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Machine Learning Techniques with Low-Dimensional Feature Extraction for Improving the Generalizability of Cardiac Arrhythmia

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Abstract—Automatic heartbeat classification is an important stage in identifying cardiac arrhythmia. Several machine learning (ML) techniques have been proposed to perform this, but they produce an accuracy result of below 99%. In this study, a deep neural network (DNN) structure is applied to improve ML performance. The feature selection method is based on the combination of discrete wavelet transform (DWT) and principal component analysis (PCA). To avoid computational complexity, the components of PCA are derived by low-dimensional DWT coefficients. The results show that the proposed ML model achieves good performance, producing 99.76% accuracy, 91.80% sensitivity, 99.78% specificity, 93.02% precision, and 92.31% F1-score. To benchmark the proposed model, the support vector machine (SVM) and random forest (RF) techniques are used as the baseline models. The DNNs are 2.3% more sensitive than SVM, while the RF fails to classify the ECG heartbeat. Four datasets are used to analyze the robustness and generalization performance of the proposed model: MIT-BIH, SVDB, MITDB, and IncartDB. All testing results produce satisfying performance. The proposed ML model offers a potential solution to improve the generalizability of a DNN-based model in different cardiac datasets for classifying tasks.

Index Terms— Arrhythmia, Support Vector Machine, Deep Neural Networks, Principal Component Analysis

I. INTRODUCTION

MANUALLY learning a large amount of data generated by electrocardiogram (ECG) requires much time. Abnormalities in the electrical activity of the heart must be recorded over a long period with information from several

perspectives. Moreover, clinical and diagnostic analyses sometimes become unrealistic, especially for long-term monitoring of cases or long-term cases in remote areas [1][2]. There is also the possibility of human error while analyzing ECG signal recordings due to fatigue. However, the process is necessary to produce an accurate diagnosis of cardiovascular disorders [2][3]. Therefore, an alternative solution is required for using computational techniques for the automatic classification of heartbeat abnormalities. The automatic classification of heartbeats is one of the most important steps in identifying pathology using ECG. The ability of the classification algorithm and the features to accurately represent heartbeats are crucial for successful classification. Although many methods have been reported, their direct comparisons are questionable due to their differences in the types of heartbeats being classified [4–15], ECG features [4][5][9][10][6][7][16][17], and classification models [1][4][5][6][7][11][13][15][6][18][19][20][21]. Based on the the Association for the Advancement of Medical Instrumentation (AAMI) standard, most previous research have examined validation performance, but the results are below the average 99% for all classes [22]. Such a condition occurs because of highly imbalanced medical datasets. Moreover, the accuracy value is misleading because the majority class always contributes to the high accuracy value. This case may be dangerous if the unhealthy status is misclassified. Therefore, an accurate classifier that could predict ECG signals with imbalanced data should be investigated.

Feature extraction is part of data representation, and this stage is key to the success of the classification process of ECG signals. Several techniques have been implemented, including principal component analysis (PCA) [18][23][24][25] and independent component analysis (ICA) [23][24][26]. However, the power is quite limited, as PCA is better at reducing noise, whereas ICA is better at feature extraction. The combination of these two techniques can provide great benefits. Another technique is kernel principal component analysis (KPCA), which is superior to the PCA technique for classifying heartbeats from ECG signals due to its nonlinear structure [27][28]. However, KPCA produces more complex algorithms than PCA. Another technique used in the feature extraction of ECG signals is wavelet transform [24][29]. The most popular classification is based on discrete wavelet transform (DWT) because of its easy implementation [29]. The DWT method is used for feature extraction processes and eliminating noise.

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Continuous wavelet transform has also been used for feature extraction because it can overcome some DWT deficiencies [30]. However, the primary choice of wavelet function used in feature extraction is crucial for the final performance of the classification model [26][30][31]. It should be carefully analyzed to avoid eliminating the important details of ECG signals. Therefore, selecting the appropriate features without losing important information in the ECG signals needs to be investigated in depth.

A heartbeat is defined as the sequence of electrical events that occur in a cardiac cycle, that is, from depolarization to repolarization. A normal beat in sinus rhythm includes the P-wave, the QRS-complex, and the T-wave [2][32]. Heartbeat classification focuses on the automatic identification of beats of different natures, which can be useful for detecting ectopic beats or arrhythmic events [2]. Many classifier techniques have been developed to solve the ECG signal classification task and have indicated good results. In [8], the SVM technique is used to process 50 features and 100,441 beats using a 10-fold cross-validation scheme. Their proposed model produces 98.91% accuracy, 98.91% sensitivity, and 97.85% specificity. In [33], SVM is combined with particle swarm optimization (PSO) to reduce heartbeat features and speed up the classification process. The number of features is reduced from 303 to 46 using PSO. However, the SVM classifier only has 89.72% accuracy for detecting five heartbeat classes, namely normal, atrial premature beat, ventricular premature beat, right bundle branch block, left bundle branch block, and paced beat.

