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BIOMEDICAL HEALTHCARE SYSTEM FOR ORTHOPEDIC PATIENTS BASED ON MACHINE LEARNING

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ABSTRACT

Recently, the use of artificial intelligence (AI) in medical applications is widely increased and demanded to handle, diagnose, treats, and detect as many diseases as possible. The internet of things (IoT) is a common abbreviation related to AI recent technology. This technology aims to connect and interpret the sensors applied to the patients in different places easily and flexibly. In this paper, we proposed a healthcare system based on machine learning for orthopedic patients. The proposed system transfers the six biomechanical attributes derived from the shape and orientation of the pelvis and lumbar spine using IoT to classify these features. We utilize supervised machine learning approaches linear regression, neural networks, support vector machine, and random forest as a classifier to evaluate, compare, and classify input features. In the absence of one feature or other words the malfunction in one or more sensors, we proposed an imputation algorithm to predict the missing features that will be helpful to the doctors to diagnose and evaluate the pathological case for the patients.

Keywords: artificial intelligence, internet of things, orthopedic patients, linear regression, neural networks, support vector machine, and random forest.

1. INTRODUCTION

A Healthcare system based on the internet of Things (IoT) is defined as a system used for examining various body parameters to form the body area network (BAN). Through BAN different sensors are attached to patients' bodies to track and diagnose temperature signals, blood pressure, and breathing [1]. Therefore, we can state that the application of the IoT revolutionizes health care.

There exists one major problem for the poor people who have dangerous and emergency health care service at the dangerous event. Recently, it is easier to implement a health care system for the patients who stays at home that is not reactive so there is a need to develop a reactive system.

In this paper, we implement a healthcare integrated IoT system which can make integration in medical devices and the availability of data exchange capabilities. Therefore, it is an important role in maintaining patient safety and health, in addition to improving how doctors provide care, enhancing patient participation and satisfaction by allowing patients to spend more time interacting with their doctors.

In this work, we study the patients that suffer from orthopedic diseases in which each patient is represented in the data set by six biomechanical attributes derived from the shape and orientation of the pelvis and lumbar spine which are pelvic incidence, pelvic tilt, lumbar lordosis angle, sacral slope, pelvic radius, and grade of spondylolisthesis.

Although the use of IoT technologies in the healthcare system is very important and vital for communication between remote people in remote places through sensors. This paper presents an algorithm to anticipate some features extracted from the enrolled sensors. Figure-1 shows the steps of the proposed Healthcare IoT system based on orthopedic patients.

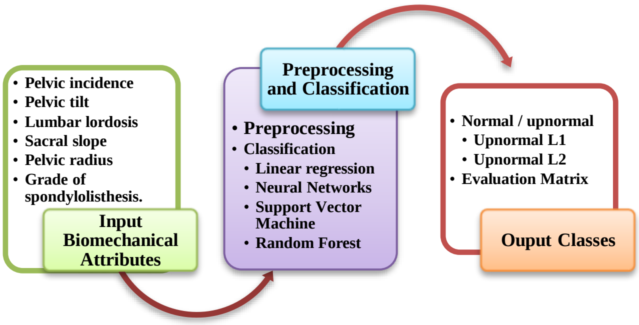

Figure-1. Schematic diagram of the IoT healthcare system based on orthopedic patients.

As shown in Figure-1, there exist 6 features that are undergoing a preprocessing and classification linear regression, neural networks, support vector machine (SVM), and random forest.

The contribution of this paper can be listed as follows:

a) We present a healthcare IoT-based system to handle remote orthopedic patients in different places.
b) We presented different classifiers to evaluate and compare the results to ensure the robustness and reliability of the proposed system.
c) The proposed system is utilized to handle the absence of one or more applied sensors using an imputation algorithm.

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This paper is organized as follows. Section 2 covers a brief review of IoT healthcare techniques. In Section 3, the proposed healthcare IoT system in detail. Section 4 introduced simulation and experiments while section 5 comprises results and discussion. Finally, Section 6 outlines the main conclusions and presents some future work.

