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A Framework Classification of Heart Sound Signals in PhysioNet Challenge 2016 Using High Order Statistics and Adaptive Neuro-Fuzzy Inference System

BASSAM AL-NAAMI [1,2], HOSSAM FRAIHAT [3], NASR Y. GHARAIBEH [4], AND ABDEL-RAZZAK M. AL-HINNAWI [5]
[1]Department of Medical Engineering, Al-Ahliyya Amman University, Amman 19328, Jordan
[2]Department of Biomedical Engineering, Faculty of Engineering, The Hashemite University, Zarqa 13133, Jordan
[3]Department of Electrical Engineering, Al-Ahliyya Amman University, Amman 19328, Jordan
[4]Department of Electrical Engineering, Al-Balqa Applied University, Salt 21163, Jordan
[5]Faculty of Allied Medical Sciences, Al-Isra University, Amman 11622, Jordan

Corresponding author: Bassam Al-Naami (b.naami@hu.edu.jo)

ABSTRACT To investigate the performance of Adaptive Neuro-Fuzzy Inference System (ANFIS), activated by spectral analysis features, for detection of abnormal cardiac valves sound signals. A dataset of 1837 heart sound signals were acquired from international PhysioNet Challenge 2016 databases (classes A, B and E). This included 1369 normal and 468 abnormal signals. The signals were de-noised using Notch and Butterworth filtering, fed to Discrete Fourier Transform, and 5 features using High Order Spectral (HOS) analysis were extracted from the third Cumulant. Later, the ANFIS neural network was trained and tested to discern abnormal signals. The results showed that the selected features were statistically significant ($p<0.05$). The proposed method was tested and achieved classification of 63-89% accuracy, 63-100% sensitivity, and 62-100% specificity, respectively. The results were compared with reports utilizing different neural network techniques, indicating competitive performance. The HOS spectral features can be reliable to participate in neural network systems to sort heart sound (HS) signals as normal or abnormal. The bispectral matrix is a new presentation of attributes describing signals. The ANFIS is a suggestive successful tool, which has not been attempted in Physio-net challenge 2016. The HOS attributes and ANFIS can participate successfully in PhysioNet Challenge 2016.

INDEX TERMS ANFIS neural network, heart sounds, high order spectrum, PhysioNet-Challenge 2016.

I. INTRODUCTION

The dysfunction of cardiac valves is serious part of cardiovascular diseases (CVDs) leading to mortality. In USA, the cost of health care services related to CVDs is about $ 320 billion annually and it may approach to 1 trillion by 2030 [1]–[3]. The assistive-diagnostic cardiac technology such as ultrasound, cardiac CT, and monitoring system is also costly and -heavy demand instruments.

Long time ago, the auscultation of heart sound (HS) known as Phonocardiography (PCG) is a complementary essential procedure to assess heart functioning. Distinguishing defects in heart sounds by means of hearing aid (stethoscope) depends on physician's experience. Lately, electronic systems (Electronic Cardiac Microphone) were introduced to provide clear PCG signal. Four different frequencies (S1, S2, S3, and S4), characterizing the mechanical functions of heart valves, were recognized [4]. Clinical trials proved that many cardiac valve diseases such as Aortic Stenosis, Murmurs, Paradoxical Splitting, and others abnormal heart conditions (HC), are related to the components of S1 and S2 [5]. Signal processing (e.g. computer aided diagnosis (CAD)) can help, but careful analysis to S1 and S2 is substantially required. However, PCG is complicated non-stationary signal. Furthermore, PCG is nonlinear low frequency bio-signal, easily affected by surrounding sources of signals, resulting in challenge. The interference sources could be 50/60Hz, skin impedance, technical properties of electrodes, and electronic noise.

The challenge mission for signal processing researchers is to distinguish the healthy HS against the pathological

