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A Decision-Tree Based Classifier for Providing Telehealth Services

ABSTRACT

This study proposes a heuristic decision tree telehealth classification approach (HDTTCA), a systematic approach to classify those who are eligible for telehealth services. HDTTCA identifies three of the most important attributes in the data set for the patients who qualified for telehealth service: clinical records, convenience, and social-economic status. By acquiring a large volume data set from the National Health Insurance in Taiwan, this study verifies the efficiency and validity of HDTTCA. The results indicate that HDTTCA is able to find a decision tree to classify the patients that should benefit from telehealth service.

KEYWORDS: Telehealth Service, Decision Tree, Data Pre-processing, Data Sampling, Attribute Selection

INTRODUCTION

The emergence of wireless technologies and advancements in on-body sensor design can enable change in the conventional health-care system, replacing it with wearable health-care systems, centered on the individual (Zerkouk, et al., 2014). In particular, devices and techniques for monitoring blood pressure, blood glucose levels, cardiac activity and respiratory activity are recent progresses in non-invasive monitoring technologies for chronic disease management. However, telehealth service is not cheap and insurance providers should carefully consider and calculate its cost.

Health insurance scheme is an insurance policy leveraging the medical expenses of future illnesses. An insurer needs to develop a finance structure by charging monthly premium or payroll tax to ensure that the money is available to pay for the medical expenses in the insurance agreement. The health insurance not only compensates the clinical medical expenses of the insurers but also give subsidy to the vendors providing indirect medical care.

A new concept called “Elderly Welfare” has emerged by adopting health welfare and the development of telehealth system for the ageing population. The business of telecare around the world is also more and more prosperous. Few people use the telehealth service because users need to pay at their own expenses without insurance reimbursement. Patients have less motivation to use these kinds of services due to three reasons: lack of knowledge, low cost-effectiveness and lack of support from insurance policy (Lee, et al., 2010). However, an elderly who lives alone in a remote village may spend more than eight hours roundtrips in transportation in order to see a doctor in a hospital, which, in turn, makes his or her situation of chronical disease even worse. On the other hands, without automatic detection of physiological value, the patient in diabetes or hypertension might be unaware of the abnormality and miss the crucial time to go to a doctor. With the proper help of telehealth services to reduce the urban-rural gap, residents in remote areas can have access to medical treatment in advance without going through the long transportation time.

The Department of Health in Taiwan also introduced a pilot project for telehealth services in 1995 (Lee, et al., 2010). However, a review of government plan in 2013 shows that the number of cumulative applicants was only 9,606, added up to 343 thousand times of services at the end of 2011. Researchers found several main reasons why patients in Taiwan seldom use telehealth services. First, the price that a patient is willing to pay for a telehealth service is below 1000 New Taiwan Dollars (NTD) monthly while renting a remote physiological monitoring equipment is at least 3,000 NTD monthly, not to mention the service fees (Lee, et al., 2010). Outpatients prefer to have medical advice face to face and people are not accustomed to use the telehealth services. Last but not the least, since the telehealth services is not included in the NHI coverage, paying for prevention is not a wise option compared to the deductibles in medical treatment. Despite these reasons, researchers (Chen, et al., 2013; Chiang, et al., 2012; Ho, et al., 2014; Kailas and Ingram, 2009) still found numerous social benefits to utilize telecare services, including deduction of the hospitalized frequency for patients; reduction of the medical costs for hospitals; and relaxation of the caregiver's burden.

Because health insurance policy has not officially recognized telehealth services as an efficient treatment, we have no information to compute the cost and benefit of utilizing telehealth services if reimbursed by health insurances. We first need to classify all the patients into two groups: need telehealth service and do not need telehealth service. However, it is time-consuming to classify all patients one by one without computer-aid. We will need a proper classification algorithm from the assistance of the telehealth experts. Among the many classification algorithms, decision tree stands out as the best suitable approach in this study because of its characteristics (Quinlan, 1986). Decision tree is simpler to understand and interpret than association rule or logistic regression. Decision tree also has easier data preparation stage and is capable to handle categorical data. By using the decision tree, we can classify all patients into several groups by a reasonable rule set, such as Necessary, Long-term Necessary, or Not Necessary. However, since the patient information does not contain this classified attribute, we need a classification algorithm based on an unsupervised decision tree.

