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BACK PROPAGATION NEURAL NETWORK AND NON-LINEAR REGRESSION MODELS FOR DENGUE OUTBREAK PREDICTION

NOR AZURA BINTI HUSIN

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Faculty of Computer Science and Information Systems Universiti Teknologi Malaysia

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To my beloved mother and father.

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ABSTRACT

Malaysia has a good dengue surveillance system but there have been insufficient findings on suitable model to predict future dengue outbreak since conventional method is still being used. This study aims to design a Neural Network Model (NNM) and Nonlinear Regression Model (NLRM) using different architectures and parameters incorporating time series, location and rainfall data to define the best architecture for early prediction of dengue outbreak. The case study covered dengue and rainfall data of five districts in Selangor from year 2004 until 2005. Four architectures of NNM and NLRM were developed in this study. Architecture I involved only dengue cases data, Architecture II involved combination of dengue cases data and rainfall data, Architecture III involved proximity location dengue cases data, while Architecture IV involved the combination of all criteria. The C programming and Matlab software were used by this artificial intelligent method to develop the NNM and NLRM. The parameters studied in this research were adjusted for optimal performance. These parameters are the learning rate, momentum rate and number of neurons in the hidden layer of architectures. The performance of overall architecture was analyzed and the result shows that the Mean Square Error (MSE) for all architectures by using NNM is better compared to NLRM. Furthermore, the results also indicate that architecture IV performs significantly better than other architectures in predicting dengue outbreak using NNM compared with NLRM. It is therefore proposed as a useful approach in the problem of time series prediction of dengue outbreak. These results can help government especially for Vector Borne Disease Control (VBDC) Section of Health Ministry to develop a contingency plan to mobilize expertise, vaccines and other supplies and equipment that may be necessary in order to face dengue epidemic issues.

ABSTRAK

Malaysia mempunyai sistem pengawasan denggi yang baik namun begitu masih terdapat kekurangan dalam mendapatkan model yang sesuai untuk meramal peletusan denggi pada masa hadapan memandangkan kaedah manual masih lagi digunakan. Kajian ini bertujuan untuk mereka bentuk Model Rangkaian Neural (NNM) dan Model Regresi Tak Selari (NLRM) dengan mengguna seni bina-seni bina yang berbeza dan parameterparameter yang berkaitan siri masa, lokasi dan julat hujan seterusnya mengenalpasti seni bina yang terbaik bagi meramal lebih awal perebakan wabak denggi. Kajian kes ini merangkumi data denggi dan jumlah hujan di lima daerah di Selangor dari tahun 2004 sehingga 2005. Empat seni bina NNM dan NLRM dibina untuk tujuan kajian ini. Seni Bina I melibatkan hanya data kes denggi, Seni Bina II melibatkan kombinasi data kes denggi dan jumlah hujan, Seni Bina III melibatkan data kes denggi di kawasan terhampir, manakala Seni Bina IV melibatkan kombinasi kesemua kriteria. Program C dan perisian Matlab digunakan oleh kaedah kepintaran buatan ini bagi membina NNM dan NLRM. Parameter-parameter yang terlibat dalam penyelidikan ini dilaras bagi mendapatkan perlaksanaan yang optimal. Parameter yang digunakan dalam penyelidikan ini merangkumi kadar pembelajaran, kadar momentum dan bilangan nod tersembunyi. Perlaksanaan keseluruhan Seni Bina telah dianalisa dan hasil keputusan menunjukkan bahawa kadar Ralat Kuasa Dua untuk kesemua seni bina menggunakan NNM lebih baik berbanding NLRM. Di samping itu, hasil keputusan menunjukkan Seni Bina IV memberikan hasil keputusan yang terbaik berbanding seni bina lain dalam meramal peletusan wabak denggi menggunakan NNM berbanding dengan NLRM. Ini sekaligus membuktikan ia adalah kaedah yang berguna dalam mengatasi masalah meramal siri masa peletusan wabak denggi. Hasil keputusan ini diharap dapat membantu pihak kerajaan khasnya pihak bahagian Kawalan Penyakit Bawaan Vektor bagi merangka rancangan untuk persediaan kepakaran, vaksin, pembekalan dan perkakasan yang berkemungkinan amat diperlukan dalam menghadapi isu wabak denggi.

