A Random Forest-based Approach for Automated Heart Diagnosis from Cardiac Tomography Data

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Summary
Myocardial perfusion imaging or scanning (MPI or MPS) system is a technology used for nuclear medicine to demonstrate heart muscle function. A computerized diagnosis of myocardial perfusion from cardiac single photon emission computed tomography (SPECT) images is a very important diagnostic tool for cardiologists. Machine learning methods are effective tools for analyzing pathological cases in many applications of medical images. Even though there are several methods of machine learning that can be used for myocardial perfusion diagnosis, selecting a suitable diagnosis method remains a major concern. In this paper, we propose to use a random forest (RF) for analyzing the heart abnormalities from the SPECT images. The RF classifier is proposed in this paper because of its ability against over-fitting and under-fitting problems. The approach is evaluated on a SPECT Heart dataset, consisting of 267 instances. This dataset was divided into 50% instances for training and 50% instances for testing. The RF classifier is also trained on the dataset using 10-fold cross-validation method and tested on the whole dataset. The experiment shows the ability the proposed RF classifier to classify the instances of patients in the testing dataset into normal and abnormal categories better than the other machine learning classifiers in the state-of-the arts.

Keywords:
Myocardial perfusion imaging, SPECT tomography images, Random forest algorithm, 10-fold cross-validation technique, machine learning methods.

1. Introduction

There are many problems in medical domain that need accurate techniques to make a categorical decision. Therefore, it is very necessary to improve diagnostic process and treatment. Medical domain is one of the leading and sensitive areas in life. It is related to the health and life of humans and how to deal with emergency situations. Indeed, there are lots of procedures that are taken and must be accurate. Hence, medical decision making plays an important role in which the outcome can be critical for the patients. Noteworthy, the medical domain grew dramatically over the last decades [1]. The quantitative revolution of medical knowledge is more difficult to be maintained by the physicians. Different diseases, symptoms, treatment and diagnosis process are factors that impact in medical domain. Physicians need to accommodate huge and growing information in order to be available in a timely.

Heart disease is one of the important causes of mortality in the world [2]. It causes disorder in heart's task which distributes blood to all parts of the body. There are different types of heart disease such as: Coronary heart disease, Cardiomyopathy, Cardiovascular disease and Ischemic heart disease. The diagnosis of these diseases includes multiple procedures in different levels using necessary tools [3]. In the meanwhile, the generated information is analysed to a better interpret. So, the early diagnosis of heart disease plays a crucial role in the efficiency of a patient's treatment. This leads to the need of making accurate decisions in appropriate time [4].

Machine learning and soft computing methods have been used in medical field for performing different tasks [5, 6]. There are multiple diagnostic levels to detect these diseases through signs and symptoms. Also, analysing medical data efficiently by the clinicians has become difficult due to the large amount of data for each patient. In this regard, machine learning techniques play a crucial role in medical diagnosis in order to improve medical data classifications and obtain good results [7]. These techniques have an ability to discover the relationships and provide objective interpretation upon available data in order to increase predictive accuracy [8]. So, this work focuses on diagnosing heart disease, particularly single photon emission computed tomography (SPECT) heart data, using effective machine learning methods [9]. It provides a competitive classifier that meant to achieve advanced performance level comparable with cardiologists.

In medical domain, diagnosis plays an important role for medical decision making, in which the outcome can be critical for the patients. It is very necessary that diagnosis must be accurate and less errors [10]. This relies on efficiency of physicians and accuracy of diagnostic procedures. From this point of view, the medical decision

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support system provides a diagnostic tool used for different diseases in order to:

1- Assist cardiologists to detect different heart diseases via providing a powerful tool that can interpret these images correctly.

2- Reduce risks coming from misdiagnosis.

3- Save time and effort which will affect the diagnosis process.

Nuclear medicine is a branch of medicine that focuses on the diagnosis or treatment of different diseases using radioactive substances [11]. It is considered as a fusion of different disciplines such as physics, chemistry, engineering, and medicine. These disciplines in nuclear medicine provide a rich domain to support diagnosis process in terms of discovering new medical techniques, especially in imaging [12]. In this regard, nuclear medicine includes several techniques that are used for diagnostic procedures which assist in testing functions of the human body as a series of physiologic processes, not as static structures. Therefore, nuclear medicine imaging is different, compared with traditional imaging (e.g. CT or MRI) in terms of its scanning the organ or tissue (e.g. heart scan, bone scan, etc.) while conventional imaging works on a particular section of the body. So, the main idea behind this concept is a radioactive tracer that is taken either intravenously or orally. Then, external detectors (gamma cameras) are used to acquire multiple nuclear images where they trace gamma rays that are emitted due to radioactive substance within the body.

