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Support Vectors Machine-based identification of heart valve diseases using heart sounds

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ABSTRACT

Taking into account that heart auscultation remains the dominant method for heart examination in the small health centers of the rural areas and generally in primary healthcare set-ups, the enhancement of this technique would aid significantly in the diagnosis of heart diseases. In this context, the present paper initially surveys the research that has been conducted concerning the exploitation of heart sound signals for automated and semi-automated detection of pathological heart conditions. Then it proposes an automated diagnosis system for the identification of heart valve diseases based on the Support Vector Machines (SVM) classification of heart sounds. This system performs a highly difficult diagnostic task (even for experienced physicians), much more difficult than the basic diagnosis of the existence or not of a heart valve disease (i.e. the classification of a heart sound as 'healthy' or 'having a heart valve disease'): it identifies the particular heart valve disease. The system was applied in a representative global dataset of 198 heart sound signals, which come both from healthy medical cases and from cases suffering from the four most usual heart valve diseases: aortic stenosis (AS), aortic regurgitation (AR), mitral stenosis (MS) and mitral regurgitation (MR). Initially the heart sounds were successfully categorized using a SVM classifier as normal or disease-related and then the corresponding murmurs in the unhealthy cases were classified as systolic or diastolic. For the heart sounds diagnosed as having systolic murmur we used a SVM classifier for performing a more detailed classification of them as having aortic stenosis or mitral regurgitation. Similarly for the heart sounds diagnosed as having diastolic murmur we used a SVM classifier for classifying them as having aortic regurgitation or mitral stenosis. Alternative classifiers have been applied to the same data for comparison (i.e. back-propagation neural networks, k-nearest-neighbour and naïve Bayes classifiers), however their performance for the same diagnostic problems was lower than the SVM classifiers proposed in this work.

1. Introduction

Heart auscultation, defined as listening and interpretation of the sound produced by the heart, has been a very important method for diagnosing heart diseases from the early stages of medicine, since most heart diseases are reflected to the sound that the heart produces [1]. It is an operationally simple, low cost and non-invasive method of high sensitivity to most heart diseases. Although some new methods, such as Echocardiography, and Medical Imaging modalities (i.e. Ultra-

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sound Imaging (US); Computed Tomography (CT); Magnetic Resonance Imaging, (MRI), etc.), can provide more direct and accurate evidence of heart disease than heart auscultation, these methods require sophisticated and expensive equipment and specialised personnel, so they are much more costly and operationally complex [2–4]. These methods are suitable for use in well organized healthcare environments, but not in small health centres of the rural areas and generally in primary healthcare set-ups. In these healthcare establishments the heart auscultation remains the basic tool for a first screening of patients and deciding which of them should be referred to more complex and costly medical examinations and tests (e.g. based on advanced imaging techniques) and/or specialised cardiologists. Also, many heart diseases cause differentiations of heart sound in much earlier stages before they can be observed in other comparable techniques, such as the Electrocardiogram (ECG) [4,5]. Therefore increasing the accuracy and the whole effectiveness of heart auscultation is of critical importance for improving both the health level of the populations (by diagnosing heart diseases in their early stages) and also the economics of the health systems (by avoiding unnecessary costly medical examinations and tests due to incorrect screening). Furthermore, it should be taken into account that in some circumstances, such as in the developing countries, the auscultation is the only available tool for diagnosis of heart diseases for most of their population. The computer assisted auscultation requires only an electronic stethoscope and a personal computer along with the necessary software as will be described further on in this paper.

Physicians require a lot of training and experience in order to become capable to distinguish correctly all the components of a heart sound in an objective and reproducible way, and then based on them to make a correct diagnosis. However, most internal medicine and cardiology training programs underestimate the value of heart auscultation and provide insufficient (or even not at all) such training, so junior physicians are not adequately trained in heart auscultation. Especially the primary health care physicians, who are usually young and inexperienced, have been reported to have poor heart auscultation skills. The pool of skilled for this specific task clinicians, who have been trained in the era before echocardiography, continues to age, and the skills for heart auscultation is in shortage and in danger to disappear [6–9].

For the above reasons it is quite useful to develop appropriate decision support systems that support clinicians in making heart sound diagnosis, which will be quite beneficial, especially in rural areas, in homecare and in primary healthcare. Such decision support systems may serve as diagnostic adjunct or training tools for young physicians practicing in remote health centers. As described in the next section, extensive research and development work has been conducted in this area, motivated both by the value they can offer to the clinicians and the recent advances in information technology systems, in digital electronic stethoscopes, in digital signal processing methods and in pattern recognition and classification methods [10–15,101]. Appropriate devices allow nowadays the digitization and storage of heart sounds in digital format, their inclusion in electronic health records, their transmission to other (possibly remote) systems (e.g. using wireless technologies, the Internet, etc.), their presentation on a screen (both in the time and in the frequency domain) and their processing in order to remove noise and other undesirable components. More advanced systems can also perform intelligent processing and provide suggestions of diagnostic nature to the doctor, e.g. concerning the existence of additional sound components, such as the third heart sound (S3), the fourth heart sound (S4), various murmurs, clicks, snaps, etc., or even the existence of particular heart diseases. This combination of the 'traditional' auscultation with the modern information and communication technologies is expected to revitalise the interest in and use of auscultation in the near future [14].

In this paper initially the previous research work concerning automated detection of various heart diseases and pathological conditions from heart sound signals is reviewed. Then a Support Vector Machine (SVM)-based diagnostic system is proposed for heart valve disease identification using heart sounds, which offers significant advantages analyzed in the following sections. This system using low cost heart sound signals, which can be acquired even in the smallest primary healthcare center in an easy and non-invasive way, performs a highly difficult diagnostic task (even for experienced physicians), much more difficult than the basic diagnosis of simply the existence or not of a heart valve disease (i.e. the classification of a heart sound as 'healthy' or 'having a heart valve disease'): it identifies the particular heart valve disease. In particular, it classifies heart sound signals at a first stage into normal and disease-related and at second stage the unhealthy sounds are categorized into four classes corresponding to the four most usual heart valve diseases: aortic stenosis (AS), aortic regurgitation (AR), mitral stenosis (MS) and mitral regurgitation (MR). This disease classification is performed in two cascading steps. In the first step the sound heart signal is classified as having either a systolic murmur (which means AS or MR) or a diastolic murmur (which means AR or MS) using a two-class SVM classifier. In the second step there are two different two-class SVM classifiers; the first of them classifies the heart sound signals with systolic murmur (according to the decision of the first step) as AS or MR cases, while the second one classifies the heart sound signals with diastolic murmur (according to the decision of the first stage) as AR or MS cases. During the study of these classification problems, several alternative SVM kernels have been examined in order to find the optimal automated classification scheme with the highest performance. The work presented in this paper constitutes the following step of previous research that has been conducted by the authors concerning the differential diagnosis of heart valve diseases from heart sound signals using decision trees [3,75], now attempting to investigate more recent algorithms (i.e. advanced sound processing and SVM-based classification) for this critical problem.

The rest paper is structured as follows: in Section 2, the previous related research work is surveyed, while in Section 3 the data (heart sound signals) we used for constructing and testing the SVM-based classifiers and the proposed heart sound signals pre-processing methodology, aiming at the removal of the noise and the extraction of the features, are described. Section 4 presents the SVM classifiers that were developed for the identification of heart valve diseases and an evaluation of their performance for various kernel functions and parameters. The same section compares their performance to the performance of a number of alternative classification approaches that have been applied to the same data, such as back-propagation neural networks, k-nearest-neighbour and naïve Bayes classifiers. Finally Section 5 discusses the findings and concludes the paper.

