Psychiatria Danubina, 2021; Vol. 33, Suppl. 13, pp S236-246
Medicina Academica Mostariensia, 2021; Vol. 9, No. 2, pp 236-246 *Original paper*

FROM HEART MURMUR TO ECHOCARDIOGRAPHY – CONGENITAL HEART DEFECTS DIAGNOSTICS USING MACHINE-LEARNING ALGORITHMS

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received: 31.7.2021; revised: 13.12.2021; accepted: 20.12.2021

SUMMARY

The most common clinical sign in pediatric cardiology is heart murmur, which can often be uncharacteristic. The aim of this research was to present the results of development of a classifier based on machine learning algorithms whose purpose is to classify organic murmur that occur in congenital heart defect (CHD). The study is based on the data collected at Pediatric Clinic, Clinical Center University of Sarajevo during three-year period. Totally, 116 children aged from 1 to 15 years were enrolled in the study. Input parameters for classification are parameters obtained during basic physical examination and assessment of patient. First, analysis of relevance of the feature for classification was done using InfoGain, GainRatio, Relief and Correlation method. In the second step, classifiers based on Naive Bayes, Logistic Regression, Decision Tree, Random Forest and Support Vector Machine were developed and compared by performance. The results of this research suggest that high accuracy (>90%) classifier for detection of CHD based on 16 parameters can be developed. Such classifier with appropriate user interface would be valuable diagnostic aid to doctors and pediatricians at primary healthcare level for diagnostic of heart murmurs.

Key words: *congenital heart defect - heart murmur – pediatrics – screening - machine learning - classifier*

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INTRODUCTION

Statistics show that an estimated 15 million infants and children die or experience some kind of complications annually by treatable or preventable heart disease in low- and middle-income countries (Musa et al. 2017). The leading cause of death among those infants and children is congenital heart defect (CHD) (Oster et al. 2013). CHDs present defect in the structure of the heart or great vessels that are present at birth and characterized by organic heart murmur (Masic et al. 2018, Wren et al. 1999, Sun et al. 2015, Abqari et al. 2016, Blue et al. 2012, Begic & Begic 2017, Begic et al. 2016, Wang et al. 2019). Survival of patients suffering from CHD depends on the severity of the defect, but also on the timely diagnosis and treatment. Poor healthcare infrastructure, competing health priorities and shortage of clinical specialists, but also their varying ability to diagnose CHD are some of the reasons why this disease is causing such high mortality rates in low- and middle- income countries among infants and children.

Common clinical sign in pediatric cardiology (Masic et al. 2018, Wren et al. 1999) is heart murmur. In children and adolescents, in 50% of the cases, heart murmurs can be auscultated by a stethoscope at rest. Heart murmurs can be sign of CHDs, but in highest percentage they are harmless sounds made by the blood circulating normally through the heart's chambers and valves or blood vessels near the heart (Begic et al. 2016). However, this clinical sign, when detected by doctors at primary healthcare level or pediatricians is the reason why patients are sent for the further cardiological examination conducted by specialist at secondary or tertiary healthcare level (Masic et al. 2018, Sun et al. 2015, Abqari et al. 2016, Blue et al. 2012). This is because doctors at primary healthcare level or pediatricians cannot differentiate between these harmless or heart murmurs linked to CHDs, so every patient with heart murmur is subject to further analysis and tests.

Classical methods of pediatric cardiac diagnostics with a good knowledge of murmur characteristics are usually sufficient for the differentiation between organic and inorganic heart murmurs (Masic et al. 2018, Begic & Begic 2017). Several examination methods are used to collect the parameters needed for establishing diagnosis. In most cases, those are: (1) anamnesis, (2) clinical examination, (3) electrocardiogram (ECG), (4) laboratory diagnostics and possibly (5) X-ray (Masic et al. 2018, Begic et al. 2016). Clinical cardiac examination classically uses inspection, palpation, percussion, auscultation and measurement of arterial blood pressure (Masic et al. 2018, Begic et al. 2016). Also, usual method for diagnosis murmurs is echocardiography. However, it should not be a routine method for every murmur (Masic et al. 2018, Begic et al. 2016, Wang et al. 2019, Dolk et al. 2011) because although it is vastly available and provides unique, non-invasive information with minimal discomfort or risk it's indiscriminate use could lead to inappropriate further testing or interventions which lead to higher discomfort of patient, stress for the family and needless expenditure of healthcare system.

