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Personalized Health Monitoring System of Elderly Wellness at the Community Level in Hong Kong

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ABSTRACT Rapid advances in information and sensor technology have led to the development of tools and methods for personalized health monitoring. These techniques support timely and efficient healthcare services by tracking the vital signs, detecting physiological changes and predicting health risks. In this paper, we propose an integrated system to monitor the wellness condition of elderly. This system is conceptualized to provide a computer-aided decision support for clinicians and community nurses, by means of which they can easily monitor and analyze an elderly's overall activity and vital signs using a wearable wellness tracker and an all-in-one satiation-based monitoring device, offering an efficient solution with a reduction in time cost and human error. We design a data-preparing scheme for acquiring data and processing data from multiple monitoring devices, and propose a personalized scheme for forecasting the elderly's one-day-ahead wellness condition via data integration and statistical learning. We conduct a pilot study at a nursing home in Hong Kong to demonstrate the implementation of the proposed system. The proposed forecasting scheme is validated by the collected data.

INDEX TERMS Classification, data mining, health monitoring system, smart elderly care, wellness forecasting.

I. INTRODUCTION

Hong Kong faces the challenge of a rapidly growing population of elderly and rising healthcare spending. According to the Hong Kong Census and Statistics Department, the population of elderly aged 65 years old or above will expand significantly from 15% in 2014 to 36% in 2064 [1]. The healthcare expenditure provided to the elderly by public healthcare sector has been found to be much higher than those of younger population. Elderly care, therefore, has become one of the highest priorities in local government concerns [2]. There is an urgent need for seeking effective strategies for easing the heavy burden on elderly care. A smart system for continuous health monitoring is a key technology in helping the transition to more proactive and affordable healthcare. Restructuring health care systems toward proactive approach, characterized by early detection of a negative health condition, prevention, and long-term healthcare management emerge as a possible solution.

With advances in technology and data communication, plenty of health monitoring systems have been developed in past decade [3]–[7]. Most recent studies involved chronic conditions [8]–[10], rehabilitation [11]–[13], cardiovascular disease [14]–[16], fall [17], [18], and general wellness [19]–[22]. Most of these studies focused on the system aspects based on a specific area of disease. The current research on health monitoring system can be divided into two main categories. The first category lies in hardware development, including easy-to-use, reliable wearable sensors and centralized utilization system; while the other category focuses on data analysis using data gathered from various healthcare related sources. In recent years, the research trends have shifted from hardware development and measurement validity to the application level and from institution-centric support systems to patient-centric system [23]. However, wider acceptance of the existing systems for continuous monitoring is still limited due to the following restrictions: (i) data processing and analysis are performed offline; (ii) most of the current systems focus on the use of the individual smart device and offer mainly instantaneous single-parameter measurement. Thus, to take next big steps in healthcare requires a computing and analytics framework to integrate big data, discover deep knowledge, and provide a personalized assessment of health.

Personalized health monitoring system takes advantage of data mining, decision support system, and context-aware system to facilitate diagnosis, treatment, and care based on an individual's genetic lifestyle. These systems allow individuals to closely monitor his or her own vital signs and alert medical personnel when a life-threatening change occurs. The recent study results [24]–[28] imply that the implementation of personalized health monitoring system, with the use of appropriate statistical analysis and data mining tools, can be an effective solution to provide efficient healthcare services. In addition, the idea of using a centralized system to integrate health monitoring measurements through different sources with the aid of smart devices has been proposed as a useful tool for both raising health awareness in the community and elderly home monitoring [29]–[32]. The integrated use of data from multiple sources is useful for obtaining more reliable information than individual measurement obtained from a single type of sources. Thus, it is very important to have simultaneous access to different types of health-related data, such as continues activity record and routine inspection data for on-time prevention, management, and rehabilitation.

To the best of our knowledge, the idea of integrated personalized health monitoring via wearable devices for elderly care is new to Hong Kong. There is currently no smart system integrating data from multiple sources, intelligent processing and triggering alarms to support care plan decision and interact easily at any moment with the health provider. Motivated by the limitations, we focus on constructing an integrated system to monitor the general wellness condition of elderly at the community level, with the help of multiple electronic devices.

In this paper, we propose a personalized health monitoring system of elderly wellness. The system consists of an electronic wearable wellness tracker and an all-in-one station-based health monitoring device that continuously monitors the elderly's overall activity and collects elderly's daily vital signs respectively. We design a data-preparing scheme for acquiring data from multiple monitoring devices. We then propose a solution to integrate continuous activity data and discrete physiological data for subsequent data modeling and analysis. A personalized health monitoring scheme is developed for forecasting the one-day-ahead wellness of elderly by selecting the most be-fitting data mining models for identifying at-risk elderly through daily monitoring.