2. Related research work and background

Extensive research has been conducted concerning the exploitation of the heart sound signals for automated and semi-automated detection of various heart diseases and pathological conditions. This research covers several levels, from the signal processing level up to the final signal classification (diagnosis) level, so we can distinguish in it a number of research streams; the most important of them are:

- The analysis of the heart sound signals, aiming at their optimal representation, using various methods, such as time-frequency representations, wavelet transforms, matching pursuit, short-time Fourier transform, high order statistics, etc. [16–22].
- The removal from the heart sound signals of various types of noise (e.g. from the surroundings, from the lungs, etc.), which distort their basic components and characteristics and decrease their diagnostic potential; various methods have been used for this purpose, such as adaptive filtering, wavelet transform, reduced order Kalman filtering, independent component analysis, multiscale products and linear prediction, etc. [23–28].
- The analysis of the heart tones S1, S2, S3, S4 and murmurs, aiming to achieve highly accurate spectral estimation of them, in order to enhance their diagnostic potential; the main methods that have been used for this purpose are wavelet transform, short-time Fourier transform, autoregressive modelling, matching pursuit and a number of distributions (e.g. Bessel, Binomial Reduced Interference, Cone-Kernel (CKD), etc.) [29–36]; this stream also includes a number of studies dealing with the extraction of the aortic and pulmonary components of the second heart sound (S2) and then based on them (on the normalized splitting interval between them) the estimation of the pulmonary artery pressure [37–39].
- The segmentation of the heart sound signal into heart cycles and then the partitioning of each heart cycle into S1, systolic phase, S2 and diastolic phase; various methods have been used for this purpose, such as power spectral density calculation based on autoregressive models, normalized average Shannon energy calculation, wavelet transform, homomorphic filtering, K-means clustering, etc. [5,40–43]; to this stream also belongs a study by Hebden and Torry [44], which proposes a back-propagation neural network-based method for distinguishing between S1 and S2 peaks in both normal and abnormal heart sound signals.
- The detection of problems and mechanical changes of prosthetic heart valves from heart sound signals using various methods, such as wavelet transform, spectral analysis and digital filtering, fast Fourier transform, Fast Orthogonal Search (FOS), Multiple Signal Classification (MUSIC), neural networks, nearest neighbour classifiers, etc. [45–51].
- The diagnostic classification of heart sound signals; since the present paper belongs to this heart sound research stream, we are going to analyse it in more detail. Part of these studies are dealing with the discrimination between normal (from healthy subjects) and abnormal (from subjects having a disease) heart sound signals [52–55], or with the discrimination between innocent and pathological murmurs in children [2,56–62]. Other studies are dealing with the detection from heart sound signals of particular heart diseases, such as coronary artery diseases [63–67] and heart valve diseases [68–75]. It should be emphasized that in most of the studies of this research stream the diagnostic classification of the heart sound signals is based on neural networks of various types (e.g. back-propagation, radial basis function, self-organizing map, probabilistic neural networks, etc.) [52–55,57,59,61–66,70,73,74]. On the contrary there are only a few studies using other classifiers, such as discriminant functions [58,72], decision trees [75], Bayesian networks [54], etc.; therefore the diagnostic potential in this domain of other classifiers than the neural networks has not been sufficiently explored yet, so further research is required in this direction.

The early diagnosis of heart valve diseases, which is the main subject of the present paper, is a very significant issue in cardiology; for this reason considerable research has been conducted for the development of computerised systems that support the clinicians in diagnosing heart valve diseases. Part of this research uses heart sound signals. Nygaard et al. [68] assess the severity of aortic valve stenosis by estimating the transvalvular pressure difference through spectral analysis of cardiac systolic murmurs. Hebden and Torry [69] proposed a method for distinguishing the systolic murmurs arising from aortic stenosis and mitral regurgitation by estimating the frequency content of S1 and S2. Brusco and Nazeran [70] describe an 'intelligent' PDA-based wearable digital phonocardiograph, which can not only record and display the heart sounds but also apply several signal processing and statistical techniques to segment these signals into four parts (S1, systole, S2 and diastole) and then to perform diagnostic classification of them using multilayer perceptron (MLP) neural networks; also they describe the use of this system for classifying heart sounds into the following five categories: normal, aortic regurgitation, aortic stenosis, mitral regurgitation and mitral stenosis. Herold et al. [71] propose a heart sound analysis method for diagnosing aortic valve stenosis based on wavelet filtering and envelope calculation and then on calculation of correlations on the basis of these envelopes. In a similar direction Voss et al. [72] describe a system aiming to support the general practitioner in discovering aortic valve stenosis at an early stage; it is based on wavelets and Fourier transform for the extraction of appropriate parameters of the heart sound signals, and then on linear discriminant function analysis for the detection of aortic valve stenosis from these parameters. Higuchi et al. [73] propose a three-layered artificial neural network analysis of phonocardiogram recordings for the diagnosis of the heart condition in patients with heart murmurs; it enables the classification of heart sounds into the following seven categories: mitral stenosis, mitral regurgitation, aortic stenosis, aortic regurgitation, ventricular septal defect, atrial septal defect and patent ductus arteriosus. Ahlstrom et al. [74] developed a system for systolic heart murmur classification; initially from the heart sound signals, using a combination of techniques (Shannon energy, wavelets, fractal dimensions, recurrence quantification analysis and finally Pudil's sequential floating forward selection) it extracts a number of features, and then based on them and using neural networks it classifies the murmurs as physiological or pathological ones. Pavlopoulos et al. [75] propose a decision tree-based method for the differential diagnosis of aortic stenosis from mitral regurgitation using heart sounds. Recently Chauhan et al. [76] have developed an automatic heart sound classification system (classification of healthy heart sounds, systolic murmurs, diastolic murmurs and continuous murmurs), which uses a probabilistic approach based on Mel-frequency cepstral coefficients (MFCC) and Hidden Markov Models (HMM).

Significant research on the computerised diagnosis of heart valve diseases has also been conducted based on other more costly signals, such as Doppler Heart Sound (DHS), Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) [77–82]. In this direction Turcoglu et al. [77] have developed a system for diagnosis of heart valve diseases from DHS; initially it extracts features from the DHS using wavelet transforms and short time Fourier transform, and then based on these features it classifies the DHS as 'normal' (healthy) or 'abnormal' using a back-propagation neural network. An improvement of this system is described by Turcoglu et al. in Refs. [78,79]; it consists of two layers: a 'wavelet' layer, which performs adaptive feature extraction in the time-frequency domain based on wavelet packet decomposition and wavelet packet entropy, and a 'multi-layer perceptron', which is a feed-forward neural network that performs classification of DHS as normal or abnormal. Uguz et al. [80] and Comak et al. [81] propose two more enhancements of the above system, which are based on a Hidden Markov Model and Support Vector Machines respectively. Vogel-Claussen et al. [82] are dealing with a combination of electrocardiographically gated multi-detector row Computed Tomography and Magnetic Resonance Imaging for the non-invasive visualization and assessment of the heart valves.