The incidence of CHD in different studies varies from about 4/1.000 to 50/1.000 live births (Jenkins et al. 2019, Hoffman et al. 2002), which further emphasizes the importance of adequate clinical examination, and the importance of examination on the primary level of health care. Classical approach puts the family of infant or child through unnecessary stress and secondly increases the burden to clinical specialists, as well as the healthcare costs at tertiary level. So, if the rate of accurately diagnosed heart murmurs by doctors and pediatricians at primary healthcare level increased that would significantly contribute to the improvement of care for patients on one side, but also would have positive effects for healthcare at secondary and tertiary level. It would cause decrease in costs and specialists and subspecialists of pediatric cardiology would have more time to address other more serious conditions.

Unrecognized or misinterpreted heart murmurs can have fatal outcome to the patient that is why there is a strong need for systems that would enable classification and recognition of heart murmurs linked to CHDs. Over the years, the application of technological solutions for enhancing diagnosis have been investigated (Seckanovic et al. 2020, Divovic-Mustafic et al. 2019, Alic et al. 2018). Nowadays, different tools based on artificial intelligence (AI) are available in healthcare (Sharif et al. 2000, Randhawa & Singh 2015, Dominguez-Morales et al. 2018, Hadi et al. 2008). Application of intelligent classifiers for prediction of disease or diagnosis are not uncommon (Mandal et al. 2010, Yadav et al. 2020, Azmy 2015, Kumar et al. 2010, Olmez & Dokur 2003, Xu & Goodacre 2018, Jiang et al. 2007, De Mello & Ponti 2018). Researchers have investigated different methods for heart murmur classification which included heart murmur sound signal analysis, neural networks or machine learning algorithms (Tougui et al. 2020, Chorba et al. 2021, Lv et al. 2021, Soto-Murillo et al. 2021).

The aim of this research is to investigate which parameters, that can be obtained by basic physical examination of the patient at primary healthcare level, have higher impact for CHDs linked heart murmur classification – organic heart murmurs. In this paper we present the results of development of a classifier based on five machine learning algorithms whose purpose is to classify organic murmur that occur in congenital heart defect.

SUBJECTS AND METHODS

Dataset

Patient population

The study is based on the data collected at Pediatric Clinic, Clinical Center University of Sarajevo during three-year period. Totally, 116 children aged from 1 to 15 years were enrolled in the study (Table 1). Upon ethical approval of the study, the information about the patients was extracted from their medical records. As it can be seen from Table 1, the database consists of 56.9% of male subjects and 43.1% female subjects whose average age is in average 7 years. The database doesn't include patients with acquired heart disease, arrhythmias, and previously diagnosed heart abnormallities, as well as genetic syndromes.

Table 1. Patient related information (116 patients)

Gender	Male	Female
	66 (56.9%)	50 (43.1%)
Age (average)	7 years	7 years
Minimum	1 year	1 year
Maximum	15 years	14 years
Average age of patient parents	Father 29	Mother 25

All information included in the study are results of previous examinations performed by experienced specialist or subspecialist in pediatric cardiology. These examinations were performed on the basis of a protocol for diagnosis of the heart murmur used at the Pediatric Clinic, Clinical Center University of Sarajevo. Following the protocol, during patient examination following steps were conducted:

- Obtaining general information about patient,
- Obtaining anamnestic data about patient,
- Obtaining information from mother about habits during pregnancy.
- Performing patient assessment using standard clinical methods: (1) physical examination, (2) auscultation, (3) phonocardiography, (4) laboratory diagnostics, (5) X-ray and (6) electrocardiography (ECG).

During collection of the data, special attention was paid to the possible existence of possible risk factors in pregnancy.

Dataset parameters

Parameters obtained during the examination of the patient following protocol for diagnosis of CHDs are shown in Table 2. Total of 68 parameters is grouped into 9 classes, where each class represents one method for data collection. Some of the parameters recorded are simply in terms of yes/no information, while others represent measurements of physiological parameters such as ECG, blood count, oxygen saturation and others.

