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ORIGINAL PAPER

Artificial Neural Network in Clinical Pathway Variance Prediction: General Framework

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ABSTRACT

Patient in modern health care demands superior health care quality. Clinical pathways are introduced as the main tools to manage such quality. A clinical pathway is a task-oriented care plan that specify steps taken for patients cares. It follows the clinical course according to the specific clinical problem. During clinical pathway execution, variance or deviation of specified care plan could occur and it may endanger patient's life. In this paper, a proposed framework for artificial neural network (ANNs) in clinical pathway variance prediction is presented. We give a review of the neural network model to predict variation in Acute Decompensated Hearth Failure clinical pathway. The main objective of this paper is to introduce the general framework of clinical pathway variance prediction.

INTRODUCTION

Clinical pathway (CP) is set of tools which play important role in improving patient quality of care and increasing healthcare organizations efficiency by supporting standardize treatment process.

The clinical pathway was introduced in mid-1980 by Zander and Bower. The clinical pathway can be described as the guidelines of clinical practice for specific groups of patients based on particular diagnosis. Clinical pathway specifies categories of care, activities, and procedure that need to be conducted to the patient until patient discharged from hospitals in a timeline display. Deviation of actual care from the standardized care activity may happen anytime during the episode of care called variance is also managed and handled by the clinical pathway.

Clinical pathways can bring benefits to the healthcare provider.

Among its benefits are: 1) improvement in patient clinical outcomes;

2) help in reducing hospital cost; and help hospital management to optimize resources in terms of equipment or personnel. The common practice of clinical pathway requires medical professionals to manually fill in predefined paper documents. This practice known as the paper based clinical pathway is limited and not dynamic which brings to several problems. These problems include:

- Limited to the capacity of data collection and recording
- Separated from hospital information system.
- Lack of support for real time patient monitoring.
- Complex logical and timing relationship of different activities cannot be described with the simple description in term of forms.
- Unable to detect and handle variance dynamically.

To overcome some of these problems, the electronic clinical pathway is introduced. This effort of developing computerized or electronic clinical pathway has already been started since 1990s where the linear sequential model of the electronic clinical pathway is developed in early 1990s. Since then, electronic clinical pathway has evolved to state transition model of electronic clinical pathway is in the late 1990s, adapting structural design in 2000s and further developed to utilized ontology design in 2007. Furthermore, the capability of the electronic clinical pathway is further enhanced by embedding electronic clinical pathway with electronic medical records and integrating electronic clinical pathway with nursing process.

Most of the current practice of electronic clinical pathway is not dynamic and adaptive. During the event of variance, most of the current electronic clinical pathway only provide the means to detect, record or handle the variance occurrence. Most of the method proposed for variance management in clinical pathway usually deals with one type of variance and rely on the fuzzy rules provided by the domain expert in which difficult to obtain.

This research proposed the method to predict variance during clinical pathway in order to give better preparation for the treatment. Artificial Neural Network (ANN) prove to be powerful tools for mapping nonlinear data and are known to be useful in solving nonlinear problems where the rules to solve the problem is difficult to obtain or unknown. This paper proposed the use of artificial neural networks to predict variance for acutely decompensated heart failure (ADHF) clinical pathway. The objective of this paper is to show the framework of artificial neural networks for variance prediction in ADHF clinical pathway.

RELATED WORK

Most of the researchers in clinical pathway mainly focus on documenting, classifying, analyzing and variances handling. S. Wakamiya and K Yamauchi has proposed systems that capable of managing clinical pathway variances]. Low cost implementation and portability are the main features of the proposed systems. Previous systems prior to the systems proposed by Wakamiya and Yamauchi needs specialized hardware and software. This software and hardware are not easy to adapt for the use of other institution. The proposed system could be implemented to various clinical pathways. Among clinical pathway that been implemented using the proposed systems for disease related to Gastroenteritis, Cardiac Catheterization

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Bronchitis, Pneumonia, Cataract, Acute Myocardial Infarction, Transurethral Ureterolithorispy and infant bruising.

Clinical variance management and analysis (CVMA) application has been proposed by Kate L Hyet et al in 2007. This application is designed to collect variance data for documentation, classifying and variances analysis. The variance analysis application enabled collection of variance data from clinical pathways and is readily changed to accommodate new clinical pathways or additional variances. Unfortunately, this application is not integrated with electronic medical records or any electronic clinical pathway systems. The capabilities of this systems only limit to the managing of reported variances data and unable to automatically redesign clinical pathway based on the reported variances. 15 clinical pathways are used in this study that covers small rural hospitals and large regional hospitals.

