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ORIGINAL RESEARCH

An elderly health monitoring system based on biological and behavioral indicators in internet of things

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Abstract

Advancement of sensor technologies has conducted to the rapid evolution of platforms, tools and approaches such as Internet of Things (IoT) for developing behavioral and physiological monitoring systems. Nowadays, According to growing number of elderlies living alone without their relatives scattered over the wide geographical areas, it is significantly essential to track their health function status continuously. In this paper, an IoT-based health monitoring system is proposed to check vital signs and detect biological and behavioral changes via smart elderly care technologies. It provides a health monitoring system for the involved medical teams to continuously monitor and assess a disabled or elderly's behavioral activity as well as the biological parameters, applying sensor technology through the IoT devices. In this approach, vital data is collected via IoT monitoring objects and then, data analysis is carried out through different machine learning methods such as Decision Tree (J48), Sequential Minimal Optimization (SMO), Multi-Layer Perceptron (MLP) and Naïve Bayes (NB) classifiers for detecting the level of probable risks of elderly's physiological and behavioral changes. The experimental results confirm that the SMO, MLP and NB classifiers meet approximately close performance considering the accuracy, precision, recall, and f-score factors. However, the J48 method shows the highest performance for health function status predicting in our scenario with 99%, of accuracy and precision, 100% of recall and 97% of f-score. Moreover, the J48 performs with the lowest execution time in comparison to the other applied classifiers.

Keywords Internet of things · Health monitoring system · Smart elderly care · Data mining

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1 Introduction

Today's world involves various challenges of fast-rising population of elderlies and consequently increasing healthcare expenditures (Cai et al. 2018). Regarding the general risks and rapid decreasing health condition of elderlies in a short time, aged people's health issues become a crucial problem that arouse research interests (Naranjo et al. 2018). Fortunately, new emerging sensor and network technologies provide the context of the Internet of Things (IoT) (Asghari et al. 2020), in which many connected things can communicate to each other to transfer essential data for accurate and real-time decision making in critical situations (Asghari et al. 2019a). IoT effectively contributes to provide smart healthcare systems for assisting aged and disabled people especially when they may have some possible reasons to independently live alone (Henze et al. 2016).

With respect to progress in applying modern sensor technology and IoT (Hussain et al. 2015; Souri et al. 2019), many smart healthcare and medical monitoring systems and frameworks have been provided (Hamim et al. 2019). For instance in (Al-Khafajiy et al. 2018), a novel framework was proposed that could benefit from the Fog technology through improvements in quality of service (QoS) provided for healthcare systems that involve with dealing out of delay sensitive data which must be rapidly processed for real-time checking of patients. Also in (Al-khafajiy et al. 2019), a remote monitoring system for tracking health status of aged people through wearable sensors was presented (De Maio et al. 2019). The proposed framework in this paper comprises wearable sensors and a smart-phone application in which the required patient's vital signs values are collected and referred to a cloud data center for storing and analyzing process to detect possible abnormal variations in patent's health status. Also, according the importance of the issues related to resource management in medical monitoring and health care systems, the challenges and solutions in this direction have been focused in some researches. For instance in (Dighriri et al. 2018), a scheme for effective and operative deployment of the 5G radio resources for smart objects collaboration with network slicing was proposed. High multiplexing improvement in packet data convergence protocol layer of the relay node layer which is provided for data packets from a number of devices is the advantage of this work, besides considering various priorities to address the end-to-end delay of packets. As well, in (Oueida et al. 2018) a framework for resource management by Petri net using edge computing was proposed that meet the requirements such as reliability, efficiency and security of emergency departments systems like healthcare systems.

Most research studies focused on prediction of diseases such as autism, thyroid disorders, and diabetes (Asghari et al.). However, besides monitoring elderlies' vital signs other physiological factors involve of activity forms of the elderlies are also indispensable for decision making systems (Fried et al. 2001). These limitations lead us to provide an elderly health monitoring system based on the health function status of aged people in an IoT platform that tracks both of biological and behavioral indicators simultaneously. The proposed system comprises of biomedical sensors and health nursing tools that unceasingly monitor the elderly's general health function status. We propose a method for combining the behavioral information and physiological vital sign values for data analysis. Our proposed system is developed for detecting the high risk situations such as heart attack and high diabetes and also, identifying changes in physical activities such as poor vision, insomnia, incontinence and weight loss in elderlies via data mining methods over the regular monitoring. The main contributions of this paper are as follows:

1. Online data collecting in IoT context.
2. Predicting elderly's Health Function Status (HFS) through continuously monitoring two different categories of influencing health parameters. (a) The first sort of the required data comprises the related changes in behavioral status including the alterations in vision, hearing, weight and appetite, and also monitoring them for possible happening of insomnia, incontinence and falling down. (b) The second group of the essential considered data consists of important vital signs such as heart rate, respiratory rate, oxygen saturation, body temperature, blood glucose, and blood pressure. These two groups of parameters were not considered simultaneously in previous relevant studies while monitoring and analyzing both of the groups can aid efficiently to detect emergency situations in aged and disabled people.
3. Assessing the behavioral and biological changes through different data mining methods in order to evaluate the elderly's health function and compare the outcomes to prove which method has the highest effectiveness for accurate elderly's health monitoring.