2. RELATED WORK

The efforts to implement, diagnose, treat, and perform surgical training using healthcare IoT are now a reality. Cecil *et al* [2] proposed an IoT-based cyber training framework for orthopedic surgery. They proposed six training modules which are assembly, insertion, positioning, fracture reduction, screw insertion, and guide removal module. A speech-based automation system to assist patients in an orthopedic ward to automate processes using voice commands is presented by Jat *et al* [3].

There is convergence in the United State (US) healthcare system toward a more centralized organization. Instead of a direct government-initiated effort, the recent trend in centralization in the US healthcare system has been more of an indirect consequence of legislative efforts as presented by Luis M. Tumialán [4]. Otherwise, Ashley *et al* [5] presented The National Health Service (NHS) in England by serving an implant register to collect data for multi-center research studies by which the variables including a frailty index can also be collected before surgical procedures, and cost-utility analysis should also be an objective.

Chen and Xiang [6] present an overview of the health care system in China using most quality measures consist of process and structural measures rather than capturing patient outcomes. Patients in China choose their operating hospital based on health insurance arrangements, although they can choose whichever hospital they want to go to within a given system.

In Brazil, Oliveira *et al* [7] presented a partnership of 450 primary healthcare professionals who were trained, including nurses and physicians. They investigated that the partnership between medical services of different levels of complexity allowed for the establishment of a safe and effective program for treating orthopedic infections.

Moreover, Cecil *et al* [8] proposed a cyber training framework for orthopedic surgery for medical education and training. Sullca *et al* [9] presented an algorithm based on machine learning techniques for detecting Diseases in Blueberry Leaves using SVM and the most common approaches.

In this work, we presented a system using applied soft computing approaches such as linear regression, neural networks, SVM, and random forest to classify the pre-processed features results from the enrolled 6 sensors that represent each orthopedic patient.

3. HEALTH-CARE IOT PROPOSED SYSTEM

For the data collected from different sensors to detect the health status of the orthopedic patients, two cases affect the whole accuracy of the system which are the degree of the orthopedic diseases, and the normal and/or abnormal classification of the disease.

Figure-2 illustrates the configuration and steps of the proposed health care IoT system.

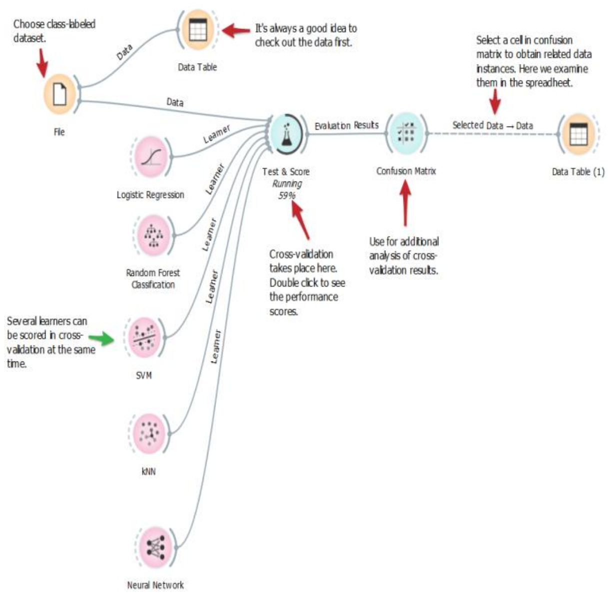

Figure-2. The structure of the proposed health care IoT system-based classification approaches.

The collected data is learned and classified using different classifier which is presented briefly as follows:-

a) Neural Networks

Neural networks (NN) is a promising algorithm for classifying and learn the enrolled data extracted from different sensors in a precise and perfect manner especially for anon-linear input data.

