# Applying Data Mining Techniques on Thai Traditional Medicine Treatment

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## ABSTRACT

Thai Traditional Medicine (TTM) has been popularly practiced in Thai culture and society since the Sukothai period. For the past decade, Thai government and private sectors have collaboratively worked to restore it to common use, after many years of inactivity. Many hospitals now combine TTM with western treatments. Data mining techniques were applied to a comprehensive dataset of TTM treatments collected between 2012 and 2015 by Bangkrathum Hospital. The original data with 56,160 records was preprocessed, cleaned and transformed to achieve a useable dataset for use with data mining techniques. Two different techniques were applied to discover symptom relationships and models. The association rule technique was applied to a 2,000 record dataset with 134 different symptoms, and the classification technique analyzed a dataset of 15,963 records. By applying the association rule technique using the *a priori* algorithmic approach, some symptoms that often occur simultaneously were discovered and coded in if-then type rules. Applying these rules suggests symptoms that could simultaneously occur with other symptoms. The classification techniques of Artificial Neural Network, Decision Tree and Naïve Bayes, were applied to create models to predict likely diagnoses from symptoms recorded in new patient records.

Ten rules for symptom association prevalence were identified using the association rule approach, based on the prevalence of 8 symptoms. The construction of a Decision Tree was proven to be the best classification technique. The data mining approach applied in the study and the resulting models can be effectively used by TTM practitioners for modeling patient diagnoses based on identified symptoms.

*Keywords: Thai Traditional Medicine Treatment, Association Rule, Artificial Neural Network, Decision Tree classifier, Naïve Bayes classifier*

## INTRODUCTION

Traditional Medicine (TM) encompasses the knowledge, skills, and practices based on cultural beliefs and experiences applied in the maintenance of health and the prevention, diagnosis, improvement or treatment of physical or mental illness (World Health Organization, 2013). The practice of traditional medicine can be found in many countries and societies around the world, based on different cultural knowledge and beliefs in each place, and which have been developed and transferred over the generations through inherited knowledge, including importantly the understanding of local materials, particularly plants. Examples of traditional medical practices include Traditional Chinese Medicine (TCM) such as acupuncture and Chinese tuina massage, Traditional Korean Medicine (TKM) using ginseng and moxibustion, and Thai Traditional Medicine (TTM) such as Thai massage and traditional herbal remedies.

The World Health Organization (WHO) has promoted TM as being the diversity of health practices to be applied singly or in combination with modern medicine to maintain well-being, and to treat, diagnose, and prevent illness (World Health Organization, 2013). WHO has reported that over 70%-80% of developed and developing countries have TM as the primary health care. In China, 90% of general hospitals offer TM for both outpatients and inpatients. Almost 80% of Lao people, who live in rural areas, use TM as primary health care. Also, about 30% of the Taiwanese population rely on TM for treatment of their various illnesses (Lin *et al*., 2013). In African countries, such as Mali, Nigeria, Zambia and Ghana, almost 80% of population has TM as a primary health care (Jamshed, Khan, Ahmad, & Elkalmi, Acupuncture 2016). This is because TM is cheap, easy to access and is in accordance with local belief, culture and tradition (Ekor, 2013). However, using TM for health care is not without its dangers, and can result in drug overdose and become ineffective over time (Abudayyak, NATH, & ÖZHAN, 2015).

Thailand offers "Thai traditional medicine" (TTM) as alternative health care. TTM has been promoted to Thai people according to the protection and promotion of TTM in 1977. TTM, as defined in that Act B.E.2542(2000), is a process dealing with the examination, diagnosis, therapy, treatment, or prevention of diseases, or promotion and rehabilitation of the health of humans or animals, midwifery and Thai massage, as well as the preparation and production of Thai traditional medicines and the making of devices and instruments for medical purposes. All of these are based on the knowledge or texts that have been developed, initially developed from trial-and-error experiences, recorded and passed down from generation to generation over 2,000 years in many societies.

TTM can be traced in Thai culture and society for many centuries, from the Sukothai era to Ayutthaya to Thonburi and later in the Rattanakosin era (World Health Organization, 2011), and is rooted in Ayurveda or Ayurvedic medicine from ancient Indian Civilization (Chokevivat *et al*., 2012).

TTM can be divided into three parts: 1) Traditional herbal medicines or traditional recipes 2) Therapeutic massage (Nuad Thai) for rehabilitation and 3) Herbal steam bathe for therapeutic purpose (World Health Organization, 2011).

