A Multi-level Cloud-based Virtual Health Exam System on Health Cloud

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Abstract

The design purpose of preventive health exams (PHEs) is to identify early asymptomatic disease and function that may affect health, making the exams a crucial measure in preventative healthcare. However, in practice, before health examinations, the majority of the public lacks practical personal health assessment for planning personal health examinations. This greatly affects the results and effectiveness of PHEs. To address this problem, this study proposes a virtual health examination (VHE) system that predicts examination results prior to health examinations, allowing people to conveniently select relevant test items before deciding to proceed with the actual examinations. The VHE model is designed to facilitate the support of all examination items and various grades or levels of health examination. The model uses cloud computing virtualization technology to rapidly integrate existing exam prediction models or newly developed models and follows a multi-level prediction framework. Therefore, different levels of VHE models can be constructed for each examination item, allowing the system to assemble various grades or levels of VHEs. Additionally, to respond rapidly to the large quantity of enquiries from the public, the system employs a cloud computing architectural design. Specifically, the VHE models deployed within the system are driven by the collaborative operations of two units in the system, vheMap and vheSum, to increase computing efficiency. This allows people to obtain their virtual exam reports quickly.

Keywords: Preventive health exam (PHE), Multi-level prediction framework, Cloud-based prediction model, Cloud virtual machine (VM), Support vector machine (SVM)

1. Introduction

The design purpose of preventive health exams (PHEs) is to identify early asymptomatic disease and function that may affect health, making these exams a crucial measure in preventative healthcare [1-4]. In practice [3-10], PHEs have several common problems that influence effectiveness: (1) the people receiving examinations do not clearly understand the test items and their meanings and are unable to select critical ones; (2) hospitals’ packaged health exams are mostly segmented by price and overlook the individual differences of those receiving exams; (3) unnecessary invasive procedures create the risk of infection or injury, resulting in the payment of higher fees and poor healthcare; (4) most people choose exam items without the recommendation of physicians or experts, resulting in serious medical treatment waste; (5) healthcare or health insurance institutions only provide basic health exam services (preliminary exam results are presented for each item without subsequent analysis and follow-up). Consequently, to mitigate these problems, it is necessary to provide the public with a complete personal health exam plan. Personal health assessment should occur before a medical exam, and test items related to the physical or mental abnormalities that the person is more likely to suffer from or diseases that are more likely to occur should be selected. An in-depth analysis should be conducted following the exam to identify disease risks that are difficult to detect. These measures can improve healthcare.

The key to a personal health exam plan is health status evaluation before a medical exam. Having physicians or experts perform health status assessments and health exam plans for every person is infeasible due to high costs. In
addition, for the current health management services or healthcare community platform [11-17] provided by Health Cloud or Clinical Cloud, the healthcare stage mostly occurs during the period after the health exam has been completed or during the treatment or recovery period. Health Cloud and Clinical Cloud only provide general rules and advice for health exam advanced planning. Previous studies [18-25] have shown that statistical analysis, image recognition, and data mining technology provide good results for disease prediction or interpretation of test or exam data; this can also be used to measure some health situations or conditions. However, the results of these studies are difficult to apply to the health exam plan because research data are obtained through complete physical or biochemical tests and many related exams are conducted only after the patient or physician suspects that a specific disease has been contracted. Thus, these tests are a part of the clinical examination stage. In summary, IT methods for providing the public with health assessments before health exams is an important and worthy topic for research.

This study proposes a multi-level cloud-based virtual health exam system to predict examination outcomes prior to health exams to assist people in evaluating their health conditions and selecting relevant test items before deciding to proceed with actual examinations. To achieve this goal, a virtual health exam (VHE) model, which applies cloud computing virtualization technology [26-29] and enables the system to rapidly integrate existing exam prediction models or newly developed ones, is designed. This is done to allow the system to support all examination items. Second, a multi-level prediction framework is designed for the VHE models. By following this framework, VHE models of different levels can be established for each examination item, allowing the system to integrate or combine multi-level virtual health exams. Third, based on this framework, diverse information regarding various people can be processed and different levels of virtual exam predictions can be implemented, enabling people to obtain a reference report before health exams. Fourth, this study adopts a cloud computing architectural system design [26,30,31], and drives the VHE models deployed within the system through the collaborative operations of two control units in the system, namely vheMap and vheSum. This increases computing efficiency to respond rapidly to the large quantity of enquiries from the public.