Single-photon emission computed tomography (SPECT) is one of nuclear medicine imaging techniques [12]. It is a three-dimensional tomographic technique that is based on obtaining a series of two-dimensional images from multiple angles by using a gamma camera. These projections are processed via applying a tomographic reconstruction algorithm in order to gain a 3-D data set. Typically, SPECT technique can be used in different applications to provide 3-D information that assist in the diagnosis. Myocardial perfusion imaging is an application of SPECT imaging that is related to functional cardiac imaging [13]. It considers a diagnostic method used for the diagnosis of heart disease [14]. The principle is based on performing two studies by injecting the patient with radioactive tracer (e.g. Thallium 201) and acquiring two sets of 3-D images. The first set is called stress study (stress image) which is collected after 10-15 minutes from injection during maximal stress. And the second set is called rest study (rest image) which is collected after 2-5 hours from injection. These images represent left ventricle (LV) muscle perfusion which they refer to the distribution of the tracer within the myocardium. They are presented in form of three sets of 2-D images which contain a series of intensity slices (short, vertical and horizontal axis). After that, cardiologists use visualization methods to interpret the cardiac SPECT images. They compare stress and rest studies in order to find defects in the LV perfusion. Whenever all parts of the image are clear and bright, this means that the perfusion of myocardium is well. Otherwise, when part of the image is not visible the perfusion is suspected [15].

Therefore, the need to automate heart disease diagnosis process from SPECT heart images using machine learning techniques is very important. Figure 1 shows the discipline of machine learning for heart disease diagnosis.

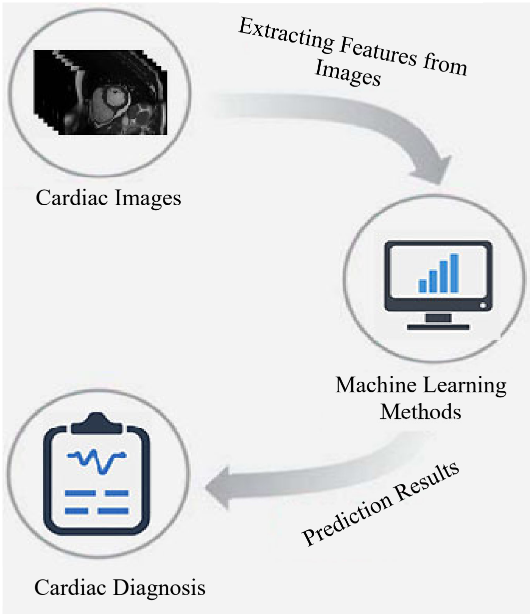

Fig. 1: Machine learning-based heart disease diagnosis discipline.

Even though there are several methods and approaches have been proposed for classifying heart disease data, they are still facing some limitations due to local minima and over-fitting problems, as well as it has many parameters which need to be optimized [16].

In this paper, an effective automated diagnosis model of heart functions from cardiac tomography data using random forest (RF) method will be introduced. The model is able to learn the features extracted from SPECT heart images and reduce the under-fitting and over-fitting problems.

This paper is organized as follows: a literature review on computational models and methods for heart functions diagnosis and abnormality detection will be given and reported in Section 2. The proposed approach for diagnosing SPECT heart data using the proposed solution is introduced and explained in Section 3. Section 4 explains the experiments and discussion including the results and comparisons. In Section 5, the conclusion and future work is summarized and presented.

2. Literature Review

Recently, the computing revolution trends to combine different areas. It helps in discovering new technologies and methodologies that support each area. Combination between computer science and medical domain is an important hybridization that draws the attention of researchers [17-19]. Most researchers agree with the importance of learning in order to make computers more intelligent. Therefore, machine learning is the most popular branch of computer science that can achieve this main goal, in which it needs a deep discovery.

