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Coupling a Fast Fourier Transformation With a Machine Learning Ensemble Model to Support Recommendations for Heart Disease Patients in a Telehealth Environment

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ABSTRACT Recently, the use of intelligent technologies in clinical decision making in the telehealth environment has begun to play a vital role in improving the quality of patients' lives and helping reduce the costs and workload involved in their daily healthcare. In this paper, an effective medical recommendation system that uses a fast Fourier transformation-coupled machine learning ensemble model is proposed for short-term disease risk prediction to provide chronic heart disease patients with appropriate recommendations about the need to take a medical test or not on the coming day based on analysing their medical data. The input sequence of sliding windows based on the patient's time series data are decomposed by using the fast Fourier transformation in order to extract the frequency information. A bagging-based ensemble model is utilized to predict the patient's condition one day in advance for producing the final recommendation. A combination of three classifiers–artificial neural network, least squares-support vector machine, and naive bayes–are used to construct an ensemble framework. A real-life time series telehealth data collected from chronic heart disease patients are utilized for experimental evaluation. The experimental results show that the proposed system yields a very good recommendation accuracy and offers an effective way to reduce the risk of incorrect recommendations as well as reduce the workload for heart disease patients in conducting body tests every day. The results conclusively ascertain that the proposed system is a promising tool for analyzing time series medical data and providing accurate and reliable recommendations to patients suffering from chronic heart diseases.

INDEX TERMS Recommender systems, time series analysis, intelligent systems.

I. INTRODUCTION

Chronic diseases have been one of the main public health concerns worldwide, which account for over 50% of global mortality [1] and thus requires more and more medical attentions and resources in today's increasingly aged societies. Heart disease, one of the most common chronic diseases, is currently registering one of the highest death rates of the non-infectious diseases, causing a high associated cost in prevention and treatment [2]. Due to a lack of medical recommendations that can be automatically generated for a better treatment and care, the life quality of chronic heart disease patients has been significantly affected.

Telehealth systems are becoming increasingly popular and are effective means to cope with the challenges posed by the cares of patients with chronic diseases, and therefore have enjoined fast developments in many countries due to its low-cost and fast service delivery. Most telehealth services are delivered through Web-based applications which use Web browsers and Internet, together with sensors, mobile and wearable devices. Given the importance of disease risk prediction in the medical domain [26] as well as the urgency of obtaining more effective analytic techniques for disease risk prediction, great efforts are needed to enhance the quality of evidence-based decisions and recommendations in the telehealth environment. For the case of chronic heart disease patients, they need to undertake various daily medical tests to monitor their overall heart health conditions through the telehealth system. Yet, carrying out various medical test every day in the current practice brings lots of inconvenience and even burden to the patients and adversely affect their life quality. Producing accurate intelligent recommendations to guide their daily medical tests can effectively reduce their workload in taking those tests while keeping the associated health risk in an acceptable low level.

In many cases, an accurate medical recommendation is based upon the prediction of patients' short-term disease risk, which is one of the most important functions in telehealth systems. A set of disease risk prediction models have become available in the medical literature using statistical analysis tools and approaches based on data mining tools. These models have been utilized for different healthcare and medical issues [3]–[11]. However, little of the existing work deal with chronic heart disease issue. Also, most of them only focus on the long-term medical prediction. Nevertheless, the short-term prediction, which is studied in our work, has turns to be more challenging than the long-term prediction as patients' conditions may experience more dramatic and abrupt changes during the short-term timeframe.

In this work, we utilize the fast Fourier transformation (FFT) to process the time series medical data of heart disease patients to facilitate the subsequent data analytics to produce the accurate prediction and recommendations. Fast Fourier transformation is an efficient technique for computing the discrete Fourier transformation (DFT) and its inverse. It is a robust tool for classification and is faster than the standard DFT. Due to its predictive effectiveness, the fast Fourier transformation has been used in many different research areas such as analyzing and forecasting electricity consumption in buildings [12], [13], detecting epileptic seizures in electroencephalography (EEG) [16], [17] and forecasting water demand [14], [15].

The intelligent, accurate medical recommendations in our work rely on the use of classification approaches to produce reliable prediction of the short-term medical risks of the patients. By nature, this is a classification problem which involves using classification methods (called classifiers) to predict the necessity of taking body test of a given medical measurement. In our work, machine learning techniques are combined together to build an ensemble classifier. There are several reasons that pushed us to construct the ensemble classifier. First, it provides an efficient solution for building a single model for applications of which the amount of data may be very large [18]. Second, it has also been proven to be an effective tool thanks to its ability to improve the overall accuracy of the prediction model. Empirical results showed that machine learning ensembles are often more accurate than the individual classifiers that make them up [19]. Bagging aggregation is a machine learning ensemble algorithm designed to enhance the accuracy and stability of machine learning algorithms [21], which was proposed by Breiman in the mid-1990's [20]. It has been proven to be a very popular, efficient and effective method for building an ensemble model.

Several studies in the literature have been conducted using ensemble approaches, with some success, in medical domain [22]–[25]. Yet, none of them approached or solved the problem that we deal with in our study to provide accurate recommendations to advise chronic heart disease patients to take or skip the medical tests on the coming day.