Table 2. Input related information

Source of information	Parameter
Information about parents	Sex: male or female Age Father age Mother age Parents education Location: canton in Federation BH
Anamnestic data	Association with other diseases: yes/no Precordial pain: yes/no Positive history: yes/no Susceptibility to respiratory infections: yes/no Poor tolerance to effort: yes/no Subjective sense of general condition: good/poor
Habits of mother during pregnancy	Chronic diseases: yes/no Infections: yes/no Habits (risk for fetus)
Phonocardiography	First tone: changed/unchanged Second tone: yes/no Amplitude Duration Frequency: low, medium, high Shape: 1-diamond 2-spindle 3-rhombus 4-regular
Physical examination	Habitus: good/poor Body weight Body height Psychomotor development: good/poor Signs of heart disease: yes/no Cyanosis: yes/no Dyspnea: yes/no Oedema: yes/no Secondary effects of hypoxia: yes/no Appearance of precordia: physiological/pathological Pulsations: yes/no Thrill: yes/no Heart apex: regular/deviated Blood pressure Habitus: good/poor

Dataset Division

Every patient that was examined by experienced clinical specialist or sub-specialist of pediatric cardiology was diagnosis either for having innocent heart murmurs or as a patient with organic heart murmurs which are linked to CHDs, Table 3.

Out of 116 patients, 67.2% (n=78) were patients with innocent heart murmurs, while 32.8% (n=38), were patients with organic heart murmurs suggesting CHDs and in need for further therapy.

Table 2. Continues

Source of information	Parameter
Electrocardiogram	Rhythm: sinus/nodal Frequency Baseline: 1-normal axis 2-right axis 3-left axis P-wave PR-interval QRS complex QTC interval RS-ratio T-wave: lead II or V5 Right atrial hypertrophy: yes/no Left atrial hypertrophy: yes/no Right ventricular hypertrophy: yes/no Left ventricular hypertrophy: yes/no Biventricular hypertrophy: yes/no
Auscultation	Murmur: yes/no Rhythm: regular/irregular Tones: good/pathological Extratones: yes/no Duration: systolic, diastolic, systolic-dyastolic Location: pulmonal area, aortic area, Erb, apex Point of maximal intensity: at the origin, out of origin Quality: 1-vibrate 2-blowing 3-humming 4-turbulent Intensity Radiation: yes/no Position dependence: yes/no
Chest X-ray	Situs Index Cavity Blood vessels: 1-normal 2-convex 3-concave Drawing: normal, emphasized, lowered
Laboratory diagnostics	Complete blood count Oxygen saturation

Table 3. Output parameter information

Murmur	Number of samples
Innocent	78 (67.2%)
Organic	38 (32.8%)
Total	116

Dataset presented in Tables 2 and 3 was used as a basis for development of machine learning based classifiers for classification of heart murmurs.

Development of machine learning classifiers

A block diagram of the heart murmur classifier is presented in Figure 1. It initially consists of 68 inputs and 1 output parameter. System inputs are parameters presented in Table 2. System output can have one of two possible values: innocent or organic heart murmur (Table 3)

The development of the classifier was done in two phases. First, methods for feature extraction were applied and then five different machine learning algorithms were used for development of classifier that is able to differentiate between organic and innocent heart murmur, Figure 2.

In the first step, for the feature selection, following machine learning algorithms were used: Weight by InfoGain (Tougui et al. 2020), Weight by GainRatio (Tougui et al. 2020), Weight by Reliefe (Tougui et al. 2020) and Weight by Correlation (Tougui et al. 2020).

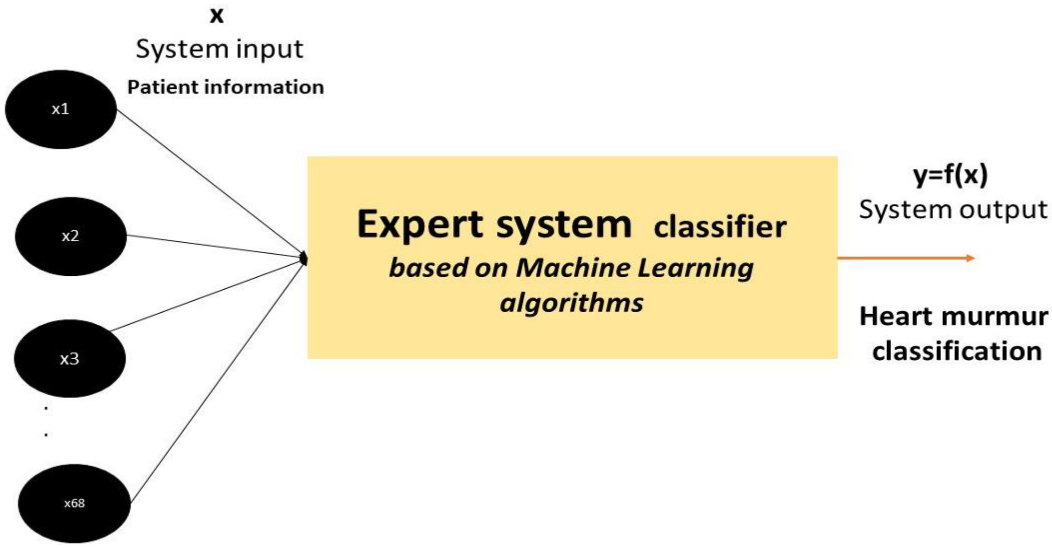

Figure 1. Block diagram of the expert system – classifier for classification of heart murmurs