The rest of this paper is organized as follows. Section 2 provides a momentary review on existing related works in this area. In Sect. 3, the explanations about the proposed model are presented that consists of four stages that are responsible for collecting data and analyzing them by means of data mining methods for predicting the elderly's Health Function Status (HFS) based on biological and behavioral indicators. Section 4 illustrates the experimental results of the proposed system by statistical analysis using some existing data classification methods and comparing the obtained results. In Sect. 5, conclusions and some future research directions in this context are proposed.

2 Related work

A number of research studies have been presented in IoT-based healthcare systems in recent years. For example, Kaur et al. (2019) applied different techniques of machine learning including K-NN, Support Vector Machine (SVM), Decision Trees, Random Forest (RF), and Multi-Layer Perceptron (MLP) besides healthcare datasets stored in the cloud space for improving the interaction between doctors and patients based on IoT infrastructures, which makes remote health monitoring possible. In this study, the prediction systems were assessed for heart disorder, diabetes, breast cancer, thyroid, dermatology and liver disorder. The experimental results revealed that the RF technique achieved the highest accuracy of 97.26% on dermatology dataset. Hamim et al. (2019) presented an android application based on IoT which consists sensor of a heart pulse, body temperature sensor and sensor of galvanic skin response. All the data obtained from the sensors stored and transferred to cloud space to remote health monitoring. In this paper, we extract behavioral and biological parameters of low-ability elderly through IoT based healthcare systems and then had merged to proposed appropriate medical service. The similarity of this paper with the previously studied articles is few and relatively insignificant.

Recently, some effective frameworks and scheme have been proposed in healthcare scenario. For instance, Al-Khafajiy et al. (2018) got into details and challenges of Fog-driven IoT healthcare systems. The authors presented a novel framework that could benefit from the Fog technology via improvements in quality of service (QoS) provided for healthcare systems that involve with dealing out of delay sensitive data which must be rapidly processed for real-time checking of patients. In this paper, a three-layer architecture comprising IoT-things or sensor layer, fog layer and cloud data layer was presented beside a framework for Fog2Fog collaboration to provide optimal job allocation and proper management of resources to obtain the best possible QoS in IoT-things layer such as healthcare systems that deal with delay sensitive applications and data. Also, Al-khafajiy et al. (2019) proposed a remote monitoring system for tracking health status of aged people through wearable sensors. A frame work was presented in this paper that consists of wearable sensors and a smart-phone application in which the required patient's vital signs values are collected and sent to a cloud data center for storing and analyzing process to detect possible abnormal changes in patent's health status. The obtained result from simulation revealed that the proposed systems with gaining low latency and low packets-lost can be a cost-effective solution for healthcare systems.

Dighriri et al. (2018) suggested a scheme for effective and operative deployment of the 5G radio resources for smart objects collaboration with network slicing. The resources are used and shared by the objects to increase the performance of the system. The offered resource allocation scheme allocates the resources in a dynamic manner with a heuristic approach to permit slices based on the existing load of traffic and considering the well using of the smallest untie of physical resource blocks via gathering the data from a number of devices in 5G networks. In this scheme, a high multiplexing improvement in packet data convergence protocol layer of the relay node layer is provided for data packets from a number of devices besides considering various priorities to address the end-to-end delay of packets. The experimental outcomes revealed that the superior network resource management and also the cell throughput enhancement and end-to-end delay of 5G data traffic improvement were met by this approach.

Also, Oueida et al. (2018) proposed a framework for resource management by Petri net using edge computing that meet the requirements such as reliability, efficiency and security of emergency departments systems like healthcare systems. The simulation results of the offered framework showed the major enhancements in patient length of stay, waiting time, and resource exploitation.

Finally, in some research studies (Balasubramanian et al. 2020; Chung et al. 2020; Maio et al. 2015; Shah et al. 2019) deep learning and machine learning approaches were applied to evaluate critical chronic diseases respectively. Also, important factors such as accuracy, precision and error rate have been compared to evaluate the proposed approaches.

Table 1 indicates a brief summary of the main objective, applied technology, applied algorithm and evaluation factors in the studied papers and our proposed model.

3 Proposed IoT-Based elderly health monitoring system

The proposed system encompasses four phases including: (1) Determining the required data for Health Function Status (HFS) assessment according to the biological and behavioral indicators, (2) Data collection via bio-medical sensors and smart IoT devices, (3) Data preprocessing, (4) HFS assessment process based on the proposed diagnosis algorithm and data mining methods. The modular structure of the proposed system is illustrated in Fig. 1.

Figure 2 shows the conceptual model of the proposed IoT-based elderly health function monitoring system.