The rest of this paper is organized as follows. Section 2 describes the problem. In Section 3, we present our heuristic decision tree telehealth classification approach (HDTTCA) to resolve the patient classification problem for telehealth service efficiently. Section 4 compares the results obtained with our heuristic algorithm against those obtained with other heuristic methods, to evaluate the HDTTCA's efficiency and accuracy. Finally, in Section 5 we offer conclusions and suggestions for further research.

PROBLEM DESCRIPTION

This study aims at solving the problem of classifying the patients that are candidates of receiving the telehealth services through health insurance reimbursements. Specifically, patients with chronic diseases can be assisted by the non-invasive monitoring technologies devices such as blood pressure, blood glucose level, cardiac and respiratory activity. However, these non-invasive monitoring technologies devices need to be operated by a telehealth management system and professional health care staffs. Because designing a telehealth system with professional health care staffs is a very cumbersome and costly task, it is important that not too many patients are approved to receive this benefit of the telehealth services to continuously operate the system. Therefore, before implementing the telehealth reimbursement policy by insurance providers, it is critical to know who are qualified to receive the telehealth services to ensure the services assisted the most needed patients but not only the wealthy ones.

The first issue addressed in this study is identifying patients who would benefit most from telehealth services. Governments around the world now focus on the issues of the aging population, the disabled people and the patients with the chronic diseases and form healthcare policies to provide better services. Researchers found that telehealth services can eliminate the possibility of misuse of resources and reducing disparities in urban-rural gap [2]. Therefore, a new healthcare policy, called "Elderly Welfare", targeting the aging population and the patients with chronic diseases, is formed by adopting health welfare and telehealth system.

Nevertheless, most governments do not include telehealth services in their health insurance schemes because of the expensive telehealth service fees. In this study, we aim at identifying the potential receivers of the telehealth services if introducing telehealth services into health welfare or health insurance schemes. Because telehealth services are not compensated by the health care insurance before, there exists no target variable for the classification approaches to learn or train from. The problem of classifying the patients as candidates of receiving the telehealth services becomes a non-supervised classification problem. Therefore, the first challenge of this study is to generate the target variable.

The type of data associated with any target variable (interval, ordinal, or nominal) determines which data mining techniques can be used. For a problem of classifying the patients into receivers or not, the target variable is usually the patient's status (e.g., not qualified or qualified). These binary definitions can be transformed into a 0/1 code and applied easily in many data mining techniques, including decision trees and logistic regression. The target variable can also be defined according to different classes, to match their various meanings. For example, we can classify all patients into several classes, such as "Necessary", "Maybe Necessary in the Long-term", or "Not Necessary". However, the more classes exist, the more frequently misclassification occurs, because the individuality of each class gets diluted, causing a more easily misclassified situation for similar classes. It also could lead to an overfitting problem, caused by too many predictor variables for a multi-class target variable but not enough data points. Consequently, the number of classes should be limited to a reasonable level.

However, some of the attributes cannot be obtained directly from the dataset. In a telehealth classification problem, attributes are the patients' personal and outpatient information, provided when they submit their telehealth service applications. Hence, the second challenge of this study is to generate the needed information from the existing attributes to decide the suitable receivers of telehealth service. Ultimately, the result of this study ensure that the insurance providers receive a detailed medical history of a patient for telehealth services. HDTTCA generates the decision tree based classifier by using criteria such as "Health", "Distance", and "Socio-Economic" based on previous research (Durrani and Khoja, 2009; Fujimoto, et al., 2000; Shaw, 2009).