Deep learning is inspired by NN that contains stacked multi-hidden layers to increase the efficiency and accuracy of the labeled and unlabeled data [10]. Some cases need to be augmented to increase the visibility of the data and many approaches are used like geometry transformation and generative adversarial networks (GAN) algorithms [11].

In this work, we used a class labeled dataset which makes the recognition more easer based on a supervised machine learning algorithm. Therefore, we used a traditional NN to classify and learn the class-labeled data.

b) Support Vector Machine

In Support Vector Machine (SVM) the well-known and important supervised classification approach is used for learning the class labeled data [12] [13]. In this paper, there are several learners can be scored in cross-validation at the same time. The major demand of the SVM is to find the separating hyper-plane between positive and negative examples of input data and is called large margin classifier because the algorithm seeks the hyperplane with the largest margin, that is, the largest

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distance to the nearest sample points. Figure-3 demonstrates how SVM works as a classifier.

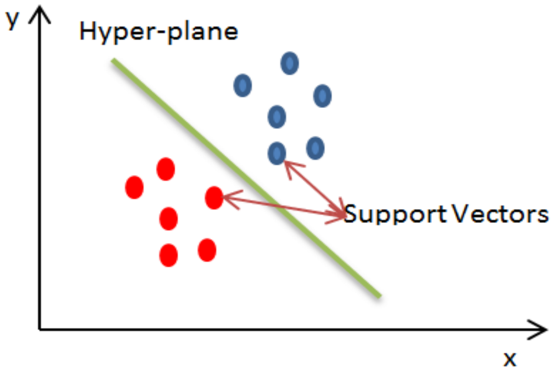

Figure-3. Support vector machine classifier.

c) Logistic Regression

In logistic regression as a supervised classification algorithm, its target is to classify the dependent variable (Y) as a discrete category or a class (not a continuous variable as in linear regression) [14]. Khan [15] proposed an algorithm for heart disease prediction based on deep convolutional neural networks classifier compared with logistic regression. It is different from linear regression where the dependent or output variable is a category or class. The target is a discrete category or a class (not a continuous variable as in linear regression), for example, Class1 = normal, Class2 = up normal.

d) Random Forest

To create multiple random subsets where data may or may not overlap. Therefore determination of a randomized decision tree based on the random selection of data and random selection of variables is required. One important property is that trees protect each other from their error if the data is taken unbiased. Subsequently, we rank the classifiers according to their votes. This provides a class of dependent variables based on many trees. Thus, random trees create a random forest [16].

e) KNN

KNN assumes that all instances are points in some n-dimensional space and defines neighbors in terms of distance (usually Euclidean in R-space). Jayatilleka *et al* [17] proposed a review of the latest IoT devices, sensors, and systems of smart healthcare for various diseases using KNN compared with different applied soft computing techniques. Algorithm 1, presents the steps of the proposed health care IoT system.

Algorithm 1: Healthcare IoT system for Orthopedic Patients
Input: The extracted features of the enrolled 6 sensors are pelvic incidence, pelvic tilt, lumbar lordosis angle, sacral slope, pelvic radius, and grade of spondylolisthesis. **Initialization:** Initialization of each learned classifier by setting all enrolled feature sensors to zero. **Output:** The confusion matrix including Sensitivity, Specificity, Precision, Accuracy, and F1score of the matching scores produced for each class. **Procedure:** 1. Choose class-labeled data set from the data table. 2. Update each class labeled based on the extracted prepossessed features results from each sensor. 3. Classify the updated class labeled data using a. Neural Networks b. SVM c. Logistic regression d. Random Forest e. KNN 4. Select a cell in the confusion matrix to obtain related data instances. 5. Determination of the confusion matrix of additional analysis of cross-validation results from each learner. (see Figure-2)

4. RESULTS AND DISCUSSIONS

In this section, we attempt to ensure the reliability and robustness of the proposed system compared with the recent IoT healthcare system. In this work, we have collected the data that is have been organized in two different but related classification tasks.

First is the Normal and abnormal classes, and the second using three classes using the same datasets that have 6 normal features, abnormalL1, and abnormal L2.