In this paper, a novel short-term recommendation system for chronic heart disease patients is proposed. This system is developed using the fast Fourier transformation with a machine learning ensemble model to provide patients in a telehealth environment with appropriate recommendations for the necessity of taking a medical body test on the coming day. Such recommendations are established based on the prediction of their heart conditions using their time series medical data from the past few days.

The performance of our proposed recommendation system are evaluated using three metrics we developed: i.e., *accuracy*, *workload saving* and *risk*. The experimental evaluations are conducted on a real-life time series dataset collected from a pilot study in an collaboration with Tunstall Healthcare on a group of chronic heart disease patients. The experimental results showed that the proposed system yields a high recommendation accuracy and can effectively reduce the workload required in medical tests for those patients. It also achieves a very low risk for the patients due to possibly incorrect recommendations. The proposed system is a promising tool in healthcare of chronic heart disease patients. Please note that our recommendation system is very generic which can be readily applied to patients suffering from other chronic diseases in the same or similar telehealth environment.

The remainder of this paper is organized as follows. Section II introduces the details of the constituent machine learning classifiers used in the ensemble model used in our system. Section III discusses in details the proposed recommendation system for chronic heart disease patients, with the focus on the fast Fourier transformation and the ensemble model. Section IV elaborates the results of the experiments conducted to evaluate the performance of our system. Finally, we conclude the paper and highlight future research directions in Section V.

II. THEORETICAL BACKGROUND

As the theoretical background, a detailed description of the constituent classifiers used in the ensemble model is provided in this section. Specifically, the ensemble model consists of three popular and capable machine learning classifiers: Artificial Neural Networks (ANN), Least Square-Support Vector Machine (LS-SVM) and Naive Bayes (NB).

A. ARTIFICIAL NEURAL NETWORK

Artificial Neural Network (ANN) is a supervised learning machine algorithm that can be used to provide effective solutions for many complex modeling problems. This method uses a set of processing neurons or nodes which are interconnected. The network can be considered as a directed graph in which each neuron i executes the transfer function f_i as in the following equation [30]:

$$y_i = f_i\Big(\sum_{j=1}^{n} w_{ij}x_j - \theta i\Big) \tag{1}$$

where y_i is the output of neuron i, x_j is the jth input to the neuron and w_{ij} is the connection weight between neurons i and j. θ is the threshold bias of the neuron. f_i is usually nonlinear taking, for example, a sigmoid, Heaviside, or Gaussian function.

B. LEAST SQUARE-SUPPORT VECTOR MACHINE

Least Square-Support Vector Machine (LS-SVM) [27] is a supervised machine learning technique that is based on statistical learning theory. It has been used in some applications for medical prediction, such as for heart disease prediction [28], muscle fatigue prediction in electromyogram (sEMG) signals [27] and breast cancer prediction [29].

A linear LS-SVM, which is the most popular form of LS-SVM, is designed to classify a dataset that contains two separable classes represented as $\{1, -1\}$ [3]. This method attempts to map the given data into a high-dimensional space and then uses a hyperplane separating the two classes involved by maximizing the distance between the plane and the support vectors. Suppose the training data consist of n data $(x_1, y_1), (x_2, y_2), \ldots, (x_m, y_m) \in R^m$. LS-SVM finds the optimal separating hyperplane (with the maximum margin) to separate these classes. LS-SVM is based on the following rules for solving the given problem:

$$y_i[(wx_i) + w_0] = 1 - \xi_i, \quad i = 1, \ldots, m, \tag{2}$$

$$1/2\|w\|^2 + \frac{c}{2}\sum_{i=1}^{m}\xi_i^2 \tag{3}$$

According to the above formulas, the problem to be solved by LS-SVM can be formulated as follows:

$$(w, b, \alpha, \xi) = 1/2\|w\|^2 + \frac{c}{2}\sum_{i=1}^{m}\xi_i^2 - \sum_{i=1}^{m}\alpha_i\{y_i[(wx_i) + w_0] - 1 + \xi_i\} \tag{4}$$

C. NAIVE BAYES

The Naive Bayes classifier (NB) is a machine learning classifiers that is based on probability theory with the supposition that the features are independent from each other [31]. It is often used for classification problems in machine learning as well as medical predictions. According to the Bayes theorem, the conditional probabilities involved in the problem can be obtained using the following formula:

$$P(C_x|Y) = P(C_x) \times \frac{P(Y|C_x)}{P(Y)} \tag{5}$$

where Y is a given example that needs to be classified. C_x is a class label and $P(C_x|Y)$ is the probability that the vector Y belongs to C_x.

III. THE PROPOSED RECOMMENDATION SYSTEM

The main purpose of the study is to investigate the coupling of the fast Fourier transformation with a machine learning-based ensemble in providing medical recommendations to patients suffering from chronic heart disease as to the necessity of taking a medical test on the coming day. In this section, an overview is first presented on the architecture of the recommender system followed by the detailed discussion on the fast Fourier transformation and the ensemble learning model, two major technical components of the system.