The present paper, as mentioned in the introduction, is dealing with the use of Support Vector Machines for the identification of heart valve diseases from heart sound signals. In the latest years, significant research work has been published in the literature concerning automated diagnostic systems based on the Support Vector Machines algorithm. Chazal et al. [83,84] deal with the automatic processing of the Electrocardiogram and the classification of the heartbeats into one of the five beat classes recommended by ANSI/AAMI EC57:1998 standard, i.e. normal beat, ventricular ectopic beat (VEB), supraventricular ectopic beat (SVEB), fusion of a normal and a VEB, or unknown beat type. Statistical classifiers and two stage classifiers (local and global) have been adopted in their research, which prove significant results of classification performance over previous studies. Campadelli et al. [85] propose an automated system for the detection of lung nodules based on chest radiographs; the automated classifiers are based on Support Vector Machines and the system is extensively trained with various SVM kernel functions. Fan et al. [86] propose a method for classification of structural brain Magnetic Resonance images using a combination of deformation-based morphometry and machine learning methods; the feature selection and the final classification algorithm implemented are based on SVMs and the reported results approximate the accuracy of 91% using leave-one-out cross-validation procedure. As it can be derived from the above exhaustive review, the research community has not extensively utilized yet the SVM methodology, for the problem of heart sound diagnosis, dealt in this paper.

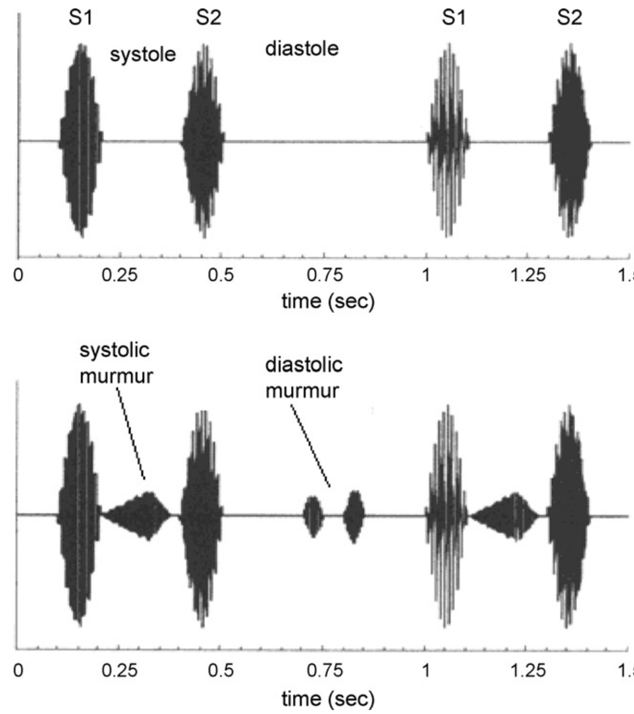

Fig. 1 – Typical heart sound signals from a healthy heart (upper part) and from a pathologic heart generating systolic and diastolic murmurs (lower part).

3. Heart sound signals pre-processing

The heart sound signal from a healthy heart has the form shown in the upper part of Fig. 1. Its basic components are: the first heart sound (S1), which is generated by the nearly simultaneous closure of the mitral and the triscupid valve, being followed by the systolic phase, and the second heart sound (S2), which is generated by the nearly simultaneous closure of the aortic and the pulmonic valve, being followed by the diastolic phase. Most heart diseases generate additional components in the heart sound, such as murmurs in the systolic or/and the diastolic phase (see lower part of Fig. 1), third heart sound (S3), fourth heart sound (S4), clicks, snaps, etc. Concerning the heart valve diseases dealt with in this paper, aortic stenosis and mitral regurgitation generate systolic murmurs, while aortic regurgitation and mitral stenosis generate diastolic murmurs [1,3].

It should be emphasized that several factors related to the acquisition method affect significantly the characteristics of the acquired heart sounds. The most important of these factors are: the type of stethoscope used, the sensor that the stethoscope has (e.g. microphone, piezoelectric film, etc.), the stethoscope use mode (e.g. bell, diaphragm, extended), the filtering applied to the heart sound signals (e.g. anti-tremor filter, respiratory sound reduction filter, etc.), the way the stethoscope is pressed on the patients skin (firmly or loosely), the patient's position (e.g. supine position, standing, squatting), the auscultation areas (i.e. apex, lower left sternal border, pulmonic area, aortic area), the medicines that the patient is taking, etc. These factors cannot be controlled in the everyday medical practice, since it is very difficult to have fixed predefined values of all the above factors in the everyday heart auscultations; the uncontrolled variation of these factors adds high levels of noise to the acquired heart noise signals (i.e. generates additional components) and makes the detection of various heart diseases and pathological conditions from these heart sound signals even more difficult. Therefore an effective system of heart diseases diagnosis from heart sounds should be able to cope with this problem. For this purpose it is necessary both for constructing the classifiers and for testing them to use a 'global' and representative dataset consisting of heart sounds from various sources and recorded with different acquisition methods and different values of the above factors. In this direction for our research such a global and representative heart sounds dataset has been created with heart sound signals from eight different heart sound sources (educational audiocassettes, audio CDs, CD ROMs, files of existing heart sound databases, etc.), which are mentioned in the references section [87–95]. So this global dataset includes heart sound signals acquired with various types of stethoscopes, sensors and filters, in various modes, subjects' positions and auscultation areas, from subjects of various ages, heart conditions and medical treatments. Such a dataset is more 'noisy' and therefore more 'difficult' for the classifiers, than the more 'homogeneous' ones used by most similar studies, but it offers the serious advantage that it enables a more realistic investigation of classifiers' construction and performance. For the purposes of the present study, this dataset was completed with normal heart sounds collected by healthy persons (students at the ages of 18–22) using an electronic stethoscope (Master Elite type manufactured by Welch Allyn). All the young subjects were checked by a physician participating in the study and the samples that correspond to abnormal heart sounds were excluded from the healthy dataset. The total number of heart sound signals used in the experiments were 198: 38 normal heart sounds, 41 heart sound signals with AS systolic murmur, 43 ones with MR systolic murmur, 38 ones with a AR diastolic murmur and 38 signals with a MS diastolic murmur. Each of these pathological heart sound signals had been diagnosed by a specialised cardiologist and classified to one of the above four basic heart valve diseases.

Also, due to the noise generated by the uncontrolled variation of the above factors it is necessary initially to apply an efficient heart sound pre-processing for noise removal and feature extraction. The pre-processing method we used and the feature vector it produces is based on the algorithms presented in Refs. [3,75], and we outline it here as well for reasons of paper completeness. It consisted of three phases. In the first phase of the segmentation of the heart sound signals is performed, i.e. the cardiac cycles in every signal are detected by locating the S1 and S2 peaks (see Fig. 2). For this purpose the collected heart sound samples were analyzed with the Wavelet decomposition method described in [41], with the only difference being that the 4th and 5th level detail was kept (i.e. frequencies from 34 to 138 Hz), followed by calculation of the normalized average Shannon Energy. Then a morphological transform was applied aiming at the amplification of the sharp peaks and the attenuation of the broad ones [5]. The method described in Ref. [40] is used next to locate the peaks corresponding to S1 and S2 and reject the others. Heart sound segmentation was completed with an algorithm that determines the boundaries of S1 and S2 in each heart cycle, while a method, similar to the one described in Ref. [44], was used to distinguish S1 from S2 peaks.