These data are collected from different sensors based on the parity of the enrolled features from each sensor. The pre-processing was implemented to produce the numeric that are classified based on the mentioned NN, SVM, LR, RF, and KNN. That is performed to investigate the accuracy of the proposed IoT healthcare system.

We have made two experimental; the first experiment is using two classes and the second using three classes.

Experimental 1

In the classification phase using two classes that determine the normal and abnormal patients are performed. We elected the confusion matrix to evaluate the proposed IoT healthcare system based on two classes. Figure-4 shows the accuracy, F1, Precision, and recall of the proposed NN, SVM, LR, RF, and KNN classifiers. We noticed that the results are more accurate and enhanced in using SVM than other classifiers. In this experiment, we used Disk Hernia and Spondylolisthesis that were merged into a single category labeled as abnormal. Thus, the second task consists of classifying patients as belonging to

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one out of two categories: Normal (100 patients) or Abnormal (210 patients).

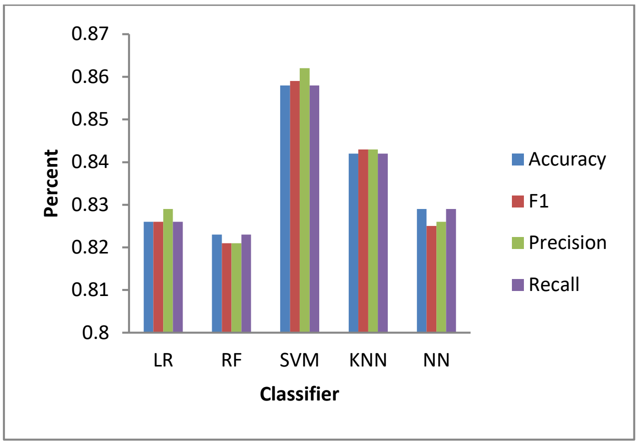

Figure-4. Accuracy, F1, Precision, and Recall of the two classes of normal/ abnormal patients using NN, SVM, LR, RF, and KNN classifiers.

Experimental 2

Using three classes than Normal and abnormal are performed such that (100 patients), Disk Hernia (60 patients), or Spondylolisthesis (150 patients). In this experiment, we determine the factors of the confusion matrix and we found that accuracy, F1, Precision, and Recall of the three mentioned classes normal/abnormalL1/ abnormal L2 of the enrolled patients using NN, SVM, LR, RF, and KNN classifiers as shown in Figure-5.

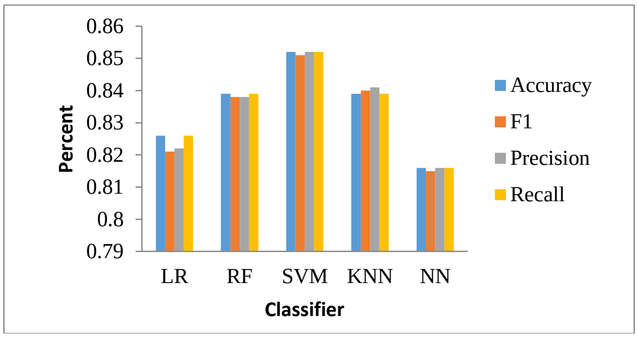

Figure-5. Accuracy, F1, Precision, and Recall of the three classes normal/up normal (L1)/ abnormal (L2) patients using NN, SVM, LR, RF, and KNN classifiers.

One of the important benchmarks used to boost the proposed healthcare IoT system is the calculation of the area under the curve. It can be implemented to ensure that the diseases covered under that area and how can be handled.

For evaluation, the sensitivity, specificity, precision, accuracy, and F1score from the confusion matrix for the proposed system have been calculated based on equations 1, 2, 3, 4, and 5 [18].

$$\text{Sensitivity} = TP/ (TP+FN) \tag{1}$$

$$\text{Specificity} = TN/ (TN+FP) \tag{2}$$

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

$$\text{Accuracy} = (TP+TN)/ (TP+TN+FP+FN) \tag{4}$$

$$F_1\text{score}= 2TP/ (2TP+FP+FN) \tag{5}$$

where TP: true positive, TN: true negative, FP: false positive, FN: false negative.