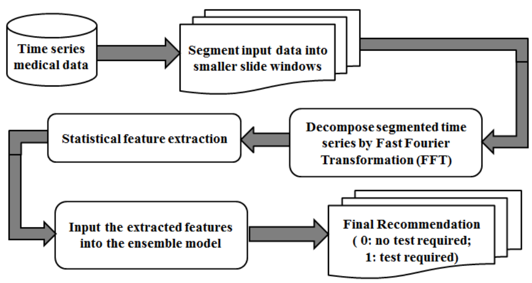

FIGURE 1. The architecture of our recommendation system.

A. AN OVERVIEW OF OUR SYSTEM

Fig. 1 illustrates the overall architecture of our recommendation system used for chronic heart disease patients in the telehealth environment. In the system, the time series medical data of a given patient will be segmented into smaller overlapped sliding windows based on the size of the sliding window used in the data analysis. Then, each sliding window is passed through the fast Fourier transformation in order to extract the statistical features. The main purpose of using the fast Fourier transformation in this work is to study the properties of the time series data in the frequency domain, which could be difficult to obtain in the time domain. This involves re-expressing the original time series as a new sequence which determines the importance of each frequency component. The extracted statistical features from the time series data are then input into our ensemble learning model to produce a binary recommendation concerning whether that patient needs to take a medical test on the coming day for a certain medical measurement such as the heart rate or blood pressure.

B. FAST FOURIER TRANSFORMATION OF THE TIME SERIES DATA

The fast Fourier transformation (FFT) is an efficient technique to compute the Discrete Fourier Transform (DFT) and its inverse. It is similar to the wavelet transformation as a windowing technique [36], [37]. The DFT decomposes the input data sequence (i.e., the data in the sliding windows of the given time series data of the patients) in order to extract frequency information for the purpose of predicting the patient's condition one day in advance.

Before the fast Fourier transformation is performed, the input variables are scaled using a normalization technique. The normalized variables take on values within the interval of [0,1] [38]. The normalization is performed based on the following equation:

$$D_{norm} = \frac{D_{orig} - D_{min}}{D_{max} - D_{min}} \tag{6}$$

Here, D_{norm} is the normalized data value, D_{orig} is the original raw data, D_{min} and D_{max} are respectively the minimum and maximum data values of the entire dataset.

Let $x(t)$ be a time series bonded by a sliding window. The Discrete Fourier Transformation of $x(t)$ can be defined as:

$$X(c^{jw}) = \sum_{t=-\infty}^{\infty} x(t)c^{-jwt} \tag{7}$$

where t is a discrete time index and w refers to the frequency. There are T input time series $x(t)$, so the transform pair of the DFT can be defined as

$$X(P) = \sum_{t=0}^{T-1} x(t)W_T^{tp} \Leftrightarrow x(t) = \frac{1}{T}\sum_{p=0}^{T-1} X(P)W_T^{-tp}, \quad where \quad W = c^{-j2\Pi/T} \tag{8}$$

Furthermore, the DFT can be presented as a discrete-time Fourier transform of a cyclic signal with period T as:

$$x = \begin{bmatrix} x(0) \\ x(1) \\ \vdots \\ x(T-1) \end{bmatrix}, \quad X = \begin{bmatrix} X(0) \\ X(1) \\ \vdots \\ X(T-1) \end{bmatrix} \tag{9}$$

$$W = [W_T^{pt}] = \begin{bmatrix} 1 & 1 & \dots & 1 \\ 1 & W_T & \dots & W_T^{T-1} \\ \vdots & \vdots & \vdots & \vdots \\ 1 & W_T^{T-1} & \dots & W_T^{(T-1)(T-1)} \end{bmatrix} \tag{10}$$

The following equation presents the relationship between x and X:

$$X = Wx \Leftrightarrow x = \frac{1}{T}W^H X \tag{11}$$

Based on the above equations, the DFT matrix W requires T^2 complex multiplications for a given time series input signal $x(t)$ with a length of T. Therefore, the required implementation cost for factorizing the fast Fourier transformation W into a matrix is lower than that of the direct Fourier transformation since each stage of the fast Fourier transform only requires $T/2$ multiplications and T additions [34], [35].

In our system, the input time series data, represented as $X = \{y_1, y_2, y_3, \dots, y_n\}$ which contains n data, is segmented into a set of overlapped sub-segments based on a predefined value of parameter k that specifies the size of the sliding window, corresponding to each sub-segment. The input time series are analyzed using the fast Fourier transformation to extract frequency information in order to predict the patient's condition. Five frequency bands (i.e., α, β, γ, δ, and θ) are acquired using the fast Fourier transformation for each sliding window, as shown in Fig. 1. Since the high frequency band captures most of the information of the sliding window, so it is further divided into eight sub-bands. The original sliding window is also added, as a reference, to the extracted feature set. As a result, a total of 14 ($5 + 8 + 1 = 14$) frequency bands are generated for each slide window. In addition, the power of the FFT coefficients is calculated for all the 14 frequency bands. This allows the computation of the square of the absolute value of the Fourier coefficients. As a result, there can be a total of 28 ($14 + 14 = 28$) frequency bands extracted for a sliding window. Fig. 2 shows the 28 frequency bands that can be extracted from a sliding window.

