Prediction of COVID-19 Patients Recovery using Ensemble Machine Learning and Vital Signs Data Collected by Novel Wearable Device

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Abstract—**During the spread of a pandemic such as COVID-19, the effort required of health institutions increases dramatically. Generally, Health systems' response and efficiency depend on monitoring vital signs such as blood oxygen level, heartbeat, and body temperature. At the same time, remote health monitoring and wearable health technologies have revolutionized the concept of effective healthcare provision from a distance. However, analyzing such a large amount of medical data in time to provide the decision-makers with necessary health procedures is still a challenge. In this research, a wearable device and monitoring system are developed to collect real data from more than 400 COVID-19 patients. Based on this data, three classifiers are implemented using two ensemble classification techniques (Adaptive Boosting and Adaptive Random Forest). The analysis of collected data showed a remarkable relationship between the patient's age and chronic disease on the one hand and the speed of recovery on the other. The experimental results indicate a highly accurate performance for Adaptive Boosting classifiers, reaching 99%, while the Adaptive Random Forest got a 91% accuracy metric.**

Keywords—Machine learning; COVID-19; wearable device

I. Introduction

Pandemics produced by infectious diseases always had a negative impact on the community at large. Currently, the globe is witnessing the advent of SARS linked to a novel coronavirus (SARSCov2) [1]. Patients with suspected exposure or symptoms should be identified as soon as possible. In respiratory infections, vital signs such as body temperature, heartbeat, and blood oxygen saturation are acknowledged as crucial strong indicators [2], [3]. Their monitoring is crucial for detecting early physiological abnormalities in patients who are deteriorating. They play a critical role in triaging patients for proper care and predicting whether they will improve or deteriorate [4], [5].

Approximately 82% of SARSCov2, also known as COVID-19, patients have minimal symptoms, recover quickly, and do not need to be hospitalized. 10 to 20% of patients who require hospitalization require care in intensive care units (ICUs), 3 to 10% require intubation, and the case fatality rate ranges from 2 to 5% [6]. Patients with mild illness are typically treated symptomatically, with home isolation as the last resort [7]. COVID-19's incubation period (the time between infection and beginning of symptoms) ranges from 2 to 14 days, with an average of (5 to 6) days [8]. Vital signs have to be monitored by the patients who have been assigned to a quarantine zone.

Wearable remote patient monitoring systems have made it possible to monitor vital indicators in a regular basis outside medical facilities and/or where mitigating contact with health workers is required [9]. However, with long-term monitoring and vital signs recording, a large amount of data is generated continuously, and health workers find it hard to extract information. This information is crucial to setting health policies and determining patient treatments. Thus advancements in machine learning combined with medical systems have resulted in a revolutionary discovery [5]. Commercial introductions of such gadgets without medical validation studies have occurred recently, rendering them inappropriate for medical use [10].

Generally, the classification process in data mining aims for the descriptive or predictive task. A descriptive analysis may be utilized to illustrate data relationships in a way that decision-makers can comprehend. In predictive analysis, the classification model can also be used for forecasting future values for the target class. One of the most popular data mining techniques is the decision tree DT. It is a simple and effective method that is used for both tasks. In [11], the proposed system presents a wearable device capable of monitoring the patient's vital signs (body temperature, oxygen saturation, heartbeat) and analyzing these data to predict the patient's recovery using ensemble classifiers with a DT as a based learner. The main contributions of this manuscript is:

- Utilizing an IoT-based monitoring health system to collect COVID-19 patients data set.
- Analysing the collected data and extracting crucial medical information using ensemble machine learning techniques.
- Evaluating and discussing the key findings of the main features of the medical data set.

The rest of this research is organized as follows: Section II reviews some related works. Section III describes the proposed classification system architecture along with the deigned wearable device. Section IV discuss the collected patient dataset and its characteristics, while Section V analyze this dataset and the performance of ensemble classifiers. Section VI discuss the results, limitations, and possible applications of the proposed system. Lastly, Section VII summarizes the main conclusions of this work.

II. Related Work

A. Health Monitoring Systems

Recent advancements in IoT and wearable device technologies enabled significant improvements in health applications, especially in the current pandemic that has become a global issue and threat to public health. For instance, Albassam $etal.$ Proposes an IoT-based health monitoring system for COVID-19 patients to measure various vital signs such as temperature, heart rate, oxygen saturation, and cough count, as well as to report patient GPS location data to medical authorities in real-time [12]. The system includes a wearable body sensor, web API, and a mobile application. The monitoring system is connected to the (IoT) cloud, where data is processed and analyzed.