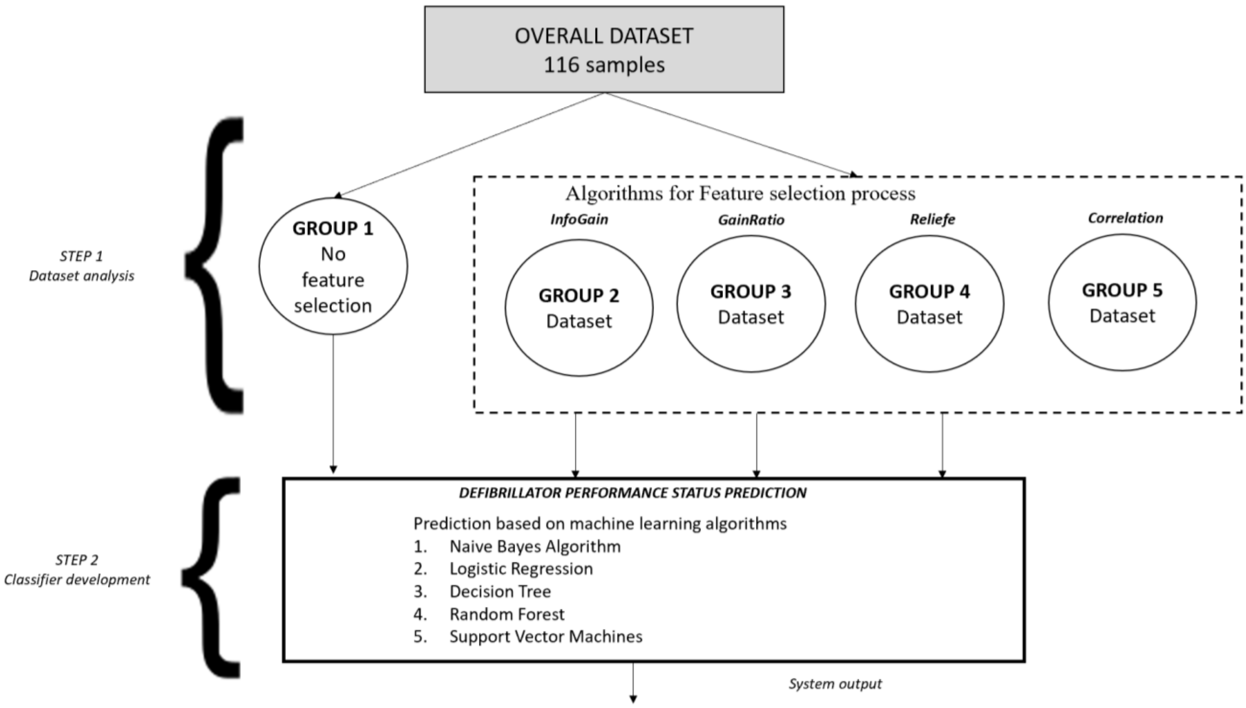

Figure 2. Steps for development of the classifier

In the second step, following the practice of usage variety of machine learning techniques, for the development of predictive models in biomedicine (Vepa et al. 2009) investigation of application of different machine learning algorithms for classification of heart murmurs based on optimized number of parameters that can be obtained by basic, low-cost clinical methods was conducted.

Feature selection

Weight by InfoGain calculates the relevance of the attributes based on information gain and assigns weights to them accordingly. Weight by Information Gain Ratio operator calculates the weight of attributes with respect to the label attribute by using the information gain ratio. Information gain ratio is used because it solves the drawback of information gain. Weight by Correlation operator calculates the weight of attributes with respect to the label attribute by using correlation. Weight by Relief is considered one of the most successful algorithms for assessing the quality of features due toits simplicity and effectiveness. The key idea of Relief is to estimate the quality of features according to how well their values distinguish between the instances of the same and different classes that are near each other. Relief measures the relevance of features by sampling examples and comparing the value of the current feature for the nearest example of the same and of a different class. In all mentioned algorithms, the higher the weight of an attribute, the more relevant it is considered. The attributes with higher weight are considered more relevant.