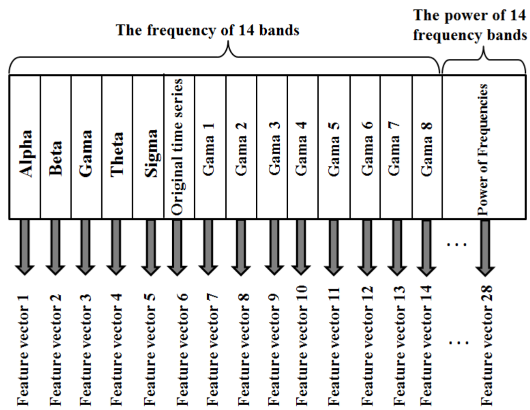

FIGURE 2. The decomposition of a sliding window into 28 bands.

From each frequency band, eight different statistical features can be extracted. The extracted features are denoted by X_{Min}, X_{Max}, X_{SD}, X_{Med}, X_{Mean}, X_{RG}, X_{FQ} and X_{SQ}, respectively. Short explanations of the statistical features are provided in Table 1. The best performing features are dataset dependent. Some time series data are symmetrically distributed while others may have a more skewed distribution. General speaking, the min and max are considered appropriate measures for a time series with a symmetric distribution, but for a skewed distribution, the mean and standard deviation are better used to measure the centre and spread of a dataset [39]–[41]. In our work, the extracted features from each band are grouped into one vector and used as the input to the ensemble learning model to predict the patient's condition. Experimental evaluations are conducted to evaluate the impact of different combinations of the extracted features on the final recommendation generated. The detailed results are discussed in the experimental results section.

TABLE 1. Short explanations of the statistical features.

Feature name	Formula	Description
Maximum value	$X_{Max} = Max[x_n]$	Where $x_n = 1, 2, 3, ..., n$ is a time series, n is the size of the sliding window and AM is the mean of the sliding window.
Minimum value	$X_{Min} = Min[x_n]$	
Mean	$X_{Mean} = \frac{1}{n}\sum_{1}^{n} x_i$	
Median	$X_{Med} = (\frac{N+1}{2})^{th}$	
Standard Deviation	$X_{SD} = \sqrt{\sum_{n=1}^{N}(x_n - AM)\frac{2}{n-1}}$	
Range	$X_{RG} = X_{Max} - X_{Min}$	
First Quartile	$X_{FQ} = \frac{1}{4(N+1)}$	
Second Quartile	$X_{SQ} = \frac{4}{4(N+1)}$	

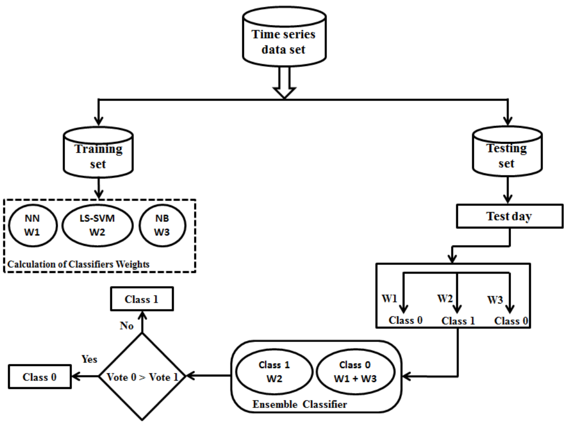

FIGURE 3. An example of a bagging algorithm.

C. BOOTSTRAP AGGREGATION (BAGGING)

An ensemble approach is a very effective method that combines the decisions of multiple base classifiers in order to overcome the limited generalization performance of each base classifier and generate more accurate predictions than individual base classifier. Bootstrap aggregation, a.k.a bagging, is a machine learning ensemble algorithm designed to enhance the accuracy and stability of machine learning algorithms [32], [33]. In the bootstrap method, the classifiers are trained independently and then aggregated by an appropriate combination strategy. Specifically, our ensemble model can be divided into two phases. In the first phase, the model uses bootstrap sampling to generate a number of training sets. In the second phase, the training of the three base classifiers, i.e., Neural Network, Least Square-Support Vector Machine and Naive Bayes, is performed using the bootstrap training sets generated during the first phase. Fig. 3 shows an example of the bagging algorithm which involves the three classifiers to build our ensemble model. In this study, the training set was divided into multiple datasets using the bootstrap aggregation approach, and then the classifiers were individually applied to these datasets to generate the final prediction. It is noted that different individual classifier in the bagging approach may perform differently. Therefore, we assign a weight to each classifier's vote, based on how well the classifier performs. The classifier's weight is calculated based on its error rate. The classifier that has a lower error rate is considered more accurate and is therefore assigned a higher weight. The weight of classifier C_i's vote is calculated as follows:

$$w(C_i) = \log \frac{1 - error(C_i)}{error(C_i)}, \quad 1 \leq C_i \leq 3 \tag{12}$$