The rest of the paper is organized as follows. We first describe our clinical study conducted at a nursing home in Hong Kong. We then explain the data acquisition and data processing from each electronic device. Next, we detail the mechanism of our personalized monitoring system. Following that, we use a case study to illustrate the implementation of the system. Finally, we draw our conclusions and discuss future work.

II. PERSONALIZED HEALTH MONITORING SYSTEM

The proposed personalized health monitoring system involved four main steps: (1) data collection; (2) data acquisition; (3) data processing, and (4) personalized health monitoring scheme. The following subsections explain each of these steps in detail.

A. DATA COLLECTION

Eleven elderly aged 65 years old or above were recruited from an elderly nursing home in Hong Kong for a three-month study. The study aimed to demonstrate the integrated use of electronic devices for real-time continuous measurements of vital signs of the elderly, regarding personalized health monitoring and management. They were invited to conduct daily non-invasive assessments with the use of a commercial station-based all-in-one health monitor equipment (TeleMedCare Health Monitor, TeleMedCare, Sydney, Australia), as shown in Fig. 1 (a) [33]–[36]. Trained and qualified research staff visited the elderly nursing home and assisted the elderly to accomplish the daily assessments around 2 pm on each assessment day. Besides, the participants were also asked to wear a commercial electronic wearable wellness tracker (Sony SmartBand 2, Sony Corporation, Japan), as shown in Fig. 1 (b). The participants were instructed not to remove the device at any time. Meanwhile, we develop a 10-point scoring system, named as health index (HI), to quantify the general health conditions of the elderly. As reported by Brent and Carlson, self-perceived physiological parameters were commonly evaluated with tailor-made questionnaires [37]. For example, the SF-36 questionnaire is an assessment designed to evaluate the subject's functional health and well-being, physical functioning, body pain, general health, vitality and mental health. For this study, we considered the daily general wellness of the elderly as the indicator of elderly general well-being. Hence, each participating elderly were asked to self-evaluate their wellness and chose the most appropriate health index (HI) describing their current daily health conditions (Table 1) immediately after their telehealth monitoring device assessment.

(a)

(b)

FIGURE 1. (a) TeleMedCare Health Monitor; (b) Sony SmartBand 2.

B. DEMOGRAPHIC CHARACTERISTICS OF THE ELDERLY

In our study, the eleven recruited elderly's demographic information is summarized in Table 2. In this study, there were six female participants and five male participants. 63.64% of the recruited elderly was aged between 80 to 90 years old. The most prevalent diseases claimed were hypertension

TABLE 1. **10-point self-evaluated health index and their descriptions of the health conditions.**

Health index (HI)	Description of the elderly health conditions
1	Feeling terrible
2	Feeling very unwell but not terrible
3	Feeling worse than average
4	Feeling a little worse than usual
5	Feeling very slightly off but close to usual
6	Feeling very slightly better than usual
7	Feeling a little better than usual
8	Feeling better than usual
9	Feeling much better than usual but not terrific
10	Feeling terrific

TABLE 2. **Demographic characteristics of study population.**

Characteristic	Number	Percent
Age		
65-70	1	9.09
71-80	1	9.09
81-90	7	63.64
91-100	1	9.09
101-103	1	9.09
Gender		
Female	6	54.55
Male	5	45.45
Disease		
Hypertension	8	72.73
Heart disease	0	0.00
Stroke	1	9.09
Diabetes mellitus	5	45.45
Cancer	1	9.09
COPD[a]	0	0.00
High cholesterol	1	9.09
Asthma	0	0.00
Others	1	9.09
Number of medications		
1-4	3	27.27
5-12	8	72.73
Medications		
Antihypertensive drugs	9	81.82
Lipid modifying drugs	1	9.09
Chinese medicine	1	9.09

[a]Chronic obstructive pulmonary disease

and diabetes mellitus, where 72.73% and 45.45% of the participating elderly had claimed those diseases respectively. In addition, three out of eleven recruiting elderly have been prescribed less than 4 drugs and eight of them been prescribed 4 or more drugs at the same time. Nine out of these eleven elderly was having anti-hypertensive drugs, while only one of them was having a lipid-modifying agent and one of them was having Chinese medicine.

C. DATA ACQUISITION

The data available from each elderly were collected from the telehealth monitoring device, Sony SmartBand wellness tracker, and self-reported wellness diaries. The telehealth monitoring device (TMC) allows to daily measure elderly's usual vital signs, including systolic blood pressure (SBP), diastolic blood pressure (DBP), body temperature (BT), heart rate (HR), blood oxygen level (SPO2) and body weight (BW). Each day, these measures were sent electronically to a centralized location after the assessment at 2 pm.