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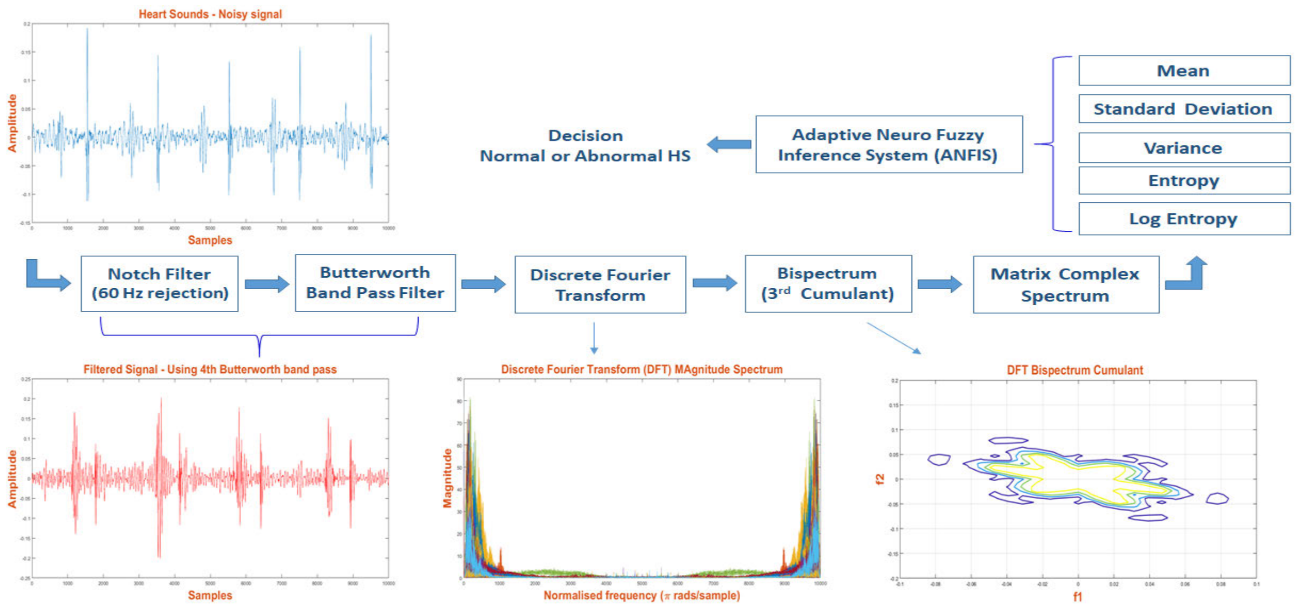

FIGURE 1. Block diagram of the proposed framework.

signal arising from HC. Thus, international databases of normal HS and HC were generated and made available via internet worldwide. In this work, the database by PhysioNet/Computing in Cardiology (CinC) Challenge 2016 was utilized [6]. This database is considered as reference for comparing CAD's outcomes.

In the current study, due to the nonstationary and nonlinearity nature of HS signals, we attempted the Fourier spectrum analysis along with HOS of the third cumulant (i.e. bispectrum) to generate linear HS features without noise. These features after statistical normalization were inserted into ANFIS neural network, which has not been attempted in literature, to detect normal HS from HC signals.

In literature, many studies attempted the signal processing challenge on the international database (i.e. PhysioNet Challenge 2016). Due to the noisy cardiac sound background, most state of art techniques focused on de-noising HS signal and establishing the most significant features. For example, features in time, frequency, statistical, and wavelet domains had been addressed by many authors [7]–[10]. The neural network methodologies and learning machine algorithms were implemented intensively to reach to the best classification accuracies. This includes algorithms as Convolutional Neural Network (CNN), Drop Connected Neural Networks (DCNN), Gram polynomials and probabilistic neural networks, AdaBoost classifier, LogitBoost, Random Forest, and a Cost-Sensitive Classifier [11]–[15]. Martin *et al.* [16] used the deep learning machine during the detection of chronic heart failure disease and to improve classification accuracy. Other approaches achieved an acceptable accuracy using clustering techniques for cardiac sound classification such as the k-nearest neighbors (kNN) algorithm [17], threshold-based methods, and decision trees [18]. Support vector machine (SVM) had been also proved its capability having different kernel functions for HS classification [19]–[21]. Some HS features were generated from phase components of Fourier spectrum [22] and [23]. They claimed that phase information could be useful if the complete phase spectrum was employed appropriately.

This paper presents the results of new attempt (i.e. framework) based on utilizing High Order Spectral (HOS) analysis and ANFIS, which, to best of our knowledge, has not been addressed in literature. The method was applied to same international database, PhysioNet Challenge 2016, and the outcomes were compared with similar attempts in literature. Figure 1 shows the block diagram of our attempt.