Moreover, A real-time wearable monitoring system for the COVID-19 patient had been proposed [13]. A wearable chest patch and a pulse oximeter are used to send patients vital signals, including heart rate, respiration rate, and peripheral oxygen saturation, via wireless Android tablet devices to the nursing ward. The proposed system offers a technical wearable device (bracelet) to make it more unrestricted and give patients complete freedom of movement and do all activities without restrictions inside the home or hospital. The system added the technology of quarantine monitoring for those infected with the virus by adding GSM technology.

On the other hand, Mizher $et\,al.$ propose an internet of medical things (IoMT) based healthcare monitoring system that uses a wearable device [14]. This wearable device includes two sensors to measure blood oxygenation, temperature, and heart rate to monitor the health status of COVID-19 patient and limits virus spread. Their proposed system provides more services at a lower cost with the ability to change functions according to the requirements of medical staff, whether during the epidemic period or afterward.

Gloria.C $etal.$ [15] proposes a systematic review on accuracy and metrological characteristics of wrist-worn and chest-strap wearable devices. According to this system, aspects such as calibration procedure, number of test protocols, measured quantities, absolute error percentage, and correlation coefficient should be considered to evaluate the accuracy of wearable devices. The evaluation of the accuracy of wearable devices performed by a methodology was based on the calibration technique, the number of test protocols, measured quantities, absolute error rate, and correlation coefficient. However, in all the mentioned studies, either the wearable device design requires further efficiency or the produced health data lack a smart data analysis for this nontrivial big stream of data. This study aim to address this by proposing an efficient and smart health system.

B. Machine Learning in Health Applications

In order to extract or predict useful information from medical health dataset, many studies had proposed machine learning techniques. For instance, two machine learning techniques had been utilized for classifying COVID-19 against influenza data [16]. The first stage of their model was to make two clusters using Fuzzy C-Mean, then a Back Propagation classifier was built based on the clustering result. The implementation of their model included creating a mobile application that receives medical test data from the user and applies the classification within the mobile environment. Another classification framework proposed by [17] for detecting COVID-19 infection in the chest radiograph. X-ray images are classified using a convolutional neural network (CNN) and generative adversarial network (GAN) for data augmentation in their framework.

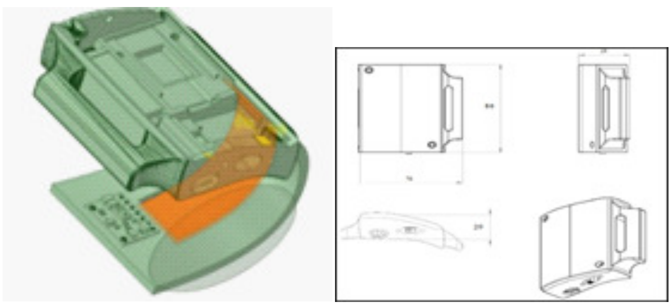
A smartphone-based recognition classifier is proposed by [18] for differentiating the normal coughs and uninfected persons from COVID-19 infected ones. Their work included a comparison of seven classification techniques, and the results showed that the neural network based on residual had the best performance. The author in [19] proposed a CNN classification model for classifying Computer Tomography (CT) images of COVID-19 patients. Their model required a low computational resource as it can be implemented in a personal computer without GPU acceleration. However, the works mentioned in this section are concerned with detecting COVID-19 infection, not the recovery status. In addition, two of them used medical images that are only available in the medical centers.

III. Proposed System Architecture

The proposed health classification system continuously records the sensors' output values alongside other medical information for COVID-19 patients and predicts their recovery. In addition, the system monitors the status of a patient; whenever the system recognizes a predefined critical level for any of the patient's vital signs, the system will send an alert to the responsible health staff. This system contains various components: (1) the Bracelet, which contains sensors for reading the patient's vital signs and passing them to the basic control unit, and (2) The Base Control Unit for receiving, analyzing, classifying, storing, and displaying data for each patient, (3) the user interface is designed to arrange and engage all system functions, inputs, and outputs for patients and users [9]. Moreover, it displays the instant patient vital signs to health workers.

A. Bracelet Design

Wearable electronics devices are starting to include many fundamental and even leisure functionalities due to market demands. In this research, the wearable device, which is the bracelet, has been designed to perform a vital task in the patient monitoring system. When constructing such systems, stability, durability, safety, and acceptable form factors must all be taken into account. Several layouts were implemented in this initial investigation, and the one illustrated in Fig. 1 was selected [20].



(a) (b)

Fig. 1. Bracelet Designed Layout.