Another work focused on discriminant analysis for feature reduction for the SVM classifier [34]. This ML model is used for the arrhythmia classification of six classes: normal, premature ventricular contraction (PVC), atrial fibrillation (AF), sick sinus syndrome, ventricular fibrillation, and second-degree heart block. The number of features is reduced from 15 to 5, and the SVM classifier has 99.16% accuracy [35]. In [36][37], the random forest (RF) model with five-fold cross-validation for heartbeat classification is investigated. They use 150 features for six classes (i.e., normal, PVC, paced, atrial premature beat, and left and right

bundle branch blocks). Their proposed model has 92.16% accuracy and 89% for ischemic and non-ischemic. The fuzzy clustering neural network technique is used for heartbeat classification, such as normal beats, sinus bradycardia, ventricular tachycardia, sinus arrhythmia, atrial premature contraction, paced beats, right and left bundle branch block, AF, and atrial flutter on the 5,342 segments feature [34]. It has 99.09% accuracy for arrhythmia classification. In [38], stacked denoising-auto-encoders are proposed for the active classification of ECG signals, and the feature representation automatically processes from the input data for two classes: ventricular escape beat (VEB) and ventricular escape beat (SVEB). The proposed model produces 98.11% accuracy for SVEB and 98.71% accuracy for VEB. Among all the mentioned techniques, the ML technique is the only one that produces 99% accuracy. Nevertheless, the best ML model still needs to be investigated comprehensively.

Most ECG signal feature extraction techniques verify the feature performance of the classifier based on training and testing sets randomly selected from the database. Therefore, the selected techniques in the classifier process must include the effects. This study analyzes the performance of feature extraction and classification techniques in several datasets with highly imbalanced data. The contributions of this study are summarized as follows:

- We propose the best ML model for heartbeat classification with high performance.
- The process of feature selection is performed using the DWT to produce low-dimensional coefficients, and the components of PCA are derived from the DWT coefficients.
- To increase the generalization power of the selected ML model, four datasets are used: MIT-BIH, SVDB, MITDB, and IncartDB.

The rest of this paper is structured as follows: Section 2 describes the materials and methods. Section 3 presents the experiment for heartbeat classification. Section 4 discusses the results and concludes the study.

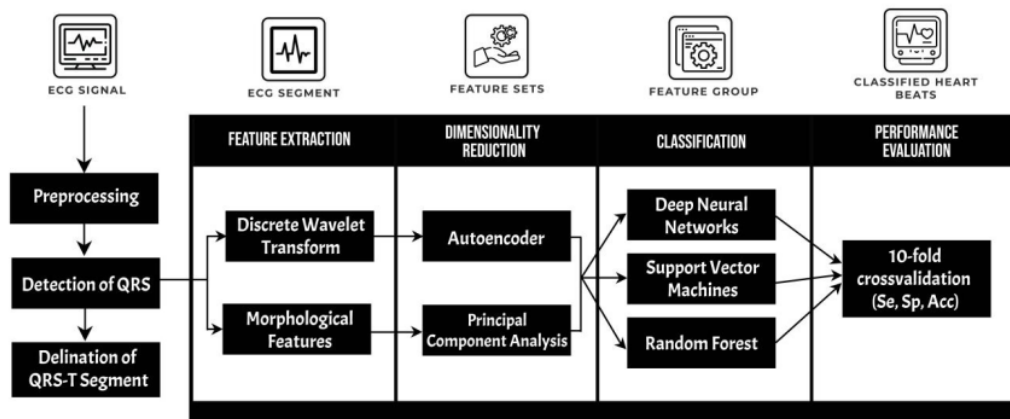


Fig. 1. Processing step of arrhythmia classification with a 10-fold validation scheme.

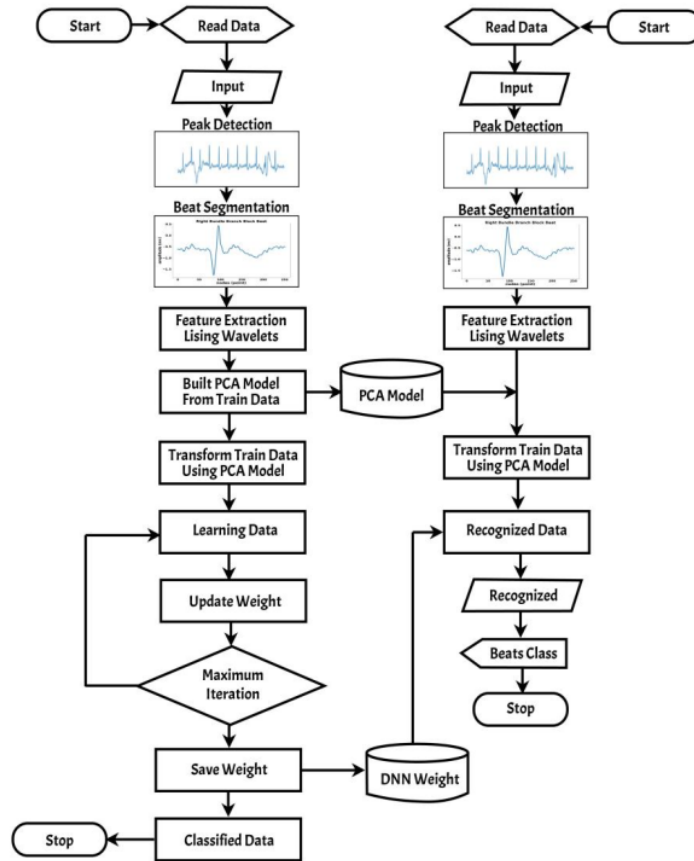


Fig. 2. Flowchart of the classification process.