In the Sony wellness tracker, there are photoplethysmography (PPG) sensor and accelerometer installed. We focused on three types of measurement collected, including 'sleep,' 'step' and heart rate (HR). The 'sleep' and 'step' are counted and logged for every minute while the 'HR' is recorded for every ten minutes. The Sony wellness tracker also tracks the status of sleep, i.e., light or deep, types of step, i.e., walking or running, and their corresponding durations. We considered these data as continuous health-related monitoring data. Because different sensors record each measurement with the uses of a different algorithm, we used different data acquisition approaches. These continuous data were first temporarily stored in the internal storage of the wellness tracker and were uploaded to the servers via different smartphone apps. We used Sony SmartBand 2, Sony Lifelog for the 'sleep' and 'step,' and used Google Fit for the 'HR' for the long-term storage. Subsequently, we developed a tailor-made App to extract the cleaned and encrypted data in the form of Microsoft Excel CSV files from the servers. The 'sleep' and 'step' data were extracted from the Sony server, and the HR data was extracted from the Google server. The flowchart of the acquisition of continuous data was shown in Fig. 2.

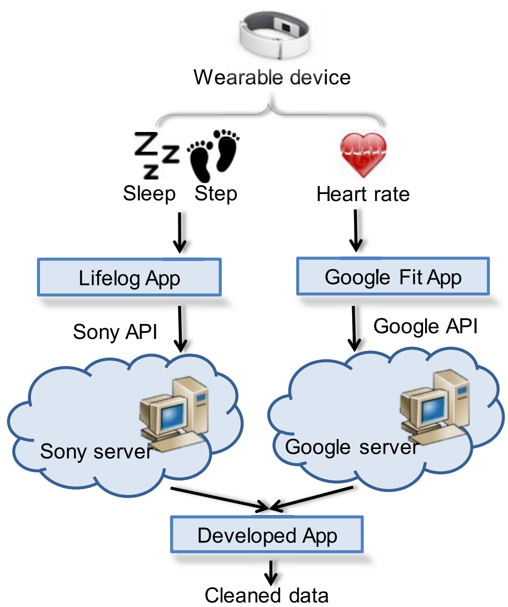

FIGURE 2. **The flowchart of the acquisition process of continuous data measured by the Sony wellness tracker.**

D. DATA PROCESSING

In our context, SONY and TMC devices use different physical principles, cover different information space, and generating data in different formats at different sampling rates.

Based on those effects, we propose a novel method that properly processes the collected data from those two measurement devices for subsequent monitoring. To do so, we further look into the raw SONY wellness tracker data acquired from servers. As mentioned earlier, the measurement from the telehealth monitoring device was available at 2 pm each day. We thus considered 2 pm as the cut point of daily measurements in our analysis. Firstly, for the HR continuous measures, we segmented one-day period into six 4-hour time intervals, i.e., 2 pm-6 pm, 6 pm-10 pm, 10 pm-2 am, 2 am-6 am, 6 am-10 am, and 10 am-2 pm. The variations of HR data within each time segment were calculated and considered as the predictor variables associated with the wellness, named Var(HR)_1 to Var(HR)_6, respectively. The rationale behind is that the HR of an elderly varies according to their activities, the data aggregated in each time interval can describe their activities in a more indicative way. The HR included in each time interval are hypothesized to be monotonous and representative as the elderly was observed to have similar activities within the same time interval. Next, we aggregated the 'sleep' and 'step' data into day-by-day epochs, called total sleep duration (TSD) and total number of steps (TSC). This aggregation can help delineate the general daily lifestyles of the participating elderly. Besides, an additional variable called deep sleep state ratio (DSSR) was generated by

$$\text{DSSR} = \frac{\textit{Total Deep Sleep Time}}{\textit{Total Sleep Time}} \tag{1}$$

The deep sleep state is vital for health as the body recovery process always happens during the deep sleep state. Also, it is one of the critical components determining the sleeping quality, which affects the ground truth of wellness in the next day. After processing, these newly created variables are ready to use, together with the measurements collected from the telehealth device, to provide a single picture of each elderly's daily health.

In our study, we regarded the self-reported HI as the ground truth of an elderly's daily health wellness. The self-evaluations usually are subjective, and thus the distribution of HI of each elderly varied even if their health conditions were similar. This is caused by the difference among individual self-perception on their health conditions. It has been emphasized in the literature about the importance of preprocessing the scores collected from questionnaire before analysis. Data normalization is a common strategy to remove the effects of variation. The objective of normalization is to reduce the difference in shape between a set of scores belonging to the same subject. Recent research has shown that the Fisher-Yates normalization approach is successful for removing noise, bringing data into the same scale and reducing skewness of the data [38], [39]. Generally, the procedure for Fisher-Yates normalization is: suppose x_i is the i^{th} score e of an elderly. Let r_i be the rank of i^{th} score, $1 \leq i \leq I$. Then x_i will be replaced by $\Phi^{-1}(r_i/(I+1))$, i.e.,

$$y_i = \Phi^{-1}(r_i/(I+1)) \tag{2}$$

After the Fisher-Yates normalization applied on individual self-reported HI, we further categorized the elderly's normalized HI into a dichotomous variable. We categorized the values less than 0 into one class, and the rests into another class. The dichotomous outcomes can be interpreted as feeling worse or better than/same as his or her usual well-being health condition. This categorization can lead to less biased and more informative response variable for identifying the high-risk elderly. Fig. 3 summarizes all the generated variables according to the setting of daily scheduled health assessments.