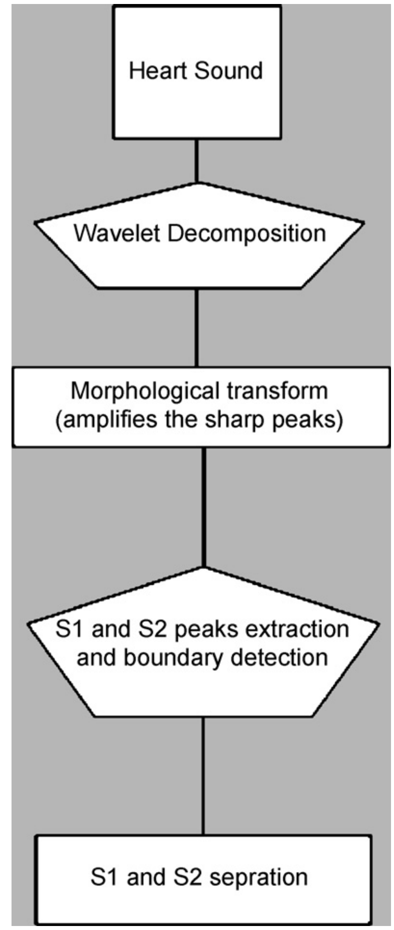

Fig. 2 – Heart sounds pre-processing procedure.

In a second phase, for each of the transformed heart sounds that were produced in the first phase were calculated the standard deviation of the duration of all the heart cycles it includes, the standard deviation of the S1 peak values of all heart cycles, the standard deviation of the S2 peak values of all heart cycles and the average heart rate. These values are the first four scalar features (F1–F4) of the feature vector of each heart sound signal.

In a third phase, the rest of the features used for classification are extracted. For this purpose we calculated for each transformed heart sound signal two mean signals for each of the four structural components of the heart cycle, namely two signals for the S1, two for the systolic phase, two for the S2 and two for the diastolic phase. The first of these mean signals focused on the frequency characteristics of the heart sound, while the second mean signal focused on the morphological time characteristics of the heart sound. In particular, the first signal is calculated as the mean value of each component, after segmenting and extracting the heart cycle components, time warping them and aligning them. The second signal is calculated as the mean value of the normalized average Shannon Energy Envelope of each component, after segmenting and extracting the heart cycles components, time warping them and aligning them. The second S1 mean signal is then divided into 8 equal parts, for each part the mean square value is calculated and the resulting 8 values are used as features (F5–F12). Similarly 24 scalar features for the systolic period (F13–F36), 8 scalar features for S2 (F37–F44) and 48 scalar features for the diastolic period (F45–F92) were calculated. Finally the systolic and diastolic phase components of the above first mean signal were passed from four band-pass filters: (a) a 50–250 Hz filter giving its low frequency content, (b) a 100–300 Hz filter giving its medium frequency content, (c) a 150–350 Hz filter giving its medium–high frequency content and (d) a 200–400 Hz filter giving its high frequency content. For each of these 8 outputs, the total energy was calculated and was used as a feature in the heart sound vector (F93–F100). The above three processing phases result in a heart sound feature vector consisting of 100 components for each signal. These feature vectors were used for the SVM-based classification described in the next section.

4. Heart sounds SVM classification: implementation and results

4.1. *Basic principles of the Support Vector Machines*

Support Vector Machines are a relatively new type of learning machine, first introduced by Vapnik and colleagues [96–98], that exhibit great performance in pairwise classification and regression problems, while recently efficient algorithms have been developed that extended their applicability to multi-class classification problems [99,100]. SVMs separate a given set of binary labelled training data with a hyperplane that is maximally distant from them (named the "maximum margin hyperplane"), as it is depicted in Fig. 3.

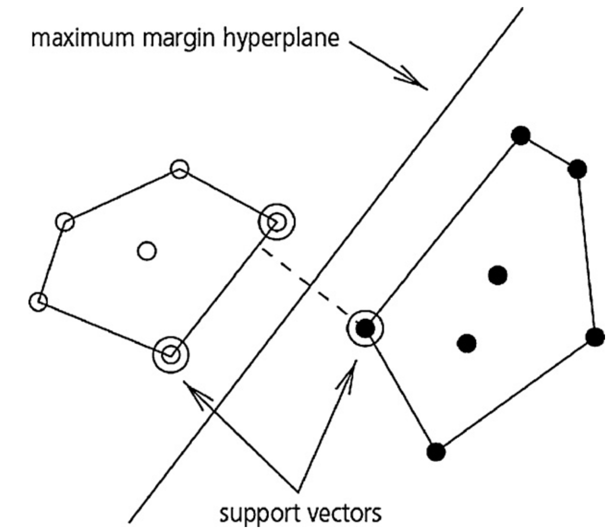

Fig. 3 – The maximum margin hyperplane.

Generally, the input space of N training data points ($\mathbf{X}_1$, y_1), ($\mathbf{X}_2$, y_2), ... ($\mathbf{X}_N$, y_N) can be separated by a hypeplane $H: w * \mathbf{X} - b = 0$. This hyperplane H is located by determining two parallel hyperplanes H_1, H_2 that have the maximum margin $2/||w||$ with the conditions that there are no data points between them. The resulting optimization problem can be formed as a convex quadratic problem in (w, b) in a convex set. Using Lagrangian multipliers and the Wolfe dual formulation, the optimal values w and b are calculated, where w is expressed linearly with a selected number of the training data which are the support vectors. In the case that no linear separation is possible, various kernel functions are employed in order to transform the data into a non-linear feature space. The hyperplane found by the SVM training algorithm in the transformed feature space corresponds to a non-linear decision boundary in the initial input space as it is illustrated in Fig. 4.

In the present research work, the kernel functions we examined during the development of the SVM models were polynomial, Gaussian and exponential, given by the following

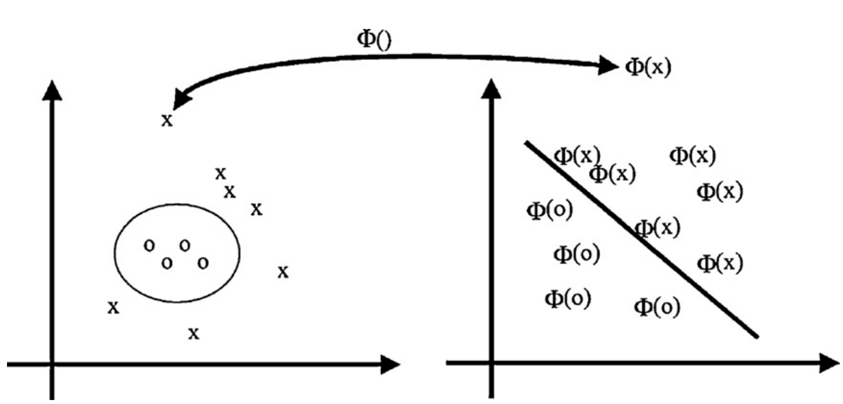

Fig. 4 – Data transformation $\Phi(x)$ into a non-linear space.

Table 1 – Results of the SVM algorithm for the classification between "healthy" and "unhealthy" patient cases, where GRBF stands for Gaussian Radial Basis Function.