Using this system, people can enter known personal health information into the system before the health exam, and the system then conducts various virtual exams. The exam results are provided for the users, allowing them to decide necessary test items. This then becomes the basis for health exam planning. After the actual health check, the user can conduct another more accurate virtual exam based on the real exam report and decide whether to perform advanced tests for a particular disease. Consequently, users can confirm and focus on key exam areas, receiving better healthcare at lower cost. To verify the proposed system, a prototype system was implemented. In 2009, among 9,052 test participants at National Taiwan University Hospital, we first focused on 4,488 male participants and separately conducted different levels of virtual exams for diabetes and fatty liver disease. The experimental results show that the system performs well.

2. System description

As shown in Fig. 1, the system consists of three parts: the user interface (UI) service, cloud-based VHE control, and cloud-based multi-level VHE models. The UI service employs a Web-based online service to receive user requests, perform data validation and conversion, and provide virtual test results to users. Cloud-based VHE control manages and delivers requests to all VHE models in the cloud and then receives feedback results. Every cloud VHE model then conducts a certain virtual exam prediction. For high availability and scalability, the system was designed using a cloud computing architecture [26-32]; all system components within the three parts are replicated and distributed on cloud virtual machines (VMs).

Figure 1. Architecture of proposed system.

2.1 Cloud-based virtual health exam control

There are three major units in cloud-based VHE control: vheManager, vheMap, and vheSum. vheManager is responsible for managing all VHE models in the cloud and maintains the information of every VHE model, such as VHE cloud ID, virtual exam items, prediction level, and prediction performance. It also monitors the status and load of the VHE model. vheMap selects the VHE model with the lightest load for each virtual exam item from vheManager, it then sends the user request to these VHE models and notifies vheManager and vheSum regarding relevant information. vheSum is responsible for receiving the prediction results sent by the VHE models activated by vheMap. It employs a timeout mechanism to avoid endless waiting. It references prediction performance from vheManager, organizes and sorts all prediction results, and then provides feedback to the UI service part. Similar to the operational relationship between Map and Reduce for Hadoop [32], through the collaboration of vheMap and vheSum, the system can immediately activate massive amounts of
computing performance and rapidly complete all virtual exam predictions after receiving user requests.

2.2 Cloud-based VHE model

The third part of the system is mainly composed of the various health exam prediction models. The data processing unit and the system link and control unit are collectively known as the VHE model. These health exam prediction models can be rule-based, classification, logistic, linear, or nonlinear regression models, and lengthy research and verification are required to acquire them [33]. Considering the differences among existing prediction models in their operating environments (such as operating system (OS), programming language, and data methods or modes), the models may need to be redeveloped or may experience transplantation difficulties if they are limited to a particular operating environment. This will also limit the research and introduction of new models in the future, which is not conducive to system development. A universal framework based on cloud computing technology was thus designed. As shown in Fig. 1, each VHE model is individually deployed on a cloud VM, becoming a loosely coupled subsystem. A cloud VM [27-29] installs the OS and packages required for the prediction model, thereby overcoming the restrictions or limitations for operating environments. The data processing unit conducts the output and input data conversion processing of the system and the prediction model, and thus overcomes differences in data processing. The system link and control unit are composed of standard system components and mainly process the VHE models and the operations of VHE control part. This design allows the system to rapidly integrate existing exam prediction models or newly developed ones, and can use cloud characteristics to provide rapid and highly usable system services.