Following the methodology presented in Figure 2, five groups of data were made for the purpose of development of the classifier. The first subset was original dataset containing all features, and four more as a result of application of feature selection algorithms. All groups of data were then divided into training and testing subset. Splitting ratio which was used is 70-30 (%) which is common for application of machine learning algorithms on smaller datasets (Seckanovic et al. 2020, Tougui et al. 2020, Chorba et al. 2021, Lv et al. 2021). Training subset consisted of 81 samples, and testing subset consisted of 35 samples.

Heart murmur classification

Artificial intelligence is revolutionizing the way healthcare is provided to patients. Nowadays, number of AI based solutions can be found in the filed of classification of heart murmurs as well. Researchers are developing expert systems based on different AI methods, including artificial neural networks, machine learning and deep learning.

Current available research shows that expert systems for classification of heart murmurs are being developed based on data acquired using digital stethoscope (Lv et al. 2021, Soto-Murillo et al. 2021, Chen et al. 2021, Takahashi et al. 2021, Wang et al. 2020, Oliveira et al. 2021) or based on only one clinical examination method (Chowdhury et al. 2019, Andrès et al. 2012). Such systems have the power to make a huge difference in the way patient care is provided, but there are several challenges. Some of these systems require data acquired with expensive medical devices, that are not accessible to everyone. Also, some developed system again require expert knowledge of experienced clinician to interpret the data.

The study presented investigates how parameters of patient assessment which can be obtained by simple, low-cost, accessible-everywhere clinical methods impact the accuracy of AI based heart murmur classifier.

For the purpose of heart murmur classification (Step 2) the following machine learning algorithms were used: (1) Naïve Bayes algorithm (NB), (2) Logistic Regression (LR), (3) Decision Tree (DT), (4) Random Forest (RF), (3) and (5) Support Vector Machine (SVM).

Classifier performance assessment

System performance was evaluated by the means of accuracy calculated as:

$$Accuracy = (TP+TN)/(TP+FP+TN+FN) \quad (1)$$

Where: TN (true negative), TP (true positive), FN (false negative), FP (false positive) - representing the number of correctly/incorrectly classified instances belonging to output negative/positive group of instances.

Accuracy is defined as the number of correctly classified results compared to the 'true' value. True positive (TP) is the proportion of actual positives that are correctly identified as such. True negative (TN) is the proportion of actual negatives correctly identified as such. False positive (FP) is a negative value identified as a positive value, and false negative (FN) is a positive value identified as a negative value.

RESULTS

Feature selection – diagnosis parameters

This section presents the results of feature extraction for heart murmur diagnosis based on machine learning algorithms. The results of application of feature selection machine learning algorithms to the dataset (Tables 2-3) are presented in Table 4.

As it can be seen from the table, the lowest number of dominant features is 4 which presents around 6% of the data collected from the patient. The highest number of extracted features by this process is 16, which on the other hand represents around 24% of the data collected from the patient. Extracted features are classified into three categories based on their impact to overall heart murmur classification, as follows: high, medium and low impact.

Table 4. Results of feature selection based on machine learning algorithms

Feature importance classification	Weight by InfoGain *GROUP 2 Dataset*	Weight by GainRatio *GROUP 3 Dataset*	Weight by Relief *GROUP 4 Dataset*	Weight by Correlation *GROUP 5 Dataset*
High	10 Position dependence • Drawing • Duration • Frequency • Radiation Second tone • Signs of heart disease • Blood pressure • Body weight • T-wave (lead II or V5)	9 Position dependence • Cavity • Drawing • Duration • Frequency • Point of maximal intensity • Radiation Second tone • Signs of heart disease	4 Position dependence • Point of maximal intensity • Radiation Second tone	16 • Amplitude • Appearance of precordia • Cavity • Drawing • Duration • Frequency • Index Position dependence • Point of maximal intensity • Radiation Second tone • Shape • Signs of heart disease • Susceptibility to respiratory infections • Heart tones • Body weight
Medium	15 • Amplitude • Appearance of precordia • Cavity • Frequency • Index • Intensity • Pulse • Pulsations • P-wave • Quality • RS-ratio • Shape • Susceptibility to respiratory infections • Tones - Auscultation • Body height	12 • Amplitude • Appearance of precordia • Cyanosis • First tone • Index • Intensity • Pulsations • Quality • Shape • Susceptibility to respiratory infections • Thrill • Tones	7 • Appearance of precordia • Cavity • Frequency • Intensity • Pulsations • Signs of heart disease • Susceptibility to respiratory infections • Tones	23 • Age • Association with other diseases • Baseline • Blood vessels • Cyanosis • Dyspnea • Extra tones • First tone • Frequency • Apex • Intensity • Location • Poor tolerance to effort • Pulse • Pulsations • Quality • RS-ratio • RVH • Rhythm • Blood pressure • Thrill • Body height • T-wave
Low	43	47	57	29