Treatment with TTM is based on the belief in four fundamental human elements; earth, water, fire and air (or wind). Any imbalance in these four elements, probably influenced by the season change, age and inappropriate eating, working and emotion, causes human illness. (Chokevivat & Chuthaputti, 2005).

The promotion of modern medicine in Thailand in the early 20$^{th}$ Century resulted in the abandonment of TTM in 1915. However, subsequent Thai governments and private sector organizations and individuals soon realized the significance of TTM and worked collaboratively to restore TTM. The government launched the 4$^{th}$ Primary Health Care Development Plan 1977-1981 as a key policy promoting TTM in Primary Health Care, and many hospitals started providing TTM, as an alternative method in conjunction with western treatments.

Currently many hospitals in Thailand apply TTM for various treatments. The top 10 TTM treatments, in 2014, are shown in Figure 1, which also shows the large number of patients coming to hospitals for TTM (Information Services of Thailand

Traditional Medicine, 2014). From Figure 1, you may notice, there are a lot of patients coming to hospitals for pain syndrome, only some for other syndromes e.g. cough. As all hospitals maintain extensive patient records, a very large, multi-year database of patient information is available, to which we can apply data mining techniques to gain insight knowledge, treatment patterns and relationships in TTM treatments which can enable recommendations of benefit to for the treatment and screening of TTM patients. Data mining is the process of discovering meaningful knowledge, hidden patterns and trends by sifting through large amounts of data in repositories (Larose, 2014) including classification, regression, association rule and clustering techniques.

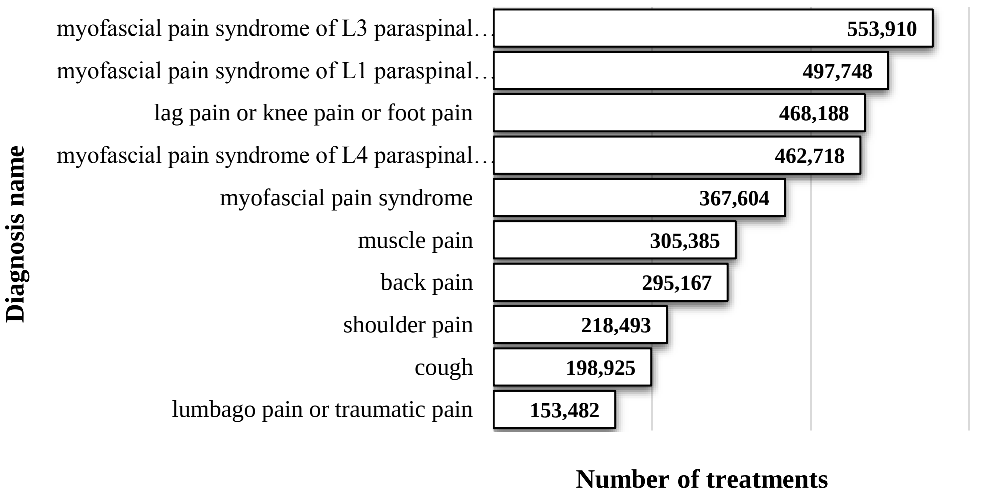


**Figure 1** Top 10 of treatment with TTM, Health Care in FY 2014.

Bangkrathum Hospital, located in Phitsanulok, is one of many Thai community hospitals, which offers TTM together with conventional medicine for patient treatment. Bangkrathum Hospital has TTM medical professionals and TTM expert physicians, and is able to produce herbal and traditional products such as herbal medicines, herbal drinks and herbal cosmetics for patient treatment (Bangkrathum Hospital, 2016). About 70 TTM patients per day attend the hospital, and the data recorded and stored on each patient is comprehensive.

This paper describes the application of data mining techniques on the TTM treatment data collected during the period 2012-2015 in Bangkrathum Hospital. These data mining techniques included the association rule technique for relationships and pattern discovery. Our intention was to design and develop classifiers of patient symptoms, which can be further used to foresee the patient's causal illness, disease or condition.

In the next sections, we will explain what materials and methodology used and how to design and develop the association rules and classification models respectively. Finally, the result and conclusion is presented and discussed.