For stratified 10 fold cross-validation the target class is the average over classes. The Confusion matrix for Logistic Regression (LR) showing the number of instances is shown in Figure-6.

		Predicted		
		Abnormal	**Normal**	**∑**
Actual	**Abnormal**	180	30	**210**
	Normal	24	76	**100**
	∑	**204**	**106**	**310**

Figure-6. The confusion matrix of LR and the corresponding instances number in two classes normal and abnormal.

Similarly, we evaluated the confusion matrix in the case of NN, KNN, SVM, and RF in both two and three classes. In Figure-7 the relation between the false positive rate (FP) horizontally and the true positive rate (TP) vertically is calculated to determine the ability of each classifier to classify the enrolled features for each patient to produce class as its output. We found that the area under the curve is enhanced to increase the whole accuracy of the proposed system. The default threshold is between 0.4 and 0.5 and the above line represents the performance line between TP and FP. The desired area under the curve should be 100 but in fact, as following in Tables 1 and 2 the area under the curve is varied to reach the tensed line that represents the accuracy. The performance of the proposed IoT health care system is enhanced in the case of using SVM. The collected dataset is founded in the following link https://www.kaggle.com/uciml/biomechanical-features-of-orthopedic-patients [19]. To impute the missing features of the enrolled feature for each sensor we used the algorithm as in [20].

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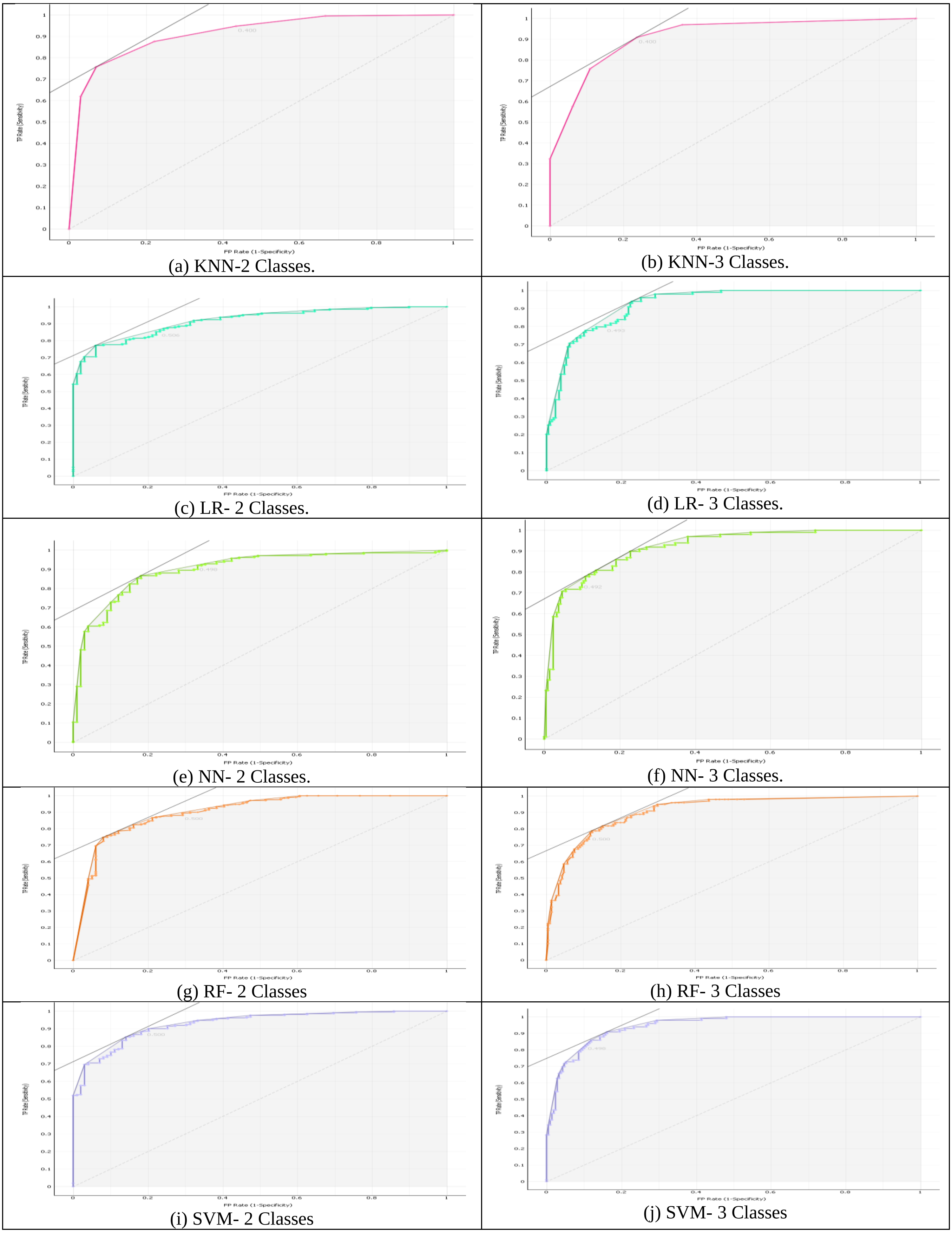