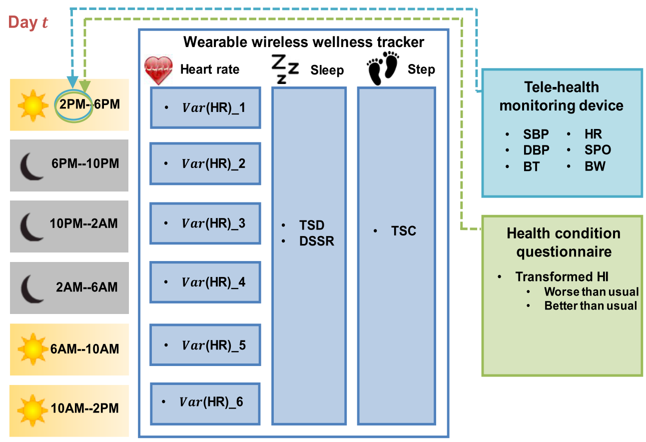

FIGURE 3. The diagram illustrating the meanings of the variables based on the health assessment setting.

E. PERSONALIZED HEALTH MONITORING SYSTEM AND WELLNESS FORECASTING

As explained in more detail below, we considered the use of different data mining tools, together with the use of integrated data sources to forecast the individual wellness of elderly and build the personalized monitoring scheme.

1) DATA INTEGRATION

Generally, data integration is the process of putting together information obtained from many heterogeneous sources into a single composite picture of the environment. In our system, for each elderly, we denoted the 9 predictor variables generated from the wellness tracker records, i.e., Var(HR)_1 to Var(HR)_6, TSC, TSD, DSSR, as $\mathbf{X_{SONY}} = (\mathbf{x_1}, \ldots \mathbf{x_9})$, and denoted 6 predictor variables recorded from the telehealth monitoring device, i.e., SBP, DBP, BT, HR, SPO2, BW, as $\mathbf{X_{TMC}} = (\mathbf{x_{10}}, \ldots \mathbf{x_{15}})$. All those variables are considered for forecasting an elderly's one-day-ahead wellness. We denoted the Fisher-Yates normalized HI as $\mathbf{Y}$. To fit the relationship between a response variable and predictor variables, the model can be formulated as:

$$\text{SONY} + \text{TMC}: \quad \mathbf{Y_t} = f(\mathbf{X_{SONY,t-1}}, \mathbf{X_{TMC,t-1}}) \tag{3}$$

Where $f(\cdot)$ denotes a data mining model employed on the datasets. Each SONY+TMC data record contained variables from both SONY and TMC data records on the same daily basis, which in total contained 15 variables.

The SONY device continuously records each elderly's activity data 24 hours a day. But it only provides three types of available measurements. The TMC machine records each elderly's vital signs in a very comprehensive manner. However, their measurements are collected daily. By integrating the strengths of data obtained from wearable and station-based devices, we can use them to infer each elderly's health condition accurately. In the following section, we describe the adopted conventional data mining tools in our system.

2) CLASSIFICATION METHODS

Predictive modeling is a data mining tool used to develop a model to relate a response variable with a set of predictor variables. Two most common modeling techniques are classification and prediction. Classification models predict categorical variables while prediction models predict continuous variables. In our study, each elderly's daily wellness was categorized as feeling worse or better than usual health condition. Thereby, classification methods were considered in our system for the wellness forecasting.

Our wellness forecasting problem was a typical binary classification problem. We define the input of the model was 1-day lagged aggregated continuous data acquired from the wearable wellness tracker, and l-day lagged measurements recorded from telehealth monitoring device. All those predictor variable are either continuous or discrete. The output of the model was a binary variable. We choose to include conventional classification methods in our system due to their popularity in the recently published healthcare literature [40]–[42], as well as better than average performance in our preliminary comparative studies. The six methods selected include LASSO regression (LR), artificial neural network (ANN), support vector machine with linear (L.SVM), polynomial (P.SVM) and radial kernels (R.SVM), and a decision tree (DT). By adopting these classification methods, it is possible to reveal the relationships among this 15 activity and physiological parameters. What follows is a short description of these classification models.

a: LASSO REGRESSION

Regression is used to find out functions that explain the correlation among different variables. LR is a generalized linear regression (GLM) with a certain variable selection and regularization to improve the model's prediction accuracy. The objective of this method is to prevent overfitting. It is used to shrink estimation of the regression coefficients in GLM towards zero relatives to the maximum likelihood estimates. It provides a nice probabilistic interpretation. With LASSO, coefficients of non-significant variables will be penalized to zero while important variables will be retained.