The third challenge of this study is to build a classifier to solve the problem of identifying candidates of telehealth service to receive health insurance reimbursements. Before constructing a classifier, we define T as a table which is constructed by m variables and has n records, x_1, x_2, …, and x_n. The target variable, denoted as $y_i = \{0,1\}$ where $1 \le i \le n$, is "adoptability for telehealth service". Hence, a record can be expressed as $x_i = [x_{i1}, x_{i2}, \ldots, x_{im}, y_i]$ and $T = \{ x_i \mid 1 \le i \le n\}$.

Machine learning became a fundamental research field after artificial intelligence achieved recognition as a discipline in the mid 1950's (Scott, et al., 2002). The goal of machine learning is predicting the future by using computer-recognized patterns or trends in the historical data. In this research, we aim to classify all patients into subgroups, so we build a classifier by choosing the appropriate classification algorithm from the algorithms, such as Artificial Neural Networks (ANNs), Decision Tree, Logistic Regression, Naïve Bayes, Support Vector Machine (SVM). We choose Decision Tree as our classification algorithm because the rules it generates are simple to interpret and read, which makes the result easier to understand for medical peoples and patients.

To construct a decision tree based classifier involves mainly three steps (Quinlan, 1986): variable selection, node splitting and tree pruning. Generally, researchers use entropy and information gain for the first steps, and get the local-maximize information by splitting data based on a variable. However, this method requires the data to be categorical, researchers developed many methods for interval data, such as ID3, C4.5 and CART. Building a decision tree based classifier involves choosing an appropriate method to select variables, to split nodes and finally to prune the tree. Therefore, feature selection and feature extraction can be applied to the data to enhance classification performance. Feature selection is a process of selecting representative attributes; feature extraction instead transforms the original attributes to some other form to reduce the dimensions of the dataset.

After splitting nodes to generate a tree, the next step is to prune the tree if the tree is too big with too many levels or nodes, which leads to an overfitting problem. There are two types of pruning approaches (Lillie-Blanton and Hoffman, 2005): pre-pruning stops the tree to grow before the entire training dataset is classified; post-pruning prunes the tree after the decision tree is finished. This study needs to decide which pruning approach is most suitable to build the classifier.

Finally, validation data indicate if the model's misclassification rates meet established requirements, and validation techniques consider the probability of the worst case scenario when a model's complexity is high. For example, the widely used k-fold validation technique divides a data set into k subsets and takes k – 1 subsets as the training data, with the remainder as the validation data set. The model then is trained k times, and each iteration uses the *i*-the subset, one at a time. However, the problem considered by this study is under a big data environment and it is very time-consuming even with only one scan of the dataset. Therefore, for the validation step, we use one validation.

THE HEURISTIC DECISION TREE TELEHEALTH CLASSIFICATION APPROACH (HDTTCA)

To solve the problem of classifying the patients that are candidates of receiving the telehealth services through health insurance reimbursements, the first challenge is to generate the target variable. It is unrealistic to use all the attributes and all the objects to generate a decision tree–based classifier. Instead, this study extracts the most discriminative attributes as nodes to partition the data before generating the classifier. Once the classifier is built, the prediction can be applied to future, incoming data to assign them to classes (scores). We propose a heuristic decision tree telehealth classification approach (HDTTCA) that consists of three major steps: (1) data analysis and preprocessing, (2) decision tree model building, and (3) prediction and explanation.

The raw data are collected from different sources and integrated into a single data set for usage in Step 1. To validate performance independently, HDTTCA also partitions the data set into two separated subsets. In the second step, HDTTCA establishes decision tree models from the data set thereby produced, validates the models to prevent them from overfitting, and selects the best decision tree model for future predictions. Finally, HDTTCA predicts and explains incoming data using the previously chosen model. After building the decision tree model, we use this model to predict the applicability of telehealth services. The advantage of decision tree classifier over other classification algorithms are their coherent and consistent rules and are easy to interpret whether a patient is suitable for telehealth services.