II. MATERIAL AND METHODS

The fundamental problem in the ECG signal classification process is the extensive feature dimensions derived from the data. These features provide comprehensive knowledge and patterns about the data. However, as they can also produce computational complexity, it is necessary to reduce the dimensions without eliminating knowledge representation. PCA is used because of its ability to reduce overfitting and to improve algorithm performance. However, the process required to find the eigenvectors produces a large computational load [23][24]. To overcome this limitation, PCA was designed based on the DWT decomposition to separate low- and high-dimensional features [1]. The proposed ML model consists of the following steps: data collection, beat segmentation, feature extraction, dimensionality reduction, classification, and evaluation. All the steps are described in Fig. 1

Fig. 2 shows the flowchart of the proposed DWT-PCA-DNN method. In step 1, an ECG signal is segmented into 0.7-s episodes based on the R-peak locations because of all electrophysiology processes, such as depolarization and repolarization [32]. In step 2, the DWT is used to extract and generate all features in 0.7 s, and the ECG signal episode is analyzed. In step 3, PCA is used to reduce the feature dimension using the low-dimensional data from the DWT.

The highest variant value of the number of features becomes the threshold for selecting the number of reductions. In step 4, the reduction features from the PCA are trained using the DNN model with a K-fold cross-validation scheme, and the performance of heartbeat classification is measured in terms of accuracy, sensitivity, and specificity.

A. Data Pre-processing

The raw ECG datasets used in this study are taken from the well-known MIT repository (<http://physionet.org/cgi-bin/atm/ATM>) [39][40]. All ECG beat data are annotated at R-peak locations, and there are up to 16 different types of arrhythmias. Following the AAMI standard [4], the database contains 22 types of beats in five groups of arrhythmias. However, in this study, only 10 types of ECG beats are used [3][4][32]: normal (N), atrial premature contraction (A), premature ventricular contraction (V), right bundle branch block (R), left bundle branch block (L), paced (P), ventricular flutter wave (!), fusion of ventricular and normal (F), fusion of paced and normal (f), and nodal escape (j) (Fig. 3). As shown in Table 1, all datasets are split into 80% for training and 20% for testing data.

B. Segmentation

The various segments and intervals of ECG waveform signals have different physiological meanings. This implies that diagnostic and bio-physical significance is given to the

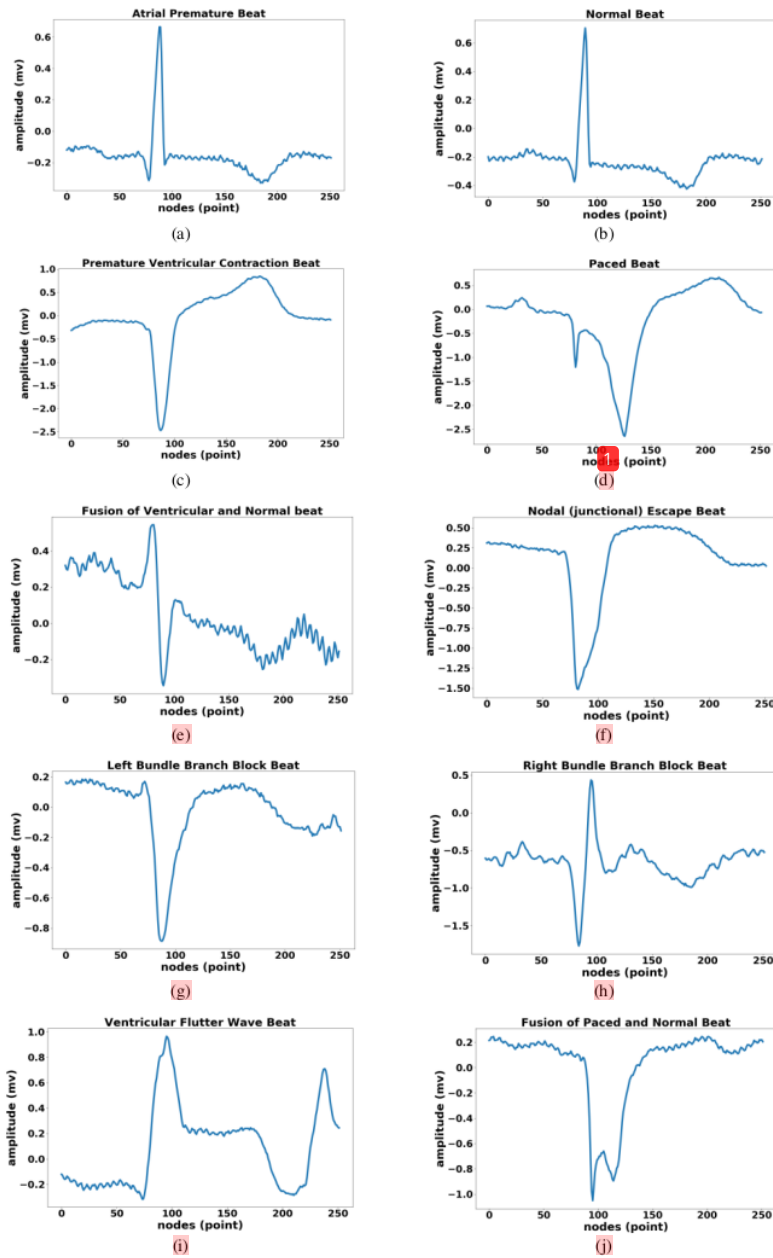


Fig. 3. Heartbeat extracted from MIT-BIH which are ten classes of arrhythmias condition.