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
ANN	Artificial Neural Network
CDC	Centers for Disease Control and Prevention
DF	Dengue fever
DHF	Dengue haemorrhagic fever
DHO	District Health Office
HLANGAT	Hulu Langat
HSEL	Hulu Selangor
KM	Kilometres
KSEL	Kuala Selangor
MAD	Mean Absolute Deviation
MAPE	Mean Absolute Percentage Error
MLP	Multilayer Perceptron
MMD	Malaysian Meteorological Department
MOH	Ministry of Health, Malaysia
MRN	Model Rangkaian Neural
MRTS	Model Rangkaian Tak Selari
MSE	Mean Square Error
NLRM	Nonlinear Regression Model
NN	Neural Network
NNM	Neural Network Model
OLS	Ordinary Least Square

RBF	Radial Basis Functions
RM	Regression Model
RMSE	Root Mean Square Error
RNN	Recurrent Neural Network
SHD	State Health Department of Selangor
SSE	Summation of Square Error
VBDC	Vector Borne Disease Control Section
WHO	World Health Organization

LIST OF SYMBOLS

У	Output node
x	Input node
f	Transfer/ activation function
W	Weight
V	Function of weights vectors
a	Learning rate / intercept
β	Momentum rate / Slope
3	Error
(Wji, Wkj)	Bias
$(heta_{ji}, heta_{kj})$	Initial values of weight
Egrad.	Gradient error
Emin	Minimum error
$\overline{\mathrm{W}}$	Weight vector
Δw	Change in the weight
δj	Error associate with <i>j</i>
o'j	Sigmoid prime
Е	Total prediction error
е	Error (residual)
Ν	Number of sample
Σ	Summation
$\frac{\sum}{x}$	Mean of x dataset
$\overline{ heta}$	Coefficients/ bias

sin	Sine
COS	cosine
exp	exponent
df	degree of freedom
R^2	R-Square
Н	Hypothesis
c	Center vector
exp	Exponent
у	Dependent variable
ŷ	Estimated value
d	Dengue cases data
r	Rainfall data
n	Approximate location of dengue cases data

CHAPTER 1

INTRODUCTION

1.0 Background of Studies

Dengue fever (DF) and the potentially fatal dengue haemorrhagic fever (DHF) continue to be an important public health problem in Malaysia. It has been epidemic in Malaysia for a long time (Ghee, 1993). The haemorrhagic form of the disease is a more severe form of dengue compared to DF and it can be fatal if unrecognized and not properly treated (WHO, 1997). The DHF is fairly recent, first seen only after the Second World War and has been confined to Southeast Asia. Malaysia has its first outbreak in Penang in 1962 (Ghee, 1993).

In 1998, about 26,240 of dengue fever cases were recorded by the Vector Borne Disease Control Section (VBDC), Ministry of Health. There were 53 deaths out of a total of 1,133 cases of DHF in the same year. Although Cambodia was reported to have the highest case fatality rate of about 10%, the rate in Malaysia (4.67%) was still higher

than the neighboring countries like Thailand and Indonesia, with the case fatality rates of 0.3% and 0.5%, respectively.

Nevertheless, with good medical management, mortality due to DHF can be less than 1%. WHO (1999) concluded that there is sufficient evidence on the reduction of DHF case fatality rates through application of standardized clinical management practices to warrant an acceleration of capacity building and training in the field, with a view to reduce case fatality rate to less than 1%.

According to Lian *et al* (2006), one of the main problems faced in dengue epidemiology is the inadequate knowledge on the risk factors and the association among them. This problem is more acute in rural dengue outbreak as many outbreaks were not reported or adequately investigated. Even if the outbreak is investigated; there is a lack of a sensitive vector surveillance tool to estimate the vector density in the outbreak areas. In Malaysia, despite having a good laboratory based surveillance system, with both serology and virology capability, it is basically a passive system and has little predictive capability (Gubler, 2002).

DF and DHF are known as notifiable diseases in Malaysia since 1974. Therefore, it is compulsory for all medical officers to notify the disease to the nearest district health office (DHO) within 24 hours under the Prevention and Control of Infectious Disease Act, 2000. However, confirmation of a case by laboratory diagnosis is much dependent on the time the specimen is taken and the type of test used. Problem may occur if one waits for laboratory confirmation of the case before notification. Delay in notification may lead to delay in control measure, which will further lead to occurrence of outbreaks, since dengue needs optimum time of management as the transformation of DF into a more severe form of dengue only take a very short period (WHO, 1985).

Besides, WHO (1999) have reported the value of timely interventions such as residual house spraying, and mass drug administration to control dengue epidemics has been documented but much less evidence exists about how to identify appropriate times to take such action when resources are limited.