"Today machine learning provides several indispensable tools for intelligent data analysis" [20]. This point of view believes that machine learning is the most important support to discover data in several domains. In fact, it plays a crucial role in medical domain in order to improve medical data classification and obtain good results. Achieving these goals provides a practical way to assist physicians in their diagnostic process. Indeed, machine learning contains various techniques that differ in their mechanisms. Categorization, optimization and prediction such as k-means clustering, genetic algorithms and artificial neural networks respectively, are considered as popular categories of machine learning. Using these techniques is able to achieve a highly degree of accuracy in making a decision during the diagnosis process. Also, help in saving time which is considered the critical factor in medical domain. On another hand, some requirements are important for machine learning systems used in medical diagnosis such as accuracy, understandability of knowledge and handling missing- noisy data [20].

K. Polat, R. Sekerci, and S. Gunes [21] proposed a new classifier combines between Artificial Immune Recognition System (AIRS) classifier and Independent Component Analysis (ICA). This classifier aimed to diagnose SPECT data and determine whether it is normal or abnormal. They achieved their proposed method onto two stages. First, the features of SPECT images data set are reduced by using FastICA algorithm. Therefore, three subsets of features are generated which contain 3, 4 and 5 features. Second, ARIS classifier is used to classify these feature subsets and then store the results in a matrix. They obtained good experimental results. Noteworthy, the obtained result of classifier ensemble based on AIRS and ICA is better than AIRS classifier.

L. Parthiban and R. Subramanian [22] introduced a new model called coactive neuro-fuzzy inference system (CANFIS) which was built by using neural network and fuzzy logic approach. They performed their experiments for diagnosing heart disease and obtained 0.000842 for Mean Square Error.

K. Polat and S.Gunes [23] proposed a method includes three phases which are: C4.5 decision tree for feature selection, fuzzy weighted for pre-processsing and AIRS for classification.

A. Sadooghi and M. Mikaili [24] used different classifiers with their proposed feature selection method (BBBFS). The aim is to show the best performance of the method. They applied two classifiers from IBL algorithms: K-Nearest Neighbor Classifier (KNNC) and Nearest Mean Classifier (NMC) on SPECT Heart data set. They obtained 62.50% with the first feature subset (39 of 44 features) and 60% with the second feature subset (33 of 44 features) for recognition rate.

K. Polat and S. Gunes [25] introduced KFFS as a new feature selection method. It is considered as an advanced step of classification aimed to improve classification performance and reduce the computation cost. To test their method, they applied LS-SVM as a classifier and used SPECT data set. As a result, the combination of KFFS and LS-SVM introduced better results than KFFS and LM ANN in the next section.

In 2009, C. To and T. Pham [26] introduced a new algorithm in order to diagnose cardiac imaging data to normal or abnormal. They created rules of diagnosis in form of decision tree using a classifier based on genetic programming. However, they encountered a problem in the stage of fitness evaluation which consume a lot of time. To solve this problem, parallel genetic programming is used in which can be applied in two different levels: fitness level and population level (island model). In their work, the island model is performed to improve performance and achieve better results. So, the obtained results are 79.07% and 86.67% for sensitivity and specificity, respectively. R. Das, I. Turkoglu, A. Sengur [27] presented a new approach by using of neural network (NN) ensembles in order to diagnose heart disease.

In 2011, M. Ciecholewski [28] applied Support Vector Machine on SPECT data set to diagnose the ischemic heart disease. They aimed to make a comparison between the results of classifying SPECT heart data using SVM and CLIP3 algorithm. Furthermore, they validate their classifier by calculating the performance measures specificity, sensitivity and accuracy.

The works [29-32] applied SVM to classify ECG dataset which obtained from different databases. Some of these works used feature selection methods such as: Principal Component Analysis (PCA) [30], Dynamic Programming (DP) [31], Generalized Discriminant Analysis (GDA) [32] and Linear Discriminant Analysis (LDA) [32]. The best performance was 100% for classification accuracy on ECG dataset obtained from UCI [29].

Yadav and Jadhav [33] suggested an automated approach for cardiac disease diagnosis using SVM classifier. The SVM classifier applied on SPECT data images. The authors concluded that the accuracy of classification can be improved further by containing the age and sex of patients, racial background, air pollution, diet, pathophysiology, and previous medical history as features.

Kumar and Kumar [34] introduced a review on non-Invasive machine learning methods for heart disease diagnosis. The authors stated that most of the reviewed papers are from Science Direct, IEEE Explorer, PubMed, Hindawi, Springer, MDPI and ACM digital libraries. They found that Artificial Neural Networks (ANN) and Support Vector Machines (SVM) are dominant in most of the frameworks of several studies.