2.3 Multi-level prediction framework for the VHE model

Physicians frequently conduct a series of medical tests or examinations to confirm the diagnosis of specific diseases or dysfunctions. Furthermore, follow-up examinations are typically high-cost and there is a risk of infection or injury. The performance of intuitive prediction for specific diseases varies according to the quality of available data. Furthermore, for this series of examinations, predictions conducted earlier are more significant than predictions conducted later. Based on this argument, a multi-level prediction framework is proposed for the VHE model. As shown in Fig. 2, the framework allows for predictions during a series of stages in a particular virtual examination, which is similar to the series of tests that would be used to confirm the diagnosis of specific diseases. The proposed system serves as a reference for the public by offering pre- and post-examination predictions, thereby assisting the public in deciding whether more precise examinations are necessary. The production of various levels of VHEs is influenced by the source data attributes for system training, items to be examined, and adopted prediction methods. A multi-level framework that efficiently overcomes this difficulty is proposed. The leveling guidelines are as follows. (1) Source data are divided into the following three categories: questionnaire or consultation surveys (Type Q), basic medical examinations (Type B), and advanced medical examinations (Type A). Free checkup items covered by Taiwan National Health Insurance (TWNHI) [34] are employed as a reference for Type B data. (2) Source data are replicated for each disease, and irrelevant Type A examination items are omitted to ensure that each disease has unique source data and similar Type Q and B data. (3) All source data items are designated a level index (l) according to the following four principles: a) \( l = 0 \) for all Type Q data; b) \( l = 0 \) for Type B data obtained by self-examination (e.g., weight), and \( l = 1 \) for remaining Type B data; c) \( l = 2 \) for all Type A data; and d) higher \( l \) values for Type A data categorized as invasive, harmful, infectious, or high-cost based on definitions by physicians and experts. (4) All disease source data where \( l \leq n \) are considered level-n data for that disease. (5) Level data from level-0, level-1, …, level-n are generated for all source data. A \{level-0\} \subset \{level-1\} \subset \ldots \subset \{level-n\} relationship exists for each disease. For any disease pair, level-0 and level-1 data are identical, although level-2 data and n can vary.

For example, level-0 data for a liver disease (\( n = 4 \)) case contain details that can be obtained without the patient being examined at a hospital, including personal life habits, exercise, smoking, alcohol consumption, personal and family medical history, and physical and psychological questionnaire data. Level-0 data can also include details such as height, weight, blood pressure, blood type, heart rate, and age, as well as chest, waist, and hip measurements. Level-1 data comprise Type B data, including level-0 data and the data based on TWNHI free health exams, such as body mass index (BMI), triglycerides, blood glucose, cholesterol, liver function indicators, uric acid, and basic hematometry exams. Level-2 data include level-1 and Type A data for specific diseases, such as urine glucose, high-density lipoprotein (HDL), low-density lipoprotein (LDL), liver and gallbladder serological tests, and measurement values such as aspartate transaminase (AST), alanine transaminase (ALT), and gamma-glutamyl transferase (GGT). Level-3 data include an additional abdominal ultrasound (high-cost, low-invasiveness), and level-4 data further include a liver tissue...
biopsy (high-cost, high-invasiveness, harmful/infectious).

Within these subtle distinctions and segmentations, level-0 and level-1 data attributes are constant for all diseases; thus, level-0 and level-1 data are fixed levels developed by the system in advance. Conversely, level-2 to level-n data vary because the follow-up phase focuses on advanced exams conducted for diagnosing specific diseases. Therefore, the various data levels can generate several prediction models and network with the cloud-based framework VHE model to provide a multi-level VHE service.

3. Verification experiments

The functions and operating mechanisms of the three parts of the exam system, namely UI service, cloud-based VHE control, and the model, are clear, and, during implementation, only software design and systems engineering specifications must be followed. Whether the VHE model contains the capability of multi-level virtual examination depends on whether the proposed framework can allow for predictive models to demonstrate different levels of predictive ability. This portion of the design must be verified through experimentation.

3.1 Materials

A total of 9,052 participants (subjects) who underwent a self-paid health examination at National Taiwan University Hospital from January 2009 to December 2009 were studied. All of the participants were Taiwanese, members of the general public, and did not belong to any particular socio-economic class. There were also no limitations to a particular occupational group. The participants were recruited through advertising messages for health-promotion purposes from the general population. The exam fees were approximately one-thirtieth of the gross national income per capita in Taiwan. The standard health examination protocol included a semi-managed survey, face-to-face conversation with a physician, physical examination, blood biochemical analysis, plain radiography for the chest and abdomen, abdominal ultrasonography, a urea breath test (UBT), an immunochromatographic fecal occult blood test (i-FOBT), and bidirectional endoscopic examination for both the upper and lower gastrointestinal (GI) tracts. Before the test, all participants (subjects) were required to complete a standard questionnaire in which the following information was collected: demographics, common symptoms involving all body systems in the past three months, medical and medication history, and social habits (smoking and alcohol). The presence of each symptom was recorded and verified by internal medicine consultation. This study was approved by the Ethical Committee of National Taiwan University Hospital.