One of the solutions is to implement a simulation of dengue spread in all dengue endemic countries of the world, with emphasis on an early prediction of dengue outbreak (Gubler, 2002). It may improve public health problem in Malaysia since an accurate and well-validated simulation to predict the dengue outbreak is needed to enable timely action by public health officials to control such epidemics and mitigate their impact on human health (McConnell *et al* 2003). This statement is supported by Centers for Disease Control and Prevention (CDC), which noted that having an early warning surveillance system, which could predict epidemics is really important.

However, study on dengue outbreak prediction is only useful if a model, which enables a good prediction upon these criteria, is selected. Unfortunately, no such study has been done to predict the dengue outbreak in Malaysia and there has been insufficient discussion about the suitable model to predict future dengue outbreak. Therefore in this research, several prediction models based on disease location, time and data variability will be studied.

Neural network model also proved to have been useful in time series prediction. Study has been done by Kutsurelis (1998) in predicting future trend of stock market indices by using neural network, the results of which is compared to the result of multiple linear regression. The finding indicated that neural network achieved a 93.3% accuracy of predicting market rise and an 88.07% accuracy of predicting a marker drop and it was concluded that neural networks do have the capability to forecast better than multiple linear regressions. The finding was supported by Roselina (1999) study, which found that NN performed better time series prediction than Box-Jenkins model. Besides, previous study about rainfall prediction done by Lee *et al* (1998) comparing linear regression with radial basis function network revealed that radial basis function networks produced good predictions compared to linear models. Money *et al* (2002) studied the real-time modeling of influenza outbreak by using a regression model.

Findings of the study showed that the model performance become less reliable at the extreme ends of the range of data source. However, in spite of the limitation of regression model that prevent its adoption as a definitive predictive tools the model moved to has capacity to provide a dynamic weekly revisable estimate of the likely severity of an ongoing flu outbreak. Therefore Neural Network and Regression model was selected based on good prediction resulted of previous research (Roselina (1999), Kutsurelis (1998), Lee *et al* (1998) and Mooney *et al* (2002). More detail critical discussion will be provided in Chapter 2.

However, modeling of dengue outbreak prediction that incorporates location, time and related data (dengue cases, rainfall and approximate location data) are needed to aid prediction of dengue outbreak accurately and rapidly (Nor, 2005). Therefore, other data such as rainfall data and location proximity of dengue cases are also taken under consideration in this research. Its purpose is to identify the best data variability that maybe of help to predict dengue outbreak more accurately.

From the above discussion, it can be concluded that neural network and regression model are likely to be able to predict dengue outbreak prediction based on location, time and data variability. Therefore, these two prediction models will be implemented in this study to investigate the acceptable method in predicting future dengue outbreak.

1.1 Problem Statement

Observation reveals that the study on prediction of dengue outbreak is rarely done especially in Malaysia. Therefore, it is important to have a prediction model that can better predict the spread of dengue outbreak. These questions need to be studied in order to describe the issue:

- 1. How effective can neural network model and nonlinear regression model predict the spread of the dengue outbreak when only dengue cases data is used?
- 2. How effective can neural network model and nonlinear regression model predict the spread of the dengue outbreak when the combination of dengue cases and rainfall data is used?
- 3. How effective can neural network model and nonlinear regression model predict the spread of the dengue outbreak when the combination of dengue cases and proximity location data is used?
- 4. How effective can neural network model and nonlinear regression model predict the spread of the dengue outbreak when dengue cases, rainfall and proximity location data is used?

1.2 Objectives of Study

The objectives of this study are:

- 1. To design a neural network and nonlinear regression based method using dengue data to predict the spread of dengue outbreak.
- 2. To design a neural network and nonlinear regression based method using dengue and rainfall data to predict the spread of dengue outbreak.
- 3. To design a neural network and nonlinear regression based method using dengue and proximity location data to predict the spread of dengue outbreak.

- 4. To design a neural network and nonlinear regression based method using combination of all parameters to predict the spread of dengue outbreak.
- 5. To compare methods for prediction of spread of dengue outbreak pattern.

1.3 Scope of Study

The scope of this research is limited to the following:

1.3.1 Data to be used

The data that will be used for this research are:

- 1. dengue data
- 2. rainfall data

with variation in terms of

- 1. location
- 2. time

Dengue data from location of cases in five administrative districts in Selangor, which involved Sepang, Hulu Selangor, Hulu Langat, Klang and Kuala Selangor (Department of Statistics Malaysia, 2005), will be used. Another four districts in Selangor are not included due to incomplete rainfall data. Selangor was selected for the case study as it has a high number of dengue cases and also due to it diverse population distribution with a variety of rural and urban areas.