II. MATERIALS

The PhysioNet-Challenge 2016 [6] is an international database that contains more than 3000 HS recordings. The HS signals are distributed in Class A, B, C, D, and E. We collected 1837 HS signals from class A, B, and E. They were divided into training and testing sets with 80-20% (class A), and 85-15% (class B and E) split protocols respectively, as seen in Table 1. These HS samples were selected based on consideration that there is no emergency noise source (e.g. voices from humans or machines), deteriorating the HS recording; we will discuss this point in the discussion section. The time duration of each HS signal is up to 120 sec. Each signal is sampled to 2000Hz. These are the original specifications provided by PhysioNet challenge webpage.

III. METHOD

A. PRE-PROCESSING STEP

Both types, the normal HS and HC signals, are noisy and intersect in frequency characteristics. Therefore, two preprocessing steps were utilized. First we applied band pass notch filter to reject the 50-60 Hz noise. Second, 4^{th} Butterworth

TABLE 1. Dataset distribution.

Class	Sets	# Subjects	Abnormal HC	Normal HS
A	Training	313	218	95
	Test	78	54	24
B	Training	301	66	235
	Test	50	8	42
E	Training	930	104	826
	Test	165	18	147
A + B + E	Training	1544	388	1156
	Test	293	80	213
Total		**1837**	**468**	**1369**

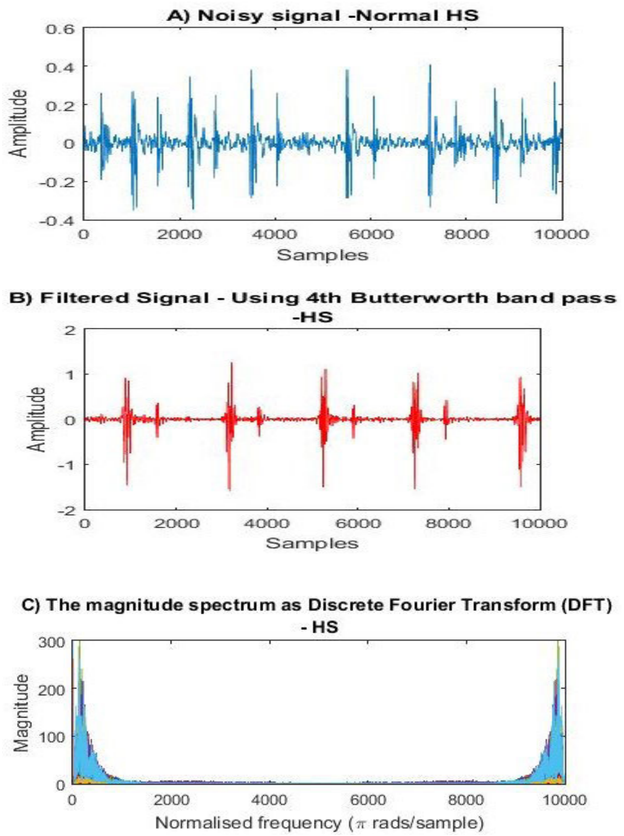

FIGURE 2. Normal HS, original (a), filtered (b), and Normalized DFT(c).

band pass filter was applied. Figures 2 a-b and 3 a-b illustrate the results on a 5 second segment, which contains S1 and S2 of normal HS and HC signals. In Butterworth filter, we implemented two cut off frequencies. These are the FC1=0.025 and FC2=0.4, which were tested and recommended by reference [24].

B. HIGH ORDER STATISTICS

The Discrete Fourier Transform (DFT) was applied on the preprocessed signals, as seen in Figure 1. The DFT can sort frequencies constituents of the signal. Therefore, the magnitude spectrum was normalized and plotted as shown in Figure 2-c and 3-c, indicating perceptual difference between normal HS and HC spectrums. Then, the high order spectral (HOS) analysis was applied. The HOS have different moments (i.e. cumulants), where each cumulant itself can be expressed by moments. The third cumulant is same as the central moment, it is called as Bispectrum Fourier [25]. This bispectrum can investigate the nonlinear coupling information, quantifying the oscillatory between basic frequencies f_1, f_2, and their modeling $f_1 + f_2$. However, the expression of bispectrum can be calculated from the Fourier Transform of the 3rd order correlation in which HS signal is analyzed [26]:

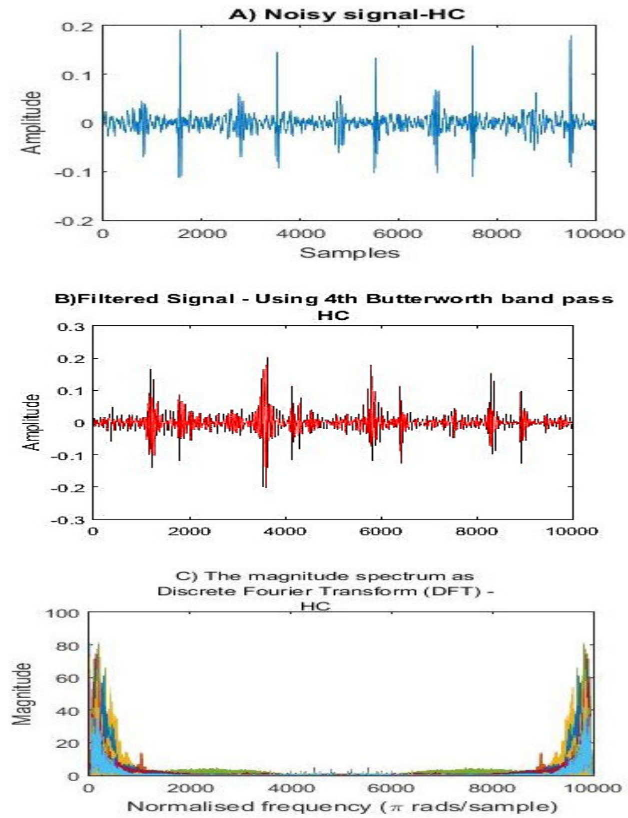

FIGURE 3. Abnormal HC, original (a), filtered (b), and Normalized DFT(c).

$$Bis\,(f_1, f_2) = \lim_{T\to\infty}\left(\frac{1}{T}\right) E[X\,(f_1 + f_2)X^*(f_1)X^*(f_2)] \quad (1)$$

where:

$X(f)$ is Fourier transform 3rd order of the HS signal (i.e. time series).

(*) is the complex conjugate.

E stands for the expected/ estimated value.

In order to compare normal HS with HC quantitatively, set of statistical parameters were extracted from the matrix of bispectrum (i.e. 2D mapping for all frequencies pairs of cardiac sound signal). The drawn segments of cardiac sound were divided into several sub-segments using the 2D priestly window (Figure 4) of bispectrum. Consequently, it forms a bispectral matrix size of 128 × 128 points as shown in Figure 5 [27].

C. FEATURES EXTRACTION

The Bispectral matrix contains the result of mapping frequencies in form of *real* and *imaginary* components. Many *attributes* may be extracted. We investigated the HOS

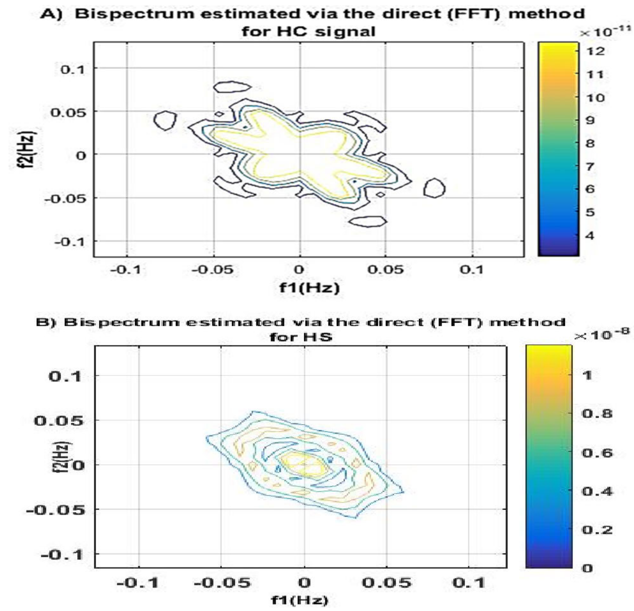

FIGURE 4. Contour plot of Bispectrum response for normal HS (Top) and HC (Bottom).

$$\begin{bmatrix} -8.07e^{-16}+2.93e^{-15i} & \cdots & -1.58e^{-15}-3.67e^{-15i} \\ \vdots & \ddots & \vdots \\ -1.58e^{-15}-3.67e^{-15i} & \cdots & -1.56e^{-15}-8.94e^{-16i} \end{bmatrix}$$

$$\begin{bmatrix} 8.67e^{-12}-7.20e^{-13i} & \cdots & 9.47e^{-12}+8.08e^{-13i} \\ \vdots & \ddots & \vdots \\ 9.47e^{-12}+8.071e^{-13i} & \cdots & 1.61e^{-12}+7.61e^{-12i} \end{bmatrix}$$

FIGURE 5. Bispectral matrix examples of HC (top) and normal HS (Bottom).