Method for automated variance identification and analysis is proposed by Xiang Li et al 2014. The proposed method able to automatically identify the deviation between actual patient traces in electronic medical records and a multistage clinical pathway]. Clinical pathway variance analysis method proposed by Xian Li et al use clinical pathway and patient traces of cohort in Electronic Medical Record as an input and variance analysis report as an output. Clinical pathway used in this study is congestive heart failure clinical pathway. Even though the proposed method able to identify deviation in clinical pathway, it's still unable to define whether the deviation is positive (reduce length of stay e.g.) or negative outcomes (prolonged length of stay e.g.).

Several researchers have proposed methods for variance handling. Yan Ye et al (2009) has presents knowledge-based variance management system which has been developed based on unified modeling language (UML) with the use of generalized fuzzy ECA (GFECA) rules and typed fuzzy Petri net extended by process knowledge (TFPN-PK) models for analysis and handling of clinical pathway variances. The architecture of proposed system consists three level which is client level, application level, and knowledge base level. The client level consists user interface for different types of users and clinical pathway workflow system. The application level consists of four modules where it includes fuzzy reasoning and variance handling engine. The knowledge based level consists medical knowledge which represented using ontology. Variance handling engine is activated by clinical pathway workflow system when the variance information and handling request is sent. The engines search the appropriate rules matching the variances in the GFECA rule base. If the rules are found, it performs rule reasoning; otherwise, it activates the TFPN-PK based fuzzy reasoning engine. This system can be implemented to any clinical pathway.

Gang Du et al proposed the use of Takagi-Sugeno (T-S) fuzzy neural network with novel hybrid learning algorithm for handling variances in the liver poisoning of osteosarcoma preoperative chemotherapy clinical pathway. The proposed method integrating random cooperative decomposing particle swarm optimization algorithm (RCDPSO) and discrete binary version of PSO algorithm to optimize structures and parameters of the T-S fuzzy neural network.

The fuzzy neural network based variance handling method recommend the dosage of liver protection drugs based on two lab test

(Alanine Aminotransferase and Aspartate AminoTransferase) and patient experience index. Even though the proposed method successfully improving optimization performance, it still has premature convergence and low precision that has not been solved completely. With the implementation of double mutation in RCDPSO, the aforementioned problems are resolved.

METHODS

This research proposed the method for ADHF clinical pathway variance prediction using ANN model. The case study used in this study is based on Acute Decompensated Heart Failure (ADHF) clinical pathway. Data collection phase will be conducted in National Heart Institute (IJN) in Kuala Lumpur, Malaysia. After data collection process, data analysis is conducted to identify variance and input data. Then, data preprocessing is conducted along with the determination of Neural Network structures. Neural network simulation is conducted after dataset and neural network structures are finalizes. Several parameters need to be set before neural network simulation is conducted. These parameters include network algorithm, training function, transfer function and performance function.

After all the simulation is conducted, the results will be compared to find the best ANN model for ADHF clinical pathway variance prediction. The main criteria to determine the best ANN model are the lowest fitness function and prediction accuracy. Fitness function used for evaluation is the same with the performance function used by the network. The method used to develop ANN based variance prediction of ADHF clinical pathway can be summarized in figure 1.

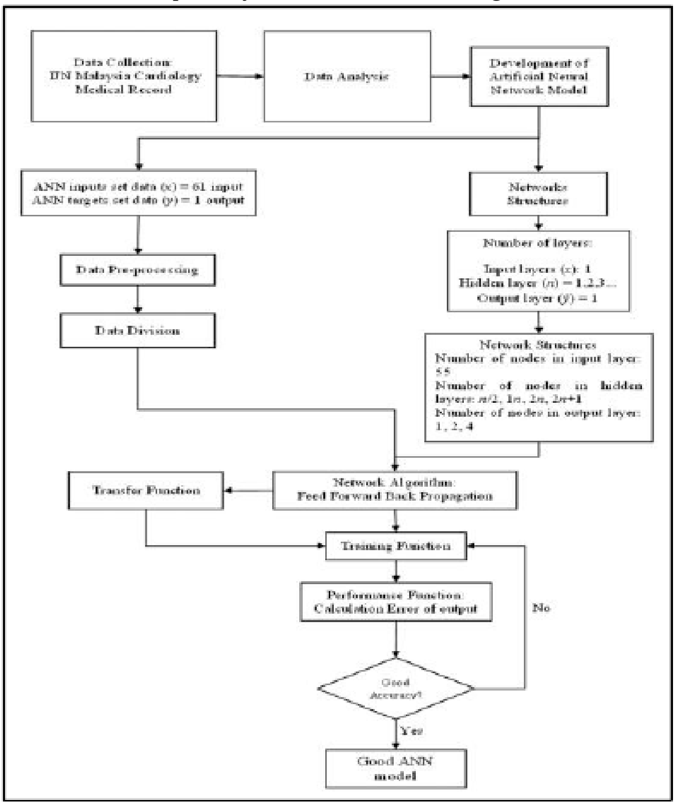

Fig 1 ANN-based model development flow for ADHF clinical pathway variance prediction.