As shown in Fig. 2, the proposed conceptual model for elderly HFS monitoring system includes three blocks including IoT environment, data mining block and medical care center for executing the mentioned procedure for predicting the HFS:

Table 1 Comparison of related works

Reference	Main objective	Applied technology	Applied algorithm	Evaluation factors				
				Accuracy	Precision	Recall	F-score	Execution Time
Kaur et al. (2019)	Remote health monitoring	IoT	Random forest (RF)					
Hamim et al. (2019)	Making a remote health monitoring system	IoT	–					
Al-Khafajiy et al. (2018)	Presenting a new framework for Fog-driven IoT healthcare systems	IoT Fog Cloud	–					
Al-khafajiy et al. (2019)	Proposing a remote health monitoring system for elderly using wearable sensors	IoT Cloud	–					
Dighriri et al. (2018)	Proposing a data traffic aggregation model and algorithm in fixed relay nodes for uplink in 5G cellular networks	Cloud	–					
Oueida et al. (2018)	Proposing an Edge computing based smart healthcare framework for resource management	IoT Edge Cloud	–					
Our proposed model	Proposing an IoT-based model for elderly health monitoring system based on biological and behavioral indicators	IoT Cloud	Decision Tree (J48), Sequential Minimal Optimization (SMO), Multi-Layer Perceptron (MLP), Naïve Bayes (NB)					

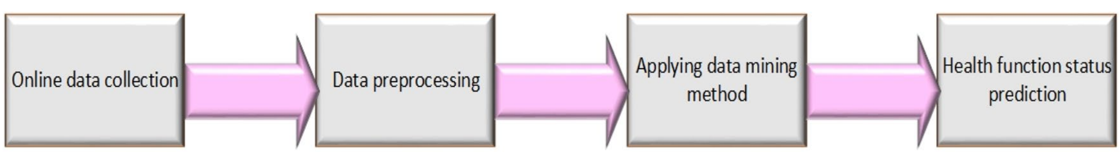

Fig. 1 The modular structure of the proposed system

- IoT environment*:* the IoT data are collected via bio-medical and wearable sensors. Similarly, clinical alterations are picked up through personal area network in patient's sphere.
- Data mining*:* The collected data are transmitted to the cloud centers for storing and any possible data mining process for detecting abnormal situation in elderly's health function status (HFS).
- Medical care center: The outcomes of the HFS prediction are distributed to the medical care centers to provide essential medical orders and health recommendations and warn the patient about her abnormal condition.

3.1 Determining the required data for HFS monitoring in elderlies

Most of the previous studies have focused on some clinical symptoms for health function monitoring in elderlies comprise of cardiovascular disorder, diabetes, and dementia (Mello et al. 2014; Naranjo et al. 2018). However, in addition to the mentioned diseases, there are several indicators for elderly's health status monitoring which all them are vital to assess (Rockwood et al. 2005; Ware 2000). The main elderly's health function parameters have two aspects consist of clinical indicators and vital signs indicators which their