The microprocessor, battery, sensors, and other components are all housed in the bracelet case, which measures (86 x 70 x 29) mm. Slots are cut into the lower and top parts of the bracelet so that the sensors can be placed on the skin with the needed accuracy, as shown in Fig. 1, the bracelet (container) is expertly created for patients of all ages and genders. The bracelet's exterior had an efficient technical curve that was made with a 3D printer with flexible materials to match the size and shape of most users' wrists. In addition, this design has shown the best accuracy in recording vital signs and communicating with the base station [20].

B. Building Ensemble Classifier

The data of a classification task with the size N consists of a set of features X $(x1, ..., xM)$ and Y, which is the class label vector, where N is the number of instances and M is the number of features. This task aims to build a model that can classify or predict the value of y depending on the given feature set X. The single model can produce unreliable predictions because of overfitting, so the ensemble classification includes building multiple weak classifiers (base learners) and merging their decisions to make one strong one. In the proposed system, the base learner is the decision tree consisting of two types of nodes; the internal node represents a condition on a data feature used to divide the data records. Only two branches produce from each internal node based on the condition in a binary tree, while the multi-branch DT can generate more than two branches from each internal node. A leaf node is a non-internal that holds a class label without any data splitting.

According to the mechanism of merging the base learners, ensemble classification is categorized as Boosting and Bagging, and both of them are used in the proposed system. AdaBoost refers to Adaptive Boosting [21]; it performs by assigning a higher weight to data records that are incorrectly classified and less weight to those that are already well-classified. This process is performed by many iterations, which is called the size of the ensemble, and it is equal to the number of base learners. For the initial iteration, the data subset is chosen randomly with the equal possibility of choosing each instance. In the following iterations, the weight of an instance will be increased if it was incorrectly classified in the previous iteration. AdaBoost predicts the unknown value for any new instance by using the weighted average of base learners' decisions. The weight of each learner is calculated base on its misclassification error. Fig. 2 illustrated steps of building the proposed ensemble classifier based on AdaBoost algorithm.

Random forest applies Bagging in which a random sub-sampling is chosen with a replacement in each iteration for the training set. In addition, a random subset of features will be selected in the splitting process of DT. Adaptive random forest ARF [22] is dedicated to dealing with data streams by applying a continual training method for the classification model to adjust to changes in data distribution. It uses a modified version of DT called Hoefding Tree of Very Fast Decision Tree, which can adapt itself as a response to changes in data distribution. Adaptive Window ADWIN is used in ARF for monitoring and detecting that change in a data stream.

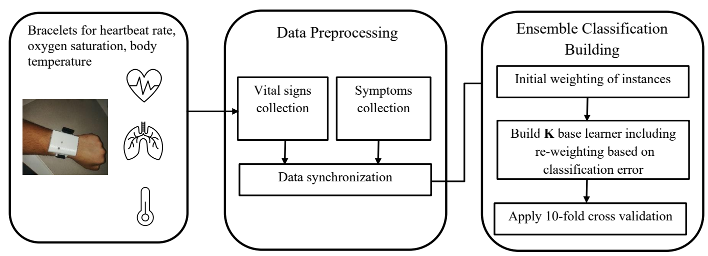


Fig. 2. Steps of Building the Proposed Ensemble Classifier

IV. Patients Data Sample

The study sample in this research is made up of a voluntary group of individuals infected with COVID-19 found inside clinics designated to treat patients with COVID-19. In addition to the vital signs from the bracelet, the patient's medical history, how long they have been infected, and their symptoms are collected with the help of health workers in these clinics. Thus, each patient record is designed to show the pathological behavior of the virus throughout the infection period. Therefore, using data analysis techniques, information might be extracted to prevent patients from reaching critical conditions.

A. Sample Demography

The system was tested on a non-governmental voluntary sample targeting patients infected with the virus during the pandemic, which had mild or moderate symptoms while attending outpatient clinics in Iraq, in the capital, Baghdad. The sample included (408) infected individuals, and their information and medical history were recorded without mentioning their names in order to preserve privacy. The collected data has been divided into two datasets; the first one, entitled Covid19-IQ01, contains data from 313 patients, one record for each patient. The second dataset, Covid19-IQ02 created by monitoring 95 patients for five days, i.e., five records for each patient and 475 in total. In the Covid19-IQ01 data set, gender is fairly distributed, as shown in Table I. In addition, the sample data is categorized into six age groups, and since most of them suffered from high to moderate infection, the age group (60-69 years old) is the highest with (27.5%). Table I also shows that 55% of 313 patients have some kind of chronic disease, and this can provide the ability to indicate their impact on recovery period of COVID-19 patients.