This study aims to identify patients that are suitable for telehealth services. Therefore, HDTTCA asks experts to assign a value to the target variable, Adoptability, first. However, it is impossible for experts to review all records in the data set and thus, HDTTCA samples a comparatively small data set as the training data set. To solve the problem of this study, we suggest to interview at least three experts in telehealth-related fields to identify the adoptability in the sampled data, i.e., doctors, social workers or managers of care centers. Except labelling the adoptability (“Y” or “N”) for each record, the experts reveal the rules of their decisions during the interview. The opinions obtained from the experts might be inconsistent for some records and thus HDTTCA integrates the outcomes of each record by the following rules: Adoptability = “Y” if more than or equal to half of the experts label it as “Y”; and Adoptability = “N” if less than half of the experts label it as “Y”.

In addition, some important attributes are not included in the dataset and thus need to be derived from other attributes. Different techniques apply such that a concise and coherent data set is available for the next step. After performing these steps, HDTTCA can proceed and partition the data set into two separate subsets to validate the performance in our algorithm.

In this study, data sampling, especially oversampling, is necessary because of the rareness of target class. Although chronic patients suffering from diabetes, hypertension and heart diseases are increasing over the past few years, our potential target are still comparatively rare within 10% or less of the total population. This imbalance characteristic of the data set may reduce the predictability of a decision-tree model. Oversampling is a helpful technique to overcome this problem. Oversampling resamples existing data of minority with slight modifications to get closer to proportion of majority. We also use stratified sampling in our research to increase the proportion of our target.

After sampling, we then partition the datasets into training and validating subsets. We use the former to build the classification model and use the latter to validate the over-fitting problem and compare the prediction rate of different models. Because HDTTCA samples a comparatively small dataset as the training dataset for experts’ opinions, we use all the experts’ opinions as the training data set and take more samples from the remaining dataset as the validation datasets.

Next, HDTTCA builds the decision tree classifier, based on the training data set, then validate the classifier using the validation data set. However, the telehealth service classification problem usually involves many attributes, which are not all essential to identify the characteristics of the target variable. Furthermore, correlations among the attributes can cause multicollinearity and inaccuracy in the decision tree based models. Before building the decision tree classifier, we thus use an attribute selection mechanism to choose the most discriminative attributes. The resulting classifier reduces significantly time complexity, without sacrificing accuracy.

Decision tree algorithms classify records by conjunctive rules (e.g. Age Group = Elder and Distance $\geq$ 60). Several decision tree algorithms, such as ID3 and C4.5, apply information theory to separate data by iteratively calculating the entropy and the information gain from splitting data based on attribute a. The decision tree selects the locally best attribute (i.e., highest information gain) as a splitting criterion. After calculating each information gain of each attribute, the decision tree algorithm will select the attribute with the maximum information gain to be a node, which splits the dataset into two or more subsets. The process iteratively proceeds until a full decision tree is built.

A well-fitting decision tree model can predict the training data set with the least misclassification cost or the highest accuracy. We use J48 in Weka [Hall, et. al], an open source Java implementation of C4.5, as our decision tree building algorithm. C4.5 is based on the information gain of each attributes, which calculates the difference of entropies among variables. The attribute with the highest normalized information gain is chosen to be the splitting node.

When using J48 in Weka [Hall, et. al], two parameters need to be determined: the confidence factor and the minimum number of objects per leaf. The smaller the confidence factor the more pruning the algorithm will do. However, pruning reduces the accuracy on the training data but (in general) increase the accuracy on unseen data. J48 in Weka offers various settings to estimate the sensitivity and accuracy better, namely training/test split or cross-validation. However, the telehealth service classification problem aimed by this study needs to consult human experts for the target variable, which leads to a very small training data set and a very large independent testing data set. HDTTCA uses different settings of the confidence factor and the minimum number of objects per leaf to discover the best spots of the pruning confidence factor and the minimum number of objects per leaf.

To identify performance across different settings of the confidence factor and the minimum number of objects per leaf, different perspectives and criteria are available. The validation techniques in J48 in Weka can assess the performances of various settings. Because the training dataset is very small, HDTTCA will not split or cross-validate the training set. Instead, HDTTCA asks J48 in Weka to randomly produce 30 datasets and apply validation and evaluation on these datasets. If the error between the training and validation data is high, overfitting or underfitting needs to be taken into account.

