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A Health Care Platform Design: Applying Novel Machine Learning Methods to Predict Chronic Cardiac Disease

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Abstract: With the aging of the global population, the number of people with chronic diseases is also increasing, and cardiac disease has become the main cause of human deaths worldwide. In this study, we propose an integrated detection system for measuring the blood pressure (BP), blood glucose (BG), blood lipids (BL), and heart rate (HR). Next, we employ five commonly used machine-learning-based (ML-based) data classification methods, namely, support vector machine (SVM), random forests (RF), k-nearest neighbors (KNN), XGBoost, and LightGBM, for predicting chronic cardiac disease. These five classification methods use the data of BP, BG, BL, and HR, to predict the chronic cardiac disease, whose result shows that RF and KNN have the highest prediction accuracy (88.52%) as compared to the new ML methods, such as XGBoost and LightGBM. In addition, the proposed system should serve as a platform for the long-term detection and tracking of users' physical health.

Keywords: chronic disease; cardiac disease; machine learning; data analysis

1. Introduction

With the rapid aging of the global population, the incidence of chronic diseases in the elderly population has also increased (Prince et al., 2015). Some of the common chronic diseases include hypertension, diabetes, cardiac disease, gastropathy, and arthritis. Of these, both hypertension and diabetes increase the risk of cardiac-related diseases (Ettehad et al., 2016). According to the World Health Organization, cardiac disease is the leading cause of death worldwide (Anderson et al., 2016). Cardiac-related chronic diseases require long-term observation and tracking. Therefore, it is very important to reduce the incidence and mortality of chronic diseases through health check-ups and regular blood pressure and blood

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glucose monitoring. These not only allow for the early detection and control of chronic diseases but can also help prevent and delay the occurrence of these diseases.

In recent years, with the growth of the elderly population and the related increase in the demand for medical resources as well as owing to various government medical policies, such as those related to long-term care, the use of information technology in the medical field has been increasing. The application of artificial intelligence in the medical field can not only help clinicians in improving their workflows and reducing medical errors but also aid in the analysis of patient data for promoting their health (Topol, 2019).

On the other hand, the medical data has accumulated to a great amount since the national health insurance implementation. Integrating Health Insurance Information and artificial intelligence not only makes good medical diagnostic but also undertakes the complicated medical document arrangement and integration (Verghese et al., 2018). Therefore, due to the solid foundation of information technology and the increasing demand for medical care, the application of artificial intelligence medical technology has become a niche for nowadays development.

Given the trends of an aging society and the increasing demand for medical care, current medical equipment available in the market mostly measures only a single parameter, such as monitors of blood pressure (BP), blood glucose (BG), heart rate (HR), and other related devices. This may reduce users' willingness of long-term use, resulting that they should not use autonomously. In this study, we integrate four major detection systems for measuring BP, BG, HR, and blood lipids (BL), providing a design platform for the long-term detection and tracking of their physical health. This platform combines machine learning methods to explore the commonly used computing methods in cardiology- such as support vector machines (SVM), random forests (RF), K-nearest neighbors (KNN) (Johnson et al., 2018), and new types, LightGBM and XGBoost. By comparing the accuracy of five algorithms for predicting chronic diseases, we aim to improve the accuracy of chronic disease prediction and provide the best medical product and service for the home-based self-test. The better prediction leads to lower risk because individuals will take a prediction of future health problems as a warning and change their behavior accordingly. Even, it will reduce the proportion of future deaths due to cardiac-related diseases. The proposed home-based self-test medical product will reduce the unnecessary use of medical resources and improve the quality of medical care. The goals of this study are listed as follows:

1. Design and develop a software prototype with a platform that provides users for the long-term detection and tracking of their health status.
2. Compare regular machine-learning-based data analysis methods with the latest ones, such as LightGBM and XGBoost.
3. Serve as a reference for the development of machine-learning-based platforms regarding the detection of cardiac disease.