b: ARTIFICIAL NEURAL NETWORKS

ANN uses a great volume of simple and interconnected artificial neurons to simulate some properties of biological neural networks. It uses non-linear mathematical equations to successively develop meaningful relationships between input and output variables through a learning process. It is most suitable for diagnostic and predictive problems. In our system, a feedforward single layer perceptron network with back-propagation is used. The structure of single-layer back propagation network is composed of an input layer, a hidden layer, and output layers. ANN is effective in the analysis of complex data with nonlinear trends and even high-order interactions.

c: SUPPORT VECTOR MACHINE

SVM classifier creates a hyperplane in original input space to separate the data points. Sometimes it is difficult to perform separation of data points in original input space, so to make separation easier the original dimensional space mapped into new higher dimension space. Kernel functions are used for mapping of input variables into a higher dimensional space. We considered linear, polynomial and radial kernels in our system. It works on the principle that data points are classified using a hyperplane that maximizes the separation between data points and the hyperplane is constructed with the help of support vectors.

d: DECISION TREE

Decision Tree is a popular classification method which is simple and easy to implement. It requires no domain knowledge or parameter setting. It constructs hierarchical decision trees by splitting data among classes of the criterion at a given step (node) accordingly to an "if-then" rule applied to a set of predictors, into two child nodes repeatedly, from a root node that contains the whole sample. It selects the input variable that has the strongest association with the dependent variable according to a specific criterion. The method produces a model that represents interpretable rules or logic statements.

3) IMPLEMENTATION AND EVALUATION

All classification methods considered were directly applied and validated on each elderly's cleaned data set to identify the best personalized models. To train our models without over-fitting as well as minimize the bias, we used leave-one-out cross-validation (LOOCV) for evaluating the performance of different classification approaches. LOOCV uses a single observation from elderly's dataset as the validation data, and the remaining observations as the training data. This is repeated such that each observation in the dataset is used once as the validation data. The model with highest prediction accuracy was selected as the most effective model. For each method, the averaged results were recorded. All the experiments were implemented in R version 3.4.0 (64- bit), a statistical Open Scours computing software developed as part of the R Project. The packages used included 'caret,' 'e1071,' 'kernlab,' 'rpart' and 'glmnet.'

TABLE 3. Confusion matrix.

	Actual(+)	*Actual(-)*
Predicted(+)	True positive (TP)	False positive (FP)
Predicted(-)	False Negative (FN)	True Negative (TN)

Evaluation measure is crucial in assessing the binary classification performance of the different methods. The confusion matrix is a specific table layout that allows assessment of the performance of each method. A confusion matrix is given in Table 3. Each column of the matrix represent the instances in an actual class while each row represents the instances in a predicted class. In this study, we focused on five well-known performance evaluation metrics including accuracy, precision, recall, F-score, and specificity. These metrics are commonly used in data mining and clinical decision support systems.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{4}$$

$$precision = \frac{TP}{TP + FP} \tag{5}$$

$$Recall = \frac{TP}{TP + FN} \tag{6}$$

$$F\text{-}score = 2 \cdot \frac{precision \cdot recall}{precision + recall} \tag{7}$$

$$Specificity = \frac{TN}{FP + TN} \tag{8}$$

From the confusion matrix, accuracy denotes the proportion of correctly classified, both positive and negative. In our case, accuracy describes what percentage of time the methods predicted an elderly's health conditions correctly, both better and worse health condition. The precision denotes the fraction of true positive predictors that are classified as positive. In our case, precision describes what percentage of the time the method predicted 'worse health condition' correctly. Recall refers to the fraction of the number of true positive predictors to the number of positive condition instances. In our case, recall referred to the percentage of the correctly predicted 'worse health condition' to the total number of 'worse health condition' instances in the dataset. There is usually an inverse relationship between precision and recall. That is, it is possible to increase the precision at the cost of decreasing the recall, or vice versa. Therefore, it is useful to combine them into a single metric such as F-score, which represents a harmonic mean between recall and precision. Specificity indicates the fraction of correctly classified true negative predictors to the actual number of negative instances in the dataset. In our case, it referred to the percentage of the correctly predicted 'better health condition' to the total number of 'better health condition' instances in the dataset. After the evaluation using employed five performance metrics, the model with highest prediction accuracy for detecting adverse health condition is selected for predicting that elderly's wellness one day ahead and will serve for personalized monitoring.

The overall system benefits the current care program significantly. For example, it is quite useful in managing nurse care of the elderly; informing the nurse when a comprehensive check is necessary because the elderly is predicted to be feeling worse than usual. An intervention providing timely care could potentially avert the need for higher-level intervention or hospitalization. Fig. 4 describes the overall personalized health monitoring framework for this study design.