timing and length of each segment. To equalize the sampling time for each record, the ECG signal waveform must be segmented to become a single beat. The segmentation process is illustrated in Fig. 4. Therefore, the ECG rhythm frequency is 60–80 per minute. The segmentation of ECG signals is conducted at 0.7 s with two intervals, t_1 and t_2 , after the R position is detected. About 252 nodes are generated at 0.7 s. The interval t_1 set for 0.25 s is equal to 90 nodes before peak position (R), and the interval t_2 set for 0.45 s is equal to 162 nodes after the peak position (R) [41].

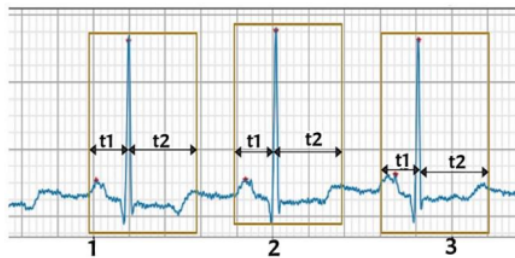


Fig. 4. Beats segmentation. The blue color is ECG signal, the brown color is the sampling time between t_1 and t_2 .

TABLE I
NUMBER OF BEATS DATA SET FOR CLASSIFICATION
Training Data

Fold	Number of beats										Total
	A	L	N	P	R	V	F	f	!	j	
1	2292	7265	67520	6323	6530	6417	722	884	425	207	98585
2	2292	7265	67520	6323	6530	6416	722	884	425	207	98585
3	2292	7265	67520	6323	6530	6416	722	884	425	206	98585
4	2292	7265	67520	6323	6530	6416	722	884	425	206	98585
5	2291	7265	67520	6323	6530	6416	722	884	425	206	98585
6	2291	7265	67520	6322	6529	6416	723	883	426	206	98585
7	2291	7265	67520	6322	6529	6416	723	883	426	206	98585
8	2291	7265	67520	6322	6529	6416	723	883	426	206	98585
9	2291	7264	67519	6322	6529	6416	723	883	426	206	98585
10	2291	7264	67519	6322	6529	6416	723	883	426	206	98585

Fold	Number of beats										Total
	A	L	N	P	R	V	F	f	!	j	
1	254	807	7502	702	725	712	80	98	47	22	10949
2	254	807	7502	702	725	713	80	98	47	22	10950
3	254	807	7502	702	725	713	80	98	47	23	10950
4	254	807	7502	702	725	713	80	98	47	23	10950
5	255	807	7502	702	725	713	80	98	47	23	10952
6	255	807	7502	703	726	713	79	99	46	23	10953
7	255	807	7502	703	726	713	79	99	46	23	10953
8	255	807	7502	703	726	713	79	99	46	23	10953
9	255	808	7503	703	726	713	79	99	46	23	10955
10	255	808	7503	703	726	713	79	99	46	23	10955

C. Feature Selection

The DWT of a one-dimensional signal $f[n]$ can be calculated by simultaneously passing it through a high-pass and a low-pass filter. Suppose that a low-pass filter has the impulse response $g[n]$. In this case, the DWT can be evaluated by calculating the convolution of an original signal with the impulse response defined as follows:

$$y[n] = (f * g)[n] = \sum_{k=-\infty}^{\infty} f[k] \cdot g[n-k] \quad (1)$$

In this study, the ECG signals, sampled at 360 Hz, are decomposed up to eight levels. Seven experiments use 3, 4, 5, 6, 7, 9, and 10 levels of decomposition before such a model is applied. To achieve good performance, the wavelet decomposition process is repeated eight times within the symmetric structure. The bio-orthogonal 6.8 filter is selected because of its larger signal-to-noise ratio compared with other filters [1]. The result of the decomposition is filtered again through the soft thresholding method (1) using the universal threshold (2)(3). The results of the first-level decomposition are used to calculate the threshold value. All levels of the DWT component are shown in Fig. 5.

$$c\hat{D}_j = \begin{cases} \text{sign}(cD_j) |cD_j| - t & |cD_j| \geq t \\ 0 & |cD_j| < t \end{cases} \quad (2)$$

$$t = \sigma \sqrt{2 \log N} \quad \text{and} \quad \sigma = \frac{\text{median}(|cD_j|)}{0.6457} \quad (3)$$

PCA can generate a lower dimensional function and reduce the dimensions using the first few principal components. However, the components are obtained using trial and error. In this study, the components of PCA are derived from the DWT coefficients. The number of ECG features extracted from DWT is 356. The large number of features can increase the computational cost. Therefore, the