SVM kernel function	Errors	FN	FP	TP	TN	Accuracy	Sensitivity	Specificity
GRBF sigma = 1.5	6	4	2	28	36	91.43%	87.50%	94.74%
GRBF sigma = 1	8	5	3	27	35	88.57%	84.38%	92.11%
GRBF sigma = 2	12	7	5	25	33	82.86%	78.13%	86.84%
GRBF sigma = 0.5	18	10	8	22	30	74.29%	68.75%	78.95%

equations:

$$k(\mathbf{X}_i, \mathbf{X}_j) = e^{-\|\mathbf{X}_i - \mathbf{X}_j\|^2/2\sigma^2} \text{(Gaussian radial basis function kernel)} \quad (1)$$

$$k(\mathbf{X}_i, \mathbf{X}_j) = (\mathbf{X}_i \cdot \mathbf{X}_j + m)^p \quad \text{(the polynomial kernel)} \quad (2)$$

$$k(\mathbf{X}_i, \mathbf{X}_j) = e^{-\|\mathbf{X}_i - \mathbf{X}_j\|^2/2\sigma^2}$$

$$\text{(exponential radial basis function kernel)} \quad (3)$$

The validation procedure employed for the SVM classifiers we developed is stratified 10-fold cross-validation. The data is divided randomly into 10 parts, in which each class is represented in approximately the same proportions as in the full dataset. Each part is held out in turn and the learning scheme is trained on the remaining nine-tenths; then its error rate is calculated on the holdout set. Thus the learning procedure is executed a total of 10 times on different training sets (which have a lot in common). Finally, the 10 error estimates are averaged to yield an overall error estimate. In the models presented next, the data are supposed to be separable therefore no penalty function is added to the optimization problem and the parameter C is set to infinity.

4.2. *SVM-based diagnosis of healthy vs. pathological cases*

The development and implementation of SVM-based automatic diagnostic system for cardiac sounds launches by studying patient cases of pathological heart murmurs and cases where no heart disease is diagnosed. The pathological heart murmurs are characterized as "unhealthy" cases in contrast with the "healthy" cases. The total data set used for the development of the model is comprised of 38 "healthy" and 32 "unhealthy" cases. The normal sounds were collected in healthy persons (students at the ages of 18–22) using an electronic stethoscope (Master Elite type manufactured by Welch Allyn) while the pathological sounds were randomly selected from the dataset described in Section 3. The validation procedure employed was stratified 10-fold cross-validation instead of using training/test sets for the reasons described in the previous section. Several polynomial, Gaussian and exponential kernel functions have been used comparatively in order to select the model with the best performance. The values of sigma differentiate the several radial basis functions used providing different hyperplanes for the classification of data during the Support Vector Machines' calculations. The performance indices calculated were accuracy, specificity and sensitivity as defined in Ref. [103].

During the experimental studies the linear SVM classifiers recognised all samples as pathological heart murmurs, which means that they were completely biased. The polynomial kernel functions were used extensively, but performed poorly with accuracies lower than 70%. Gaussian and exponential kernel functions were tried as alternative solutions. The highest performances correspond to the Gaussian kernel functions, which are presented in Table 1. The accuracy of the SVM classifiers with different kernel functions and parameters are depicted in Fig. 5a. The parameter sigma in Table 1 and Fig. 5 is the σ value in the Gaussian Radial Basis Function kernel appearing in equation 1. Since the GRBF exhibited the best performance this parameter is considered quite important for the calculation of the SVM model and it is dealt with great attention. Moreover, additional classifiers have been developed for comparison, using alternative approaches, such as k-nearest-neighbour, naïve Bayes and back-propagation neural networks [101]. The validation procedure selected was once again stratified 10-fold cross-validation and the results are illustrated in Fig. 5b. As it is concluded from Fig. 5b the performance of these alternative classifiers was lower than the best SVM classifiers, which achieves 91.43% accuracy, while the best of the examined alternative classifiers achieves accuracy below 80%.

4.3. *SVM-based diagnosis of systolic vs. diastolic phase heart murmurs*

In the second stage, an automated classifier for the discrimination between heart sound signals with systolic or diastolic murmurs has been developed using the above presented SVM algorithm. In this case we used the 160 pathological heart sounds from the collected dataset; 84 of them were diagnosed as having either aortic stenosis or mitral regurgitation (i.e. as having systolic murmurs), while the remaining 76 ones were diagnosed as having either aortic regurgitation or mitral stenosis (i.e. as having diastolic murmurs). Similar experiments were conducted as in the first stage using the same validation procedure (stratified 10-fold cross-validation).

For the sake of following the definitions of accuracy, sensitivity and specificity in all the models presented in the paper, as 'positive data' are considered the ones belonging to the first of the two categories to be discriminated, while the ones belonging to the second category are characterised as 'negative'. In this case for instance, systolic murmurs are considered as positive and diastolic as negative data.

Linear SVM classifiers were again completely biased in the heart sound data set, that is to say they recognised each

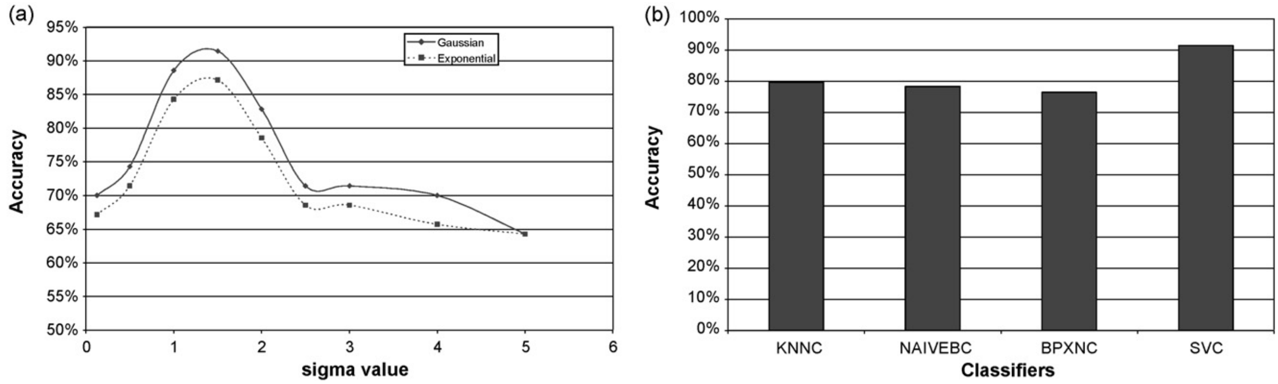

Fig. 5 – (a) Dependence of accuracy on the kernel functions used to develop the SVM classifier of "healthy" vs. "unhealthy" patient cases and their parameters (b) Comparison of alternative classification methods with the proposed SVM classifier. (KNNC stands for K nearest neighbour classifier, NAIVEBC stands for naïve Bayes classifier, BPXNC stands for neural network classifier trained with back-propagation, SVC stands for Support Vector Machine classifier.)

Table 2 – Results of the SVM algorithm for the classification between systolic and diastolic murmurs, where GRBF stands for Gaussian Radial Basis Function.

SVM kernel function	Errors	FN	FP	TP	TN	Accuracy	Sensitivity	Specificity
GRBF sigma = 2	14	9	5	75	71	91.25%	89.29%	93.42%
GRBF sigma = 1	18	10	8	74	68	88.75%	88.10%	89.47%
GRBF sigma = 1.5	18	10	8	74	68	88.75%	88.10%	89.47%
GRBF sigma = 0.5	20	11	9	73	67	87.50%	86.90%	88.16%

test set either as total systolic or diastolic heart murmurs. Polynomial kernel functions were tried with various degrees, and performed poorly with accuracies lower than 60%. The highest performances correspond to the Gaussian kernel functions, which are presented in Table 2. The accuracy of the SVM classifiers with different kernel functions and parameters are depicted in Fig. 6a. The results obtained from the use of alternative to SVM classifiers are illustrated in Fig. 6b. As it is concluded from Fig. 6b their performance was lower than the best SVM classifier, which achieves a 91.25% accuracy, while the best of the examined alternative classifiers accuracy remains below 80%. A deeper investigation of the SVM classifiers sensitivity and specificity shows quite satisfactory results, as presented in Fig. 7.