(a) KNN-2 Classes. (b) KNN-3 Classes.

(c) LR- 2 Classes. (d) LR- 3 Classes.

(e) NN- 2 Classes. (f) NN- 3 Classes.

(g) RF- 2 Classes (h) RF- 3 Classes

(i) SVM- 2 Classes (j) SVM- 3 Classes

Figure-7. The relation between TP and FP rates of the proposed KNN, LR, NN, SVM classifiers for 2 classes (a), (c), (e), (g), (i) and 3 classes (b), (d), (f), (h), (j) respectively.

Table-1. The area under the curve (AUC), accuracy (ACC), F1, precision (Pre), and recall (Rec) of the RF, NN, LR, KNN, and SVM for two classes.

	Parameter Sets(PS)				
	AUC	**ACC**	**F1**	**Pre.**	**Rec**
Random Forest	0.906	0.823	0.821	0.821	0.823
Neural Networks	0.901	0.829	0.825	0.826	0.829
Logistic regression	0.916	0.826	0.827	0.829	0.828
KNN	0.923	0.842	0.843	0.843	0.842
SVM	0.938	0.858	0.859	0.862	0.858

Table-2. The area under the curve (AUC), accuracy (ACC), F1, precision (Pre), and recall (Rec) of the RF, NN, LR, KNN, and SVM for three classes.

	Parameter Sets(PS)				
	AUC	**ACC**	**F1**	**Pre.**	**Rec**
Random Forest	0.916	0.833	0.841	0.801	0.833
Neural Networks	0.921	0.849	0.825	0.826	0.824
Logistic regression	0.916	0.826	0.817	0.849	0.826
KNN	0.943	0.842	0.833	0.863	0.840
SVM	0.968	0.878	0.899	0.892	0.898

5. CONCLUSIONS

This paper proposed an algorithm based on using supervised learning classifiers that are able two classify and labeled data extracted from different sensors in different patients. The proposed healthcare IoT system presents high accuracies for two and three classes with an enhancement of the AUC and accuracy. The proposed system can impute the missing features using imputation machine learning algorithms.

The results indicated that that the proposed biomedical system to detect and recognize orthopedic patients are reliable and enhanced in terms of confusion matrix parameters like accuracy, F1-score.

For the future direction, we plan to use the hybrid technique of one or more of the mentioned classifiers to boost the results and to forecast and predict the missing data results from each enrolled sensor.

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