Finally, predictive ability of the decision tree is a potential issue. The prediction is compared to the actual result of the target variable. Some common measurements for selecting the best decision tree classifier are the misclassification rate or the probability of being correct, denoted as accuracy. Another important criterion is sensitivity or true positive rate, which can be computed as true positive cases divided by the actual positive cases. Sensitivity indicates an ability to identify the positive case of a model correctly, so higher sensitivity implies fewer Type-II errors occur when applying the model. Lower sensitivity instead suggests poor performance in identifying wrong patients for telehealth services. Specificity is the true negative rate and tells us how accurately our model will identify true negatives. Precision is the exactness or % of tuples that the classifier labeled as positive are actually positive. Precision tells us how accurately our model will identify true positives.

In general, the misclassification rate or accuracy serves to evaluate classification models. Yet, the problem of the misclassification rate or accuracy is that it cannot reveal Type-I/Type-II error. For the telehealth service classification problem in this study, Type-II error is crucial; the patients would suffer extensive damages if the model misidentified an applicable patient as a not applicable one. Sensitivity therefore is the first criterion we apply in the evaluation process, followed by accuracy, specificity and precision.

COMPUTATIONAL ANALYSIS

To demonstrate the applicability of HDTTCA, we acquired a data set from the National Health Insurance Research Database (NHIRD) provided by the National Health Insurance Administration, Ministry of Health and Welfare in Taiwan. For the convenience of the calculation, we use the data in year 2012 as our research scope. Through HDTTCA's preprocessing step, the sizes of the data set can be reduced to about 100MB, compared with the 4.45 GB size of the original data set.

HDTTCA generates 22 derived attributes. About 91% of the patients live in non-remote area and 98% of the patients have not economic problem, which indicates that they have more accesses to medical resources. We need to encourage those who live in remote areas and need economic support to apply for the telehealth services. About 91% of the patients have the target diseases that are suitable for the telehealth services.

Because it is impossible to ask the experts to mark all patients, we need to sample a comparatively small data set. To make sure that the sampling training dataset is closely representative to the original data set, we use stratified sampling based on the two basic attributes: gender and age group. However, our problem in nature has a very imbalance distribution of the target variable, we need to ensure enough telehealth-applicable patients are sampled into the training data set. We therefore adopt the oversampling technique based on telehealth-related attributes. We take a sample of 200 out of 991,511 records.

Because elder people are more likely to be classified as telehealth-applicable patients, they are selected twice more in the sample. HDTTCA also uses other attributes, such as remoteness, economic priority, etc. to perform oversampling. It turns out that more male patients are selected into the sample than female patients because more male patients have the target diseases than the female patients.

Next, we interview three experts in telehealth-related fields to identify the target variable, Adoptability, in the sample dataset. Three experts are a doctor in medical center as expert 1, a social worker in remote area as expert 2, and a manager in long-term care center as expert 3. During each of the three interviews, we first spent 10 minutes to introduce our research target and gave each expert an outline of the dataset. After that, each expert used 30 minutes to label the adoptability of each record with “Y” or “N”. Finally, we asked the experts the criteria they use to make their decisions. We then use the adoptability and the criteria from each expert to generate the decision tree. Because the opinions from the three experts are not consistent, we need to generate the final value of each record in the training dataset by the following rules: labelling Adoptability as “Y” if two or more experts say applicable and labelling it as “N” if less than two experts say not applicable.

Because HDTTCA samples a comparatively small dataset (200 patients) for experts’ opinions, HDTTCA uses all the experts’ opinions as the training set and takes thirty random samples (each of size 20,000 patients) from the remaining dataset as the validation datasets when training the decision tree. When using J48 in Weka, two parameters need to be determined: the confidence factor and the minimum number of objects per leaf. We will use six different settings of the confidence factor and the minimum number of objects per leaf, (0.25, 0.5, 0.75) vs. (1, 2), to discover the best spot where it prunes enough to make the learned decision tree sufficiently accurate on testing data but doesn’t sacrifice too much accuracy on the training data. For the telehealth service classification problem in this study, Type-II error is crucial; the patients would suffer extensive damages if the model misidentified an applicable patient as a not applicable one. Sensitivity, therefore, is the first criterion we apply in the evaluation process, followed by accuracy, specificity and precision.