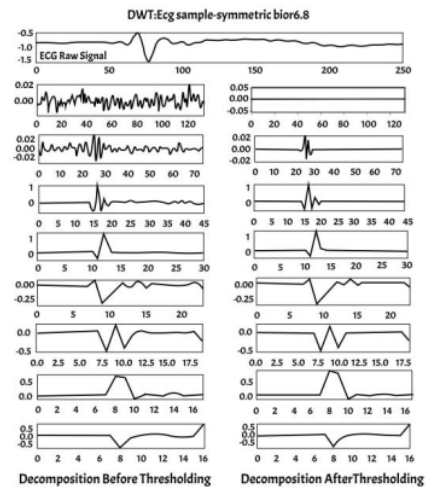


Fig. 5. The feature selection process with DWT decomposition 8 levels

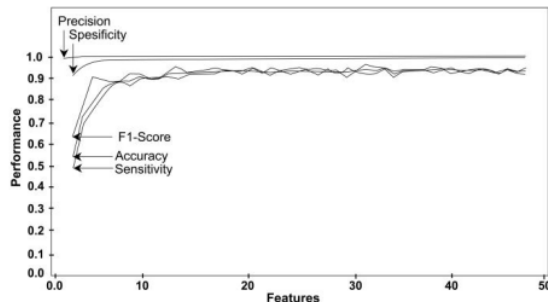


Fig. 6. PCA performance for feature reduction (accuracy, sensitivity, specificity, precision, and F1-score)

TABLE II
BEAT-BY-BEAT CLASSIFICATION BASED ON DNNs, SVM, AND RF MODEL

Class	Accuracy (%)			Sensitivity (%)			Specificity (%)			Precision (%)			F1-Measure (%)		
	DNNs	SVM	RF	DNNs	SVM	RF	DNNs	SVM	RF	DNNs	SVM	RF	DNNs	SVM	RF
A	99.56	99.59	98.38	89.96	85.73	30.86	99.78	99.92	99.99	91.19	96.33	98.77	90.52	90.69	45.14
L	99.91	99.94	99.14	99.35	99.52	88.85	99.95	99.97	99.96	99.44	99.67	99.46	99.39	99.59	93.84
N	99.16	99.13	94.71	99.44	99.76	99.82	98.55	97.75	83.61	99.34	98.98	92.98	99.39	99.37	96.28
P	99.95	99.98	99.80	99.68	99.80	98.43	99.97	99.98	99.89	99.60	99.82	98.49	99.64	99.81	98.46
R	99.94	99.94	99.22	99.67	99.50	89.13	99.95	99.97	99.94	99.44	99.61	99.11	99.55	99.56	93.85
V	99.58	99.64	98.87	96.86	97.04	87.99	99.77	99.82	99.63	96.72	97.44	94.28	96.78	97.24	91.02
f	99.92	99.96	99.30	95.41	96.73	22.45	99.96	99.99	100.0	95.82	99.16	100	95.56	97.93	36.47
F	99.76	99.80	99.57	80.38	79.75	43.75	99.90	99.94	99.98	86.44	91.26	94.36	83.27	85.04	59.58
!	99.89	99.94	99.73	85.96	85.95	38.72	99.94	99.99	99.99	88.24	99.08	94.75	86.79	91.96	54.33
j	99.88	99.87	99.79	71.30	51.30	0	99.94	99.97	100.0	74.01	77.32	0	72.291	61.30	0
Aver.	99.76	99.78	98.85	91.80	89.50	60.00	99.78	99.73	98.29	93.02	95.87	87.22	92.31	92.25	66.89

number is reduced by applying PCA based on cumulative explained variances. The reduction of the number of features is performed with the highest variance value because it represents the information from the ECG database. The result is shown in Fig. 6. The highest variance is 0.999, with 12 features representing the ECG heartbeat information.

D. Heartbeat Classifier Based on DNNs

The multiclass of cardiac arrhythmias is classified in this study using DNNs and the backpropagation algorithm. A DNN consists of several weighted connections, with the activation function represented by each node. Fig. 6 illustrates the simple structure of the proposed DNN, which is the best model with the highest accuracy based on several cases that have been processed. The deep structures have 100 nodes in each layer. The experiment is conducted by gradually increasing the number of hidden layers from one to five, and all performances are observed to choose the best ML model (Fig. 7). The rectified linear unit (ReLU) activation function is utilized to avoid overfitting in the classification process and to determine the error in the output layer using the softmax function. The backpropagation algorithm computes how accurate \hat{y} (predicted) is compared with y (actual) to obtain a global error of the classifier in the notion of a loss function. A categorical cross-entropy of the loss function measures the disagreement between \hat{y} and y and is denoted by 1. It is used because of its superior learning rate and performance to find the minimum value of the error function in weight space [18]. The testing scenario uses the beat-based scheme with 10 times the number of folds. The comparison between the training and testing data shows 80% of the training data and 20% of the testing data.