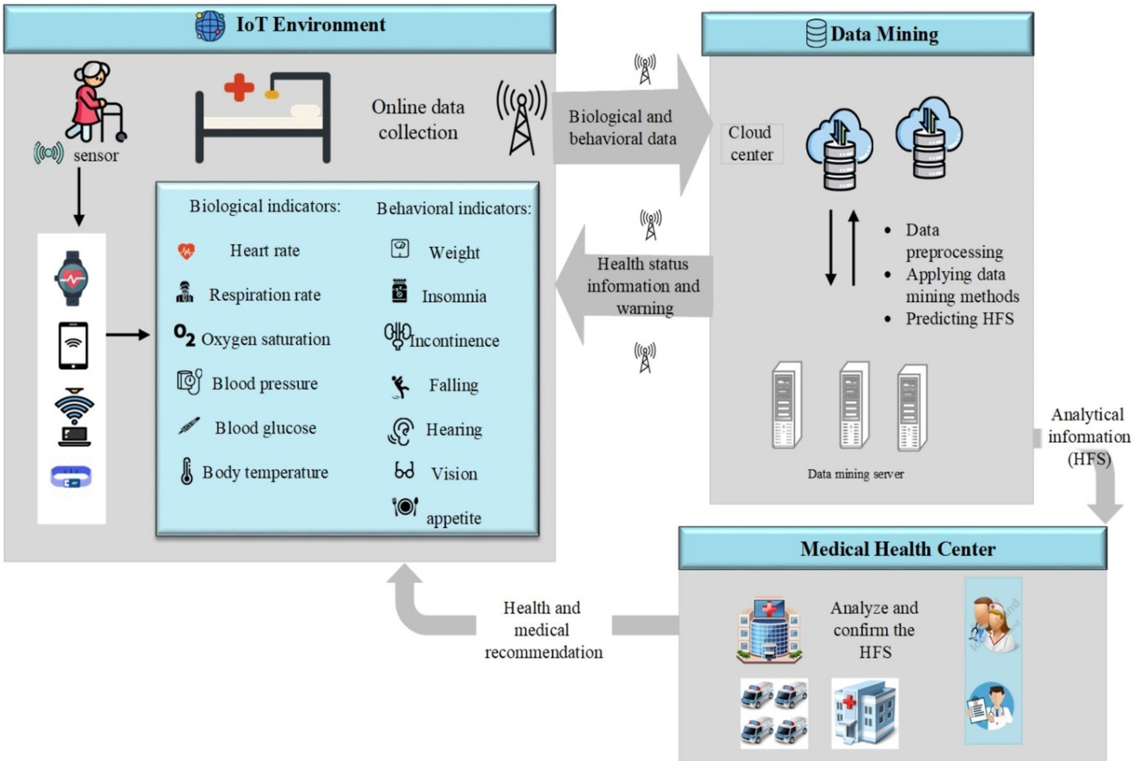

Fig. 2 The proposed elderly health monitoring system in IoT platform

Table 2 The main elderly's clinical indicators and their definition

Clinical indicator	Definition
Reduced appetite (yes/no)	Whether reduced appetite has occurred in the past 2 weeks
Weight loss (Kg.) (yes/no)	Whether over 2 kg. weight loss has occurred in the past 2 weeks
Incontinence (yes/no)	Whether incontinence has occurred in the past 2 weeks
Poor vision (yes/no)	Whether the current vision affects the performance of daily activities
Poor hearing (yes/no)	Whether the current hearing affects the performance of daily activities
Falling (yes/no)	Whether falls have occurred in the past 2 weeks
Insomnia (yes/no)	Whether insomnia has occurred in the past 2 weeks

definition and normal limits are depicted in Tables 2 and 3 (Asghari et al. 2020).

3.2 Data collection

To monitor the elderly's HFS, the IoT data ought to be collected via IoT medical devices. The collected parameters encompass the data which sensed by the deployed bio-medical sensors on the elderly's cloth or her body with Body Area Network (BAN) and embedded sensors in clothing to catch the vital signs such as systolic and diastolic blood pressure, heart rate, oxygen saturation, blood sugar, and other physiological data. Also, a Personal Area Network (PAN) can be used for monitoring the elderly's behavioral changes and emergency situations (Mainetti et al. 2016). The IoT devices unceasingly sense and collect the values of health function indicators in order to measure the HFS of the elderly.

Table 3 The main elderly's vital signs and their normal limits

Vital signs
Heart Rate (number/minute) Normal: 60–100
Respiratory rate (number/minute) Normal: 8–12
O_2 saturation (percent) Normal:≥ 96%
Blood sugar/ fast FBS (mg/dL) Normal 70–100 Diabetes: 101–125 Diabetes:≥ 126
Blood sugar/ post-meal (mg/dL) Normal ≤ 140 Pre Diabetes: 141–199 Diabetes ≥ 200
Isolated systolic blood pressure Normal: 110–139 Hypertension:≥ 140
Isolated diastolic blood pressure Normal: 80–89 Hypertension:≥ 90
Body temperature (℃) Normal: 36.5–38

3.3 Data preprocessing

It is needed to be taken a data preprocessing step for the collected IoT medical data to make them clean from noises and inconsistencies for the data mining process. Also, some feature selection techniques are used for the objective of dimensions reduction for making easy the classification phase for HFS evaluation process (Asghari, Rahmani, & Haj Seyyed Javadi).

3.4 HFS assessment in elderlies

With respect to two groups of indicators the elderly's health function can be measured. In this system the HFS of elderly is categorized in six states including: (1) Very good, (2) Good, (3) Fair, (4) Poor, (5) Very poor and (6) Emergency status. The various statuses are derived based on the values of both groups of health function parameters regarding the provided Tables 1 and 2, through performing the assessment Algorithm 1. According to the derived health status, required recommendations are provided for the elderly.

Algorithm 1: Assessment of Health function status

Input: behavioral data, vital signs
Output: Health Function Status (HFS)

Begin

1. **Read** the behavioral data, vital signs.
2. **Check for** behavioral data based on (Reduced appetite, Weight loss, Incontinence, Poor vision, Poor hearing, and Insomnia);
3. **If** all the behavioral parameters have the value of "No" then behavioral-status = 0
4. **Else** behavioral-status= number of "Yes" values which is between [1..7];
5. **Check** vital signs based on (Heart rate, Respiratory rate, O_2 saturation, Fast blood sugar, Post-meal sugar, Diastolic blood pressure, Systolic blood pressure, and body temperature);
6. **Case 1: If** behavioral-status = 0 and all the vital signs are in the normal range then HFS= "Very Good";
7. **Case 2: If** behavioral-status = 0 and 1 vital sign is out of range then HFS = "Good";
8. **Case 3: If** behavioral-status = 1and 2 vital signs are out of range then HFS= "Fair" ;
9. **Case 4: If** behavioral-status = 2 and 3 vital signs are out of range then HFS= "Poor";
10. **Case 5: If** behavioral-status = 3 and 4 vital signs are out of range then HFS= "Very Poor" ;
11. **Case 6: If** behavioral-status ≥ 4 and more than 4 vital signs are out of range then HFS= "Emergency Status" ;

15. **Return** the HFS evaluation;

End.