TABLE I. The Demography Characteristics of Sample Patients

		Covid19-IQ01	**Covid19-IQ02**
Gender	Male	≈ 53%	≈ 45.2%
	Female	≈ 47%	≈ 44.8%
Age	10-19	≈ 16.6%	≈ 17.9%
	20-29	≈ 15.6%	≈ 12.6%
	30-39	≈ 14%	≈ 16.8%
	40-49	≈ 13.4%	≈ 16.8%
	50-59	≈ 12.8%	≈ 17.9%
	60-69	≈ 27.5%	≈ 17.9%
Chronic diseases	Hypertension	≈ 28.4%	≈ 27.3%
	Diabetes	≈ 28.4%	≈ 30.5%
	Others	≈ 8%	≈ 12.6%
	None	≈ 45.3%	≈ 46.3%
Symptoms	Exhaustion	≈ 55.5%	≈ 62%
	Dizziness	≈ 61%	≈ 65%
	Fast Heartbeat	≈ 59.1%	≈ 65%
	Depression	≈ 35.4%	≈ 69%

In addition, the system was tested on a sample of (95) volunteer participants, each of whom had (5) serial measurements starting from the fifth to the tenth day and had (mild or moderate) symptoms of infections. This is due to the fact that this period represents the tipping point for various complications, especially for older patients and those with chronic diseases, such as high blood pressure, diabetes, or other [23]. This sample is divided into (six age groups) from (10-70) years and two categories based on gender (43) males and (52) females. In addition, the medical history, and chronic diseases, of the patient were adopted, as the number of participants in the sample who had high blood pressure (26) participants, diabetes (29) participants, and other diseases (12) participants. Moreover, Health experts have classified the patient's status based on interviewing the patient into three categories: Recovered, recovering, and No sign of recovery. This classification is based on the persistence of symptoms associated with the disease due to infection. Taking into account the readings of vital signs, which are summarized in Table II, especially (body temperature and the oxygen saturation in the blood). These patient data records will be used in machine learning in the next sections.

V. Experiments Results

A. Data Analysis by Visualization

In this section, we explore the patterns in the collected data Covid19-IQ01 and the relationship between the patient's condition on the one hand and age, chronic diseases, and vital signs on the other. In Fig. 3, 4, 5, 6, 7, 8, and 9,the color of the circle indicates the status of the patient, while the size of it relates incrementally to the age of the patient. RapidMiner platform [24] was used for analyzing and visualizing operations. Fig. 3 illustrates the relation between two common chronic diseases, Hypertension and Diabetes, with the progress of patient recovery. The figure showed clearly that patients with those two diseases have no sign of recovery, while there is a high ratio of recovered or recovering patients without Hypertension and Diabetes.

TABLE II. Summery of Numerical Features of Covid19-IQ01

Attribute	*Min.*	*Max.*	*Mean*	*STD*
Age	13	69	37.42	18.21
Body Temperature	36.2	38.4	37.29	0.62
Oxygen Saturation	90	97	94.62	1.5
Heartbeat Rate	55	86	69.62	6,17

Fig. 3. Covid19-IQ01 Data Visualization: Hypertension and Diabetes

The impact of body temperature collected from the thermometer sensor on the recovery status is illustrated in Fig. 4 and Fig.5. Young Patients without Hypertension or Diabetes and 37 degrees or less of temperature mostly healed. In the case of having one of the two chronic diseases, most patients don't show a sign of recovery, although their body temperature is normal.

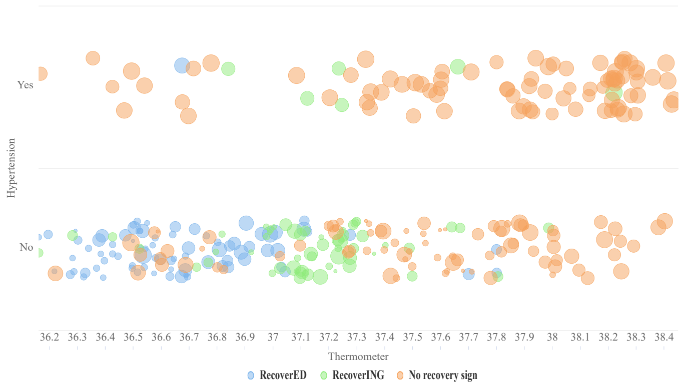


Fig. 4. Covid19-IQ01 Data Visualization: Hypertension and Thermometer.