As indicated in [35, 36], the automated cardiovascular imaging analysis such as Cardiac Computed Tomography (CCT), Nuclear Imaging, Positron Emission Tomography (PET), Single Photon Emission Computed Tomography (SPECT) is an effective manner for radiologist and can accelerate the diagnosis of heart functions.

Several classifiers have been used for heart disease classification [37, 38]. Recently, deep learning methods based on convolution neural network (CNN) have been improved over Bayesian classifiers, Decision Tree (DT), Support Vector Machine (SVM) and Artificial Neural Network (ANN) for Phonocardiograms (PCG) classification.

Moreno-Ibarra et al. [39] studied the use of ML methods for diseases classification through a comprehensive comparative study. They applied a number of classifiers on SPECT dataset for heart disease diagnosis. The study investigated the important question: "Does a classifier perform well for a particular disease?" The authors indicated that the results achieved show statistically and numerically that there are reliable classification methods to recommend for medical diagnoses. However, the performance results of adopted classifiers are still low and needs to be improved. In the next section, the proposed approach, including the machine learning method, which is used in the proposed approach will be explained in detail.

3. Proposed Approach

The proposed approach develops an effective classification ML model for accurate and automated diagnosis of heart functions from cardiac tomography data. It consists of four main steps as shown in Figure 2. These steps are loading data extracted from the SPECT images, selecting an effective machine learning algorithm based on its advantages and our experience in the field, training the model of selected ML method, and Testing and evaluating the trained ML model. In the following subsection, we explain each phase of the proposed methodology.

3.1. Loading Data Attributes Extracted from SPECT Images

This step loads the values of data attributes extracted from SPECT images for training and classification tasks. Data attributes are determined to represent the substantial characteristics of patients' cardiac problems. The approach assumes that the extraction process of the data attributes has processed based on the region of interests (ROIs) in the images and using image processing tools and methods.

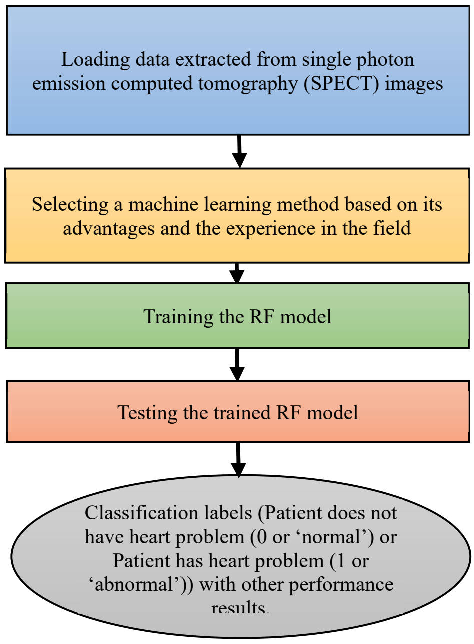

Fig. 2: The proposed approach for heart functions diagnosis.

3.2. Selecting a Machine Learning Method

In this step, an effective machine learning method is proposed based on investigating its advantages and our experience in the field. The selection step of such method will be validated experimentally through the results of some evaluation metrics in the test section. The proposed method depends on the concept of ensemble learning using a number of decision trees (DTs) trained on several subsets of data samples. It prevents the problem of overfitting and leads to a higher accuracy result. The proposed method is the random forest (RF), which is supervised learning method combines multiple classification models for solving a complex problem and improving the performance results of the required task [40].

The justification for selecting the RF method is based on the possibility that some DTs may classify the correct classification result, while others may not. However, all the DTs can classify the correct result. Moreover, the classification results from the DTs have very low correlations. The two cases of RF method for randomness are:

1. Each decision tree (DT) is randomly and separately constructed using a different training dataset sample.

2. During the building process of each DT, a part of m samples is randomly selected from the whole training data set. Then, the best split regarding the m samples is used. For an unseen example x, the RF classification model is built by the DTs, which are combined.

In this case, the RF has (N) of DTs and the probability (Pr) output of the class label (c), given that unseen input feature vector (x) is calculated using the following equation of ensemble decisions:

$$Pr(c/x) = \frac{1}{N} \sum_{i=1}^{N} Pr_i(c/x) \tag{1}$$

The final classification decision can by computed by averaging the probability of DTs applied on random data samples. Figure 3 shows the final decision of RF classification model.