ANN Framework for ADHF Variance Prediction

In this section, we briefly introduced basic neural network concept for clinical pathway variance prediction. A neural network consists of an interconnected group of artificial neurons, and it processes information using a connectionist approach to computation. ANN has been implemented in various fields. In healthcare, ANN is implemented for clinical diagnosis, drug development, image analysis and signal analysis. ANN had proven to be useful for modelling complex relationships between inputs and outputs or to find patterns in data. Among others advantages of ANN are:

1) Requires less formal statistical training to develop.
2) Able to recognize complex non-linear relationship between independent and dependent variables
3) Capable of discovering all possible interactions between predictor values
4) Can be developed using different training algorithms..

Data setup

Data used for this research will be collected from Cardiology Medical Record (Acute Decompensated Heart Failure) Database in National Heart Institute (IJN) Malaysia. Initial discussion with the medical expert in IJN indicated that two main variances that should be predicted in Acute Decompensated Heart Failure (ADHF) are patient mortality and patient length of stay.

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Neural Network Configuration

Basically, feed forward neural network consists three main layers which are input layer, hidden layer, and output layer. Input and output are usually consisted 1 layer and hidden layer could consist minimum 1 layer. Figure 2 shows the examples of feed forward neural network architecture. The numbers of input nodes and output nodes depend on the collected data while the numbers of hidden nodes for ANN are based on trial and error. Guideline by Zhang, Patuwo, and Hu (1998) recommended the number of hidden nodes according to “n/2”,”1n”,”2n” and “2n+1” where n is the number of input nodes.

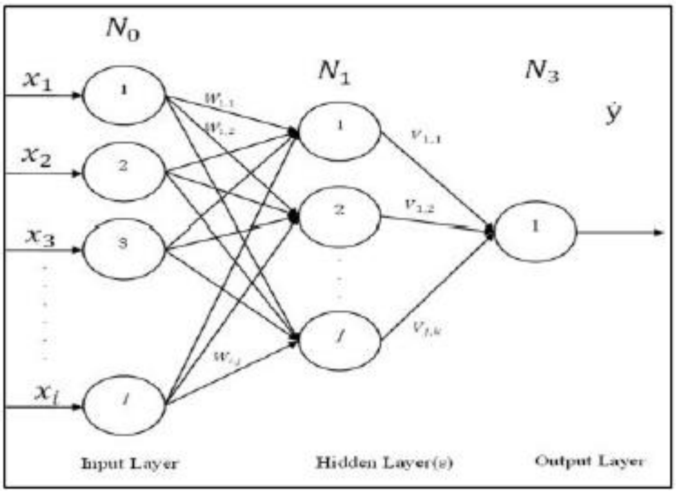

Fig 2. Feed Forward Neural Network Architecture

Multi-layer feed forward neural network is the most often used algorithm in medical diagnosis [24]. Feed forward neural network can be described in equation (1).

$$\dot{y}_l = f\sum_i w_{ij} x_i + b_i \quad (1)$$

Where ẏ is the output of the network, f is the transfer function, is the weight, is the input and is the bias. From equation (1), multi-layer feed forward neural network with 1 hidden layer can be further derived as:

$$\dot{y}_l(n) = f_k\Big(\sum_{k=1}^{N_1} V_{j,k} f_j\Big(\sum_{i=1}^{N_0} W_{i\,j} x_i(n) + b_i\Big) + b_j \quad (2)$$

Where ẏ is the output of neural network, f is transfer function of the neural network, N is the number of nodes in the respective layer (N0 the number of nodes in input layer and N1 is number of nodes in 1st hidden layer), Vj,k is the weight of neural network between a hidden layer to output layer, Wi,j is the weight from the input layer to a hidden layer, ( ) is the input of neural network and is the bias of the neural network.

CONCLUSION

Hollow anatase TiO_2 containing Ag, in the different location, has been successfully synthesized. This was proven by the images obtained using TEM. Apart from that, the existence of Ag was also confirmed by XRF and EDX. DR UV–Vis spectra showed the existence of absorbance peak for Ag at around 404–650 nm. The Ag’s particles size was measured by TEM. The results showed that the size of Ag particles inside the hollow anatase TiO_2 sample was larger (45 nm) than its particles size when it was located outside (9–20 nm).

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