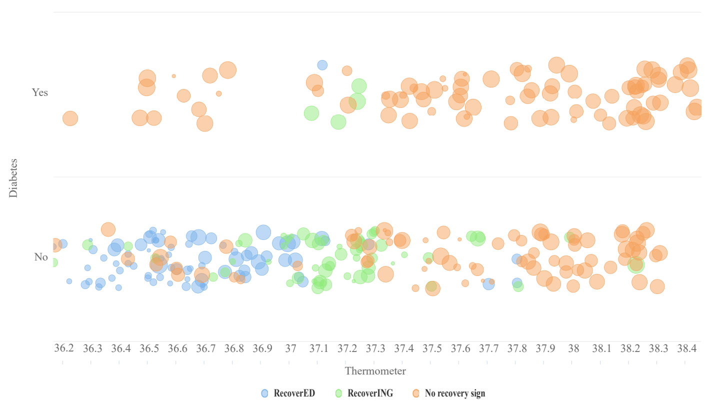


Fig. 5. Covid19-IQ01 Data Visualization: Diabetes and Thermometer.

Diabetes patients mostly have no sign of recovery regardless the age and their heartbeat rate, as shown in Fig. 6. Also, it indicates that Heartbeat rate is related to the recovery status of young patients without Diabetes. Adult patients with Hypertension mostly were not healing regardless of heartbeat rate, as shown in Fig. 7. In the normal range of heartbeat, most of the young patients were recovering or they already recovered. The same conclusions can be seen in Fig. 8 and Fig. 9 about the relation between the oxygen saturation, chronic diseases, and recovery from COVID-19.

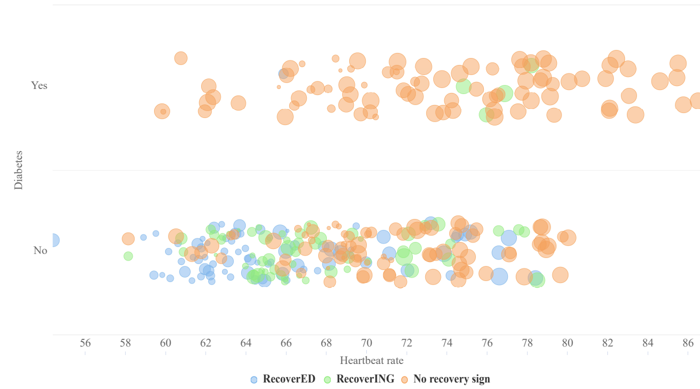


Fig. 6. Covid19-IQ01 Data Visualization: Diabetes and Heartbeat Rate.

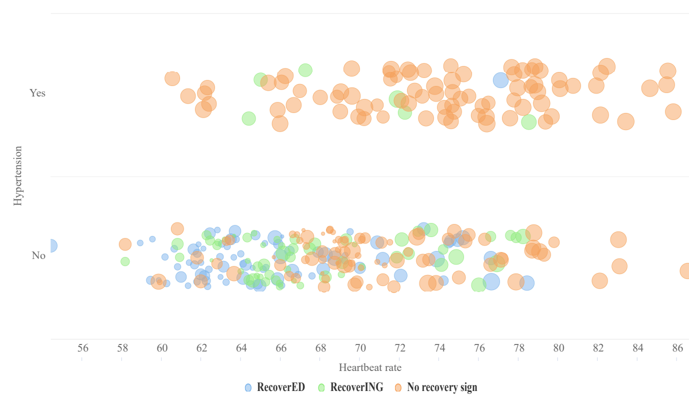


Fig. 7. Covid19-IQ01 Data Visualization: Hypertension and Heartbeat Rate.

Fig. 8. Covid19-IQ01 Data Visualization: Hypertension and Oximeters.

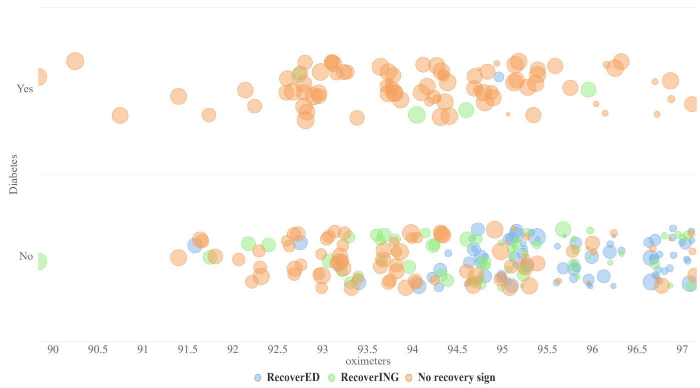


Fig. 9. Covid19-IQ01 Data Visualization: Diabetes and Oximeters.

B. Static Ensemble Classification

Waikato Environment for Knowledge Analysis [25] platform is used in this implementation for randomization, feature ranking, and classification. Implementing AdaBoost Ensemble classifier on both Covid19-IQ01 and Covid19-IQ02 datasets led to high accurate classification. The base learner for Adaboost was a J48 decision tree classifier that illustrated in Fig. 10 and Fig. 11. All the experiments in this section included 10-fold cross-validation to prevent bias, and the ensemble size was 20 for Covid19-IQ01 and 12 for Covid19-IQ02.