2. Literature review

2.1 Global status and analysis

In Taiwan, the elderly, that is, those over 65 years, account for 14.05% of the total population. It is estimated that in a very short period, approximately 8 to 9 years, the percentage of the elder population in Taiwan will reach 20%, making Taiwan become a “super-aged society”. In 2060, it may exceed 40%, making Taiwan the second aging country in the world. The National Development Council (2019) shows that countries such as Japan, South Korea, European countries, and the United States are also facing the increasingly aging society and low child birth rate, which is now an irreversible global trend. In the next 30 years, the proportion of Taiwan’s elderly population will increase rapidly and surpass many countries. Thus, it was officially announced that the country had transitioned from a 7% “aged society” to a 14% “aged society” (Department of Statistics, Ministry of the Interior, 2019). A report from the World Health Organization stated that, with the aging of the global population, chronic diseases have become the world’s major disease type (WTO, 2018). These diseases include cardiovascular diseases, diabetes, and other common chronic diseases. Approximately half of the adults in the United States have at least one chronic disease, while another 117 million are threatened by one (Ward, 2014). Eighty percent of Taiwan’s middle-aged and elderly populations suffer from more than one chronic disease, with the proportion of women (90.7%) being higher than that of men (88.7%). Chronic diseases are the main cause of death among the elderly population over 65 (Hong, 2015). One quarter of the diseases in those over 60 years of age are cardiovascular or respiratory diseases (Chatterji et al., 2015). Cardiovascular-related chronic diseases increase the risk factors for cardiac disease as well as the risk of death. According to Anderson (2016), cardiac disease is the leading cause of death all over the world. Therefore, cardiac-related chronic diseases are not to be neglected. Hence, it is of great importance to be able to detect and control the incidence of chronic diseases and reduce the mortality related to them.

Therefore, most people face the threat of a decline in their physical and mental functions along with the occurrence of chronic diseases as they age. This will not only increase the consumption of medical resources but also the risk of death in elderly people. Thus, platforms such as those proposed in this study will prove to be indispensable in the coming years.

2.2 Application of machine learning in medical field

In the era of big data, which is the result of recent advancements in information technology, several highly useful machine learning techniques have been developed. Along with advances in medical science, the use of machine learning methods in the medical field for analyzing the relationship between preventive and treatment technologies and disease prediction (Yu et al., 2018) has resulted in significant improvements in clinical outcomes. Big data and machine learning tools provide clinical assistance to doctors and promote the continuous development of medical transformation by the application of machine learning

to large-scale healthcare data (Beam & Kohane, 2017). At present, the application of artificial intelligence tools in the prevention and treatment of cardiac disease mainly includes the use of training, monitoring, and prediction technologies. Machine learning and in particular, the development of accurate prediction models for the latency characteristics of chronic diseases has resulted in significant progress in actual medical practice (Miller & Brown, 2018).

According to Shameer et al. (2018), various machine learning methods such as supervised learning, cognitive learning, and unsupervised learning can discover hidden structures in the data related to cardiac disease and can thus help prevent and treat common chronic cardiovascular diseases. Such insights may also lead to the discovery of new treatments and help improve specific cardiovascular care. In recent years, machine learning has been used in the field of cardiology for electrocardiography, myocardial perfusion imaging, and heart failure as well as for integrating clinical and imaging data using algorithms such as artificial neural networks (RNN), support vector machines (SVM), random forests (RF), and K-nearest neighbor (KNN) (Al' Aref et al., 2019). Motwani et al. (2017) showed that machine learning is a more effective way of predicting cardiac disease than using only clinical and conventional detection methods.

Therefore, in the era of big data, artificial intelligence has become a development trend in various fields and has resulted in significant progress in the medical field as well. With the prevalence of chronic diseases and given the significant changes occurring in the population, the demand for medical resources is also increasing. Using machine learning technologies for preventing and predicting the possibility of disease can not only solve the problem of limited medical resources but also offers an important auxiliary tool to assist clinicians in diagnosis.