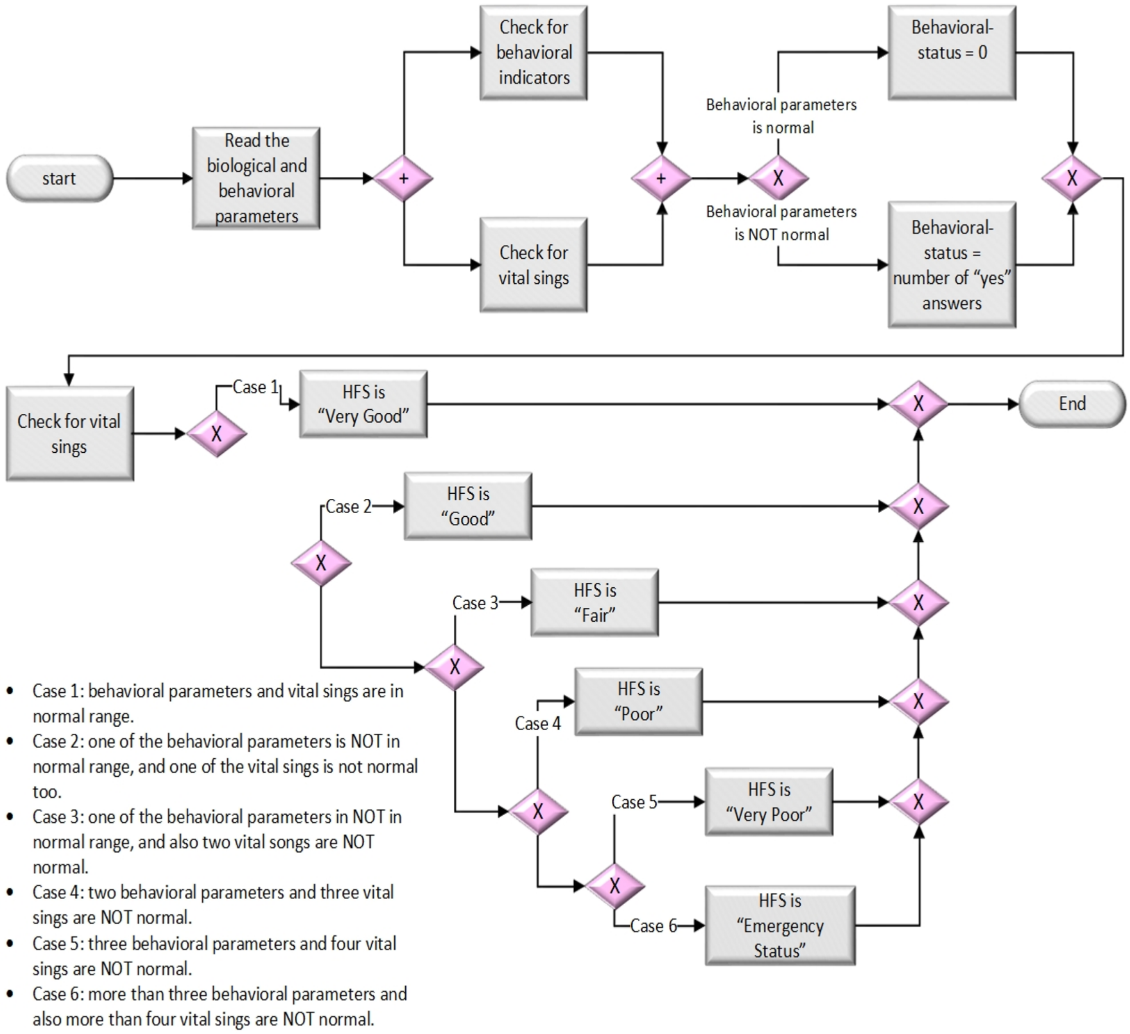

Fig. 3 The workflow of the HFS assessing

The workflow of algorithm 1 through the business process model and notation (BPMN) for HFS assessing is illustrated in Fig. 3 (Asghari et al. 2019b; Geiger et al. 2018). In this work flow, some tasks appeared in sequence form however, a number of tasks are linked by '+' gate for parallel execution of tasks. In our scenario, checking behavioral indicators and vital signs can be done in parallel at the same time. Exclusive gate which is displayed by '×' that signifies a branch regarding the happened condition. When the exclusive gate is used, only one of the tasks can be performed. Also, the other gate is inclusive, that is exposed by 'O' which defines the options for the task selection regarding the conditions

Table 4 The assessment parameters for evaluating the efficiency of the HFS prediction

Assessment parameters	Formula	Description
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$	Defines the value of correctly predicted instances as normal or abnormal samples
Precision	$\frac{TP}{TP+FP}$	Indicates the positive predictive value that defines the portion of abnormal instances between all the samples
Recall	$\frac{TP}{TP+FN}$	Indicates the portion of abnormal instances that have been retrieved over all the abnormal samples
F-score	$\frac{2\times Precision\times Recall}{Precision+Recall}$	Shows the system performance by relating recall and precision factors
Execution time	_	The time needed for completing the prediction process

that have been selected based on the current states. Here, this symbol was nor needed to use according to the proposed scenario for assessing the HFS.