3.2 Experiment design

In this experiment, two chronic diseases that are common in Taiwan (diabetes and fatty liver disease) were selected to act as the VHE prediction targets. Among the total of 9,052 subjects, the ratio of men to woman was 57:43, and more than 90% of patients were aged from 35 to 75 years. 417 cases had missing or incomplete data, such as questionnaire results, urine test results, abdominal ultrasound results, or the performance of only certain specific tests; these cases were excluded, leaving 8,635 complete records. After considering gender differences and age distribution rates within medical standards, male patients aged from 35 to 75 years were selected as study participants to achieve more rapid and accurate prediction results, resulting in a total of 4,488 subjects. Among these, 505 patients had diabetes (11.25%), and 2,312 patients had fatty liver disease (51.52%).

To evaluate the performance of the multi-level VHE, all data were randomly sampled and distributed evenly into five groups for 5-fold cross validation. Four of these groups served as training data (80%) and the remaining group served as test data (20%). Three levels of data were then produced based on the multi-level framework discussed in the previous section. Level-2 data included post-consumption blood glucose for diabetes (GLU2hrPC) and AST, ALT, and GGT measurement values for fatty liver disease, respectively. Two prediction algorithms, namely those based on support vector machine (SVM) and k-nearest neighbors (KNN), were selected [35-38]. The prediction models were trained based on level-0, level-1, and level-2 data, for a total of 12 prediction models (2 diseases × 3 levels × 2 algorithms). The prediction models were implemented using statistical computing software R, with the radial basis function (RBF) as a kernel function of libsvm, and tune.svm and tune.knn applied to obtain optimal parameters. Model training was then performed. SVM is a commonly applied high-performance algorithm in the field of biomedical informatics as well as many other fields, making it suitable for and highly representative in verifying the multi-level VHE model. As detailed in Section 2.3, multi-level framework leveling is based on correlations between data attributes and disease; therefore, this framework is applicable to the majority of prediction algorithms. However, the inclusion of additional algorithms in the calculation and experimentation might enhance the verification comprehensiveness. Therefore, a simple KNN algorithm was also used. KNN determines prediction results based on the similarity of k adjacent items. This improves the variance of the experiment, and assists in clarifying data similarity at various levels. Each prediction model predicts and collects prediction results based on the testing data with the corresponding disease and level. Five cross validation passes were performed on five unique groups of test data. Finally, the results from all predictions were compared with actual examination results. The overall performance of each level was subsequently calculated and compared.

3.3 Evaluations

To compare the performance of the VHE model in different levels, 4 measurement indicators, namely sensitivity, precision, accuracy, and F-measure (F1 score) [39,40], were used. They are respectively defined as follows:

\[
\text{Sensitivity} = \frac{TP}{(TP + FN)}
\]  (1)
Precision = \frac{TP}{TP + FP} \quad (2)

Accuracy = \frac{TP + TN}{(TP + FP + FN + TN)} \quad (3)

F - measure = \frac{(2 \times Sensitivity \times Precision)}{(Sensitivity + Precision)} \quad (4)

where:
True positive (TP): the VHE and diagnosis both detect the disease.
False positive (FP): the VHE detects the disease, but the diagnosis does not.
True negative (TN): the VHE and the diagnosis do not detect the disease.
False negative (FN): the diagnosis detects the disease, but the VHE does not.

Precision indicates the number of positive results for VHE predictions that were relevant, and sensitivity indicates the ability of VHE prediction results to detect positives. Both are crucial to patients. F-measure is the harmonic mean of precision and sensitivity, and is suitable for measuring the overall performance of VHE. This is especially the case when disease rates are low and the differences between accuracy indicator values of various levels are not obvious. Therefore, when comparing the performance of different levels of VHE, variations of precision, sensitivity, and F-measure indicators at different levels should be compared as well. A VHE with multiple levels produces higher indicator values at higher levels than at lower levels, especially the F-measure.

4. Results and discussion

The results of virtual exams using the VHE model for diabetes and fatty liver disease are shown in Tables 1 and 2.

Table 1. Experimental results of proposed multi-level VHE for predicting diabetes.

<table>
<thead>
<tr>
<th></th>
<th>KNN</th>
<th>SVM</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Level-0</td>
<td>Level-1</td>
</tr>
<tr>
<td>Sensitivity</td>
<td>0.46</td>
<td>0.50</td>
</tr>
<tr>
<td>Precision</td>
<td>0.90</td>
<td>0.97</td>
</tr>
<tr>
<td>F-measure</td>
<td>0.61</td>
<td>0.67</td>
</tr>
</tbody>
</table>

Table 2. Experimental results of proposed multi-level VHE for predicting fatty liver disease.