2.3 Application of machine learning in predicting cardiac disease

In cardiology, the most commonly used machine learning algorithms are the support vector machines (SVM), random forests (RF), and K-nearest neighbour (KNN), (Johnson et al., 2018). We discuss these algorithms in brief next.

The SVM algorithm is a classification algorithm and is used to find a decision boundary to maximize the margins between two classes so that they can be distinguished perfectly. This linear classifier can transform the slope of a classification line to find the range with the largest width and determine the point closest to the line for the two classes. The distance between a given point and the classification is represented by a vector, which is called a support vector. Some of the common classification methods used with This algorithm include linear functions, the Gaussian radial basis function, and polynomial functions. Among these, the Gaussian radial basis function is the best classification function (Manavalan et al., 2018) (Figure 2.1 (a)).

RF consist of multiple decision trees, with there being no correlation between each decision tree. When inputting new information, one repeatedly and randomly draws K samples from the original training set to generate a new training sample set. Next, each decision tree is made to judge separately. This generates K classification trees based on the sample set,

resulting in a random forest. The classification results for the new data are based on the scores assigned by voting by the classification tree. RF classification has the advantage of being able to deal with data with many characteristics. Further, in the case of unbalanced datasets, it can effectively balance the errors in the data (Wager & Athey, 2017) (Figure 2.1 (b)).

The KNN method is a supervised learning classification algorithm. It uses the feature distance between the sample points to determine the type of the new data. The training data for the KNN method must be labelled, that is, the training data must be categorized. The main application area of this classification algorithm is the classification of unknown data. An advantage of the KNN method is that it does not have to be retrained. Further, its prediction error rate can be reduced effectively (Liao & Vemuri, 2002) (Figure 2.1 (c)).

(a) Support Vector Machine

Image Source:
<https://reurl.cc/yyOR46>

(b) Random Forests

Image Source:
<https://reurl.cc/e5pM7R>

(c) K-Nearest Neighbor

Image Source:
<https://reurl.cc/M723VX>

Figure 2.1 Machine learning methods for data classification.

3. Research methods

The health status detection platform proposed in this study, a database similar to the Cleveland database with 76 attributes was established based on the study by Janosi et al. (2018). A total of 13 impact attributes related to heart disease based on the existing literature were included in the database. Then, 313 samples were evaluated the performances of the latest machine learning algorithms (i.e. XGBoost and LightGBM), and compared with those of SVM, RF, and KNN in order to improve the accuracy of cardiac disease prediction.

3.1 Design of health care platform

An inspection of the medical testing equipment available in the market showed that the products for monitoring BP, BG, HR, and other related parameters mostly measure only a single parameter. This may reduce users' willingness to have multiple medical signals

detected simultaneously. Therefore, we attempted to integrate four detection devices, i.e. BP, BG, BL, and HR, in a single platform to facilitate the simultaneous collection of multiple medical data. This was done so that the data could be used to effectively predict the user's risk of cardiac-related chronic diseases using machine learning techniques (Figure 3.1).

Steps of using this device: First, the user logs in the basic information of gender, age, and gender. Second, uses a fine needle to prick a needle on his fingertip to take blood, squeeze out a few drops of blood, drop it on a sensor test paper, and place a device to measure the blood glucose. Third, after measuring blood glucose, put your arm into a circular hole that detects blood pressure and heart rate. After pressing the button on the top of the device, the device starts that the data could be used to effectively predict the user's risk of cardiac-related chronic diseases (Figure 3.2-3.4).

Figure 3.1 (a) Intelligent health care platform developed in this study integrates four detection systems for measuring blood pressure (BP), blood glucose (BG), blood lipids (BL), and heart rate (HR). (b) After performing measurements, system predicts probability of cardiac disease using machine learning.

Figure 3.2 Intelligent health care platform use steps.