TABLE 2. List of HOS feature extracted for classification.

Symbol	Feature	Significance P Value [a]
1	Mean	< 0.05
2	SD	< 0.05
3	Var	< 0.05
4	Entropy	< 0.05
5	Log entropy	>0.05

features [26]. Table 2 reports the selected five features. They were calculated from the real (Re) of each point of matrix. These are the mean, standard deviation (SD), variance (Var), Entropy, and Log Entropy of real component of the third cumulant (i.e. bispectrum) of DFT. This set of features will be, then, used for training a supervised *ANFIS* classifier to automatically estimate the person health condition, as normal or abnormal health condition.

The fifth feature (i.e. log entropy) was omitted because of its low significance (p>0.05). The remaining features were normalized to become in the range of 0 to 1 for all signals as explained in Equation 2. That is the j_{th} feature (j=1 to 4) for "n" samples (n=1 to 1837) was normalized between 0 and 1 values. Thus, the classification process, which will be explained in the forthcoming section, will not be affected

TABLE 3. Internal ANFIS parameters for best classification.

TYPE	SUGENO
FIS andMethod	Prod
FIS orMethod	probor
FIS defuzzification Method	Wtaver (Weighted average performance of all rule outputs)
FIS implication Method	Prod
FIS aggregation Method	sum
FIS inputs	1 × 4 fisvar
FIS Outputs	1 × 1 fisvar
FIS rules	5 fisrule
Epoch number	200
Range of influence	0.4
FIS Creates a Sugeno FIS	fis.Name="sug41"

by different magnitudes/scales of the considered signal.

$$\vec{F}_{j,normalized} = (\vec{F}_j - F_{j,min})/(F_{j,max} - F_{j,min}) \quad (2)$$

where:
F_j and $F_{j,normalized}$ are the original and normalized *j-th* feature, respectively;

$F_{j,min}$ and $F_{j,max}$ are the minimum and the maximum of the *j*-th feature values calculated for all "n" samples (i.e. 1837 samples), respectively.

D. ADAPTIVE NEURO FUZZY INFERENCE SYSTEM

ANFIS classifier is a suggestive artificial intelligence technique for data classification. The ANFIS architecture relies on five layers of nodes. They are incorporated to compare the input signal against previous knowledge (training) stored. Two layers of ANFIS are adaptive while the rest consist of fixed nodes [28] and [29]. The Input parameters that fed into ANFIS are: Mean, SD, VAR, and Entropy. The resulting abnormal output (HC) was denoted by 1, while number 2 was used to denote the Normal HS. The training parameters of ANFIS are given in Table 3.

The PRECISION and RECALL statistical metrics were calculated using Equations 3, 4, and 5

$$\text{Precision} = \text{TP}/(\text{TP}+\text{FP}) \quad (3)$$

$$\text{RECALL} = \text{TP}/(\text{TP}+\text{FN}) \quad (4)$$

$$\text{F-score} = 2^{*}\text{precision}^{*}\text{RECALL}/[\text{precision}+\text{RECALL}] \quad (5)$$

where:

TP: true positive represents the abnormal samples detected correctly

FP: false positive represents the normal samples detected as abnormal

TN: true negative represents the normal samples detected correctly

FN: false negative represents the abnormal samples detected as normal

IV. RESULTS AND DISCUSSION

The proposed approach attempts to eliminate noise, selects significant spectral features using HOS attributes, and

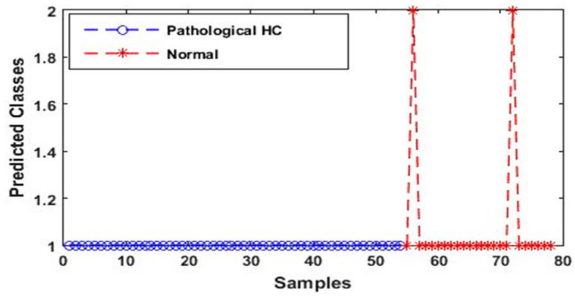

FIGURE 6. The ANFIS's outputs on 78-test samples for class A in dataset.

employs ANFIS neural network. This framework was applied to all 1837 HS signals in the dataset. As a result, a matrix with entries containing complex values (Real and Imaginary) was obtained for each HS signal. The bispectrum showed peak placed around (0, 0) Hz for normal HS signals, and between 0.02 and -0.02 Hz approximately for HC signals (Figure 4). This led to deduce four HOS significant spectral features, which are, in turn, fed to ANFIS neural network. For instance, Figure 6 shows the ANFIS's outputs for 78 test samples in Class A. All abnormal signals (i.e. 54 HC) were successfully detected (indicated by blue color), while normal samples (indicated by red color) were well detected (i.e. 24 normal HS), except two cases.