## MATERIALS AND METHODS

A dataset of TTM during the period 2012-2015 was obtained from the Department of Public Health of Bangkrathum Hospital. The dataset contained 56,190 records, which included data on visit date, patient personal data and diagnosis and treatment notes, which was encoded according to the International Classification of Disease and Health Related Problems, 10th edition, Thailand Modification (ICD-10-TM, 2015). Examples of ICD-10-TM code are U6670 for heartburn, U742 for hyperlipidemia and U643 for cough .

The raw data contained some errors from recording, such as missing values, duplications and ambiguities, so the Knowledge Discovery from Databases (KDD) process (Han and Kamber, 2006) was applied. The KDD process includes 3 steps: data cleaning, data transformation and data mining techniques.

1) Data cleaning – the data cleaning process enables missing, incomplete and inconsistent data to be identified and, where possible, rectified, corrected and reconstructed, and where necessary deleted. To achieve a set of valid, useable, records, both the association rule technique, and the classification technique, were applied. This is further discussed later.

2) Data transformation – data was transformed into useable formats, such as the patient's age being calculated from the patient's date of birth, and importantly, also being used to identify the patient's 'element': earth, fire, water and wind. The concept of 'element' is important in traditional medicine and assists in diagnosing symptoms and potential causes of illness, and is calculated according to traditional methods (Somchintana, 1988).

3) Data mining techniques – there are several data mining techniques that can be applied. We selected 2 main techniques: **association rules** and **classification**. Appropriate to our purposes, the association rule has previously been used in studies of traditional medicine, to identify treatments and relationships in traditional medicine (Chen *et al*., 2011, He *et al*., 2012, Fu *et al*., 2013, Chu *et al*., 2015). Most recently, Yang *et al.* (2015) applied association rules to find patterns in Chinese herbal medicine formulae used in Taiwan.

The classification technique focuses on constructing predictive models, and has also been applied to Traditional Chinese Medicine (TCM) data (Zhao *et al*., 2014). Tokunage *et al.* (2014) used decision tree to classify a class of Kampo medicine for oversensitivity.

- **Association rules**

The association rules technique is used to find hidden relationships in the dataset which may be of interest to the analyst. The technique was originally applied to product purchasing behavior, in a market basket dataset, to find the association of products or items purchases based on the frequency of items included in the basket. An example of the association rule, showing its two main parts, is

"if {antecedent}, then {consequent}"

e.g. {Garlic, Ginger} -> {Chili}.

The rule suggests that a relationship exists between buying garlic and buying ginger which appears to indicate that the purchaser will most likely also purchase chili. The rule is then "if buying garlic and ginger, then will buy chili also". To obtain such relations, two measures are considered here; first, how frequently these three items appear together in the basket and, second, how confident can we be that chili will be purchased as the third item (Tan, Steinbach, & Kumar, 2006). These two measures are called support and confidence.

**Support** is an indication of how frequently the item set appears in the dataset.

Freq(X) is a number of X in the dataset.

Therefore,

$$Supp(X \rightarrow Y) = \frac{Freq(X \cup Y)}{N} \tag{1}$$

where, N is a total number of transactions.

**Confidence** determines how frequently an item in Y appears in transactions that contain X.

$$Conf(X \rightarrow Y) = \frac{Freq(X \cup Y)}{Freq(X)} \tag{2}$$

For instance, if we have the dataset as shown in Table 1, Supp({Garlic, Ginger} -> {Chili}) is 0.40 and Conf({Garlic, Ginger} -> {Chili}) is 0.67.

**Table 1** An example of market basket transactions.

| TID | Items |
|---|---|
| 1 | {Ginger, Galangal, Pepper, Onion, Turmeric ,Lemon , Carrot} |
| 2 | {Ginger, Garlic, Chili, Onion, Carrot , Turmeric, Eggplant, Lettuce, Olive} |
| 3 | {Galangal, Garlic, Chili, Pepper, Lemon , Avocado, Broccoli} |
| 4 | {Garlic, Ginger, Chili, Asparagus, Cabbage Turnip, Potato} |
| 5 | {Ginger, Galangal, Garlic, Pepper, Carrot , Corn, Celery} |

In order to obtain such association rules, we have to define the values for these two measures for different levels of rule strength, based on level of interest.

- **Classification techniques**

Classification techniques are used to construct the predictive model, in which the predictive values must be categorized in what is termed a class. The predictive model is practically used to predict a class of new objects. The process of constructing the model starts by dividing the dataset into a training set and a test set. The training set is used to build a classification model, while the test set is used to determine the accuracy of that model (Tan, Steinbach, & Kumar, 2006).