<table>
<thead>
<tr>
<th></th>
<th>KNN</th>
<th>SVM</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Level-0</td>
<td>Level-1</td>
</tr>
<tr>
<td>Sensitivity</td>
<td>0.68</td>
<td>0.75</td>
</tr>
<tr>
<td>Precision</td>
<td>0.67</td>
<td>0.72</td>
</tr>
<tr>
<td>F-measure</td>
<td>0.69</td>
<td>0.73</td>
</tr>
</tbody>
</table>

The prediction results of the classification algorithms, SVM and KNN, show an increasing trend in all three levels, proving that the proposed framework can establish exam prediction models for different levels, allowing the system to assemble a multi-level virtual health exam. SVM had good performance for the 12 prediction models, and showed high values for the diabetes prediction measurement indicators of sensitivity, precision, accuracy, and F-measure (0.71, 1.0, 0.96, and 0.83, respectively) in level-0. Compared with an average attack rate of 0.11, a high prediction result was obtained in level-0. Also, the prediction performance of fatty liver disease was good, the level-0 measurement indicators were 0.73, 0.75, 0.72, and 0.74, respectively. Compared with the average attack rate of 0.52, these prediction results are also superior. Moreover, the indicator values of level-1 and level-2, which show excellent prediction results, for the diabetes predictions are 0.78, 1.0, 0.97, and 0.88, and 0.84, 0.99, 0.98, and 0.91, respectively, and those for fatty liver disease predictions are 0.76, 0.80, 0.77, and 0.78, and 0.77, 0.80, 0.78 and 0.79, respectively.

The prediction result distribution for the 35 to 75 age group was further analyzed. Diabetes and fatty liver disease showed a stable trend in the three levels, with no significant changes produced by age difference. Figure 3 shows the various measurement indicator values for SVM’s prediction of fatty liver disease occurrence for various ages in level-0,
level-1, and level-2, respectively. Comparing the performance of the two classifiers (shown in Tables 1 and 2), although KNN is inferior to SVM, KNN results are satisfactory and indicate that health examination data demonstrate proximal clustering. This is useful for subsequent research. In addition, the high indicator value prediction results of level-0 show that whether the participants belong to a high risk group for a certain disease can be predicted before they receive a health exam, which confirms that disease is collectively affected by personal factors, environmental factors, and pathogenic factors. If a high indicator value appears in the level-1 prediction stage and the value is close to that of level-2, it indicates that the participants only require basic exams to accurately predict whether they belong to a high-risk group for a certain disease. The participants do not require excessive exams and should consider directly consulting a professional physician for diagnosis and treatment.

In practice, the data attributes of level-1 correspond to the TWNH free health exam items [34]. The experimental results show that insurance institutions can use the proposed system to rapidly identify high-risk groups according to public health examination results. These institutions can then provide relevant medical care or preventive healthcare measures to improve the quality of public healthcare and reduce the large medical costs after a disease occurs. Although the designed cloud system can rapidly provide tremendous computing performance, establishing the system requires a significant amount of equipment. The experiments had certain limitations, including the fact that only one year of information was obtained from National Taiwan University Hospital, the selected data attributes did not include all exam items, and a majority of the participants may have belonged to a higher economic capacity group. If the system is to be widely applied, further verification must be conducted.

5. Conclusion

This study proposed a cloud-based VHE model and a multi-level prediction framework that can rapidly integrate existing exam prediction models or newly developed models, and construct different levels of examination prediction models, allowing the system to assemble various grades or levels of VHEs. The proposed cloud system produces a large amount of computing efficacy through the collaborative operations of two units in the system, vheMap and vhe$sum, enabling the public to obtain virtual examination reports quickly. Moreover, the cloud overcomes obstacles such as the incredible amount of disk space required for storing health examination data, as well as the computing capacity required for analyzing large amounts of data. The experimental results indicate that all 3 levels of prediction results improve as the levels increase. This verifies the applicability and feasibility of the proposed framework. The research results are encouraging enough to warrant further in-depth study. In the future, based on the proposed system, the performance for other diseases or examination items and that of different models and machine learning algorithms within VHEs will be investigated.

References