Temporal

The time between the bite of a mosquito carrying dengue virus and the start of symptoms averages 4 to 6 days, with a range from 3 to 14 days. An infected person cannot spread the infection to other persons but can be a source of dengue virus for mosquitoes for about 6 days. Since, these infections spread rapidly; choosing appropriate window of time for dengue outbreak prediction is important. The collected data consists of weekly and monthly confirmed dengue cases over an average of 2 years from State Health Department in five administrative districts in Selangor. The data were obtained from passive surveillance system in the each region for the years 2004 and 2005, which consist of 52 weeks for each year.

Data Variability

i) Dengue Cases Data

Dengue virus infections may be asymptomatic or may lead to undifferentiated fever, dengue fever (DF) or dengue haemorrhagic fever (DHF) (WHO, 1997). (Figure 1.1)

Patients suspected of dengue fever infection will be examined to determine whether they have symptoms related to the dengue infection. Only the symptomatic patient's sample will proceed to the next step, which requires laboratory diagnosis. Usually, results come out in on of three categories; undifferentiated fever, DF and DHF. In this study, only DF cases will be taken as dengue cases since undifferentiated fever cases may be caused by other viral infection.

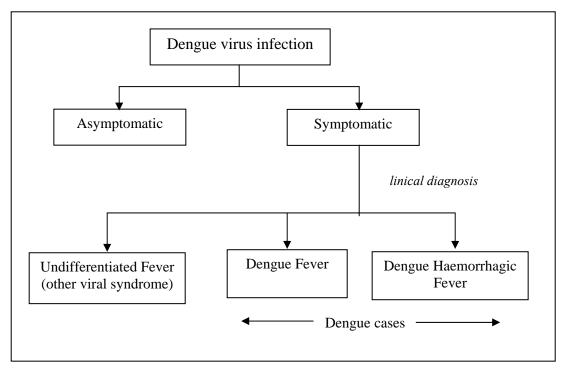


Figure 1.1: Manifestations of dengue infection

ii) Rainfall Data

The Malaysian Meteorological Department provides meteorological and seismological services of high quality to fulfill the socio-economic and security needs. The main service are weather forecast service, seismological and tsunami service, cloud seeding service, marine meteorology and oceanography service, climatological service, agrometeorological service and environmental meteorological service.

Malaysian Meteorological Department strives to give the public the most updated data. In this research, rainfall data are collected from weather forecast service and all enquiries concerning information for weather condition such as rainfall information through telephone calls or personal visits to the forecast offices at any time will be attended within 24 hours including Sundays and public holidays.

Categorization of daily rainfall intensity can be divided by four:

- 1. Light 1-10 mm
- 2. Moderate 11-30 mm
- 3. Heavy 31-60 mm
- 4. Very heavy rain more than 60 mm

Intensity rain more than 60 mm in 2 to 4 hours duration may cause flash floods. However, monsoon rains are typically of long duration with intermittent heavy bursts and the intensity can occasionally exceed several hundred mm in 24 hours.

1.4 Output to be predicted

The collection of several types of data sets provides inputs to predict future dengue outbreak. The acquired outputs will be modeled using the NNM and NLRM in order to predict the occurrence of future dengue outbreak based on location and time that evaluated by accuracy of prediction in terms of mean square error (MSE). This information is collected and reviewed weekly, and over time, to allow public health epidemiologists and laboratories to understand the spread of dengue outbreak in their catchments area, providing them with the real-time information they need to detect small changes that may be important. Comparison of prediction performance of NNM and NLRM for each architecture is done by testing on data of dengue cases in Selangor from year 2004 to 2005 and measuring their Mean Square Error (MSE). The architecture that produced the least MSE will then be chosen to simulate the dengue outbreak prediction.

1.5 Benefit of the Research

The results of this study can better predict dengue outbreak by using acceptable method to better predict dengue outbreak. The results will hopefully help the Malaysian government especially for Vector Borne Disease Control (VBDC) section to develop contingency plan to secure a rapid mobilization of expertise, vaccines, and other supplies and equipment that may be necessary at short notice in order to face 'dengue epidemic' issue. Also, let people be more aware and understanding about the criterion that may contribute to the outbreak of this epidemics.

1.6 Description of Remaining Chapters

This thesis contains five chapters; Introduction, Literature Review and Research Methodology, Result and Discussion, and Conclusion. The details of the chapter are as follow.

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