4 Experimental results

In our study, in addition to vital signs that have been applied as required features in previous studies, the behavioral features shown in Table 3 are applied for effective elderlies' HFS prediction, however none of them were not considered in other studied papers. For evaluating our proposed model, a dataset with 300 samples were used that includes all the features shown in Tables 2 and 3.

For assessing the efficiency of HFS prediction, five key factors of precision, accuracy, f-score, recall and execution time are calculated. Table 4 explains the assessment parameters with a description and their equations based on the confusion metrics which are commonly used for evaluating the machine learning classifiers performance (Lakshmanaprabu et al. 2019).

The confusion matrix holds the samples which contain four parameters including: (1) True Positive (TP) that defines the samples which have been correctly classified as abnormal instances, (2) False Negative (FN) that indicates the abnormal samples which have been classified wrongly as normal ones. (3) False Positive (FP) that defines the normal samples which have been classified incorrectly as abnormal cases, and (4) True Negative (TN) that shows the normal samples which have been correctly classified (Cai et al., 2018).

In the proposed system, different classification methods are applied for HFS prediction process on collected samples (Brunström et al. 2016; Horr et al. 2016). This research also considers the mentioned parameters to estimate the performance of applied classification methods. The classification results attained by Weka 3.6 with the different machine learning classifiers including: Decision Tree (J48) (Kaur et al. 2014), Sequential Minimal Optimization (SMO) (Mishra et al. 2016), Multi-Layer Perceptron (MLP) (Pal et al. 1992) and Naïve Bayes (NB) (Devasia et al. 2016). The dataset is verified by trained classifier.

Here, the k-fold cross-validation method is applied wherein the dataset is divided into k mutual-exclusive folds of near equal size randomly for k times training and testing the classifier. This method is used to lessen the bias of random selection of samples in the training phase for evaluating the accuracy of different classifiers. Stratified k-fold cross validation method, is a common technique in which the folds are made of an equal portion of labels for making the different dataset. Mostly, the stratified k-cross technique provides assessment results with minimum variance and bias in contrast to fixed k-fold cross-validation. In the cross-validation method, the accuracy parameter is measured as the whole number of correct classifications, which is separated by the samples in the dataset. Correspondingly, the accuracy parameter of cross-validation is commonly based on the random scattering of the instances into k dissimilar folds. Here, for assessing the performance of the mentioned classifiers, a stratified k-fold cross-validation is applied with values of 1, 5, 10, 15 and 20 for k.