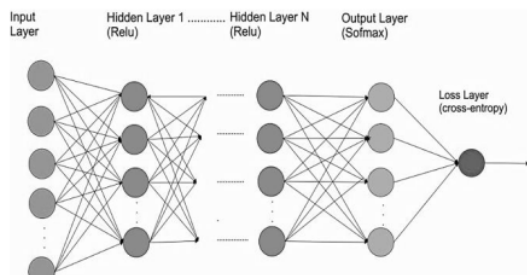


Fig. 7. The proposed model of the DNNs structure

III. RESULTS AND DISCUSSION

In this study, the experiment is conducted using several DNN models. The model is created by changing the number of hidden layers. As shown in Fig. 8, five DNN architectures are measured using accuracy performance, as the accuracy is still below 99% using ML in previous studies. The results show that the highest accuracy is obtained when the number of hidden layers is two, with an average accuracy of 99.87%, an interval of accuracy value of 99.55%–99.88%, and a standard deviation of 0.09. After the highest accuracy is achieved, the selected structure is observed from the other performances of the 10 classes. Aside from examining the effectiveness of the selected method, DNN is compared with SVM and the RF classifier, as shown in Table 2. In general, the average values of accuracy, sensitivity, specificity, precision, and F1-score of the SVM with the radial basis function (RBF) kernel performance are as good as those of the five layers of DNNs. DNN produces a higher sensitivity value at 91.8% than SVM at 89.5%, whereas SVM is 2% more precise than DNN. However, RF has poor performance because it fails to recognize the “j” (nodal junctional escape beat) heartbeat class, with 0% sensitivity, precision, and F1-score, respectively (Table 2).

Figs. 9 (a)–(d) illustrate the false-positive rate and the false-negative rate. For the SVM classifiers, the false-positive rate is higher for class (j), and the median value is also high. The false-positive rate of DNN for class (j) is

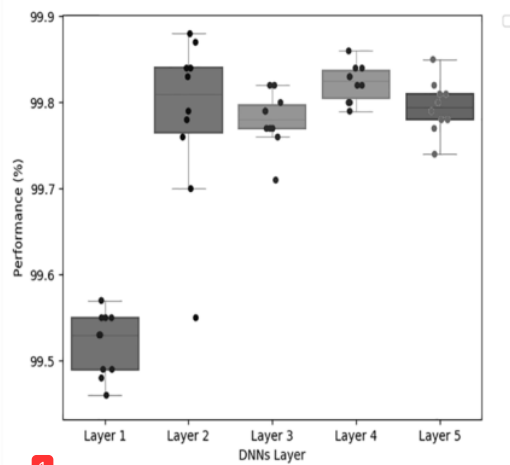


Fig. 8. Classifier Accuracy for Selecting the Best Model

lower, with a small median value, whereas the false-negative DNN is higher than the SVM. Minimizing the false-negative rate is one of the essential objectives for medical diagnostic rules, especially in imbalanced data. Medical practitioners prefer low false-negative rates to low false-positive rates. The consequences of a false-positive include an expensive diagnosis and invasive or overtreatment. Conversely, a high false-negative rate causes a late diagnosis and even death.

The box plots show the data on relative risks from Table 2, subdivided by 10 class quality levels. The boxes shift upward as the quality measure improves. The highest mean value is paced in the (P) class and the lowest in the normal class (N). This is caused by unevenly distributed data; normal classes can be considered other classes because the resulting beat resembles a normal class. From the distribution, normal data contain outlier data because of the diversity of data and the high distribution. However, as shown in Figs. 9 (c) and (d), by using the DNN class, (j) has the highest precision value, unlike the SVM. However, the number of outliers in the DNN classifier is greater than that in the SVM (Fig. 9 (c)). Normal data are also in the fusion of ventricular and normal (F) classes and the fusion of paced and normal (f) classes. Moreover, the width of the box shape in DNNs for normal classes has both minimum and maximum values compared with SVM, which only has a maximum value. This means that DNNs can observe the diversity of data in this class aside from the mean and maximum values for DNNs higher than SVM.

To ensure the robustness and generalization ability, the proposed model is compared with four conditions: (i) with other ML algorithms (i.e., SVM and RF; Table 2), (ii) the combination between two feature extraction models (Table 3), (iii) several previous studies (Table 4), and (iv) four datasets (Fig. 10). As shown in Table 3, two models of feature extraction are developed to test the five layers of DNNs. This study carries a combination of DNNs + DWT and DNNs + auto encoder (AE). AE is used as an unsupervised learning algorithm that applies to the DNNs. The difference between AE and DWT in the extraction process is that AE uses a learning algorithm, whereas DWT uses signal decomposition. However, the two feature extraction models are most suitably combined with the principle of backpropagation. Using low-dimensional feature extraction, DWT produces better performance results (Table 3). Specifically, in the ECG signal with a small number of data, such as the nodal escape (j), the proposed model still gives satisfying results, with an accuracy of 99.98%. DNNs with AE have an accuracy of 99.66% and an F1-score of 72.29%, whereas DNNs with AE only have 46.67% F1-score. In some cases, AE tends to overfit, although this can be mitigated by regularization. Moreover, it is computationally more complex and expensive. Therefore, the proposed model is robust with high generalization performance.