Figure 3.3 Intelligent health care platform 3D model design.

Figure 3.4 The prototype of intelligent healthcare platform and the scenario diagram.

3.2 Data classification using XGBoost

XGBoost is based on the boosting algorithm and improves the training speed and prediction accuracy of the boosting tree model (Chen & Guestrin, 2016). In other words, XGBoost is an improved tree model and can be considered as a collection of many tree models. It continuously performs feature splitting to generate a tree. When the tree is generated, a new function is also generated. This function will fit the previously predicted loss function (Fan et al., 2018). After training, k trees are obtained. The classification method is based on the characteristics of the samples; the predicted values of the corresponding leaf nodes in the k trees are summed to obtain the predicted values for the test sample. The objective function is generated as given in Eq. (1):

$$\hat{y} = \phi(x_i) = \sum_{k=1}^K f_k(x_i)$$

$$\text{where } F = \{f(x) = \omega_{q(x)}\} = (q : R^m \rightarrow T, \omega \in R^R) \quad (1)$$

3.3 Data classification using LightGBM

LightGBM is based on the histogram calculation method and speeds up training by using continuous features. Its calculation of the maximum split gain is needed to reduce the amount of calculation of the segmentation gain, and the method speeds up the calculations by subtracting the maximum value of the histogram from the minimum value. Only the leaf nodes of a single tree are required to establish a histogram, and the histogram of the adjacent nodes can be obtained by subtraction (Chen et al., 2019); this increases the calculation speed (Figure 3.5).

Figure 3.5 Concept of data classification using LightGBM.

4. Results and discussion

The database used is similar to the Cleveland database (Janosi et al., 2018), which contained 313 samples, and we assessed the possibility of predicting chronic cardiac disease. The data corresponded to 165 people without cardiovascular disease and 138 people with the disease. In this study, we use three commonly used classification algorithms (i.e. SVM, RF and KNN), and compare two latest algorithms: XGBoost and LightGBM, in order to determine the best data classification method. This result can increase the accuracy of chronic disease

prediction, achieve the goal of self-testing and prevention, and reduce the risk of death caused by chronic disease.

4.1 Dataset for SVM, RF, and KNN methods

We used 313 samples with attributes related to chronic cardiac disease. Before the data analysis, normalization was performed to effectively eliminate the occurrence of heterogeneous states in the attributes and transform the original data into intervals $([0, 1])$. The expression used for this was the following: $(\text{original data} - \text{minimum value}) / (\text{maximum value} - \text{minimum value})$. We performed one-hot encoding for the data features, such as the maximum heart rate and the occurrence of myocardial infarction and thalassemia, and divided these categories into multiple rows; 1 indicated that the data for this category existed, while 0 indicated that it did not. This was a categorical variable that could handle discontinuities (Table 4.1). With respect to the four levels for the maximum heart rate, cp_0 indicated no heartache, cp_1 indicates mild pain with a pain index of 1–3 points, cp_02 indicated moderate pain with a pain index of 4–6 points, and cp_03 indicated intense pain corresponding to 7–10 points. Further, with respect to the four levels for myocardial infarction, Thal_0 indicated the first type in the Killip classification system with no complications and no signs of heart failure; Thal_1 indicated the second type in Killip—mild to moderate heart failure; Thal_2 was the third type in Killip—severe left heart failure or pulmonary edema; and Thal_3 was the fourth type in Killip—psychogenic shock or systolic blood pressure below 90 mm Hg. Finally, in the case of the three levels of thalassemia, Slop_0 indicated normalcy, Slop_1 indicated fixed defects, and Slop_2 indicated reversible defects.

Table 4.1 Conversion of maximum heart rhythm, myocardial infarction, and rare disease data using one-hot encoding.