III. SYSTEM IMPLEMENTATION

A. CASE STUDY - ELDERLY 2

In this section, we used Elderly 2 as an illustrative example to explain the details of selecting the appropriate model for personalized health monitoring. By doing so, we investigated the effectiveness of aforementioned six classification approaches on predicting binary health wellness condition for Elderly 2 in our study. Following the data cleaning and pre-processing steps discussed previously, the processed dataset of Elderly 2 consisted of total 40 complete lagged records. We first looked at her self-reported HI. Table 4 summaries the reported HIs and their Fisher-Yates normalized values, which we can observe balanced cases between worse and better health conditions. We then applied the six classification approaches to the integrated data sources for evaluation and comparison. In the LOOCV, the complete 40 records were divided into two datasets, i.e., a training set and a testing set. The training set consisted of 39 records to create the personalized classification rules; the testing set consisted of the remaining 1 record. By repeating cross-validation, each prediction of HI on the leave-out data observation was recorded into the confusion matrix.

TABLE 4. Summary of elderly 2's health index.

Health index (HI)	4	5	6	7
Fisher-Yates normalized values	-1.66	-0.55	0.55	1.66
Frequency	3	17	17	3
Dichotomous health condition	worse	worse	better	better

Fig. 5 shows the performance of the six classification approaches in each evaluation metrics. To choose the best model, we first consider the accuracy measure of each method. A ROC graph, also known as recall vs (1-specificity) plot, can be employed for selecting the appropriate model in a graphic manner. Each classification method's result represents one point in the ROC space. Theoretically, the appropriate method would yield a point that is nearest to the left corner in the ROC space. In this case, we can see a comparative accuracy result among these six methods.

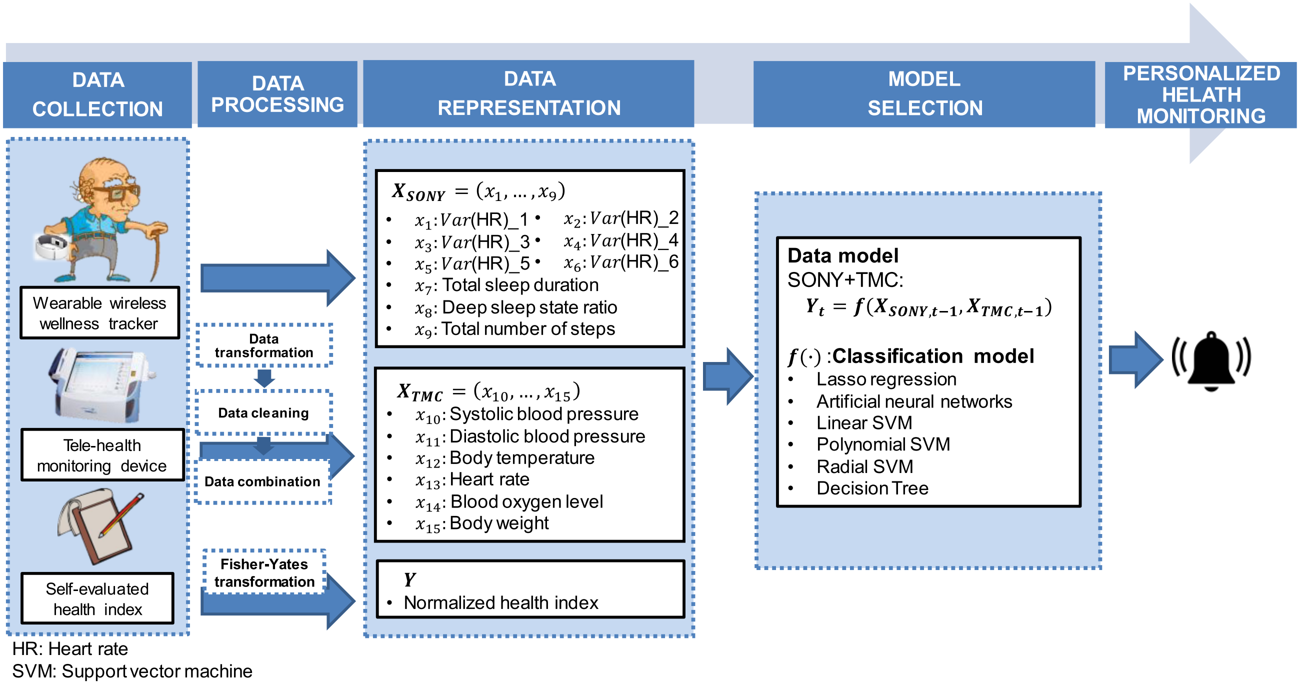

FIGURE 4. Overall procedure of the personalized health monitoring system.