Totally, J48 in Weka generates six trees for the six different settings of the confidence factor and the minimum number of objects per leaf. Therefore, we compare the performance metrics of the thirty testing datasets for these trees by using ANOVA test. Since the results of ANOVA reject all null hypotheses for these four metrics. Furthermore, we use pairwise *t*-test to compare the top two trees, (0.25-1 or 2) and (0.75, 2) and statistics t and p-value for the Sensitivity metric are

19.0614 and 3.01E-18, which rejects the null hypothesis. Hence, we can select the best one by using the Sensitivity criterion, which is tree of (0.75, 2).

In conclusion, there are three main dimensions influencing the decision of using telehealth services. First is the clinical status of the patients because of the limitation of telehealth equipment. Those diseases with non-monitored physiological value are not recommended to use telehealth service. Second, telehealth service plays an important role to patients who live in inconvenient area or who have to travel longer distances to hospitals. Finally, telehealth service benefits more to those older or in poor social status. With telehealth service subsidized in insurance, they can have a healthier quality of life. After HDTTCA producing the final version decision tree, the rules are used to assign the values of the target variables in the entire BI table. There are total 3.56% (23,262 / 653,209) of patients applicable for the telehealth services in year 2012.

The experiments compare the results of HDTTCA with the results of the logistic regression. After finding feasible combinations of the factors, models, and corresponding parameters, we conducted a series of experiments 30 times to measure their average performances and determine the better model to solve the telehealth patient classification problem. The criteria used to compare the experimental results are four important metrics: sensitivity, accuracy, specificity and precision. These metrics reflect the usability and accuracy of a model. In addition, the interpretability of the result is a crucial criterion when applying different classification methods in practice and thus is included in our discussion.

Because this is an extremely imbalance dataset (only 3.56% of patients applicable for the telehealth services), the result of HDTTCA shows very high sensitivity, accuracy and specificity (all > 0.95%) but low precision, as expected. For sensitivity, the decision tree generated by HDTTCA and the logistic regression model are on the equal ground. In terms of accuracy, specificity and precision, the decision tree generated by HDTTCA provides the better performances than the logistic regression model does. By applying HDTTCA, the decision tree model generates competitive performance and provides clear, easily understandable rules, so HDTTCA appears very suitable and is indeed a good choice for solving telehealth service classification problems.

CONCLUSIONS

This study proposes a Heuristic Decision Tree based Telehealth Classification Approach (HDTTCA) to determine those who are applicable for insurance reimbursements of telehealth services. This situation arises because the chronic patients as well as elderly patients become more and more. The economic and developing gap between urban and rural areas encourages government to establish a thorough policy. Many countries had developed corresponding long-term care policies to solve the population ageing problem. The telehealth service is one of the many solution that can be applied. To classify the people needed the telehealth service from other, we can apply HDTTCA, which finds a decision tree that is highly interpretable. The see-through rules generated by HDTTCA also give the government a clear guideline to improve the decision-making process for implementing the telehealth service.

The HDTTCA solves the problem with three steps. First, HDTTCA consolidates the database from all the related patients and hospital databases. Second, HDTTCA assigns the target variable by gathering and combining the experts' opinions. Finally, HDTTCA generates a decision tree model to identify those in needs. The rules are more understandable and interpretable than other classification models. Finally, we compare the results generated by the decision tree of HDTTCA and the results by the logistic regression model. HDTTCA outperforms the logistic regression model in every way of the four performance metrics. On top of that, the decision tree generated by HDTTCA provides clear, easily understandable rules that the authority has no trouble of applying and explaining them.

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