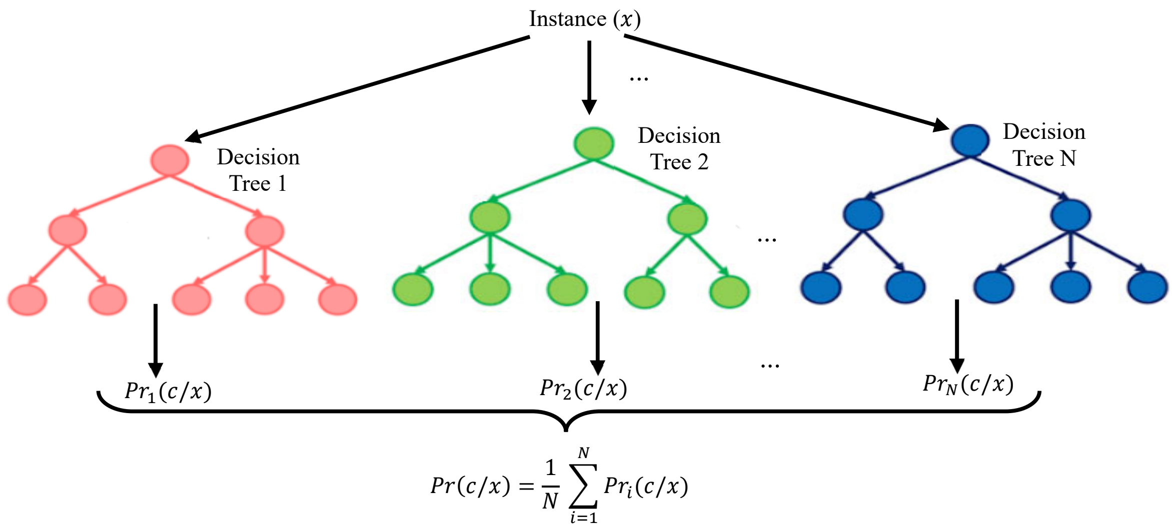

Fig. 3: The final decision of RF classification model.

Each DT in RF model splits the data samples down into smaller sets, constructing a sub-tree with leaves of decision-nodes. Every decision-node has two branches or more with leaves. Each class in the data set is symbolized by a leaf node. As the DTs in the RF rely on random samples, they lack to meaning and may have some data noise. Therefore, the RF norms the decisions of DTs to construct a model with low variance. The un-fitting DTs will cancel out each other's decisions and the only the useful DTs are used to build the trained model. There are several applications based on the RF have been emerged recently in different fields, such as image classification [41], network intrusion detection [42], and neuroimaging [43]. Algorithm 1 gives the main phases of RF model.

Algorithm 1: Random Forest (RF) pseudocode

```
procedure RANDOM FOREST
    for 1 to T do
        Draw n points D_I with replacement from D
        Build full decison/regression tree on D_I
            BUT: each split only consider k features, picked uniformly at random
                 new featues for every split
        Prune tree to minimize out-of-bag error
    end for
    Average all T trees
end procedure
```

In this research work, we explore the applicability of RF for accurate and automated diagnosis of heart functions from cardiac tomography data.

3.3. Training the RF Model

In this step, the RF classification algorithm is trained on a collected data samples using hold-out and 10-folds cross-validation modes. In the hold-out mode, the data samples are divided into 50% for training and 50% for testing. For the 10-folds cross-validation, the data samples are split into 10 parts and the RF model will be trained using nine out of them and one for validation, every time of a ten times. The final output of this step is a trained RF model.

3.4. Testing the Trained RF Model

The testing step of trained model uses a 50% of the original data samples in the hold-out technique and one different fold ten times in the 10-fold technique for evaluation and testing. In the 10-fold cross-validation, one different fold of the ten folds for ten times is used to validate the performance of each model and select the best model. After that, the best model is tested on the whole data set for getting the final evaluation result of the trained RF model.

The final output of this step is a list of classification labels with performance evaluation results.

4. Experiments and Discussion

The experiments are conducted based on the two techniques used in the testing step of the proposed approach. The first experiment is accomplished using hold-out testing technique and the second experiment is performed based on the 10-folds technique. In the following subsections, the dataset and evaluation metrics as well as the results will be explained and presented.