Table 4. presents the list of extracted features by a certain feature selection algorithm that was applied. However, to put this information into clinical perspective, it is important to see how these features are distributed to clinical assessment methods used for collecting the data from the patient. When taking into account all parameters marked with high and medium impact from all feature selection algorithms it can be seen that 35 parameters are selected, Table 5. These 35 variables are significant decrease from initial 68 parameters collected during patient assessment.

Table 5. Features extracted vs. clinical assessment method

Source of information	Parameter
Information about parents	Sex: male or female
	Age #
	Father age
	Mother age
	Parents education
	Location: canton in Federation BH
Anamnestic data	Association with other diseases: yes/no #
	Precordial pain: yes/no
	Positive history: yes/no
	Susceptibility to respiratory infections: yes/no *
	Poor tolerance to effort: yes/no #
	Subjective sense of general condition: good/poor
Habits of mother during pregnancy	Chronic diseases: yes/no
	Infections: yes/no
	Habits (risk for fetus)
Phonocardiography	First tone: changed/unchanged #
	Second tone: yes/no *
	Amplitude *
	Duration *
	Frequency: low, medium, high
	Shape: 1-diamond 2-spindle 3-rhombus 4-regular *
Physical examination	Habitus: good/poor
	Body weight *
	Body height
	Psychomotor development: good/poor
	Signs of heart disease: yes/no *
	Cyanosis: yes/no #
	Dyspnea: yes/no #
	Oedema: yes/no
	Secondary effects of hypoxia: yes/no
	Appearance of precordia: physiological/pathological *
	Pulsations: yes/no #
	Thrill: yes/no #
	Heart apex: regular/deviated #
	Blood pressure *
	Habitus: good/poor
Electrocardiogram	Rhythm: sinus/nodal
	Frequency *
	Baseline: 1-normal axis 2-right axis 3-left axis #
	P-wave #
	PR-interval
	QRS complex
	QTC interval
	RS-ratio #
	T-wave: lead II or V5 *
	Right atrial hypertrophy: yes/no
	Left atrial hypertrophy: yes/no
	Right ventricular hypertrophy: yes/no
	Left ventricular hypertrophy: yes/no
	Biventricular hypertrophy: yes/no
Auscultation	Murmur: yes/no
	Rhythm: regular/irregular
	Tones: good/pathological *
	Extratones: yes/no #
	Duration: systolic, diastolic, systolic-dyastolic
	Location: pulmonal area, aortic area, Erb, apex #
	Point of maximal intensity: at the origin, out of origin *
	Quality: 1-vibrate 2-blowing 3-humming 4-turbulent #
	Intensity #
	Radiation: yes/no *
	Position dependence: yes/no *
Chest X-ray	Situs
	Indeks *
	Cavity *
	Blood vessels: 1-normal 2-convex 3-concave #
	Drawing: normal, emphasized, lowered *
Laboratory diagnostics	Complete blood count
	Oxygen saturation

Legend: * *high impact to overall classification;*
 # medium impact to overall classification

As it can be seen from Table 5. all four algorithms detected that patient physical examination, anamnestic data, phonocardiography, auscultation, electrocardiogram and chest x-ray are important for classifying hear murmurs. This conclusion is irrelevant since it is already known from clinical practice. It is more interesting to see that data from laboratory examination is not found to have any impact in classifying heart murmurs. This information is beneficial since if these examinations are to be cut from regular protocol, cost-savings can be made, while not impacting the quality of patient care. Our results show that only 19 parameters (identified across different algorithms) have high impact to heart murmur classification. These parameters can be obtained by low cost, available anywhere clinical examinations.

Results show that two features obtained by auscultation are very important for the classification of organic heart murmur. Those features are: (1) position dependence of murmur and (2) second tone feature. Intensity of heart murmur as a parameter was detected by all four algorithms to have medium importance for classification (Table 5).

Machine learning based classifier for heart murmurs

During this study, multiple different classifiers were developed following the methodology presented in Figure 2. The results of validation of the developed classifier based on different datasets and different machine learning algorithms is given in Table 6.

