A Report on Project Work
Course Title: Biomedical Signal Processing

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I. Introduction

This work is based on this paper from [1]. The main goal is to detect arrhythmia based on DWT (Discrete Wavelet Transform) features using Support Vector Machine (SVM) and Artificial Neural Network (ANN). Here I have tried to recreate the reported results of the paper using the same classifiers on the almost same dataset, using the same feature selection process. There are some minor changes in the preprocessing step.

II. Dataset

The Database used in this work is taken from MIT-BIH (MIT- Boston's Beth Israel Hospital) Arrhythmia Database. Each ECG signal consist of 30 minutes of recording. These records were sampled at 360 Hz and band pass filtered at 0.1-100 Hz [2]. The paper used 12 patient records - '100', '102', '103', '109', '111', '113','118', '208', '217', '221', '231' and '233' of which I have used 11 (except '113') to retain the uniformity of the dataset. From these records, I have selected 24,869 heart beats of 5 classes.

Class Names	Number of data points(Heart beats)
Normal (N)	10822
Paced (P)	3570
Left Bundle Branch Block (LBBB)	4614
Right Bundle Branch Block (RBBB)	3420
Premature Ventricular Contraction (PVC)	2443

III. Methodology

This consists of 3 steps - (i) preprocessing, (ii) feature extraction, and (iii) classification.

1) Preprocessing

Database contain low frequency and high frequency noise hence there is a need to remove these noises. For each beat, a 400 ms window (144 sample points, 54 before Q peak, 89 after Q peak) was chosen to encompass the entire QRS complex [3]. 1st order Band pass filter of frequency range 0.5-45 Hz is used to remove noise. It has been found as the best one compared to the 3-20 Hz filter proposed in the paper.

2) Features Extraction

The features are extracted using Daubechies wavelet of order 2 (db2) up to 5 level. Decomposed signal comprises of detail coefficients (D1 to D5) and approximate coefficient (A5). Maximum, Minimum, Mean and Standard deviation of the wavelet coefficients in each sub band - totaling 24 features for each beat. All features in a column are then normalized by subtracting their mean and dividing their standard deviation.

3) Classification

Two classifiers – Support Vector Machine (SVM) and Artificial Neural Network (ANN) have been explored in this paper. Apart from these two classifiers, a Random Forest (RF) classifier has been also used inspired by the mother paper [4]. 20% was used for testing and the rest were used for testing. The paper used a different partition scheme.

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IV. Workflow

1) Training

For ANN, 2 hidden layers with 256 neuros has been used. Tan sigmoid is the activation function with batch size 150, learning rate 3*1e-3 and epochs 130. These hyper-parameters have been tuned to get the best result. For SVM default hyper-parameters were used. The authors haven't explicitly mentioned all the necessary hyper-parameters. The whole project was implemented using python language and its dedicated library packages for preprocessing (numpy), classification (tensorflow, scikit-learn) and plotting (matplotlib).

2) Performance Metrics

Used performance metrics are accuracy, sensitivity and specificity. Here,

Accuracy = (TP+TN)/(TP+FP+TN+FN)

Sensitivity = TP/(TP+FN)

Specificity = TN/(TN+FP)

Where, TP = True positives, positive cases predicted as positive by the classifier, FN = False negatives, positive cases predicted as negative by the classifier and FP = False positives, negative cases predicted as positive by the classifier.

V. Results and Discussions

The result obtained in this project is quite similar to reported result in the paper. The accuracies for either classifiers are quite close and sensitivity, specificity are better than the paper's results as can be seen from the following table.

Table 1: Evaluation Performance

Methods & Classifiers	ANN (paper)	ANN	SVM (paper)	SVM
Accuracy	98.60%	96.96%	99.59%	99.31%
Sensitivity	95.86%	98.10%	98.80%	99.33%
Specificity	99%	99.28%	99.75%	99.81%

The confusion matrices are shown in Fig 1, 2 and 3. Accuracy for RF is 98.67%. Sensitivity and specificity were not calculated as the paper authors didn't report results for RF. I have also done a comparative study of these 3 classifiers – how normalizing data affected them. As can be seen from Fig 4, both SVM and ANN have seen huge improvements, notably ANN but a minor improvement for RF.