The following example is presented to facilitate the understanding of our weighted bagging ensemble model:

1) Neural Network, Least Square-Support Vector Machine and Naive Bayes are used as individual base classifier in the ensemble model. Suppose that the classifier training is performed on the training data and the error rate is calculated for each base classifier as 0.25 for NN, 0.14 for LS-SVM, and 0.30 for NB;
2) As per Equation (12), the weight 0.47 is assigned to NN, 0.78 to LS-SVM, and 0.36 to NB;
3) Suppose that the three base classifiers generate the following predictions for a coming testing day: NN predicts 0, LS-SVM predicts 1 and NB predicts 0 (Here, 0 means no test is required on the testing day for a medical measurement; 1 means a test is required otherwise);
4) The ensemble classifier will use the weighted vote to generate the following prediction results:
Class 0: NN + NB $\longrightarrow$ 0.47 + 0.36 $\longrightarrow$ 0.83,
Class 1: LS-SVM $\longrightarrow$ 0.78.
5) Finally, according to the weighted vote, the class 0 has a higher value than class 1. Therefore, the ensemble classifier will classify this testing day as being in Class 0, suggesting that the patient in question can skip the test on that day for a medical measurement.

IV. EXPERIMENTAL RESULTS

Extensive experiments were designed and conducted to evaluate the performance of our proposed recommendation system using a real-life Tunstall dataset. In this section, we first discuss the setup of the experimental evaluations in our work, including the details of the real-life dataset and the performance metrics used in the evaluation. After that, we report the detailed experimental results.

A. THE EXPERIMENTAL SETUP

We used a real-life dataset obtained from our industry collaborator, Tunstall Healthcare, to test the practical applicability of our proposed system. Ethical clearance was obtained from the Human Research Ethics Committee of the University of Southern Queensland prior to the use of this dataset for our study. This Tunstall dataset was obtained from a pilot study that was conducted on a group of chronic heart disease patients, and the collected data contain the patients' day-to-day medical readings of different medical measurements in a telehealth care environment. The dataset is a time series and comprises data from six patients with a total of 7,147 different time series records acquired between May and October 2012. Each record in the dataset consists of a few different meta-data attributes about the patients, such as patient-id, visit-id, measurement type, measurement unit, measurement value, measurement question, date and date-received. The characteristics of the meta-data attributes of the dataset are shown in Table 2. Also, the dataset contains the numerical readings of several critical medical measurements for each patient on every day during the time period of the pilot study, including Heart Rate, Diastolic Blood Pressure (DBP), Mean Arterial Pressure (MAP), Oxygen Saturation (SO2), Blood Glucose and Weight, among which the data of Heart Rate, DBP, MAP and SO2 are used in the evaluation.

TABLE 2. **Meta-data attributes of the Dataset.**

Attribute name	Attribute type
id	Numeric
patient-id	Numeric
hcn	Numeric
visit-id	Numeric
measurement type	Nominal
measurement unit	Nominal
measurement value	Numeric
measurement question	Nominal
date	Numeric
date-received	Numeric

For the purpose of evaluating our system, the dataset is divided into two parts: the training set and the testing set. The base classifiers in the ensemble model are trained using the training set and then validated using the testing set as the ground truth result. In our study, 75% of the dataset was partitioned as the training data while the remaining 25% was used as testing data. For each of the four medical measurements, the recommendations produced by our system were compared with the actual readings of in the testing set to evaluate the quality of the recommendations produced by the system. Since a patient's historical medical data often have the class-imbalance problem (i.e., the number of normal data is much larger than that of the abnormal data), we carefully dealt with the class-imbalance problem when training the classifiers. The over-sampling and under-sampling methods have been used as good means to address this problem.

TABLE 3. **The average performance of the proposed model under different numbers of features.**

Feature sets	Accuracy (%)	Saving (%)	Risk (%)
2-feature set	86.80	62.00	05.20
3-feature set	**87.00**	**62.12**	**05.00**
4-feature set	92.50	64.00	04.50
5-feature set	92.70	64.20	04.20
6-feature set	**93.00**	**64.50**	**04.00**
7-feature set	94.80	64.80	03.00
8-feature set	**94.83**	**64.80**	**02.30**

The performance of each base classifier as well as the proposed ensemble model has been evaluated by three performance metrics we proposed for this work, namely *accuracy*, *workload saving* and *risk*. Accuracy refers to the percentage of correctly recommended days against the total number of days for which recommendations are provided. Workload saving refers to the percentage of the total number of days when recommendations are provided for skipping the medical test against the total number of days in the training set. Risk refers to the percentage of incorrectly recommended days against the total number of days in the training set. Mathematically, they are defined as follows:

$$Accuracy = \frac{NN}{NN + NA} \times 100\% \tag{13}$$

$$Saving = \frac{NN + NA}{|\mathcal{D}|} \times 100\% \tag{14}$$

$$Risk = \frac{NR}{|\mathcal{D}|} \times 100\% \tag{15}$$

Here, *NN* denotes the number of days with correct recommendations, *NA* denotes the number of days with incorrect recommendations, *NR* denotes the number of days with a risky recommendation that refers to a recommendation that suggests skipping a medical test for a given medical measurement but the actual reading of the measurement in the testing set is abnormal), and $|\mathcal{D}|$ refers to the total number of days in the training set. Here, a correct recommendation means that the system produces the recommendation of "no test required" ("test required") for the following day and the actual reading for that day in the dataset is normal (abnormal). The recommendations other than these two cases are considered incorrect.