As illustrated in Table 4 and based on the results, the proposed DWT-PCA-DNN model performs with high accuracy in the classification of 10 classes of beats and

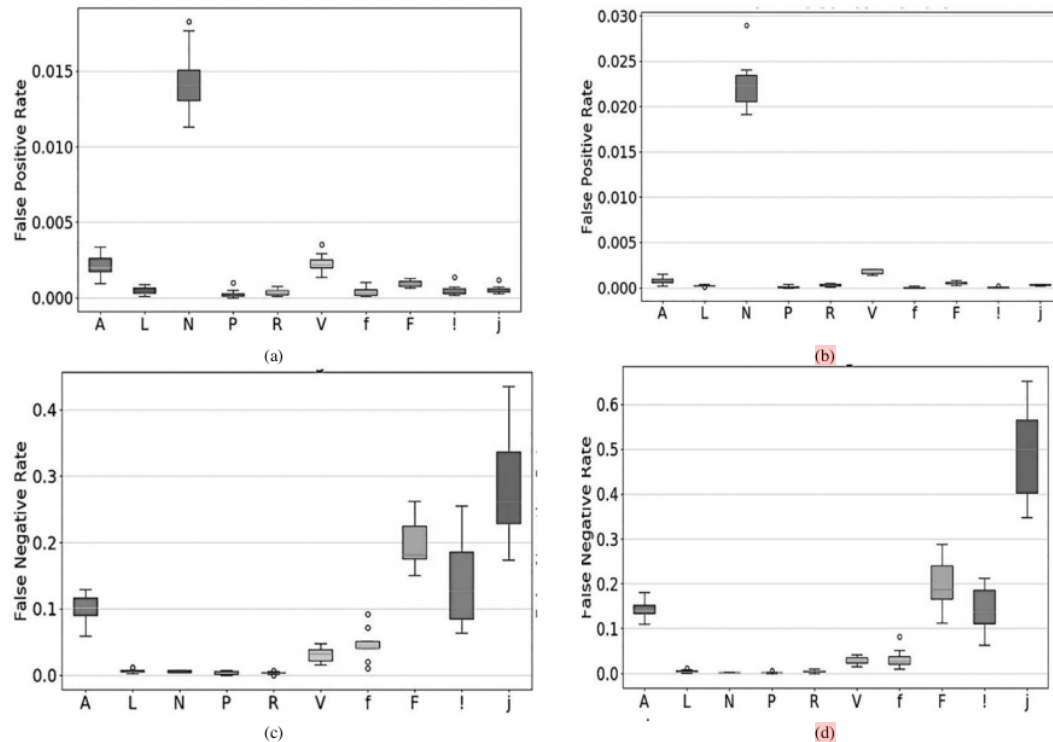


Fig. 9. Boxplot of DNNs with 5 layers vs SVM-RBF. (a) False-positive rate of DNNs, (b) False positive rate of SVM, (c) False-negative rate of DNNs, (d) False-negative rate of SVM

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TABLE III

COMPARISON CLASSIFICATION PERFORMANCE BETWEEN TWO FEATURES EXTRACTION MODELS DWT AND AUTO ENCODER

Class	Accuracy (%)		Sensitivity (%)		Specificity (%)		Precision (%)		F1-Measure (%)	
	DNNs	DNNs	DNNs	DNNs	DNNs	DNNs	DNNs	DNNs	DNNs	DNNs
	DWT	AE	DWT	AE	DWT	AE	DWT	AE	DWT	AE
A	99.56	99.49	89.96	81.74	99.78	99.87	91.19	93.07	90.52	87.04
L	99.91	99.93	99.35	99.41	99.95	99.97	99.44	99.65	99.39	99.53
N	99.16	98.75	99.44	99.57	98.55	96.98	99.34	98.61	99.39	99.09
P	99.95	99.94	99.68	99.44	99.97	99.97	99.60	99.58	99.64	99.51
R	99.94	99.95	99.67	99.72	99.95	99.97	99.44	99.59	99.55	99.66
V	99.58	99.39	96.86	93.87	99.77	99.78	96.72	96.70	96.78	95.27
f	99.92	99.84	95.41	85.71	99.96	99.96	95.82	95.45	95.56	90.32
F	99.76	99.60	80.38	66.67	99.90	99.83	86.44	74.29	83.27	70.27
f	99.89	99.91	85.96	88.00	99.94	99.96	88.24	91.67	86.79	89.80
j	99.88	99.85	71.30	43.75	99.94	99.94	74.01	50.00	72.29	46.67
Aver.	99.76	99.66	91.80	85.79	99.78	99.62	93.02	89.86	92.31	87.71