Tables III and IV represent the confusion matrix of AdaBoost with the two datasets; they show the correct predicted values in the bold numbers in the diagonal cells. The results in those tables indicate the accuracy of AdaBoost, especially in Table IV that contains only one record classified incorrectly.

TABLE III. Confusion Matrix of AdaBoost Classifier for Covid19-IQ01

	Predicted values		
Actual values	***Recovered***	***Recovering***	***No recovery sign***
Recovered	**72**	4	6
Recovering	3	**51**	9
No recovery sign	6	12	**150**

TABLE IV. Confusion Matrix of AdaBoost Classifier Covid19-IQ02

	Predicted values		
Actual values	***Recovered***	***Recovering***	***No recovery sign***
Recovered	**145**	0	0
Recovering	0	**120**	0
No recovery sign	1	0	**189**

A performance comparison is performed between AdaBoost and the other four popular classifiers. Three of them were a single classifier (J48, REPTree, and Hoeffding Tree), while the fourth is Random Forest which is an Ensemble classifier that uses bagging instead of boosting. The results of the comparison in Tables V and VI showed that Adaboost has the best results in both datasets compared with the other four classifiers based on five evaluation metrics (TP rate, FP rate, Precision, Recall, and F-Measure). Fig. 12 illustrates the importance of each feature in both datasets during the building of the AdaBoost classifier. It can be seen that AdaBoost chose a different subset from features in every dataset; only the Age feature had similar importance in both of them.

TABLE V. Classification Performance of Five Classifiers of Covid19-IQ01

Technique	*TP Rate*	*FP Rate*	*Precision*	*Recall*	*F-Measure*
J48	0.837	0.103	0.838	0.837	0.838
REPTree	0.831	0.119	0.830	0.831	0.830
HoeffdingTree	0.655	0.198	0.644	0.6551	0.648
Random Forest	0.866	0.084	0.866	0.866	0.866
AdaBoost	**0.872**	**0.079**	**0.874**	**0.872**	**0.873**

TABLE VI. Classification Performance of Five Classifiers of Covid19-IQ02

Technique	*TP Rate*	*FP Rate*	*Precision*	*Recall*	*F-Measure*
J48	0.977	0.010	0.977	0.977	0.977
REPTree	0.977	0.007	0.85	0.985	0.985
Hoeffding Tree	0.937	0.029	0.938	0.937	0.937
Random Forest	0.973	0.013	0.973	0.973	0.973
AdaBoost	**0.99**	**0.001**	**0.998**	**0.998**	**0.998**

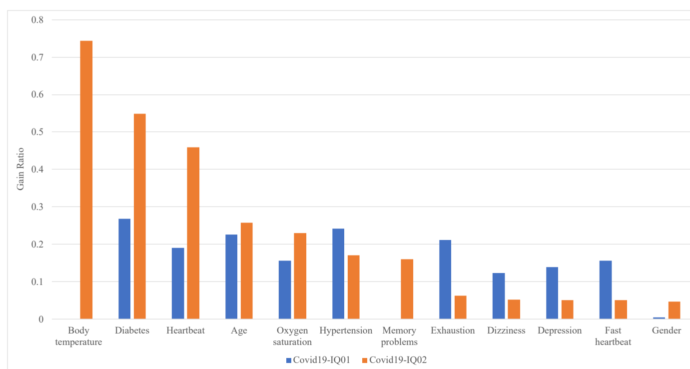


Fig. 12. Features Ranking of AdaBoost Classifer based on Gain Ratio.

C. Adaptive Ensemble Classification

Implementation of the second dataset, COVID10-IQ02, as a continuous data stream was performed in Massive Online Analysis platform and scikit-multiflow library in Python. Adaptive Random Forest ARF classifier, which is an adaptive ensemble classifier, had an incremental classification performance while receiving the stream samples with a size of 20 instances, as shown in Fig. 13. ARF obtained the best result compared with the other four adaptive classifiers by using ten base learners as shown in Fig. 14.