Each class in the dataset was randomly categorized as training and testing sets, as shown in Table 1. The ANFIS was trained for the whole dataset. That is all training sets in classes A, B, E participated in the training stage (1544 HS signals). Later, it was, first, evaluated on all testing samples (293 HS samples), and then evaluated for each test set in each class. The ANFIS outcomes were observed. The precision, recall, and accuracy were reported. Table 4 shows the results of the framework.

Since class A (391 samples), class B (351 Samples), and class E (1095 samples) have different number of HS signals, the ANFIS achieved range of values for precision (63-100%) and accuracy (63-89%). Both precision and accuracy increased with the increment of samples (Table 4). This may indicate the ANFIS ability to detect abnormal HS signals (i.e. TP responses). However, the recall (i.e. specificity) was 62%, 100% and 78% in class A, B, and E, respectively. This variation, on the one hand, may be attributed to variations in number of normal and abnormal HS *test* samples. That is, as seen in Table 1, class A included 24 normal HS test samples in comparison to 42 and 147 in class B and E, respectively. Whilst, class A included 54 abnormal HS test samples in contrast to 8 and 18 samples in class B and E, in turn. These differences have direct impact on equation (4). On the second hand, this variation in recall (and in sensitivity and accuracy) may be attributed to fact that, as stipulated by PhysioNet challenge [6], the HS recording's severity (i.e. occult) were distributed unequally among classes. Since we utilized only four features as inputs for ANFIS, these statistical metrics (sensitivity, specificity, and accuracy) are subject to improve if the number of features increases. The results

TABLE 4. The framework performance on dataset.

Class	Sets	# Subjects	Precision	Recall	F-Score
A	Training	313	0.71	1	0.83
	Test	78			
B	Training	301	0.63	0.62	0.63
	Test	50			
E	Training	930	1	0.78	0.89
	Test	165			
A + B + E	Training	1544	0.78	0.80	0.78
	Test	293			

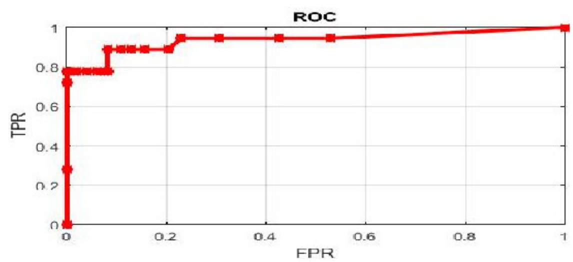

FIGURE 7. The accumulative framework performance (ROC).

in Table 4, with consideration that only four features were utilized, rationalize the conclusion that ANFIS can classify HS signals. In other words, Table 4 indicates that *ANFIS is a successful classifier on PhysioNet*, but it also indicates that there is requirement to increase the number of HS' attributes (i.e. features) to obtain close results. Increasing the number of input parameters, or collaborating ANFIS with other types of neural networks, may improve the performance. These are prospective research.

Figure 7 shows the receiver operating characteristics (ROC) describing the accumulative performance of the suggested framework (Figure 1), based on adjusting the ANFIS operating parameters.

In literature, many participations in PhysioNet-challenge 2016 were reported, addressing different types of neural networks and classifiers. Table 5 summarizes these main attempts, to best of our knowledge. It shows the author's group, technical features (i.e. methodology), features' number, neural network/classifier type, and overall accuracy. Generally, authors focused on objectives to enhance HS signals, select group of features, and apply a classifier. The wavelet domain was attracting for some authors [8], [30], and [36]. They used resampled wavelet envelope features, wavelet entropy, wavelet-based deep convolutional neural network (CNN), and spectral features. For this group, the SVM showed an accuracy ranging between 77-88.9%. The second group of authors was interested in Hidden Markov Model combined with some statistical features [31] and [37]. They reported accuracy in range of 79-82%. Third group attempted to extract features using the spectrogram method [32] and [35]. They employed classifiers like SVM, CNN, and Logistic Regression (LR). These attempts achieved accuracy of 68-81%. Other researchers attempted

TABLE 5. Literature Summary on Physio-Net Challenge 2016.