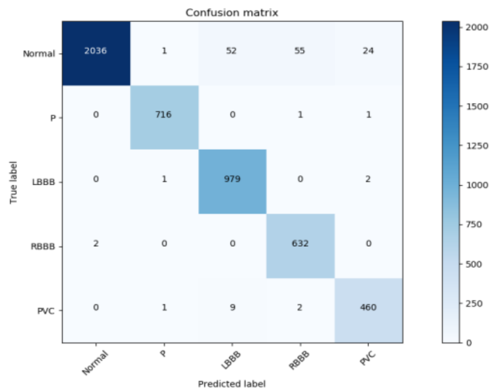

Fig. 1. Confusion Marix for ANN

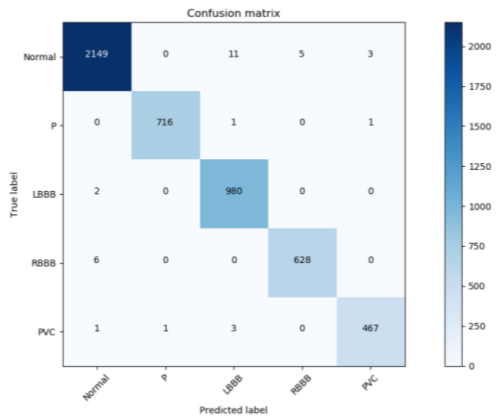

Fig. 2. Confusion Matrix for SVM

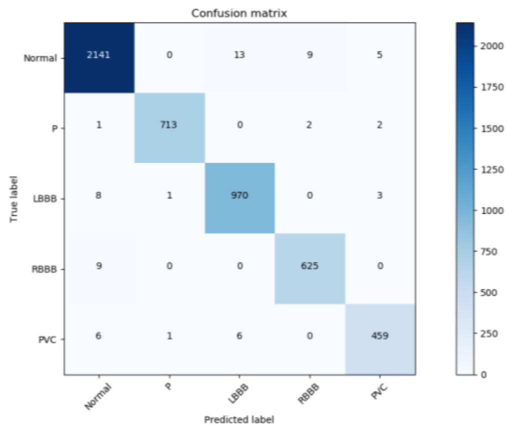

Fig. 3. Confusion Matrix for RF

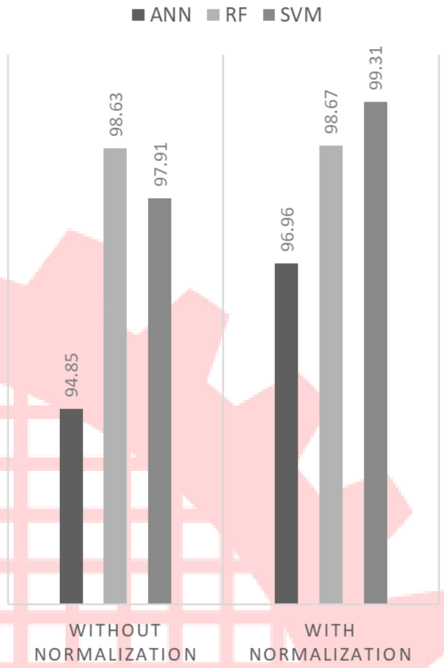

Fig 4. Effect of normalization on accuracy

Significance of features have also been explored. As can be seen from Table 2, mean is the least significant feature of all 4 types while every other feature alone can easily give an accuracy above 90%. Same trend has been seen for ANN. Also from feature correlation, it has been observed that standard deviation of D1 and D2 wavelet coefficients are same, so removing any one yields the same result - making 23 distinct features instead of 24.

Table 2: Significance of features

Selected Feature(s)	Accuracy(SVM, %)
Mean	79.614
Standard Deviation	94.9337
Maximum	92.7624
Minimum	90.8524
All except mean	99.0149
All	99.3164

VI. Conclusion

Accuracy close to the original paper has been achieved. With better parameter tuning and more analysis, a better result is possible. A notable achievement is better sensitivity and specificity than the original paper for both classes. For future works, other classifiers such as random forest, CNN may be explored for Arrhythmia detection.

REFERENCES

[1] Preeti N. Ranaware and Rohini A.Deshpande, "Detection of Arrhythmia based on Discrete Wavelet Transform using Artificial Neural Network and Support Vector Machine", International Conference on Communication and Signal Processing, 2016.

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[3] Heike Leutheuser, Stefan Gradl, Patrick Kugler, Lars Anneken, Martin Arnold, Stephan Achenbach and Bjoern M. Eskofier, "Comparison of Real-Time Classification Systems for Arrhythmia Detection on Android-based Mobile Devices", Engineering in Medicine and Biology Society(EMBC), 2014.

[4] Emina Alickovic, Abdulhamit Subasi , "Medical Decision Support System for Diagnosis of Heart Arrhythmia using DWT and Random Forests Classifier", Journal of Medical Systems, 2016
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Q/A

1. **What is PCA and MSPCA? How can these algorithms be used for denoising? Explain why they provide good results.**
PCA (Principal Component Analysis): PCA is a technique used to reduce a multidimensional data to lower dimensions for analysis. PCA consists of computation of the eigenvalue decomposition or singular value decomposition of a data set, usually after mean centering the data for each attribute. PCA is quite much the same as SVD, the only difference being SVD can be applied to any matrix while PCA can be applied on square matrices only.
MSPCA (Multiscale Principal Component Analysis): MSPCA combines the ability of PCA to extract the relationship among variables, then to decorrelate the cross-correlation with that of wavelet analysis to decompose a time-series data into several frequency scales. MSPCA reconstructs simplified multivariate signal, starting from a multivariate signal using a simple representation at each resolution level.
Reason behind good result: In MSPCA, the PCA is performed (i) on the matrices of details of different levels, (ii) on the matrices of coarser approximation coefficients and (iii) on the final reconstructed matrix. Finally, the interested simplified signals can be obtained by retaining useful principal components (PC). Multiscale matrices contain different parts of information from original signals due to Wavelet decomposition. These are responsible for diagnostic fidelity of the signal. To retain clinical components in the denoised signal it is essentially important to reconsider the multiscale matrices for the denoising operation. It is expected that if higher order Wavelet sub band matrices treated with lower number of PC we may lose the diagnostic components. The selection of PCs plays important role for denoising signals.
2. **What is recall and precision?**
Recall = TP/(TP+FN) and **Precision** = TP/(TP+FP) where,
TP = True positives, positive cases predicted as positive by the classifier
FN = False negatives, positive cases predicted as negative by the classifier
FP = False positives, negative cases predicted as positive by the classifier
3. **How CNN can be used?**
In this work a 400 ms window was used for each R-peak which is practically 144 data points (for MIT-BIH Arrhythmia Database). So an image of each peak from this 144 data points can be saved to create a new dataset with the label being the corresponding arrhythmia class. Then CNN can be applied on this image dataset. A total of 24869 peaks from 5 different classes were selected for this work. Therefore, there will be this many images as dataset to feed the CNN with the features being their pixel values.