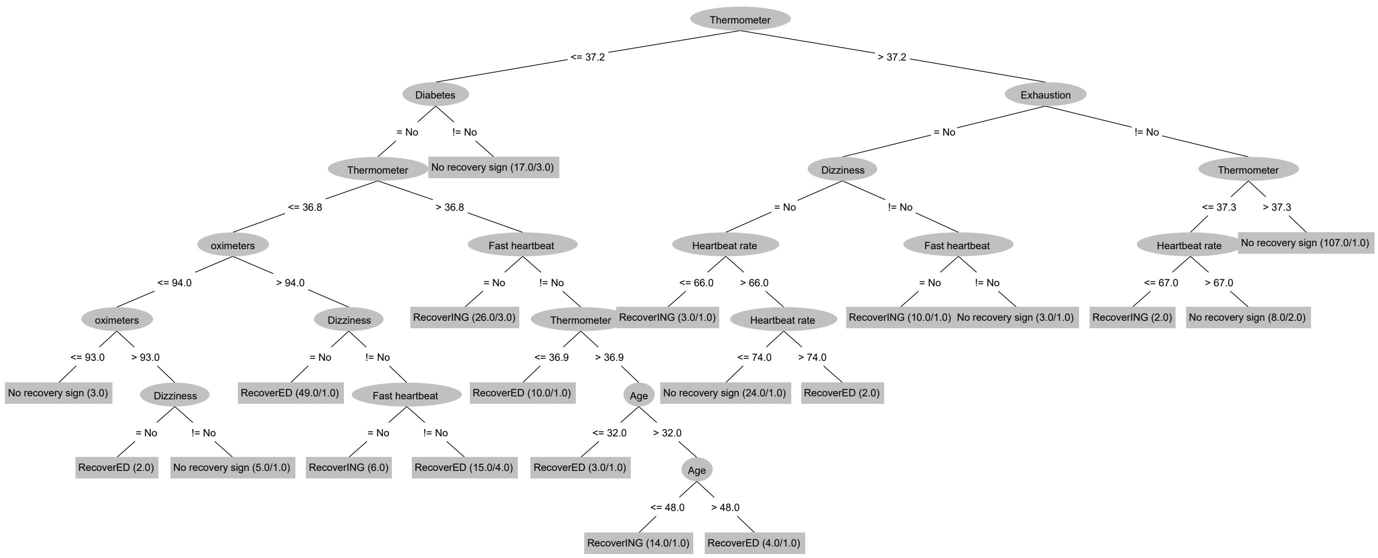


Fig. 10. Classification Tree of Covid19-IQ01 using J48 Algorithm.

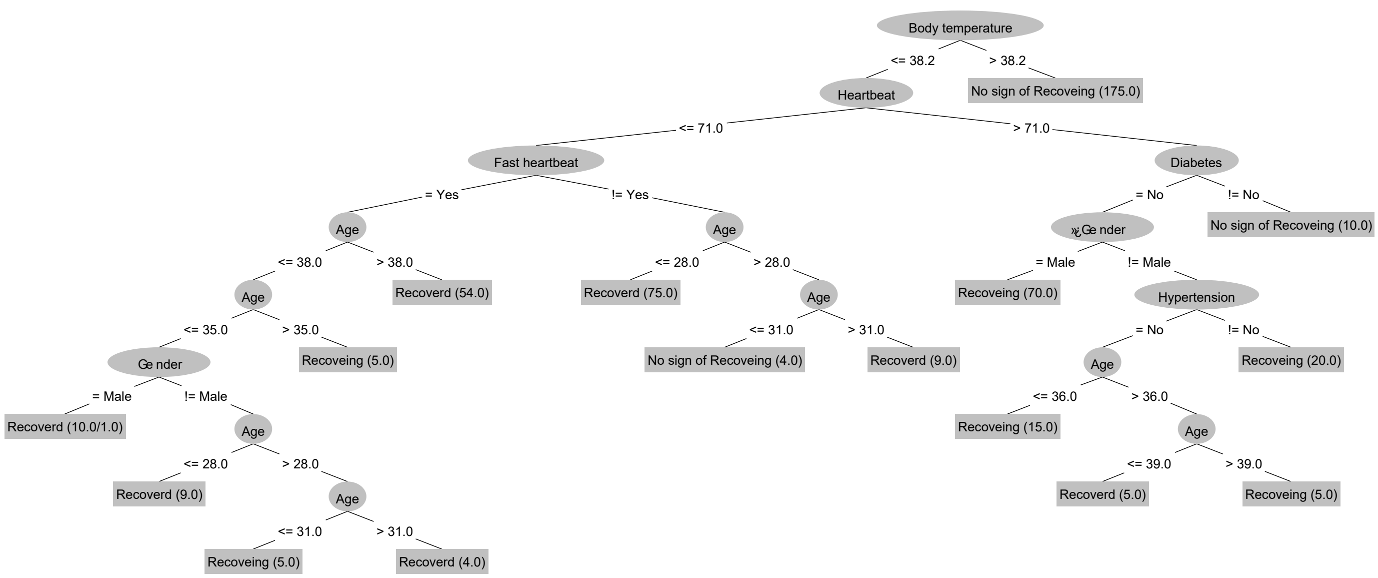


Fig. 11. Classification Tree of Covid19-IQ02 using J48 Algorithm.