Author	Methodology	# Features	Neural Network Classifier	# HS Samples	Accuracy
Goda et al. [30]	Wavelet envelope features	128	SVM	1000	81.2% (MAcc)
Grzegorczyk et al. [31]	Algorithm based on Hidden Markov Model.	48	Neural networks	3000	79 %
Langley et al. [8]	Wavelet Entropy	1 (wavelet entropy)	Classification algorithm	400	77%
Nilanon et al. [32]	Spectrogram	Many time windows	SVM, CNN, and Logistic Regression (LR)	About 3000	68- 80 %
González Ortiz et al. [33]	DTW coupled with MFCC	> 5	SVM	unknown	82.4%
C. Potes et al. [12]	Time and frequency-domain Features	124	Convolutional neural network (CNN)	3240	86%
J. Rubin et al. [34]	Transformation of 1D/2D waveforms into heat map representations using MFCCs	13	Deep Convolutional Neural Networks	3240	88%
Singh-Miller et al. [35]	Spectrogram method	20	Random forest regression	3000	81%
M. Tschannen et al. [36]	Wavelet deep convolutional neural network (CNN) and spectral features	25	SVM	3153	81.2%
S. Vernekar et al. [37]	Markov features, statistical, and frequency domain features	38	Multi artificial neural networks and gradient boosting trees	3153	82%
M. Zabihi et al. [14]	Wrapper-based feature	40	Grouped 20 feedforward neural networks	3454	Train Rule2 is 91.5% Train Rule 1 is 85.9%
M. N. Homsi et al. [38]	Nested ensemble of algorithms	131	Random Forest, LogitBoost and a Cost-Sensitive Classifier	764	86.48%
This work	High order spectrum	4	ANFIS	1837	63-89%

* MAcc stands for Modified Accuracy, which is calculated as: (specificity + sensitivity) / 2

the dynamic time warping (DTW) linked with Mel-frequency cepstral coefficients (MFCC) [14] and [33]. The DTW features were fed to SVM (training rule 1) and 20 feed forward neural networks (training rule 2). They recorded the highest accuracy in comparison to other attempts, they reported accuracy in the range of 82-91.5%. Finally, the fifth group attempted time-domain and frequency-domain features, they recorded accuracy of 86-88% [34].

Table 5 shows that the suggested framework has produced close performance to other neural network techniques. Considering the fact that this performance was achieved with only four features, whereas all other attempts had used at least 13 features to achieve accuracy in the range of 68-91.5% (63-89% in this paper), this arises that the proposed framework has exhibited signs of success. Thus, A*NFIS can successfully participate in the PhysioNet challenge*. This is the *first contribution* in this paper. It may team up with other neural networks.

On the other hand, we have selected 1837 samples. We chose the samples from Normal and Abnormal sub-folders in each class A, B, and E. We avoided the "Unsure" sub-folder in each class since the aim of this paper is to *preliminary* test ANFIS and HOS as new framework proposal. The administration of PhysioNet stipulated that some of the HS are difficult or even impossible to classify into normal or pathological condition [6]. We avoided HS signals that contain emergency voices from probably external environment (i.e. uncontrolled voices that can be heard during the recording), using our hearing skills being as biomedical engineers. If we had included all signals, the performance would have dropped. However, this is the situation with all attempts by various research institutes who had employed part of the available signals (i.e. less than 1000 samples) such as references [8], [30], [33], [38], as seen in Table 5. However, some techniques in Table 5 employed more than 3000 HS signals [14], [31], [34]–[37]; they had attempted some of these difficult signals, but they needed to explore high number of input parameters in the range of 13-124 different signal attributes. Thus, they reported better reliable performance than ANFIS, but this would not affect the suggestive capability of ANFIS to classify signals after training, particularly if the number of features was increased (e.g. more than 4 features).

Two other contributions can be concluded. First, the HOS features are possible parameters to be fed into medical decision support system for HS classification. There are other features such as skewness and kurtosis. Second, the bispectral matrix, in Figure 5, is a *new presentation* of HS signal's features. It presents the *real* and *imaginary* components of frequency constituents of the HS signal. We used only HOS attributes. The matrix may be used to extract *further attributes* describing HS signal such as co-occurrence matrices and may some of them capable to discern abnormal from normal HS signals. Those two contributions are subject for prospective research.