As it can be seen from the Table 7, performance of classifier based on Naïve Bayes algorithm was low for all five datasets tested, while the best performing algorithm was Support Vector Machine.

As it can be seen from Table 6, validation showed that classifier based on 16 features and Support Vector Machine algorithm achieved accuracy of 97.14%, but also it showed that it had better ability in recognizing innocent heart murmurs than organic ones. This is due to the restrictions recognized in this study, and that is mainly the size of the database. Finally, an optimized expert system based on data obtained by physical examination, auscultation, anamnestic data, electrocardiogram and chest x-ray has been developed. The developed expert system had 17 inputs taken from previously mentioned clinical examinations. The structure of the system is presented in Figure 3.

The validation performance of developed classifier is presented in Table 8. System validation performance is aligned with previously obtained results in this study. It is shown that such system can be beneficial aid for primary practitioners and pediatricians when deciding on further steps in diagnosis of patients with more certainty provided by such expert system.

Table 6. Validation performance result of classifiers

Classifier / Accuracy	Naive Bayes	Logistic Regression	Decision Tree	Random Forest	Support Vector Machine
All features *Group 1 Dataset*	31.8%	89.1%	47.2%	90.2%	89.4%
Weight by InfoGain *Group 2 Dataset*	35.1%	50.9%	96.1%	96.1%	96.1%
Weight by GainRatio *Group 3 Dataset*	39.1%	64.8%	28.1%	96.1%	96.1%
Weight by Relief *Group 4 Dataset*	40.1%	64.8%	6.1%	96.1%	97.0%
Weight by Correlation *Group 5 Dataset*	29.8%	51.1%	90.6%	97.1%	97.1%

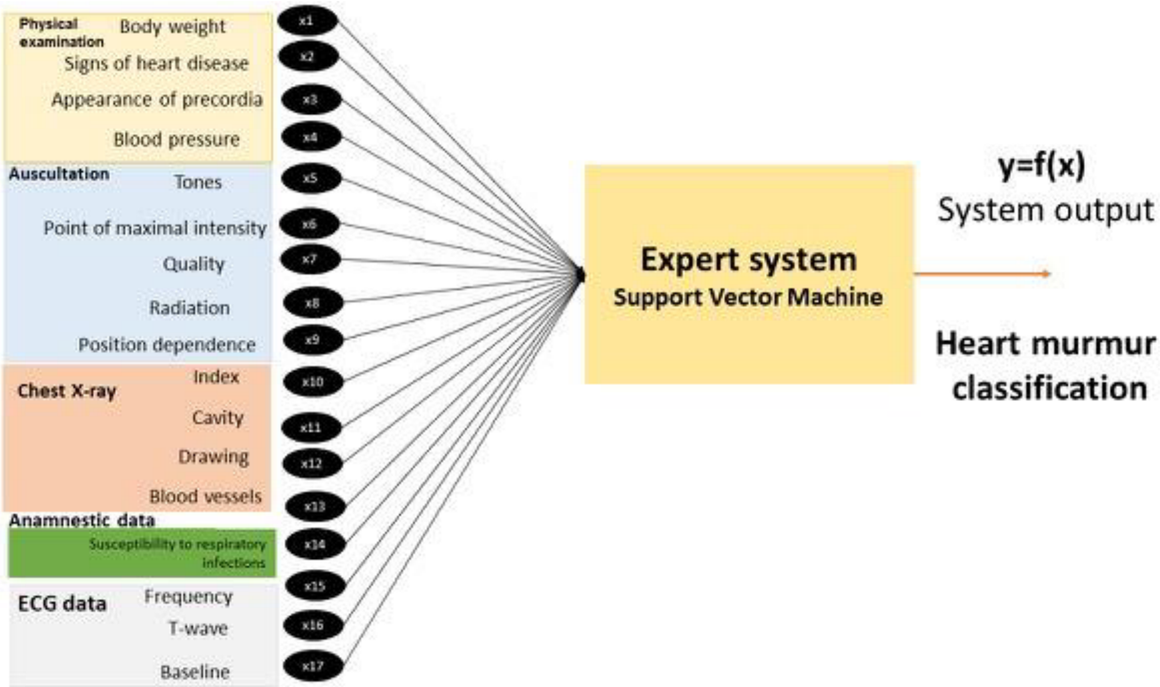

Figure 3. Developed classifier for heart murmurs based on 5 clinical assessment methods

Table 7. System validation performance

Support Vector Machine	Classification	
GROUP 5 Dataset 35 samples	Innocent	Organic
Innocent 23 samples	23	0
Organic 12 samples	1	11
Accuracy	97.14%	