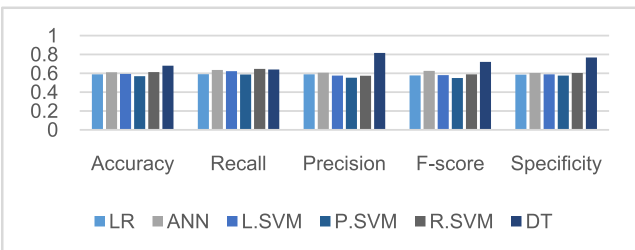

FIGURE 5. Comparison of six classification methods using SONY+TMC data.

In addition, we plot the ROC graph in Fig 6. In this figure, it is clear to see that the DT method shows superior performance. The other approaches behave comparably according to different evaluation metrics. DT method achieves a classification accuracy of 68.08% with a recall of 64.02% and a precision of 81.65%. Specifically, the F-score of this case is approximately 72.11%, indicating its relative effectiveness in predicting elderly's health condition. We also find that the determinants "SBP" and "Var(HR)_4" are the most frequently chosen variables by the DT model in the cross-validation. Fig. 7 provides a classification tree illustration for predicting health wellness for Elderly 2.

The rules for predicting that Elderly 2 will feel worse are, therefore:

- SBP (1 day ago) $\geq$ 138.
- SBP (1 day ago) $<$ 138 and the variation of HR (2am-6am) [Var(HR)_4] $<$ 34.

The rule for predicting that Elderly 2 will feel well is:

- SBP (1 day ago) $<$ 138 and the variation of HR (2am-6am) [Var(HR)_4] $\geq$ 34.

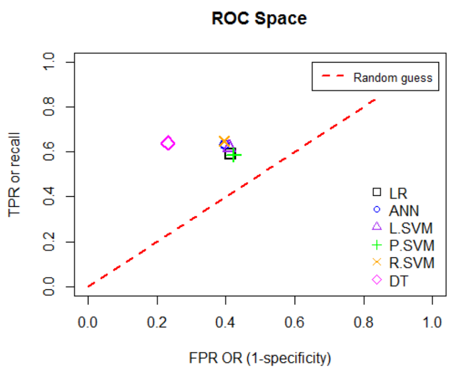

FIGURE 6. The ROC space and plots of the six classification methods.

In this example, the identified rules allow us to establish the probability of feeling unwell given that the rules have flagged or not flagged. The best combination of the vital sign measurements and their rules that predict the wellness of individual elderly was identified. A wellness forecasting scheme suggests that we need two key vital sign measurements to forecast the well-being of Elderly 2, namely, the "SBP" and "Var(HR)_4." The monitoring system predicts the following day wellness of elderly once these two key measurements are available today. More care on this elderly is required if the unwell rules are triggered.

B. BENEFITS OF DATA SOURCE INTEGRATION

Using EL2 as an example, we further compared the performance results between the integrated use of data acquired from both electronic devices and those of the separate use

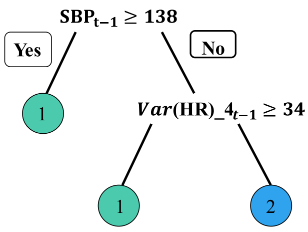

FIGURE 7. Illustration of classification tree of Elderly2.

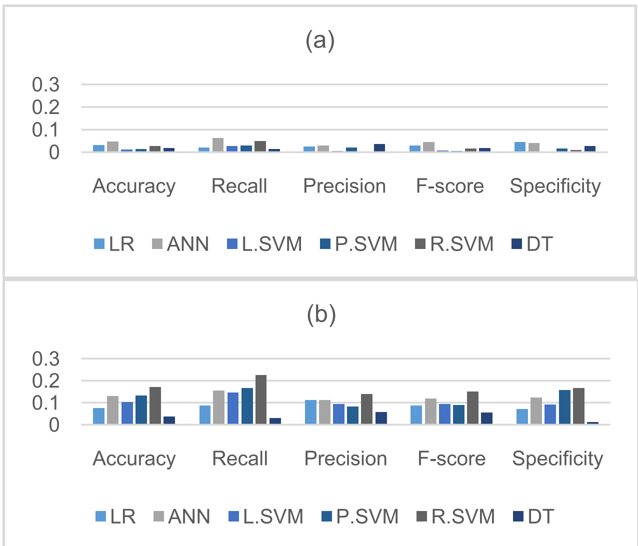

FIGURE 8. Improved performance by data source integration based on a) SONY and b) TMC.