In the current study, the classification techniques used were Decision Tree, Artificial Neural Network and Naïve Bayes.

Decision Tree is constructed in the form of a tree with a root node, internal nodes, branches and leaf nodes. Nodes denote the attributes and branches are the attribute value of each node. Figure 2 is an example of the decision tree to predict diagnosis according to particular situations in terms of Diastolic Blood Pressure value, Systolic Blood Pressure value and age. The general algorithm to construct the decision tree is as follows (Song, Y. Y., & Ying, L. U., 2015) :

Step 1: Determine the root node.
Step 2: Apply a split selection method to select a node as the best split along with the split criterion and partition the training data based on the selected split node, normally into two subsets of data records.
Step 3: Repeat Step 2 on each subset recursively until the termination criteria is met.

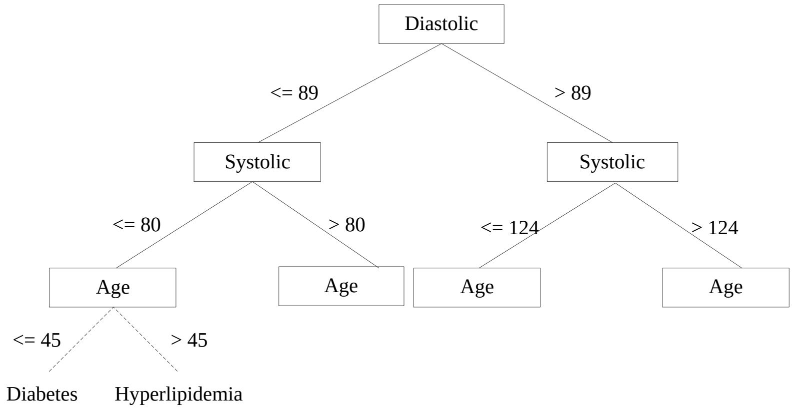


**Figure 2** An example of a decision tree.

Artificial Neural Network (ANN) is a family of models inspired by the biological neural system. It is one of the most popular techniques for predictive modeling and has been used in many applications and research projects in the past such as Na-udom, A., & Rungrattanaubol, J (2013), Adibifard, M., Tabatabaei-Nejad, S. A. R., & Khodapanah, E. (2014) and Rezaei-Darzi *et al*. (2014). ANN consists of the input layer, hidden layer and output layer. Each layer contains nodes, which are interconnected with pre-defined weights as shown in Figure 3.

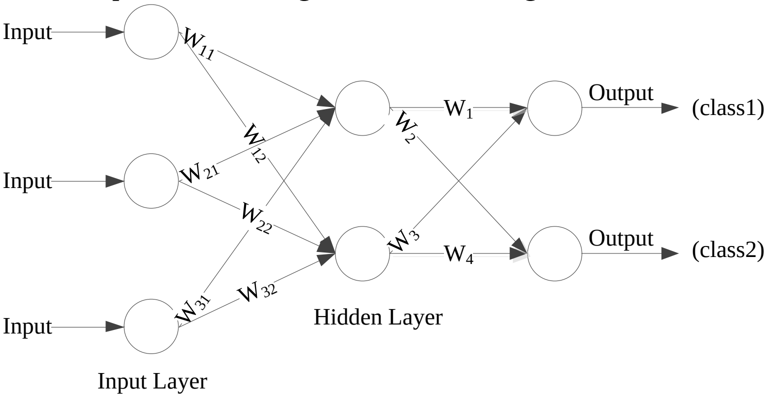


**Figure 3** An example of a basic layout of ANN.

When a new object is applied to the model, the value of each attribute of interest of the new object is assigned to an input node and these values are then transferred through the network to adjoining nodes with appropriate weightings, until the output layer is reached (i.e. class1 and class2), at which point the predicted class is obtained.