4.1 Dataset Description

The dataset used in the experiments contains 267 instances extracted from 267 Single Proton Emission Computed Tomography (SPECT) images for diagnosing the cardiac of different patients. Each patient's image is classified into two classes: 'normal' (patient does not have heart problem) and 'abnormal' (patient has heart problem). The dataset images were processed for extracting some attributes that represent the main features of the original SPECT images. Consequently, there are 44 continuous patterns or features for each patient's image. These patterns were further processed to get a 22 binary patterns or features. It is a suitable dataset for validating the proposed model. The number of instances of each class in the dataset is shown in Figure 4.

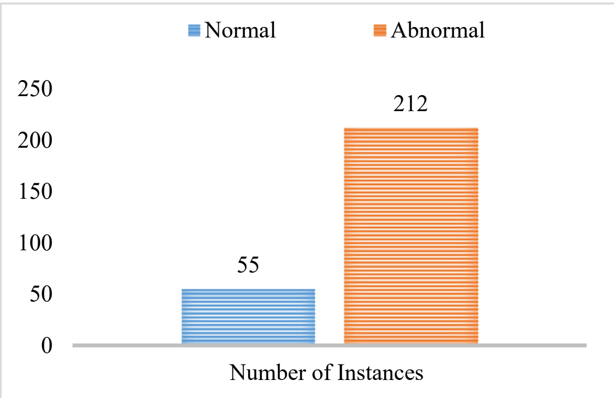

Fig. 4: The number of instances of each class in the dataset.

4.2 Evaluation Metrics

To evaluate the performance of proposed RF model, a common evaluation metrics are applied on the classification outputs. These evaluation metrics are recall (R), precision (P), and accuracy (A), and F-Measure (F).

$$R = TP/(TP + FN) \quad (2)$$
$$P = TP/(TP + FP) \quad (3)$$
$$A = (TN + TP)/(FP + TP + TN + FN) \quad (4)$$
$$F = (2 * R * P)/(R + P) \quad (5)$$

, where FN and FP are the false negative and false positive cases, whereas TN and TP are the true negative and true positive cases.

4.3 Results and Comparisons

This subsection presents the experimental results obtained by the evaluation metrics. The results of first experiment will be discussed and then the results of the second experiment. Table 1 gives the number of instances in training and test sets of the hold-out technique (first experiment).

Table 1: The number of instances in training and test sets of the hold-out technique.

Class Name	*Number of Training Instances*	*Number of Testing Instances*
Normal	20	35
Abnormal	113	99
Total	133	134

As shown in Figure 4 and Table 1, the number of instances of normal and abnormal classes are not balanced. So, the good performance of the classification method means its ability to mitigate the class imbalance problem during the training process.

Tables 2 and 3 show the confusion matrix of classification task for the first and second experiments, respectively. The diagonal cells with green colors represent the number of test instances (TP and TN instances), which are correctly classified during the first experiment.

Table 2: Confusion matrix of the classification task for the first experiment.

Predicated Class / *Actual Class*	*Normal*	*Abnormal*
Normal	(TP=10)	(FN=15)
Abnormal	(FP=10)	(TN=98)

Table 3: Confusion matrix of the classification task for the second experiment.

Predicated Class / *Actual Class*	*Normal*	*Abnormal*
Normal	(TP=24)	(FN=31)
Abnormal	(FP=19)	(TN=193)

Based on the number of TP, TN, FP, and FN instances in Tables 2 and 3, the results of the evaluation metrics are computed using equations (2)-(5) and presented in Tables 4 and 5.

Table 4: The evaluation results of RF model for the first experiment.

Class Name	*R*	*P*	*F*	*A*
Normal	0.400	0.500	0.444	81.203%
Abnormal	0.907	0.867	0.887	
Weighted Avg.	0.812	0.798	0.804	

Table 5: The evaluation results of RF model for the second experiment.

Class Name	*R*	*P*	*F*	*A*
Normal	0.436	0.558	0.490	81.2734%
Abnormal	0.910	0.862	0.885	
Weighted Avg.	0.813	0.799	0.804	

From Table 4, the results of R, P, and F for the 'abnormal' class is better than the results for the 'normal' class. The reason for this is because the effect of class imbalance problem. However, the evaluation results for the 'normal' class using the 10-fold cross-validation technique, in Table 5, has been slightly improved. Competitive accuracies have been achieved by the proposed approach in the two experiments, which are 81.203% and 81.2734%, respectively, as shown in Tables 4 and 5.