Our recommendation system was developed using MATLAB on a desktop computer configured with a 3.40 GHz Intel core i7 CPU processor with 8.00 GB RAM.

B. RECOMMENDATION EFFECTIVENESS UNDER DIFFERENT STATISTICAL FEATURES

We first carried out experiments to evaluate the recommendation performance of our system under different sets of statistical features extracted from the siding windows of the dataset.

TABLE 4. The model performance using a three-feature set.

Measurement	Classifiers	No. of bands	Accuracy (%)	Saving (%)	Risk (%)
Heart Rate	Neural Network	5	71.60	55.54	09.72
		28	72.60	56.56	09.90
	LS-SVM	5	76.49	61.55	07.30
		28	77.78	60.20	07.20
	Naive Bayes	5	72.85	54.55	09.60
		28	71.60	56.60	09.70
	Ensemble model	5	**86.44**	**61.60**	**5.70**
		28	**87.30**	**62.50**	**5.20**
DBP	Neural Network	5	70.10	54.30	09.90
		28	71.30	55.88	09.10
	LS-SVM	5	75.44	62.51	08.10
		28	77.20	60.10	07.80
	Naive Bayes	5	69.20	52.30	09.60
		28	70.36	60.60	07.50
	Ensemble model	5	**85.50**	**60.40**	**5.90**
		28	**88.40**	**61.88**	**5.10**
MAP	Neural Network	5	69.90	50.20	10.50
		28	70.10	53.50	09.80
	LS-SVM	5	73.55	59.40	09.40
		28	75.78	60.90	08.95
	Naive Bayes	5	72.20	58.60	09.95
		28	73.40	60.20	09.80
	Ensemble model	5	**84.50**	**60.20**	**6.10**
		28	**86.40**	**60.60**	**5.95**
SO2	Neural Network	5	70.75	60.50	09.85
		28	71.50	60.80	09.40
	LS-SVM	5	77.60	62.65	06.70
		28	78.20	63.40	06.10
	Naive Bayes	5	70.80	55.30	09.50
		28	71.30	56.40	09.30
	Ensemble model	5	**85.80**	**63.40**	**5.90**
		28	**86.75**	**63.50**	**5.20**

First, the eight statistical features were tested separately to evaluate the prediction accuracy of the proposed system. Fig. 4 shows the ranking of the statistical features based on their performance where the features were sorted in an ascending order based on their effectiveness in predicting patient's condition. In this experiment, the extracted statistical features from all the 28 frequency bands were used as the input for training the base classifiers in the ensemble model.

We also conducted an experiment to investigate the recommendation effectiveness of our system under different number of features. To this end, the performance of our system under different feature sets whose number of features ranges from two to eight were tested and recorded thoroughly. The results are presented in Table 3. Based on the results, it is observed that there is a positive correlation between the number of the extracted statistical features and the recommendation performance of the proposed system in terms of all the three performance metrics we used. It was found that our system becomes more accurate when the number of the statistical features used is increased.

Finally, we evaluate the performance of our system under three different feature sets containing respectively three, six and eight statistical features based on the sorted feature information presented in Fig. 4. Only the top three, six and eight set features in the figure are selected into the three sets. The detailed statistical features selected for the three evaluated sets are as follows:

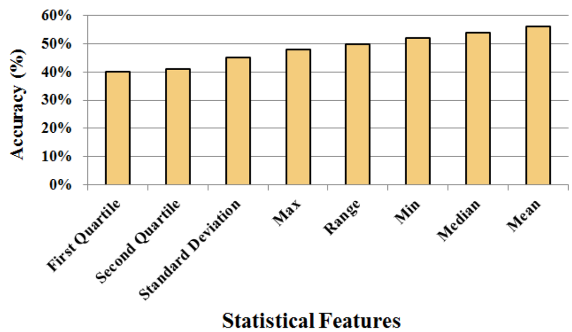

FIGURE 4. Ranking of the statistical features based on their accuracy performance.

Three-feature set: X_{Mean}, X_{Med} and X_{Min}

Six-feature set: X_{Mean}, X_{Med}, X_{Min}, X_{RG}, X_{Max} and X_{SD}

Eight-feature set: X_{Mean}, X_{Med}, X_{Min}, X_{RG}, X_{Max}, X_{SD}, X_{FQ} and X_{SQ}

For each of the three feature sets evaluated, we further evaluate the performance of our system when only five and all the 28 frequency bands are used for each sliding window which can indicate the impact of the choice of frequency bands on the performance of our system. The five frequency bands used are α, β, γ, δ and θ, respectively. Under this setup, the total number of features extracted for each sliding window in different experimental setups can be calculated as $N_b \times N_f$, where N_b and N_f represent the number of frequency bands and statistical features selected, respectively.