Naïve Bayes is based on Bayes' theorem, which estimates the class-conditional probability by assuming that the attributes are conditionally independent. The Naïve Bayes classifier is a classification technique formed by this concept. When there is a new object applied to the model, the probability of each class will be calculated based on values of each input attribute. The class with the highest probability is either the result, or is a predicted class (Wang, Y., & Tseng, M. M., 2015). The formula for calculating probability is:

$$P(Class_j|x) = \frac{P\left(x\middle|Class_j\right) \times P\left(Class_j\right)}{P(x)} \tag{3}$$

$$P(x|Class_j) = P\left(x_1\middle|Class_j\right) \times P\left(x_2\middle|Class_j\right) \times \ldots \times P\left(x_k\middle|Class_j\right) \tag{4}$$

By substituting the independence assumption, we derive the *a posteriori* probability of class j given a new instance $x^i$ as:

$$P(Class_j|x') = P\left(x'1\middle|Class_j\right) \times P\left(x'2\middle|Class_j\right) \times \ldots \times P\left(x'k\middle|Class_j\right) \times P\left(Class_j\right) \tag{5}$$

In our study, the association rule method was used to discover relationships in the dataset, and the classification technique was used to construct the predictive model. As these two techniques have different conceptual frameworks, the original dataset needed to be pre-processed differently to be suitable for use in each technique.

**Association rule**

To apply the association rule technique for obtaining relationships between symptoms based on diagnosis codes (ICD10-TM), the original dataset of 56,190 records was prepared to identify the same patients coming for TTM on several occasions, but with different diagnosis codes, as illustrated in Table 2. The results from the pre-processed data are shown in Table 3, where the dataset was rearranged in the market-basket format. The dataset for the association rule contained 2000 records with 134 different symptoms.

**Table 2** An example of part of the original dataset of TTM.

| ID | NAME | Visit data | Symptoms | diagnosis code |
|---|---|---|---|---|
| 001 | Charinee | 01/01/2011 | Flatulence | U6680 |
| 002 | Kamonsanok | 01/29/2011 | Flatulence | U6680 |
| 001 | Charinee | 02/09/2011 | Back ache | U7501 |
| 001 | Charinee | 12/31/2011 | Muscle ache | U7505 |
| 002 | Kamonsanok | 02/01/2012 | Hyperlipidemia | U742 |

**Table 3** An Example of a pre-processed data for association rule.

| Num | U742 | U6680 | U6681 | U7501 | U7505 | U7506 | |
|---|---|---|---|---|---|---|---|
| 1 | ? | y | ? | y | y | ? | ← Charinee |
| 2 | y | y | ? | ? | ? | ? | ← Kamonsanok |
| …. | | | | | | | |
| 2000 | | | | | | | |

We used the Waikato Environment for Knowledge Analysis (WEKA) (Boukaert *et al*., 2010) to find some association rules by empirically setting minimum support and confidence values to obtain the strong enough rule, their values are 0.10 and 0.70, respectively. The association rule technique in WEKA is implemented based on the *a priori* algorithm. As the result, there are 10 rules derived from the prevalent 8 symptoms including heartburn (U6670), hyperlipidemia (U742), cough (U643), flatulence (U6680), muscle ache (U7505), constipation (U6984), diabetes (U741) and back ache (U7501), as shown in Table 4.

**Table 4** Association Rules obtained from WEKA

| No | If Antecedent, then Consequent | Support | Confidence |
|---|---|---|---|
| 1 | If have heartburn and hyperlipidemia, then have flatulence | 0.10 | 0.86 |
| 2 | If have cough and hyperlipidemia, then have flatulence | 0.15 | 0.85 |
| 3 | If heartburn, the causes flatulence | 0.19 | 0.84 |
| 4 | If have cough and muscle ache, then have flatulence | 0.13 | 0.80 |
| 5 | If have hyperlipidemia and muscle ache, then have flatulence | 0.14 | 0.77 |
| 6 | If have cough, then have flatulence | 0.26 | 0.77 |
| 7 | If have hyperlipidemia, then have flatulence | 0.35 | 0.75 |
| 8 | If have constipation, then have flatulence | 0.11 | 0.74 |
| 9 | If have diabetes, then have flatulence | 0.11 | 0.73 |
| 10 | If have back ache, then have muscle ache | 0.14 | 0.72 |

Table 4 shows that the 7$^{th}$ rule has the most support value, which indicates that about 35% of the records in the dataset contain two symptoms {hyperlipidemia and flatulence} and about 75% of these records also indicate flatulence. While the 1$^{st}$ rule has the highest confidence value, with 0.10 support value. This support level confidently suggests that about 10% of the dataset contains {heartburn and hyperlipidemia, and also flatulence}.