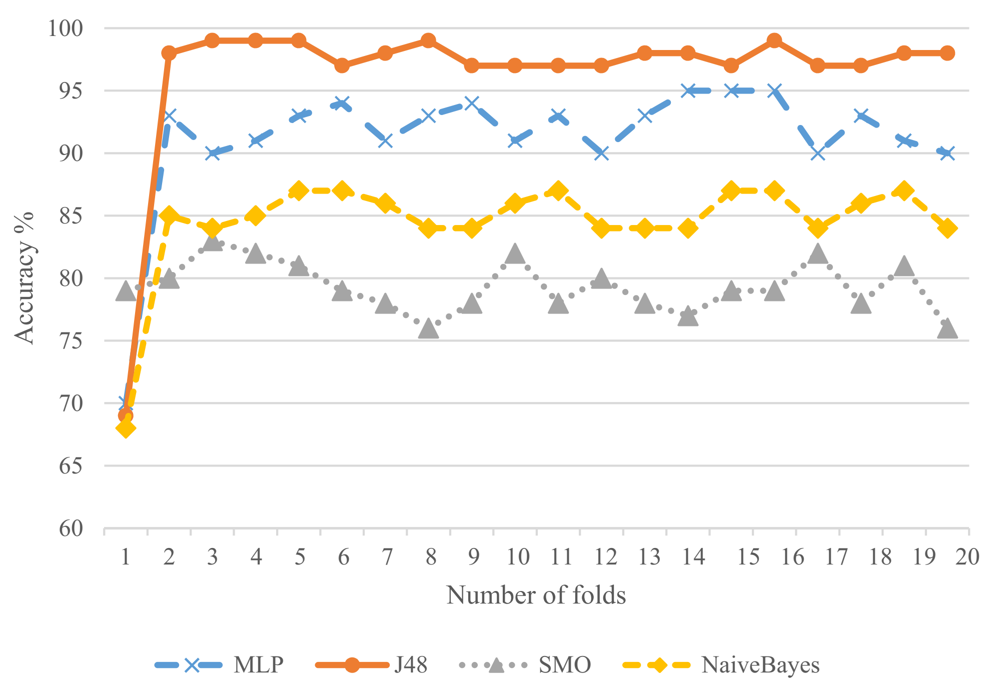

Fig. 4 Accuracy of the proposed model with 20 cross-validation fold

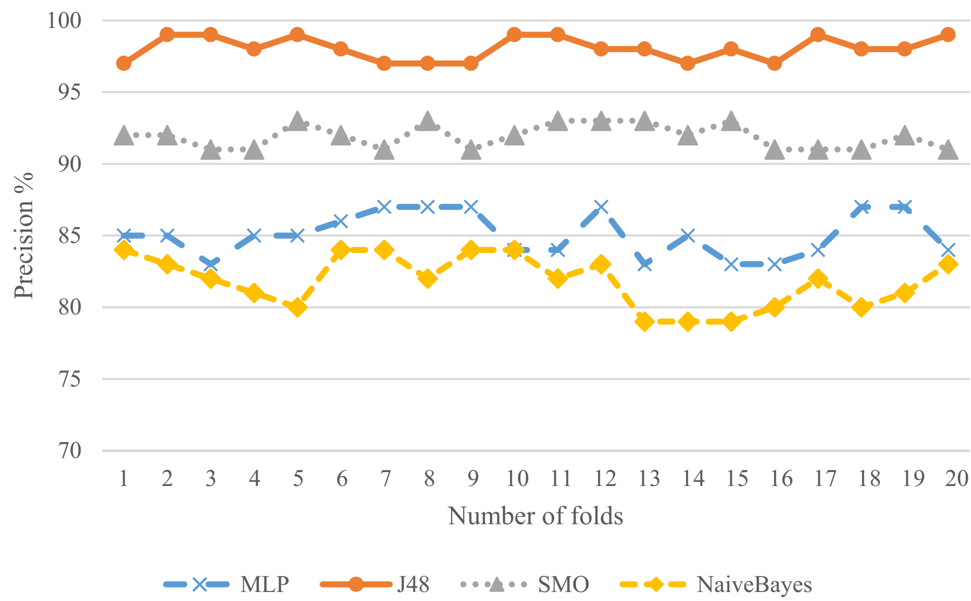

Fig. 5 The precision of each algorithm with 20 cross-validation fold

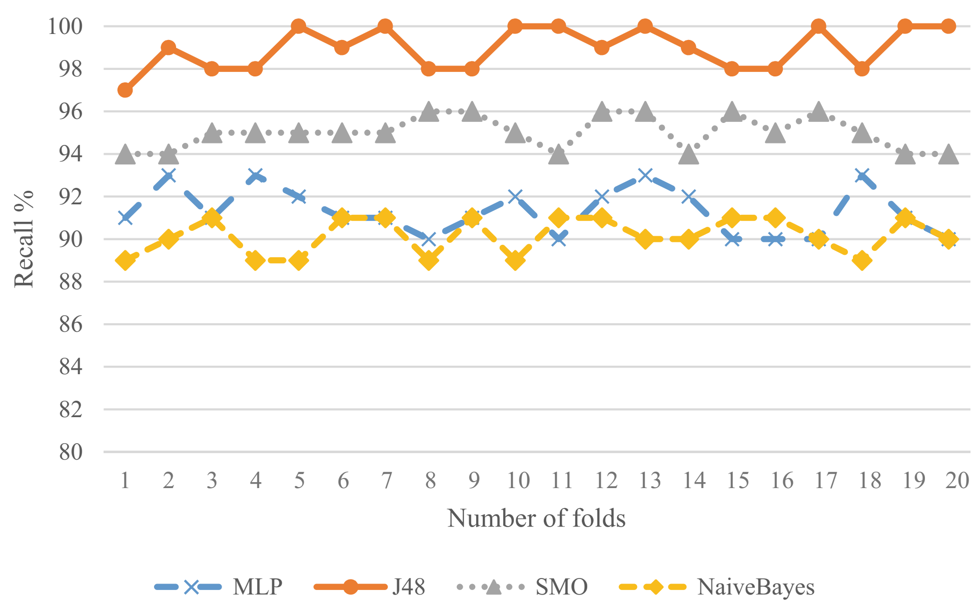

Fig. 6 Recall area of each algorithm with 20 cross-validation fold

The acquired outcomes from the different classifier are shown in Fig. 4, 5, 6, 7, 8 that indicates the performance evaluation of four mentioned classification method with different cross folds..

As shown in Fig. 4, the J48 classifier has achieved the highest accuracy of 99% in comparison to the MLP method with 95%, the NB with 87% and the SMO with 84% for this parameter.

Figure 5 shows that, the J48 method has gained the highest precision of 99% comparing to the SMO classifier with 93%, the MLP with 87% and the NB with 84% for this factor.

As shown in Fig. 6, the J48 method has reached the highest recall value of 100% comparing to the SMO classifier with 96%, the MLP with 93% and the NB with 91% for this factor.

Figure 6 reveals that the J48 classifier has gotten the highest f-score value of 97% comparing to the SMO classifier with 93%, the MLP with 89% and the NB with 84% for this parameter.

Also, as shown in Fig. 8, the SMO method has been performed with highest execution time of 97 ms among the other classifiers. The NB and the MLP methods have been executed in 78 and 41 ms, and finally, the J48 classifier has been performed with lowest execution time of 12 ms over the same dataset.