Table 8. Classifier validation performance

Support Vector Machine	Classification	
GROUP 5 Dataset 35 samples	Innocent	Organic
Innocent 23 samples	22	1
Organic 12 samples	1	11
Accuracy	94.28%	

DISCUSSION

The performance of this algorithm for the purpose of heart murmur classification has been confirmed in other studies as well. Vepa et al. obtained an accuracy of 95% for murmur classification based on cepstral features (Vepa 2009). Also, Jiang et al. used this algorithm to identify heart murmurs from heart sound signals and obtained an accuracy of 86.88% for atrial fibrillation sounds, 89.98% for aortic valvular disorders, and 90% for mitral valvular disorder (Jiang et al. 2007). Also, Chorba et al. investigated method for heart disease diagnosis utilizing optimization algorithm in feature selection, but used dataset of grown-up patients, and concluded that auscultation and ECG analysis are important in diagnosis of heart murmurs (Chorba et al. 2021).

Data processing has proven that auscultation is the most important segment of physical examination. This has been detected by research of Andres et al (Andrès et al. 2012). A physical examination should first determine if the child is ill or not, and if so, whether he or she has heart failure or not. The order of individual tests in the classical approach is inspection, palpation, auscultation, percussion and measurement of arterial blood pressure. Heart auscultation also includes careful auscultation of the lungs to the possible occurrence of crepitations as the first signs heart failure. A good knowledge of auscultation certainly gives us easier access to other diagnostic methods. Heart auscultation requires a lot of experience, practice and self-criticism. It aims to assess the frequency and rhythm of heartbeat, assess the quality of tones and the presence of additional heart tones, and detect heart murmurs. Auscultatory findings must be accurately described from examination to examination because they change depending on the evolution of findings. Auscultation of heart murmurs is of great importance, as it is very important to etiologically determine what type of murmur it is, to differentiate them based on the cardiac cycle, or their duration, stage of occurrence, with the specific characteristics. Until digital or intelligent stethoscopes are part of daily usage, systems as this one proposed in this paper are of outmost importance while performing diagnosis at primary healthcare level (Jiang et al. 2007).

In addition to the findings obtained by auscultation, the focus should include anamnestic data related to the signs of heart disease, as well as susceptibility to respiratory infections, which are characteristic of CHD, as well as non-progression in body weight, and pathological findings on chest X-ray.

There is a lot of challenges in diagnostic modality of diseases and conditions, from the simplest ones to the more complex ones in daily clinical practice. Digital technology is making an impact on the way care is provided to patients for decades now. Industry 4.0 is now introducing tools based on artificial intelligence in healthcare and it is making a huge impact on the way patients are diagnosed. Already medical devices with built in artificial intelligence tools are available on the market and used in the healthcare institutions. Such devices enable automatic diagnosis ranging from simple electrocardiography to more complex computed tomography scans. Tools based on artificial intelligence that enable classification of condition or diagnoses of disease are very useful in situations when medical specialist is not available. The application of such system is particularly important at primary healthcare level. Such system is proposed in this paper. Machine learning algorithms have been used to develop classifier that can aid doctors and pediatricians at primary healthcare level to classify between organic and inorganic heart murmurs. The benefit of this system is that it takes as inputs parameters that can be obtained by basic, low-cost clinical screening methods that are available at primary healthcare level. In this way, doctors and pediatricians at primary healthcare level have more confidence when establishing diagnosis, and number of unnecessary procedures for patients is lowered.

CONCLUSION

Proposed classifier, when accompanied with appropriate user interface and training would be beneficial diagnostic tool at primary healthcare level or remote, rural settings when medical specialists are not always available. Heart auscultation as the most important method of clinical examination is increasingly neglected at the expense of modern methods and devices. Auscultation proved to be the most important method of clinical diagnosis in order to differentiate murmur. One of the tasks of pediatricians, and especially pediatric cardiologists, would be perfect auscultation, as a sovereign method of assessing heart murmurs.

Acknowledgements: None.

Institutional Review Board Statement:

The study was conducted according to the guidelines of the Declaration of Helsinki, and approved by the Institutional Ethics Committee.

Informed Consent Statement:

Written informed consent has been obtained from the patient(s) to publish this paper.

Conflict of interest: None to declare.

Contribution of individual authors:

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Visualization, Edin Begic, Lejla Gurbeta Pokvic, Zijo Begic & Almir Badnjevic;

Supervision, Zijo Begic;

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All authors have read and agreed to the published version of the manuscript.

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