**Classification techniques**

The original 56,160 records were reduced to 15,963 records by a data cleaning process which removed incomplete records and inconsistent data, and extracting the records with the top 5 popular diagnosis symptoms which are hyperlipidemia (U742), cough (U643), flatulence (U6680), muscle ache (U7505) and back ache (U7501).

The dataset contained age, sex, element, systolic, diastolic, weight and height data, and diagnosis code (U6680, U7505, U7501 and U742) as shown in Table 5. The output of the designed model is diagnosis code (diag). and used, as the input attributes, age, sex, element, systolic, diastolic, weight and height. The statistical values (min, max, average, standard deviations and frequency) of each attribute are presented in Table 5 with correlation coefficients and p-values.

**Table 5** The statistical values of the dataset for classification.

| No | Column | Description | Cor | P-Value |
|---|---|---|---|---|
| 1 | Age | min=9, max=114, avg=54.83, sd=12.01 | .066 | <.000* |
| 2 | Sex | female(8,927), male(7,036) | .018 | .012* |
| 3 | Element | earth(4,004), water(4,136), wind(3,992), fire(3, 831) | -.026 | <.000* |
| 4 | Systolic | min=80, max=230, avg=124.49, sd=7.13 | -.171 | <.000* |
| 5 | Diastolic | min=50, max=164, avg=83.04, sd=6.29 | -.151 | <.000* |
| 6 | Weight | min=32, max=200, avg=65.86, sd=9.31 | -.006 | .434 |
| 7 | Height | min=105, max=186, avg=161.09, sd=8.15 | -.034 | <.000* |
| **8** | **Diag** | **U6680(5,318), U7505(4,949), U742(2,339) U7501(2,340) ,U643(1,017)** | | |

* significant at $P \leq 0.05$

We applied three classification techniques; Decision Tree, Artificial Neural Network and Naïve Bayes, using WEKA. The models were built based on the 5-fold cross validation method, by partitioning the dataset based on the stratified sampling. We constructed the models five times for each technique, as depicted in Figure 4. The training set was used for constructing the model and the test set was used for model validation. The accuracy of the model on the training and test sets were calculated and the results are presented in Table 6. The accuracy is the measured value that will indicate the ratio of correct predictions to total data.

$$Accuracy = \frac{Number\ of\ correct\ predictions}{Total\ number\ of\ data} \times 100 \tag{6}$$

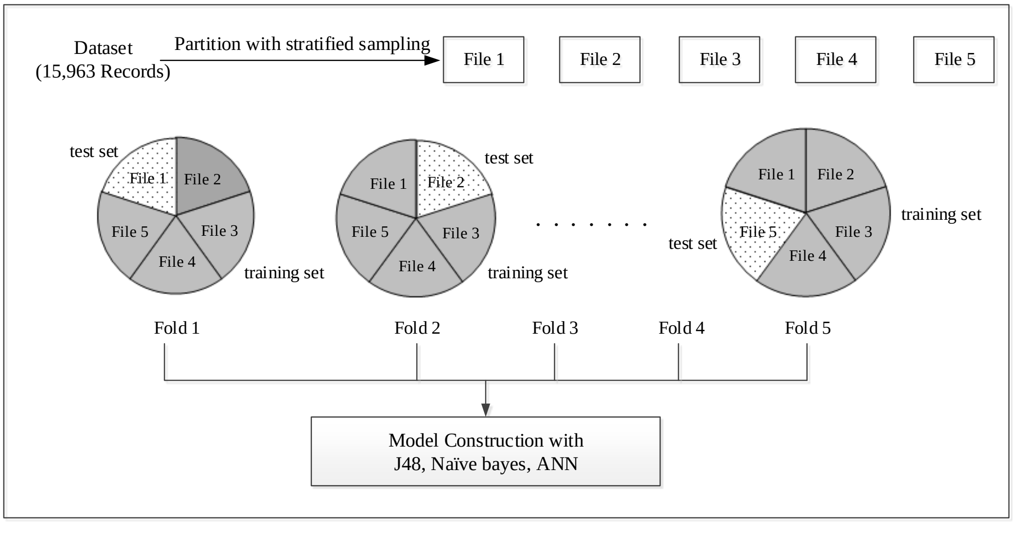


**Figure 4** The process of model construction with 5-fold cross validation method.

**Table 6** The accuracy of training set and test set based on 5-fold cross validation

| | Fold 1 | | Fold 2 | | Fold 3 | | Fold 4 | | Fold 5 | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Training | Test | Training | Test | Training | Test | Training | Test | Training | Test |
| J48 | **87.47** | **51.38** | 88.27 | 43.44 | 86.99 | 34.37 | 87.38 | 36.88 | 87.06 | 31.52 |
| Naïve Bayes | 45.20 | 40.88 | **44.64** | **43.67** | 44.82 | 39.89 | 44.83 | 35.81 | 44.59 | 36.55 |
| ANN | 50.72 | 41.38 | 47.67 | 35.10 | 49.33 | 38.13 | 48.52 | 27.50 | **48.92** | **46.78** |