TABLE 5. The model performance using a six-feature set.

Measurement	Classifiers	No. of bands	Accuracy (%)	Saving (%)	Risk (%)
Heart Rate	Neural Network	5	73.50	59.50	09.30
		28	74.60	59.80	08.80
	LS-SVM	5	78.20	62.60	06.80
		28	79.40	63.44	06.20
	Naive Bayes	5	75.30	55.20	08.30
		28	75.90	55.60	08.10
	Ensemble model	5	**91.20**	**63.50**	**4.60**
		28	**92.50**	**63.20**	**4.20**
DBP	Neural Network	5	72.70	50.80	09.70
		28	73.60	54.40	09.25
	LS-SVM	5	78.50	64.60	06.75
		28	80.40	64.80	06.10
	Naive Bayes	5	72.55	57.40	09.90
		28	73.40	58.30	09.50
	Ensemble model	5	**90.10**	**64.10**	**4.95**
		28	**92.80**	**65.70**	**4.05**
MAP	Neural Network	5	71.55	55.30	09.40
		28	72.50	56.40	09.10
	LS-SVM	5	75.60	62.54	08.25
		28	78.54	64.25	07.30
	Naive Bayes	5	73.30	63.70	09.95
		28	75.30	65.35	08.70
	Ensemble model	5	**91.60**	**64.30**	**4.20**
		28	**92.70**	**64.80**	**4.10**
SO2	Neural Network	5	75.50	61.20	08.50
		28	77.10	61.90	07.60
	LS-SVM	5	80.20	64.10	06.60
		28	81.10	64.80	06.15
	Naive Bayes	5	72.50	58.40	09.10
		28	73.50	60.50	08.95
	Ensemble model	5	**90.50**	**64.20**	**4.95**
		28	**92.50**	**64.60**	**4.30**

The detailed experiment results are presented in Table 4, Table 5 and Table 6 for three, six and eight-feature sets, respectively. First, it can be seen that the recommendation performance of our system, for all the four medical measurements, is noticeably improved compared with the performance when using only five frequency bands. This is because using all the 28 frequency bands can better capture the characteristics of each sliding window then using just five. Second, the results from the three tables reveal a similar trend that the performance of our system in terms of all the three performance metrics are generally improved when the statistical features used are increased. For example, under 28 frequency bands, the recommendation accuracy and risk of our system when using eight statistical features are approximately 2.4% and 42.9% better than using six statistical features across different medical measurements while maintaining a roughly same level of workload saving at the same time. Therefore, to achieve the best possible performance, it is suggested to use all the eight statistical features for all the 28 frequency bands if necessary for generating recommendations for patients.Finally, we can see that, using our recommender system, we can achieve a very high accuracy and workload saving as well as a very low risk. For instance, when using 28 frequency bands and eight statistical features, our system can achieve an accuracy over 94%, a workload saving over 63% while the risk is lower than 2.6%, indicating that our recommendation system is highly accurate and is able to significantly reduce the workload for chronic heart disease patients to take up their daily medical tests with a very low health risk.

C. EFFECTIVENESS COMPARISON WITH PREVIOUS APPROACHES

In the previous subsection, we have carried out a comparative study between our proposed ensemble model with the three base classifiers used in the model which are popular and widely used classification/prediction approaches. The experimental results presented earlier have shown that our system is superior to the base classifiers in terms of their recommendation performance.

In this section, we focus on comparing our proposed system with some of our previously proposed methods that tackle the exactly same problem as we do in this paper using the same Tunstall dataset for a fair comparison. For chronic heart disease patients served by a telehealth system, we proposed a basic heuristic approach earlier which produces recommendations based on some fundamental heuristic rules we developed [42]. We later used the basic heuristic approach together with the regression-based prediction algorithm as well as a hybrid approach combining them for producing recommendations [26].

Table 7 presents the performance comparison results. We can see from the results that the system proposed in this paper achieves the best accuracy among the three approaches.

TABLE 6. The model performance using an eight-feature set.

Measurement	Classifiers	No. of bands	Accuracy (%)	Saving (%)	Risk (%)
Heart Rate	Neural Network	5	80.40	60.60	06.80
		28	81.50	61.70	06.40
	LS-SVM	5	82.20	63.55	06.20
		28	83.30	64.20	06.00
	Naive Bayes	5	80.55	59.80	06.70
		28	80.90	60.20	06.60
	Ensemble model	5	**93.40**	**64.60**	**2.80**
		28	**94.80**	**64.30**	**2.60**
DBP	Neural Network	5	81.40	61.75	06.60
		28	82.10	62.30	06.30
	LS-SVM	5	82.20	64.10	06.20
		28	83.50	64.80	05.80
	Naive Bayes	5	80.40	60.20	07.80
		28	80.80	60.50	07.50
	Ensemble model	5	**94.25**	**63.30**	**2.95**
		28	**94.85**	**64.10**	**2.40**
MAP	Neural Network	5	79.40	58.30	08.10
		28	80.30	59.20	07.90
	LS-SVM	5	80.65	60.50	07.70
		28	81.45	63.60	06.60
	Naive Bayes	5	78.50	60.40	08.90
		28	79.10	61.45	08.80
	Ensemble model	5	**93.20**	**63.25**	**3.20**
		28	**94.20**	**63.70**	**2.60**
SO2	Neural Network	5	82.10	64.10	06.50
		28	83.40	64.80	05.70
	LS-SVM	5	84.20	65.30	04.90
		28	84.90	65.70	04.20
	Naive Bayes	5	81.30	62.50	06.75
		28	82.50	63.20	06.20
	Ensemble model	5	**94.80**	**64.75**	**2.40**
		28	**95.50**	**65.80**	**1.90**

TABLE 7. Recommendation performance comparison with previous methods.