4.4. *SVM-based diagnosis of aortic stenosis vs. mitral regurgitation*

Support Vector Machines were also deployed in order to achieve automated diagnosis of aortic stenosis (AS) vs. mitral regurgitation (MR) for the cases diagnosed by the SVM classifier described above in Section 4.3 as having systolic murmurs. The heart sound dataset used consisted of 41 cases of aortic stenosis and 43 cases of mitral regurgitation. The performance indices calculated for the SVM classifiers with the highest accuracy (which were again the Gaussian) are shown in Table 3 (as already mentioned above, aortic stenosis murmurs are considered as positive, while mitral regurgitation murmurs are negative data). Linear SVM classifiers and polynomial

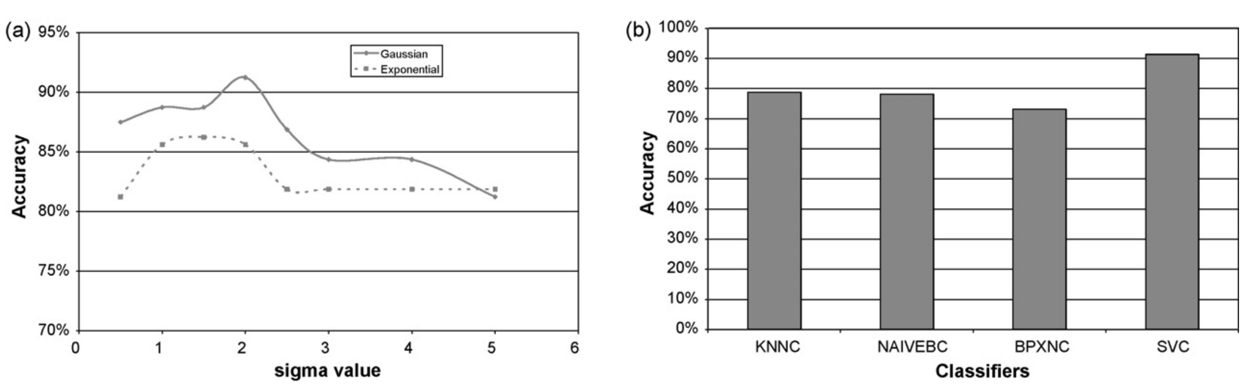

Fig. 6 – (a) Dependence of accuracy on the kernel functions used to develop the SVM classifier of systolic vs. diastolic phase heart diseases and their parameters. (b) Comparison of alternative classification methods with the proposed SVM classifier. (KNNC stands for K nearest neighbour classifier, NAIVEBC stands for naïve Bayes classifier, BPXNC stands for neural network classifier trained with back-propagation, SVC stands for Support Vector Machine classifier.)

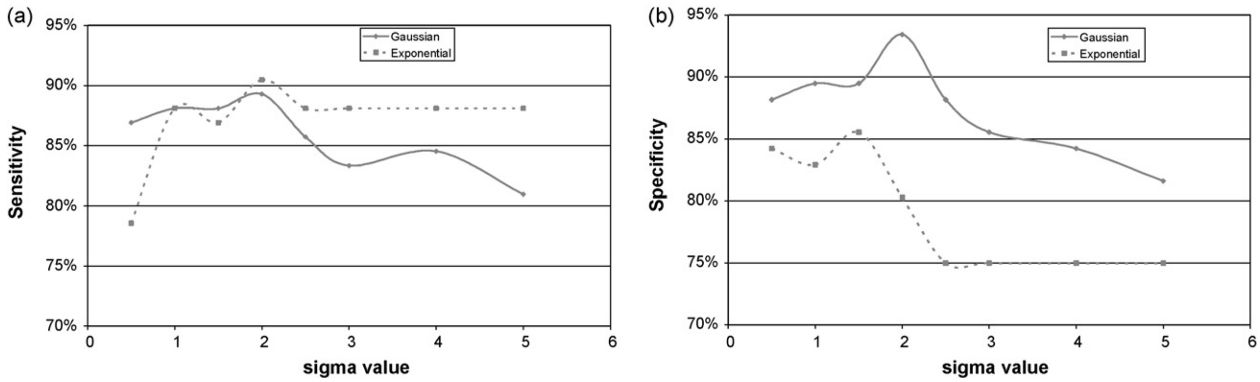

Fig. 7 – Dependence of sensitivity (a) and specificity (b) on the various kernel functions used to develop the SVM classifier of systolic vs. diastolic phase heart murmurs and their parameters.

Table 3 – Results of the SVM algorithm for the classification between aortic stenosis (AS) and mitral regurgitation (MR), where GRBF stands for Gaussian Radial Basis Function.

SVM kernel function	Errors	FN	FP	TP	TN	Accuracy	Sensitivity	Specificity
GRBF sigma = 1	7	3	4	38	39	91.67%	90.48%	92.86%
GRBF sigma = 0.5	10	3	7	38	36	88.10%	84.44%	92.31%
GRBF sigma = 1.5	12	6	6	35	37	85.71%	85.37%	86.05%
GRBF sigma = 5	12	6	6	35	37	85.71%	85.37%	86.05%

kernel functions with various degrees continued to perform poorly with accuracies less than 62%. On the other hand, Gaussian and exponential kernel functions performed satisfactorily, with Gaussian ones achieving highest performances, as shown in Table 3. Accuracy indices for the various SVM classifiers based on different kernel functions and parameters are illustrated in Fig. 8a. The alternative classifiers we examined again exhibited lower performance than SVM, which achieves a 91.67% accuracy, as it is shown in Fig. 8b. A further investigation of the above SVM classifiers' sensitivity and specificity indices is presented in Fig. 9.

4.5. *SVM-based diagnosis of aortic regurgitation vs. mitral stenosis*

Finally, an additional SVM classifier has been developed for the discrimination of aortic regurgitation vs. mitral stenosis for the cases diagnosed by the SVM classifier described above in Section 4.3 as having diastolic murmurs. The dataset used includes 38 aortic regurgitation cases and 38 mitral stenosis cases. In this case again Gaussian and exponential radial basis functions resulted in SVM classifiers with very good performance, while linear SVM classifiers and polynomial kernel functions resulted again in much lower performance. The highest results achieved with Gaussian functions are shown in Table 4 (aortic regurgitation murmurs are considered as positive, while mitral stenosis murmurs as negative data). Accuracy indices for the various SVM classifiers based on different kernel functions and parameters are shown in Fig. 10a. The performance of the alternative classifiers we examined in comparison to the proposed SVM-based ones is shown in Fig. 10b; again we remark that these alternative classifiers exhibited lower performance than SVM, which achieves a 93.42% accuracy. A further investigation of the above SVM