No	Cp_0	Cp_1	Cp_2	Cp_3	Thal_0	Thal_1	Thal_2	Thal_3	Slope_0	Slope_1	Slope_2
0	0	0	0	1	0	1	0	0	1	0	0
1	0	0	1	0	0	0	1	0	1	0	0
2	0	1	0	0	0	0	1	0	0	0	1
3	0	1	0	0	0	0	1	0	0	0	1
4	1	0	0	0	0	0	1	0	0	0	1

4.2 Dataset for XGBoost and LightGBM

For classification using XGBoost and LightGBM, we used a dataset with categorical features to perform data segmentation and created dummy variables. The classification of categorical features involves dividing the dataset into two subsets based on the categories. If there are k categories, the number of categories obtained would be $2^{(k-1)}-1$, which can then be used for data classification (LightGBM, 2019). The feature importance measure represents the importance of the attributes with respect to the final goal based on the metric used. The data used in this study had 13 attributes, and a total of 19 attributes were obtained

through category classification. The histogram was sorted based on the cumulative metric of importance. The top three features based on the importance measure as per LightGBM were the maximum heart rate (178), cholesterol (170), and age (162) (Figure 4.1), while those as per XGBoost were thalassemia intermedia (0.29), myocardial infarction (0.24), and major vessels (0.07) (Figure 4.2).

Figure 4.1 Feature map for LightGBM.

Figure 4.2 Feature map for XGBoost.

4.3. Results

As stated previously, three commonly used classification algorithms, i.e. SVM, RF, and KNN (the value of k was set to 3) were used for classification. In addition, two new algorithms (i.e. XGBoost and LightGBM) were also used for binary classification. In order to increase the accuracy and reduce the overfitting conditions, we unified the following fixed parameters

used in these algorithms: “learning rate” was set to 0.05 while “max depth” was set to 7. In the case of LightGBM, “max bin” was set to 200 and “num leaves” was set to 150. Further, of the 313 samples in the dataset related to cardiac disease, 80% were used as the training set, and the remaining 20% were used for the test set. The performances of the five algorithms were compared. We found that SVM exhibited the best performance in terms of speed at 0.007 ms, followed by XGBoost and LightGBM; With respect to prediction, the accuracies of RF and KNN were the highest at 88.52% (Table 4.2). XGBoost and lightGBM classification algorithms were based on the calculation of large-scale data, which has faster training efficiency and higher accuracy (Chen & Guestrin, 2016; LightGBM,2020). Thus, for the small dataset (313 samples) used in this study, the new algorithms (i.e. XGBoost and LightGBM) did not perform better than the existing ones in terms of speed and prediction accuracy.

Table 4.2 Comparison of efficiencies and accuracies of various machine learning classification methods.

	Efficacy	Accuracy	
SVM	0.007/ms	Train	84.71%
		Test	86.89%
RF	1.513/ms	Train	99.89%
		Test	88.52%
KNN	1.11/ms	Train	87.19%
		Test	88.52%
XGBoost	0.029/ms	Train	82.89%
		Test	82.89%
LightGBM	0.026/ms	Train	80.26%
		Test	80.45%

5.Conclusions

The rapid aging of the global population and the resulting increase in the rate of chronic cardiac disease not only increase the risk of mortality but also pose significant challenges to national health policies. Artificial intelligence can have a significant effect on the medical field. Focusing of cardiac disease, in this study, we have compared the performances of five classification methods, i.e. SVM, RF, KNN, XGBoost, and LightGBM, in predicting chronic cardiac disease. A dataset consisting of 313 samples is used, and the result shows that the latest algorithms (XGBoost and LightGBM) are inferior to SVM in terms of the calculation speed. In addition, the prediction accuracy of RF and KNN is the highest (88.52%). For further discussion, the XGBoost and lightGBM classification algorithms are based on the calculation of large-scale data, which has faster training efficiency and higher accuracy. In this study, only 313 samples (small-scale data) have been used for testing and analysis, as such XGBoost and lightGBM have not yet obtained the best results. In the era of big data, whether the novel calculation method is suitable to be used for the small-scale data will be further explored in future research.

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