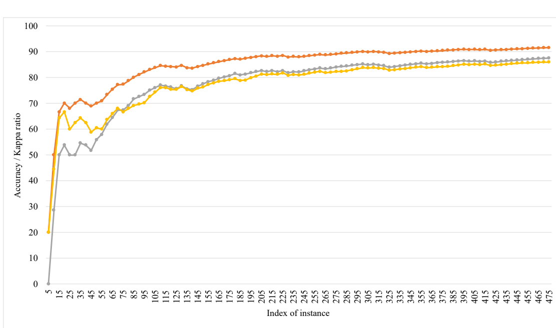


Fig. 13. Classification Performance of Adaptive Random Forest using Covid19-IQ02.

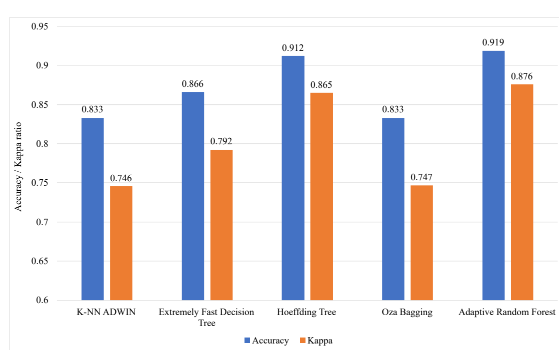


Fig. 14. Classification Performance Comparison among Five Adaptive Classifiers using Covid19-IQ02.

VI. Discussion

The COVID-19 pandemic has caused huge pressure on health systems in most countries due to a large number of infections. Thus, the focus of health institutions was to treat severe cases that needed breathing aids. Many patients were getting medical care at home in moderate and mild cases. Remote monitoring of the patient's recovery can reduce the necessary medical effort and speed up the return of the patient's normal life. This work proposes a classification system that determines whether or not a patient has recovered based on a set of patient biomedical and clinical data using machine learning techniques.

The process of collecting data on COVID-19 patients was one of the most difficult stages of this work due to the risks of transmission of the virus and continuous exposure to the virus. In addition, the quarantine laws for COVID-19 patients make them only accessible by certified health workers. Moreover, there was a challenge in finding COVID-19 patients health workers that are willing to volunteer for the study. This is due to the fact that volunteers require insurance and convincing that the proposed system guarantees security, ease of use, confidentiality, and effectiveness of using such health systems. In addition, due to the difficulty of gaining permission from governmental health intuitions to conduct this study, the focus was on private (non-governmental) medical clinics that were receiving patients, and they asked to use the bracelet to record their vital signs without using their names and any personal information using the proposed system.

The analysis of the collected data indicates that the vital signs data from the proposed wearable device sensors was more useful for the classification of the patients without chronic diseases. The patient's age significantly correlated with the recovery status, as the results showed. The younger patient tends to recover more than the adult and the elderly. However, a child or young person with a chronic disease is less likely to recover. Also, the impact of diabetes and its importance in building the classifiers, thereby predicting the recovery, was more than the impact of high blood pressure. However, the ranking of features during the process of building the classifier showed that the sensors data had more Gain ratio in the second dataset, which contains multiple readings (five) for each patient. In J48 classifier, which was the base learner for the two implementations, the root node was body temperature reading, and that can clarify the effectiveness of the proposed wearable device. Finally, as far as we know, this work is the first research analysis of COVID-19 patients' data using machine learning in Iraq. We look forward to extending the patients' sample and applying more improvements in data classification.

VII. Conclusion

Monitoring and home medical care contribute to focusing the medical effort on severe cases, especially during the spread of pandemics. The proposed system aims to design and implement a classifier capable of predicting a patient's recovery from COVID-19 and providing the medical staff with an immediate alert if the patient's condition declines. The implementation phase included collecting data from 408 patients, and the analysis of these data showed a significant correlation between the factors of chronic diseases, age, and patient recovery. The ensemble classification produced two classifiers. The first one was based on AdaBoost; it had the best accuracy of 0.874 compared with four classifiers with the first dataset and 0.998 with the second one. The second classifier was based on Adaptive Random Forest, which had the best accuracy of 0.919 compared with four adaptive classifiers. The ranking of features in AdaBoost classifiers showed more importance for the vital signs collected by the proposed system than the symptoms. Future works might include testing the the proposed classifier system on stream of data and provide instant predictions.

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