In summary, this paper is the *first attempt* to introduce *ANFIS* with four *HOS* features, extracted from *new presentation* of real and imaginary parts of HS' frequency constituents (i.e. bispectral matrix), as a possible framework to classify the HS international PhysioNet challenge signals, and profitably showed its capability on 1837 HS signals. Increasing number of input parameters, or collaborating ANFIS with other types of neural networks, would further sustain the findings in this paper.

V. CONCLUSION

This paper attempted to distinguish normal from abnormal HS signals available in PhysioNet-challenge 2016. The method collaborated Butterworth filtering, DFT, HOS spectral analysis presented as bispectral matrix, and ANFIS artificial intelligence technique. The framework was applied to 1837 samples from three different groups of HS signals in PhysioNet dataset. The suggested framework achieved 63-89% accuracy, indicating suggestive promising outcomes in comparison with other techniques attempting the challenge but on lower number of samples. It is a preliminary *first attempt* to utilize *ANFIS* on 1837 samples in contrast to other investigations, in which researchers utilized all HS samples (3126), or utilized more features and other sophisticated classifiers [37].

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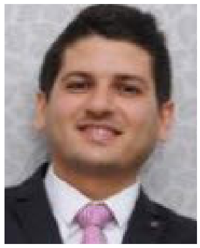
BASSAM AL-NAAMI received the Ph.D. degree in medical electronics and ergonomics from Saint Petersburg Electrotechnical University, Russia, in 2000, and the High Diploma (five years degree) in biomedical engineering from Stavropol State Technical University, Russia, in 1997. From 2001 to 2003, he was a Visiting Researcher with the School of Engineering and Information Technology, University of Sussex, Brighton, U.K. In 2003, he joined the Department of Biomedical Engineering, The Hashemite University, Zarqa, Jordan, where he is currently an Associate Professor. Since 2019, he has been an Adjunct Professor with the BME Department and an Active Member of Pharmacological and Diagnostic Research Center, Al-Ahliyya Amman University, Amman, Jordan. He has multi-disciplinary research experience and background, including signal and image processing, CAD, biomedical instrumentation, and ergonomics of virtual reality systems and haptic devices in medicine and manufacturing applications. He authored/coauthored more than 25 journal and conference papers. He was honored for his outstanding contribution in reviewing awarded by Elsevier and Springer Nature publishers, and honored by The Hashemite University for Excellence in Scientific Research, in 2013. He is an Associate Editor of the journal of *BMC Research Notes* (Springer Nature), U.K. He also acted as a reviewer for more than 30 ISI-indexed international journals and a member of TPC for more than 25 conferences.



HOSSAM FRAIHAT was born in Algiers, Algeria, in 1985. He received the B.S. degree in electronics and communications engineering from USTHB University, Algeria, in 2008, the M.Sc. degree in design implementation and quality of electronic and optoelectronic components from the University of Nantes, France, in 2010, and the Ph.D. degree in signal, images, and automatic from the University of Paris-Est, France, in 2018. He is currently working with Al-Ahliyya Amman University, Jordan. He has published several scientific articles related to visual perception, saliency object 3D, face recognition using machine learning, and fuzzy logic. His research interests include computer vision and machine learning.

NASR Y. GHARAIBEH was born in Irbid, Jordan, in 1959. He received the M.Sc. and Ph.D. degrees in biomedical engineering from Saint Petersburg Electrotechnical State University, Russia, in 1984 and 2000, respectively. He is currently working with Al-Balqa Applied University, Jordan. He published several scientific articles related to eye fundus image analysis for the purpose of detection and classification of diabetic retinopathy. His research interest includes the analysis of medical image.

ABDEL-RAZZAK M. AL-HINNAWI was born in Damascus, Syria, in 1968. He received the B.S. degree in biomedical engineering from Damascus University, in 1991, and the M.Sc. and Ph.D. degrees in medical imaging science from the University of Aberdeen, U.K., in 1995 and 1999, respectively. Since 1999, he has been working as an Assistant and Associate Professor with the biomedical engineering and medical imaging departments at the universities in Jordan and Syria. He is currently an Associate Professor with Isra University, Jordan. He has authored several SCOPUS/ISI international articles and one e-chapter. His research interest includes quantitative analysis of medical images and 3D visualization.