Tunstall dataset

Method	Techniques used	Accuracy(%)	Workload Saving(%)	Risk(%)
Raid et al. [43]	Basic heuristic algorithm	86	10	8
Raid et al. [26]	Basic heuristic algorithm, Regression-based algorithm and Hybrid algorithm	91	15	5
Proposed method	Fast Fourier transformation and ensemble model	**94**	**64**	**2**

We are able to, in the proposed system, improve the accuracy performance from 91% to 94%. The workload saving has received a tremendous improvement from 15% to 64%. The recommendation risk of our system is also lower than the two competitive approaches.

D. EFFICIENCY COMPARISON

We also conducted the efficiency study to compare the execution time of the base classifiers and the ensemble model of our system under different feature sets. Fig. 5 and Fig. 6 present the execution time of the base classifiers and the ensemble model in their training and prediction stages.

From the results, we observe that 1) The execution time of the training stage is higher than that of the prediction stage for all the models evaluated; 2) All the base classifiers and the ensemble model feature an approximately linear execution time in both the training and prediction stages under different feature sets, ensuring the necessary efficiency for producing fast recommendations for patients; 3) Among all models, the ensemble model takes more time to complete the training and prediction than the individual base classifier. This is reasonable as the ensemble model needs to aggregate the results from the base classifiers to generate the

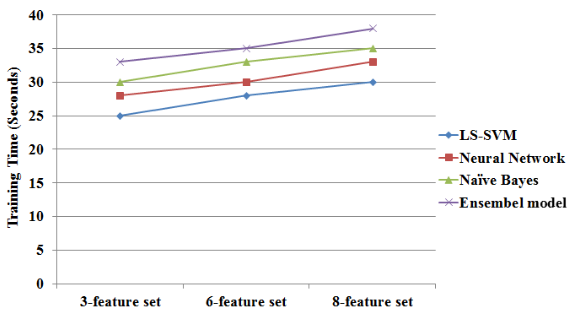

FIGURE 5. Comparison of the training time between the base classifiers and the ensemble model.

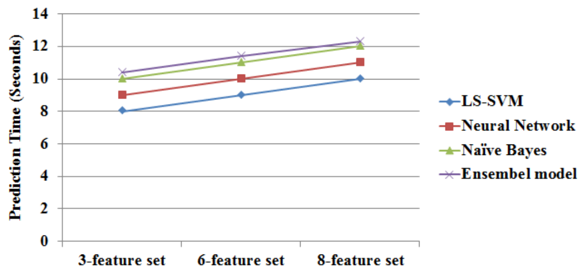

FIGURE 6. **Comparison of the prediction time between the classifiers and the ensemble model.**

weights for them and produce the final recommendation. The ensemble model sacrifices a little on the execution time for achieving better recommendation effectiveness for patients. Additionally, the training stage can be performed off-line so that it will not adversely affect the efficiency in generating recommendations for patients during the prediction stage.

V. CONCLUSION AND FUTURE RESEARCH DIRECTIONS

In this work, we propose a recommendation system supported by a machine learning ensemble model with the fast Fourier transformation for short-term disease risk prediction and medical test recommendation in the telehealth environment for patients suffering from chronic heart disease. This study applies the fast Fourier transformation, which effectively analyzes the medical time series data and input the extracted statistical features to the ensemble model to generate the accurate, reliable recommendations for chronic heart disease patients. Three popular and capable classifiers , i.e., Neural Network, Least Square-Support Vector Machine and Naive Bayes are used to construct the ensemble framework.

The experimental results show that the proposed system using all the eight statistical features produced by the fast Fourier transformation yields a better predictive performance for predicting the patient's condition compared with the other feature sets. The results also show that our system is more effective than the individual base classifiers used in the ensemble model and outperforms the previously proposed approaches to solve the same problem. Our evaluation establishes that our recommendation system is effective in improving the quality of clinical evidence-based decisions and help reduce the time costs incurred by the chronic heart disease patients in taking their daily medical test, whereby improving their overall life quality.

There are several directions for our future research work in this study. First, we want to evaluate our proposed system using additional appropriate datasets which preferably have a large number of data records. We are also interested in applying other ensemble techniques, such as boosting and Adaboost, to produce recommendations and conducting a comparative study on those different ensemble models. Finally, given the generality of our proposed model in dealing with medical time series data, we will explore the possibility to apply our system to support telehealth care for patients suffering from other type of diseases.

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