TABLE IV

COMPARISON CLASSIFICATION PERFORMANCE WITH OTHER TECHNIQUES

Feature Extraction	Dimension	Beats Type	Data Total/class	Classifier	K-fold	Sen. (%)	Spec. (%)	Acc. (%)
Wavelet transform and morphological features [42]	28	5	104569	ANN	no	88.60	96.18	97.86
Morphological features [41]	13	3	30873	SVM, NNs	no	98.52	99.19	97.14
Morphological features [43]	16	3	23590	SVM, NNs	no	92.82	93.74	92.85
Wavelet transform, cosine transform [44]	18	4	1080	SVM	no	98.60	95.50	96.50
Wavelet transform [28]	24	5	1800	SVM, GA	no	98.50	99.69	98.80
Wavelet transform [45]	20	4	720	SVM	no	98.62	99.54	98.61
Approximate entropy wavelet packet [40]	9	5	290	SVM, PNNs	no	98.70	99.70	98.60
Eigen vector method [46]	12	4	720	RNNs	no	98.89	99.25	98.06
Higher order statistics [47]	24	5	18299	RBFNN	no	92.93	98.52	95.18
Higher order spectral [17]	7	5	830	SVM	no	90.00	87.93	85.79
Geometrical features [48]	18	7	7185	SVM, k-NNs, BPNN	no	97.52	99.65	98.06
Cross correlation [49]	30	3	93246	NNs	no	97.49	-	95.24
Spectral correlation [50]	88	55	6259	SVM	10	99.20	99.70	98.60
Non-linear and center-clipping transform [51]	5	5	27280	NNs	no	98.78	99.70	98.78
Wavelet and PCA	356	12	109534/10 class	SVM	10	89.50	99.73	99.78
Wavelet and PCA (proposed)	356	12	109534/10 class	DNNs	10	91.80	99.78	99.76

1

outperforms another ML technique for all test records. The results are compared with those of other recent major techniques based on SVM by Qin et al. (2017) [1] using the same standard metrics, namely accuracy, sensitivity, and specificity, but only with six classes. The proposed ML model is compared with 15 existing models that comply with the AAMI standards and use all records from the MIT-BIH arrhythmia database (Table 4). The results were discovered using the DNN system, with 99.76% accuracy, 91.80% sensitivity, 99.78% specificity, 93.02% precision, and 92.31% F1-score. All values are compared with their SVM counterparts, and the overall performance is as good as that of DNNs. In this study, both DNNs and SVM produce high accuracy and high precision, with 90%–99% accuracy in the multiclass classification. The performance of some DNNs produces small values compared with other

DNNs. However, a drawback of the DNN and SVM classification for clinical applications is that it lacks interpretability to evaluate the effect of each feature while extracting relevant discriminant biomarkers. Other benchmarks are utilized for analyzing the generalization using the MITDB, SVDB, and IncartDB datasets [38][39]. DNNs are validated to determine the model robustness using other datasets. All records, namely normal, ventricular, and normal and ventricular fusion for the MITDB; normal, supraventricular premature beats, and ventricular ectopic beats for the SVDB; and normal, ventricular ectopic beats, and supraventricular ectopy for the IncartDB. The results are shown in Fig. 10. All evaluations produce good performances, indicating that the proposed model of the classifier is satisfied to classify the unseen class.

In conclusion, based on the experimental results, the

performance of the DNNs is stable and tends to increase along with the increasing amount of data. All works compared in this study use the MIT-BIH, MITDB, SVDB, and IncartDB datasets [39]. As shown in Fig. 10, the SVDB data recording with the noise signal in the raw data is difficult to recognize using the proposed model, although the number of data is less than that of MIT-BIH. Nevertheless, the proposed model with 175,000 data recording from IncartDB more than MIT-BIH, still produces good performances. Although the classifier performance is reduced, the overall results are always satisfying.

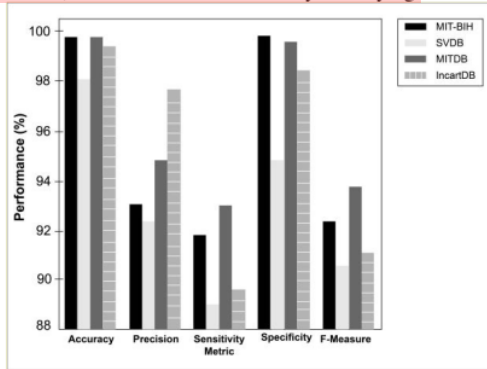


Fig. 10. Comparison Classification Performance on Four Datasets for Model Generalization Analysis

IV. CONCLUSION

An accurate morphological classification of ECG signals is important to detect abnormalities in cardiac arrhythmia to produce an accurate diagnosis. This paper proposes a comparative study between DNNs, SVM, and RF for classifying different heartbeats. DWT and PCA are combined to obtain several features to produce a low-dimensional feature. The 10-cross-validation scheme is designed to classify 10 types of ECG heartbeats using a set of 22 feature vectors from 107,049 beats. Based on the benchmarking with other techniques, the proposed ML model produces satisfactory results with 99.76% accuracy, 91.80% sensitivity, 99.78% specificity, 93.02% precision, and 92.31% F1-score. The robustness of the model is tested using two models of feature extraction: DWT and AE. The model generalization is validated using four datasets, namely MITBH, SVDB, MITDB, and IncartDB, with satisfying performance. In the future, the proposed model will be considered to use advanced pre-processing based on several feature learning techniques. Feature extraction and classification, as an integrated and directly constructed decision-making function, will be investigated as a deep learning approach. Such a method will attract more attention due to its self-optimization over input features. This is an important process because of the effort required to develop a high-performance classifier. Enriching the samples of each arrhythmia type remains the most effective and fundamental approach that is almost always overlooked.

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