The weighted averaged results of R in Tables 4 and 5 for the two experiments (0.812 and 0.813) are a little higher than the weighted averaged results of P (0.798 and 0.799). This means that there were very few samples of FN, and that the RF model is permissive to classify some samples as positive.

For comparing the performance of the proposed RF method, the results achieved in this research will be compared with the results of the state-of-the-art classification methods reported in the work published in 2021 by Moreno-Ibarra et al. [39]. Figures 5 and 6 give the comparisons in terms of accuracy and recall (sensitivity).

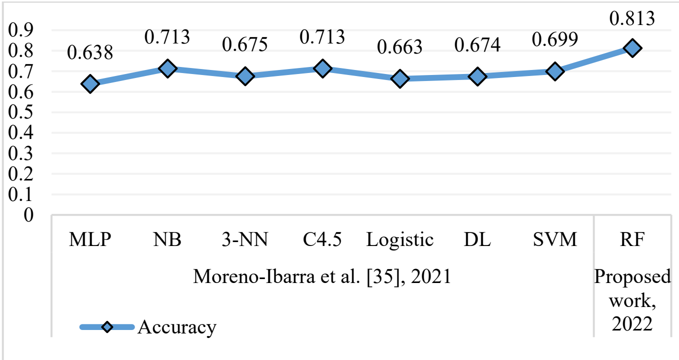

Fig. 5: The accuracy of RF method in the proposed work compared to other methods in the state-of-the-art on the same dataset.

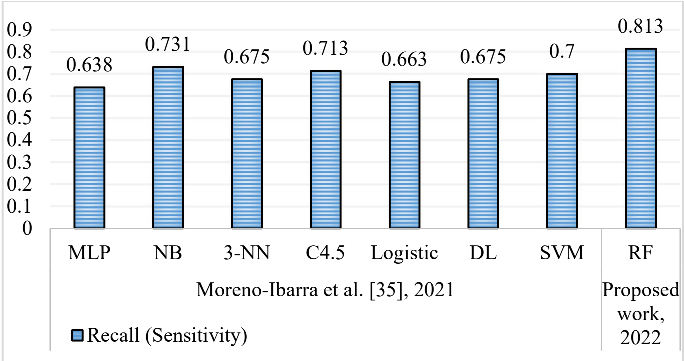

Fig. 6: The recall (sensitivity) of RF method in the proposed work compared to other methods in the state-of-the-art on the same dataset.

Classification methods used under study [39] are Multilayer Perceptron (MLP), Naïve Bayes (NB), K-Nearest Neighbors (K-NN), C4.5, Logistic, Deep Learning (DL), and Support Vector Machines (SVM) classifier. For the K-NN, the authors used three nearest neighbors to be (3-NN). From Figures 5 and 6, it is noticed that RF model attains a high accuracy result (0.813) and a high recall result (0.813) compared with the other methods in the state-of-the-art work. Additionally, from Tables 4 and 5, the RF model has a good F-measure result (0.804), which is near to the accuracy value. This means that the model is able to reduce the effect of class imbalance problem. The obtained results and comparisons confirm that the proposed approach is applicable and effective to classify the instances of patients in the testing dataset into normal and abnormal categories better than the other machine learning classifiers in the state-of-the arts.

5. Conclusion and Future Work

In this research work, an automated and accurate approach based on RF method and using cardiac tomography data is proposed for detecting abnormality of heart functions and diagnosis. The approach has selected to use the RF method because its ability and advantage to solve overfitting and class imbalance problems. The RF can generate several decision trees and create the classification output by averaging the classification resulted from all the decision trees. In many applications, the RF achieved high accuracy results than using a single decision tree method.

To test the RF classification method of the proposed approach, we used hold-out and 10-fold cross-validation techniques for training phase and testing phase.

The experiments are conducted on a public SPECT images dataset. A number of evaluation metrics such as recall, precision, F-measure, and accuracy are used to get the performance results of the approach. Seven classification methods are compared with the classification method used in this work for showing the effectiveness of the proposed approach. The experimental results confirmed the applicability and effectiveness of RF method to classify the instances of patients into normal and abnormal classes.

The comparison with the state-of-the-art methods also demonstrated the robustness of adopted classification against overfitting and class imbalance problems. In the future work, we will improve more the results of this research study by solving the problem of minority class problem in the training phase. Also, more data samples will be collected to improve and generalize the ability of ML methods.

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