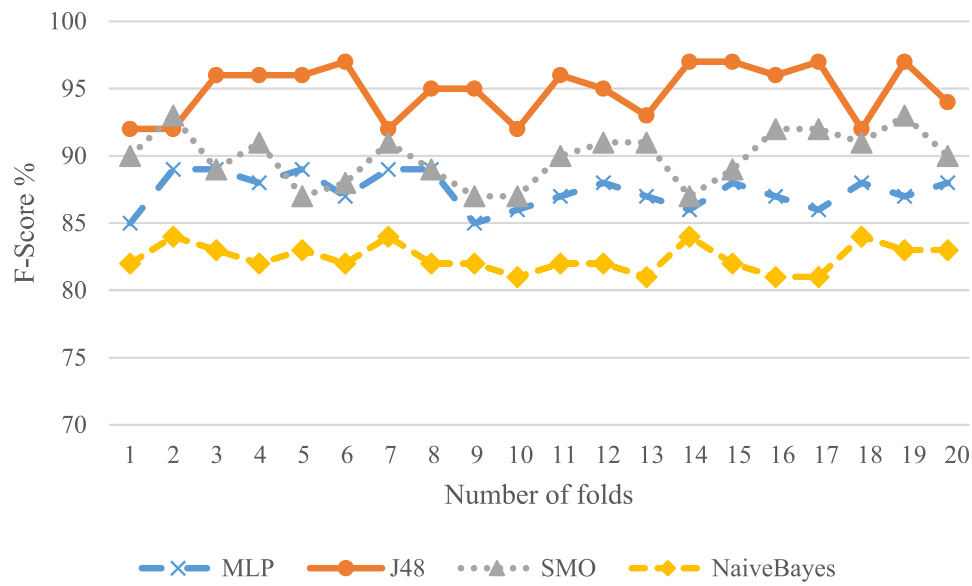

Fig. 7 F-Score area of each algorithm with 20 cross-validation fold

Regarding the obtained outcomes, all the classifiers have achieved about acceptable results regarding the values of accuracy, precision, recall, and f-score. However, considering the execution time of the applied classifiers, the outcomes have revealed that the Decision Tree (J48) method has performed in the lowest execution time with a significant difference comparing to the other methods. In summary, the J48 method with an accuracy of 99%, a precision and recall of 99 and 100% and f-score result of 97% and also, the minimum exclusion time of 12 ms is the most high-quality method compared to the others. Therefore, it can be revealed that in our HFS predicting scenario, the J48 classifier has the highest performance between the other classification methods.

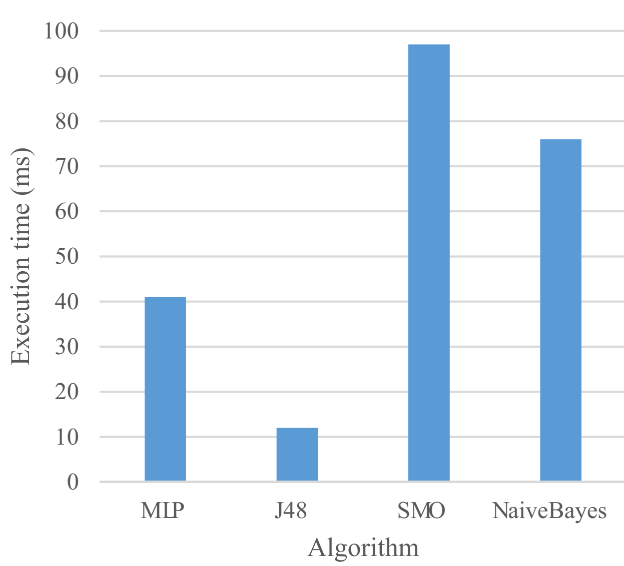

Fig. 8 Average execution time for existing algorithms

5 Conclusion and future work

According to the importance of the problem of rapid growth of elderlies' population in today's societies, living alone without their relatives is meaningfully indispensable to monitor uninterruptedly their' health function status. With emerging sensors technology, many tools and applications have been developed for elderlies' health monitoring systems in IoT. According to the crucial need for such systems, we proposed an elderly health monitoring system based on biological and behavioral indicators in IoT. Regarding the conceptual model and the modular structure of the proposed system, four steps have been considered. The steps consist of (a) determining the required data for Health Function Status (HFS) assessment according to the biological and behavioral indicators, (b) data collection via bio-medical sensors and smart IoT devices, (c) data preprocessing and (d) finally, HFS assessment process based on the proposed diagnosis algorithm and different classification methods. The decision tree (J48), Sequential Minimal Optimization (SMO), Multi-Layer Perceptron (MLP) and Naïve Bayes (NB) methods were the applied classifiers for our HFS prediction model. The experimental results revealed that the mentioned classifiers were performed with approximately close results considering the accuracy, precision, recall, and f-score. Among all the applied classification algorithms, the J48 reached the highest performance for HFS predicting in our scenario in terms of 99% for accuracy and precision, 100% for recall and 97% for f-score. Furthermore, the J48 attained the lowest execution time of 12 ms in comparison to other applied classifiers with a significant difference that make this method applicable in real-time health function status monitoring for elderlies. As the future work, we intend to consider more elderlies to check the robustness of our model with a greater dataset. Also, we are planning to implement our proposed elderly health monitoring system in a real IoT environment to get into details of challenges of the real physical world.

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