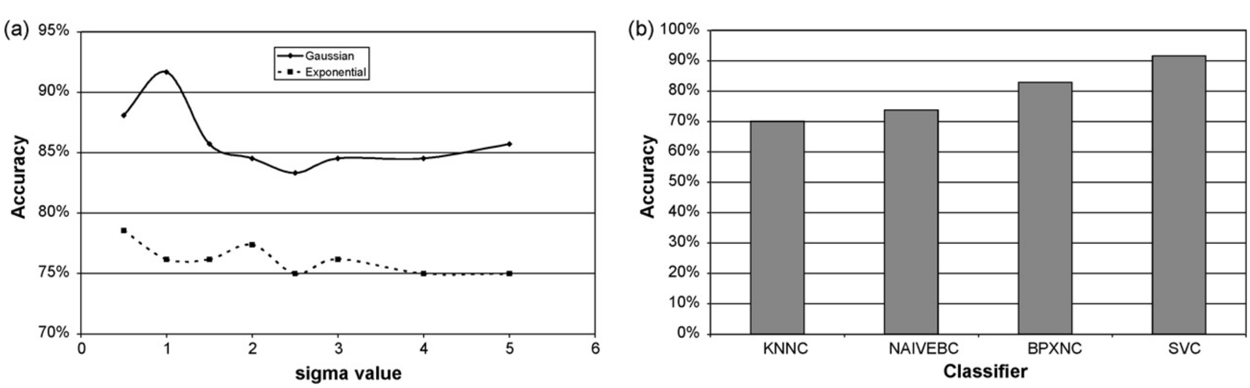

Fig. 8 – (a) Dependence of accuracy on the kernel functions used to develop the SVM classifier of aortic stenosis cases vs. mitral regurgitation cases and their parameters. (b) Comparison of alternative classification methods with the proposed SVM classifier. (KNNC stands for K nearest neighbour classifier, NAIVEBC stands for naïve bayes classifier, BPXNC stands for neural network classifier trained with back-propagation, SVC stands for Support Vector Machine classifier.)

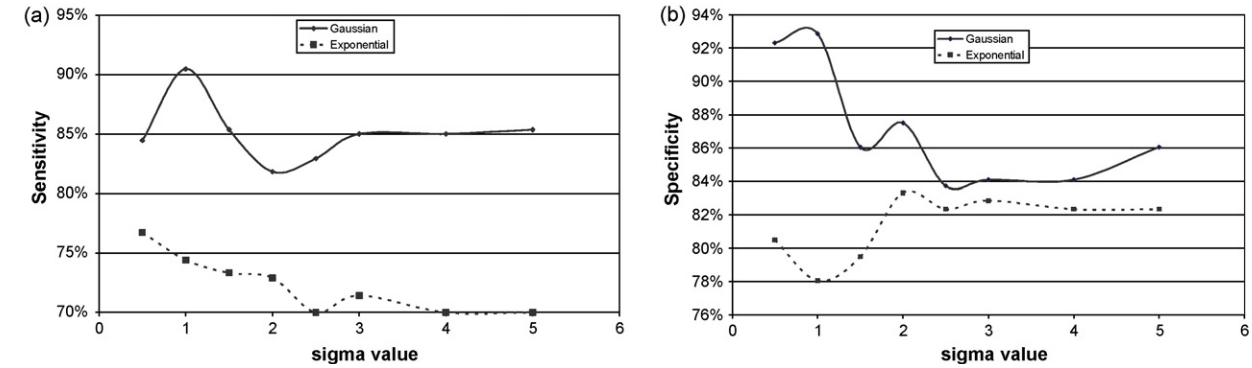

Fig. 9 – Dependence of sensitivity (a) and specificity (b) on the various kernel functions used to develop the SVM classifier of aortic stenosis cases vs. mitral regurgitation and their parameters.

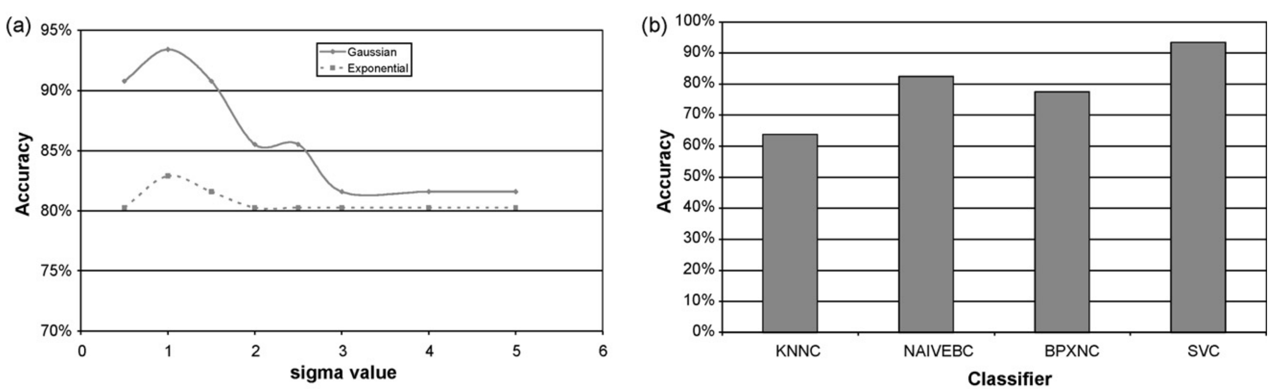

Fig. 10 – (a) Dependence of accuracy on the various kernel functions used to develop the SVM classifier of aortic regurgitation vs. mitral stenosis and their parameters. (b) Comparison of alternative classification methods with the SVM classifier. (KNNC stands for K nearest neighbour classifier, NAIVEBC stands for Naïve Bayes classifier, BPXNC stands for neural network classifier trained with back-propagation, SVC stands for Support Vector Machine classifier.)

Table 4 – Results of the SVM algorithm for the classification between aortic regurgitation (AR) and mitral stenosis (MS), where GRBF stands for Gaussian Radial Basis Function.

SVM kernel function	Errors	FN	FP	TP	TN	Accuracy	Sensitivity	Specificity
GRBF sigma = 1	5	2	3	36	35	93.42%	94.74%	92.11%
GRBF sigma = 0.5	7	3	4	35	34	90.79%	92.11%	89.47%
GRBF sigma = 1.5	7	3	4	35	34	90.79%	92.11%	89.47%
GRBF sigma = 2	11	6	5	32	33	85.53%	84.21%	86.84%

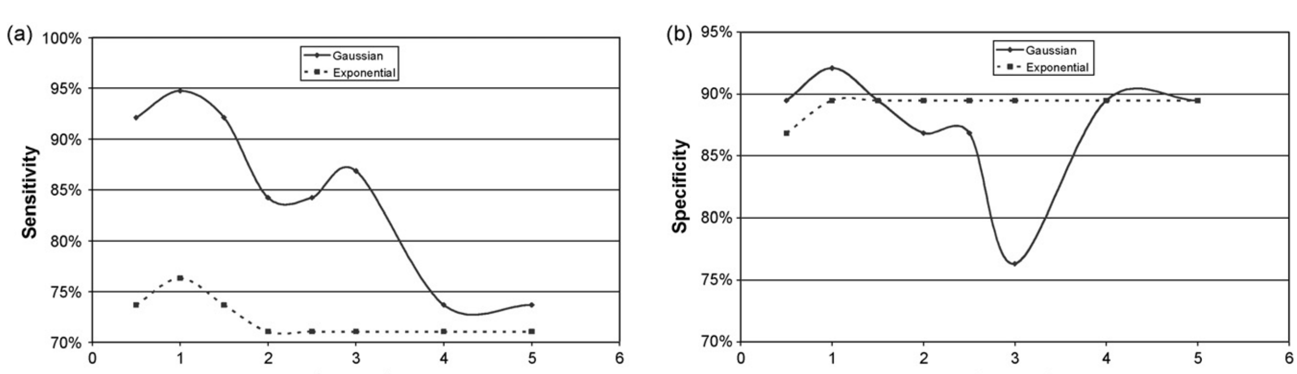

Fig. 11 – Dependence of sensitivity (a) and specificity (b) on the various kernel functions used to develop the SVM classifier of aortic regurgitation vs. mitral stenosis and their parameters.

classifiers' sensitivity and specificity indices is presented in Fig. 11.