of data from every single device. Two additional cases using different data sources as inputs in the classification model were considered here, i.e., SONY and TMC. Each SONY record contained nine determinants, i.e., $\mathbf{X_{SONY}}$, while the TMC record contained six determinants, i.e., $\mathbf{X_{TMC}}$, as the input of the classification model. The models associated with the additional two cases can be formulated in the same format of equation 3 as:

$$\text{SONY:} \quad \mathbf{Y_t} = f(\mathbf{X_{SONY,t-1}}) \tag{9}$$

$$\text{TMC:} \quad \mathbf{Y_t} = f(\mathbf{X_{TMC,t-1}}) \tag{10}$$

We then applied the six classification approaches to each of the two cases using different data sources. The results were compared with those obtained in Fig. 5. We found there was a superior performance by using the integrated data source, i.e., SONY+TMC. We plot its improvement in predictive performance compared to either using SONY or TMC data separately in Figs. 8(a) and (b). The findings on data source use are consistent with our intuition that the integrated use of data from multiple sources is useful for obtaining more reliable information than individual measurement obtained from a single type of sources. Besides, Fig. 8 dedicates the incremental performance of six approaches to different evaluation metrics. For the SONY data, the joint use with TMC data improves the average performance of different classification approaches by approximately 3.01% (LR), 4.48% (ANN), 1.08% (L.SVM), 1.70% (P.SVM), 2.06% (R.SVM) and 2.31% (DT) after averaging across evaluation metrics. On the other hand, compared to the use of TMC data, the use of SONY+TCM data significantly improves the performance of these approaches by 8.62%, 12.76%, 10.54%, 12.60%, 17.07% and 3.86% in average respectively.

To the best of our knowledge, monitoring an individual's general wellness condition by using a wellness tracker and an all-in-one station-based monitoring device is novel in Hong Kong. The closely related work to ours is that of [34]. They use a decision tree to predict the patient wellness based on the vital signs data collected by TMC. Their results show the average precision of predicting the individual patient unwell is approximately 50%. In our system, we predict the patient unwell using both TMC and SONY data. The precision of our system is nearly 80% using a decision tree. It further validates the effective use of the integrated data. To compare our system performance with existing ones as much as possible, we consider a closely related problem, which has received a lot of attention in the literature, the disease prediction. In [43], Leopord *et al.* discuss various data mining techniques for predicting disease outbreaks in terms of accuracy. Specifically, decision tree shows the maximum accuracy of 99.2% and minimum accuracy of 52% depending on various medical diseases. This supports the effectiveness of our proposed system. Our case study shows an accuracy level of 68.08%, which lies between the boundaries. As pointed out by [44], the data mining methods accuracy varies depending on the feature of the dataset and the size of data set between the training and testing sets. Besides, the sample size of the data is often seen as another character as the data available are usually in small scale. Our forecasting scheme is consistent with those results. It should be noted that there is no unique model performs best for all scenarios. The best forecasting model for each individual depends on the pattern of data sets.

IV. DISCUSSION AND CONCLUSION

Nowadays, health monitors for various vital signs, providing accurate and real-time measurements, have already been available in the market. To maximize the potential value of health monitors adoption for health monitoring and management, how to effective use of data has become the critical task that should be resolved. In this paper, we proposed a smart personalized health monitoring system of elderly general wellness and demonstrated its implementation at the community level in Hong Kong. We proposed an efficient data preparing scheme to extract raw data from the electronic wearable tracker and an all-in-one station-based health monitoring device, and a novel way to process these data for the substantial use. We further demonstrated the effectiveness of this successful prototype of an integrated health monitoring system. Our paper results showed that it could lead to a reliable, stable, real-time and convenient data sharing system, which is a rapidly expanding research field. Our study can be one of the milestones on the implementation of full-scale automatic health monitoring, which is revolutionary to the current healthcare system.

Our focus on prediction and forecasting can also help design new eHealth applications where predictions are made to personalize coaching for elderly or to facilitate decision making of health care providers. In our system, we predict the better or worse health wellness of each elderly. This is a fundamental and essential problem, as it is the direct indicator of some significant health consequences. We demonstrated that classification decision rules for an elderly could be quite useful in understanding self-health condition and manage the elderly care plan. More care is needed when the elderly are likely to be unusually unwell. An intervention providing appropriate and timely care could potentially avert the need for a higher-level intervention.

As future work, we are planning to employ more elderly with a longer duration of the implementation of the proposed personalized health monitoring system. In addition, the proposed system can be extended to other elderly facilities at community level including daycare centers or even home monitoring. The longer period monitoring data collected from elderly at different elderly care facilities would be useful to further validate the robustness of the proposed integrated health monitoring system. Our future works also include the expansion of data modeling. The state-of-art data mining techniques, such as deep learning, could be adjusted and incorporated for wellness prediction. Previous research on the use of deep learning for healthcare analytics has shown its robustness to noisy data with high efficiency [45]–[47]. Besides, it is common that the adverse healthcare events happen rarely. Thus, for the unstructured self-reported HI with highly skewed distribution, the classification methods can be integrated with rebalancing strategies to identify rare but significant cases. Last but not least, discrete self-reported health index can be adopted instead of categorical data to quantify the level of severity more precisely.

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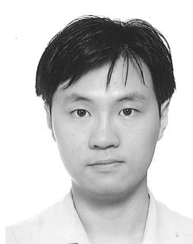

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