale frequency information can be obtained at each point of the given signal that relates to premature pulses. CNN helps to extract several features related to premature pulses and helps in correct classification. In the current method, estimation of wavelet transform on every one second duration of the signal is completed, so that there should not miss any chance of loss of pulses. Furthermore, the incremental fine tuning of CNN, helps to achieve higher sensitivity on ResNext from block 1 to FC2 layer for all classes with low false positive rate.

Table 7: Performance analysis of proposed wavelet-based CNN method with other state-of-art methods

Classifier	Accuracy (%)			Specificity (%)			Sensitivity (%)		
	Normal	P1	P2	Normal	P1	P2	Normal	P1	P2
SVM[22]	90.9	-	-	92.9	-	-	87.5	-	-
MLP[22]	72.3	-	-	76.9	-	-	66.7	-	-
KNN[22]	95.5	-	-	100	-	-	88.9	-	-
Morphological features + ANN[21]	99.3	99.5	99.8	94.2	99.6	99.8	99.4	94.2	93.1
Proposed Wavelet Transform + CNN	99.9	99.8	99.8	95.4	99.8	99.5	99.9	96.3	95.3

The classification results using CNN alone with PPG & ABP signals and wavelet-based CNN with PPG signal alone were compared in the proposed method. Performance of the proposed method were also compared with other machine learning based technique [21,22] and is given in Table 7. The sensitivity and specificity of morphological features-based ANN method [21] were 99.4/94.2,94.2/99.6 and 93.1/99.8 and the proposed method obtained sensitivity and specificity of 99.9/95.4,96.3/99.8 and 95.3/99.5 respectively for Normal, P1 and P2 pulses. The classification accuracy for morphological features-based ANN method [21] were 99.3%,99.5% and 99.8% for Normal, P1 and P2 pulses respectively, whereas the proposed wavelet-based CNN method outperformed it by 99.9%,99.8%, and 99.8%. The normalization of heart rate will be a tedious task when the classification performance of PPG signal largely depends on estimated normal heart rate [21]. The pre-processing step makes the algorithm complex and time consuming [21].The proposed algorithm eliminates these two problems, even though the time taken for training was high but for testing, it will takes only few seconds.

The limitations of the proposed study as follows. First as in [21], the labelling of Normal, P1 and P2 pulses were done manually by comparing the ECG pulses. Secondly, this method was not tested in signals recorded during physical activities.

V CONCLUSION

An automated detection and classification of PMVCs using PPG and ABP were discussed in the proposed work. The wavelet-based CNN helps to achieve good accuracy for premature pulse classification, when compared to other state-of-art methods. In the proposed work, transfer learning were used to improve the accuracy of classification using ResNext. First, the pretraining was done on the large ECG dataset called Icentia 11k and the fine tuning was done on a smaller PPG dataset obtained

from MIMC II and hospital dataset. Since PPG is the blood volume changes occured during each cardiac cycle obtained from fingertip, any changes in the ECG rhythmic activity and minute feature changes will also reflect in PPG. The proposed PMVC detector can be used in clinical application when moderate physical activities are involved.

Conflict of Interest

None.

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