Table 6 shows the result based on three classification techniques, which are J48 (representing a decision tree), Naïve Bayes and ANN. As we use 5-fold cross validation to fit the model, we constructed the model five times for each technique and select the most accurate one from each technique. The accuracy for the training set indicates how well each technique can learn from the dataset, while the test set indicates how well each constructed model can classify unseen records correctly. The average of accuracy from each technique is presented in Table 7.

**Table 7** The average of accuracy from each technique

| | Average of accuracy (%) | |
|---|---|---|
| | Training | Test |
| J48 | 87.43 | 39.52 |
| Naïve Bayes | 44.82 | 39.36 |
| ANN | 49.03 | 37.78 |

From Table 7, the three techniques perform with similar accuracy on test data (or unseen records), while J48 performs best on training data. It indicates that J48 is the best classification technique in this study with average accuracy 87.43 and 39.52 for training and test data, respectively.

## RESULTS AND DISCUSSION

We implemented the association rule from 2000 dataset. By applying the *a priori* algorithm, some symptoms that often occur simultaneously in a manner of if-then have been discovered, and these can be used to suggest the likely symptoms that could happen simultaneously with particular symptoms. The dataset contains 134 different symptoms from diagnosis code (ICD-10-TM). Table 4 shows 10 association rules. These rules were validated by consultation with TTM experts from Bangkrathum Hospital and Luang Pu Faep Supinyo Hospital. The result is the same as the principles of TTM and alternative medical practices, such as the four principles for diagnosis and the Biological Clock. The hospital experts confirmed that the 1$^{th}$, 3$^{th}$, 7$^{th}$, 8$^{th}$ and 10$^{th}$ rules are consistent with real symptoms and hence with conventional TTM knowledge. In summary, we can interpret the rules as follows:

- The 1$^{th}$, 3$^{th}$ and 7$^{th}$ rules says that the symptoms of hyperlipidemia are normally associated with heartburn and flatulence.

- The 8th rule indicates that the symptoms of constipation symptom are normally associated with flatulence, obviously due to gas increasing.
- The 10th rule says that back ache is normally associated with muscle ache.

The other association rules in Table 4 are not confirmed by the experts because it is not necessary that all rules obtained from the raw data are reasonable and usable. The confirmation from the experts is required, hence only the 1th, 3th, 7th, 8th and 10th rules are recommended.

For classification model construction we selected three classification techniques: Decision Tree, Artificial Neural Network and Naïve Bayes. The classification model classifies the diagnosis symptoms from the 7 input attributes. The dataset has 15,963 records. The most accurate models for each technique are highlighted with bold in Table 6, which are from Fold1, Fold2 and Fold5 for J48, Naïve Bayes and ANN, respectively. These three models are recommended to be used further for implementing the application.

## CONCLUSION

The association rules obtained from this study can benefit in finding relationships between symptoms from data in patient medical profile records of TTM treatments, which can then be used to suggest symptoms that are likely to happen simultaneously. The association rules can be applied as a tool to raise patient awareness for the purpose of self-care. The predicted model can be used to classify the symptom of new TTM patients as a patient screening tool. As we had data from a local TTM hospital in Phitsanulok, we consider that the result and knowledge from this study can be applied best for the hospitals and patients in this area. However, the attribute sets used in this study would be common to any set of medical conditions and likely to be seen in other traditional medical practices regardless of where they are practiced, and therefore our modeling approach can be used as a preliminary study or prototype for TTM and be adjusted or extended for broad applicability.

## ACKNOWLEDGMENTS

This paper was supported by the Bangkrathum Hospital of Thailand. The researchers would like to thank Mr. Pairoj Pampet, Pharmacist Professional Levels for supportive data and advice. Many thanks to Mr. Roy Morien of the Naresuan University Language Centre for his editing assistance and advice on English expression in this document.

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