5. Discussion and conclusions

In the previous sections a methodology for automated heart valve diseases identification using simple heart sounds, which is based on SVM classifiers has been presented. As concluded from the surveyed related work presented in Section 2, most of the previous research on the diagnostic classification of heart sound signals is based on neural networks, while the diagnostic potential of other types of classifiers in this domain has not been sufficiently explored yet. Taking into account this fact, the present paper contributes to bridging this gap.

The proposed methodology includes initially a pre-processing step of the heart sound signal, being followed by a three-step diagnosis phase based on SVM classifiers: in the first step the heart sound signal is classified as normal or pathological, in the second step the type of heart murmur (systolic or diastolic) is detected, while in the third step it is decided if the sound corresponds to an aortic or mitral disease. It should be emphasized that the proposed methodology offers significant advantages, since it uses lower cost and higher availability signals (i.e. heart sound signals, while most of the previous research is based on more costly signals, such as Doppler Heart Sounds). More specifically the required equipment consists of an electronic stethoscope (the one bought for the needs of this study was Master Elite type manufactured by Welch Allyn and costs 400$) and an ordinary personal computer with the appropriate software for sound collection, pre-processing and classification. Thus the total equipment cost for the proposed methodology is less than 1000$ (400$ if we consider that most health centers already have PCs), while the alternative solutions are much more expensive (more that 2000$ for Doppler Heart Sound, and much more for CTs and MRIs), without taking into account the processing units that need to be connected with the output of theses devices.

The presented methodology attempts to provide a highly detailed diagnosis, taking into account that it does not diagnose simply the existence or not of a heart valve disease, but it goes much further, and identifies the particular heart valve disease. In all the classification stages SVM classifiers with Gaussian and exponential radial basis functions had a quite satisfactory performance. In the first stage of categorization (normal vs. pathological) the accuracy was above 91%. In the second stage for the classification of heart signals as having systolic or diastolic murmur an equally high accuracy of 91.25% has been achieved. Finally in the third stage related to the more detailed classification as aortic stenosis or mitral regurgitation (in the case of having diagnosed a systolic murmur in the first stage) the accuracy achieved was 91.67%, while for the classification as aortic regurgitation or mitral stenosis (in the case of having diagnosed a diastolic murmur in the first stage) the accuracy achieved was 93.42%. Since the methodology involves three (3) independent steps the total accuracy of the overall heart valve disease identification system is the product of the above figures. Thus for the case of systolic diseases the total accuracy is $0.9143 \times 0.9125 \times 0.9167 = 0.7648$ or 76.48% and for the diastolic diseases the total accuracy is similarly $0.9143 \times 0.9125 \times 0.9342 = 0.7794$ or 77.94%. The reported accuracy however was characterized as satisfactory by the collaborating physicians, taking into account the highly global and heterogeneous dataset used (including heart sound signals acquired with various types of stethoscopes, sensors and filters, in various modes, subjects' positions and auscultation areas, from subjects of various ages, heart conditions and medical treatments); such a dataset enables a more realistic investigation of classifiers' construction and performance, but on the other hand it is more 'noisy' and therefore more 'difficult' for the classifiers, in comparison with the more 'homogeneous' ones used by most similar studies.

The alternative classifiers we examined for comparison purposes (back-propagation neural networks, k-nearest-neighbour and Naïve Bayes classifiers) exhibited much lower performance for the same diagnostic problems and using the same dataset than the proposed SVM-based classifiers. Also, it is worth mentioning that the performance of these SVM-based classifiers is higher in comparison with the corresponding performance of the decision trees-based classifiers, which have been investigated previously by the authors for the same diagnostic problems and using the same data [3,75]. We also compared the results of this study with the ones reported by other similar studies of the literature reviewed in Section 2 that use other different datasets of heart sounds. The study of Ahlstrom et al. [74] uses a combination of techniques (Shannon energy, wavelets, fractal dimensions, recurrence quantification analysis and finally Pudil's sequential floating forward selection) for extracting features and then neural networks for classifying systolic murmurs as physiological or pathological, achieving finally 86% correct classification of a homogeneous heart sounds dataset; this performance is lower than the 91.43% accuracy we have achieved in the classification of the heart sounds as normal or pathological, though our dataset is much more global and heterogeneous. On the contrary, the five studies of Turcoglu et al. [77–79], Uguz et al. [80] and Comak et al. [81], which are all based on a common homogeneous dataset of Doppler Heart Sounds (that require much more costly and operationally complex equipment), achieve 91–95% correct classification as 'normal' (healthy) or 'abnormal' using various classifiers, which is slightly higher than the corresponding accuracy achieved in the present study (91.43%). Similar conclusions are drawn from the comparison with the study of Chauhan et al. [76], which uses a probabilistic approach based on Mel-frequency cepstral coefficients and Hidden Markov Models, and achieves in a homogeneous heart sounds dataset the following classification accuracies: 95.7% for continuous murmurs, 96.25% for systolic murmurs and 90% for diastolic murmurs.

According to the literature [6–9], the primary health care physicians, who are usually young and inexperienced, have been reported to have poor heart auscultation skills. The pool of skilled for the specific task clinicians, who have been trained in the era before echocardiography, continues to age, and the skills for heart auscultation is in shortage and in danger to disappear. Thus, as indicated also by the performed survey, the development of automated characterization systems for heart sounds in clinical settings, aiming mostly at the diagnosis of heart valve diseases, preoccupies several R&D labs and medical teams. As clinical machine intelligence techniques mature, it seems they can offer increasingly exciting prospects for improving the effectiveness and efficiency of patient care and the development of more reliable Clinical Decision Support Systems (CDSS) in cardiology. According to a recent review [102] published studies of clinical machine intelligence systems are increasing rapidly, and their quality is improving. The field of automated characterization of heart related signals follows that rule. It seems that the introduction of such diagnostic tools may enhance preventive care in cardiology, facilitating the early diagnosis of heart diseases. Such tools are mostly intended for inexperienced medical personnel that could help them in the diagnosis of heart pathologies at early stages. In addition these decision support systems may be used for their training. When compared to medical experts in the field, even the systems with the best results, depict slightly lower performance in terms of accuracy and confidence in diagnosis. However it is admitted by the physicians that they are very useful in producing second opinions. In any case the presented system is not to be used for replacing the physicians, but only to serve as diagnostic adjunct.

The financial cost of the introduction of the presented simple CDSS for heart sound assessment is rather low; roughly estimated above less than 1.000 $. This system may be easily incorporated in routine clinical practice for heart related diseases diagnosis and prognosis. In order to convince physicians employing such tools more rigorous evaluation studies of CDSSs should be conducted including large numbers of participants and significant budgets. However the evaluation results presented in Section 4 are quite encouraging for the future. It is our belief that the methodology presented in this paper provides significant evidence to warrant trials with important clinical outcomes. The heterogeneity of the data used in this research causes several influences on the comparability of the data and limits the results of this study. Future research work should involve the collection of bigger datasets with heart sound samples under controlled conditions in order to enhance the calculation of the Support Vectors and the potential exploitation of additional features calculated using other extraction methods during the pre-processing phase. Also further research is required for the investigation of efficient feature selection tools and advanced classifiers based on fusion strategies and on the combination of several classifiers in order to improve the overall classification performance.

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