Jurnal
Teknologi

Full Paper

APPLICATION OF RADIAL BASIS FUNCTION NETWORK ON PARKINSON DATA

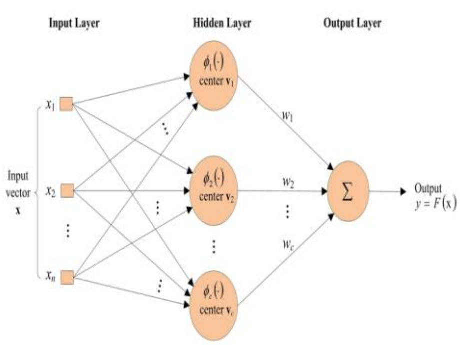
Nur Farahana Zainudin, Norizan Mohamed*, Nor Azlida Aleng, Siti Hasliza Ahmad Rusmili

School of Informatics and Applied Mathematics, Universiti Malaysia Terengganu (UMT), 21030, Kuala Terengganu, Terengganu, Malaysia.

Article history
Received
25 July 2015
Received in revised form
1 October 2015
Accepted
25 October 2015

*Corresponding author
norizan@umt.edu.my

Graphical abstract



Abstract

Radial basis function networks have many uses, including the function approximation, time series production, classification and system control. Radial basis function based diagnosis of medical diseases has been taken into great consideration in recent studies. The real data from UCI Machine Learning websites that used 500 Parkinson's patients and 7 different attributes as the subject were analyzed by using Statistical Package for Social Sciences (SPSS) 21.0. Next, the result of SPSS software will be used and run by MATLAB software. From the research that has been done by other researchers, it was found that MATLAB software is much better in producing the best results for Radial Basis Function. The value of R^2 for Multiple Linear Regression and Radial Basis Function is 0.7450 and 0.9702 respectively. Hence, the Radial Basis Function method shows that there is more variability is explained by this model.

Keywords: Radial Basis Function (RBFN), Parkinson data, R^2

Abstrak

Fungsi anggaran, pengeluaran siri masa, pengelasan dan sistem kawalan antara kegunaan utama rangkaian fungsi asas jejari (RBFN). Diagnosis perubatan menggunakan kaedah rangkaian fungsi asas jejari antara kajian yang banyak digunakan dan diaplikasikan sejak kebelakangan ini. Data asal yang diambil daripada laman web UCI Machine Learning menggunakan 500 pesakit Parkinson dan 7 pembolehubah dianalisa menggunakan perisisan SPSS 21.0. Keputusan analisa SPSS kemudiannya akan digunakan dalam perisian MATLAB. Berdasarkan kajian daripada penyelidik terdahulu, perisian MATLAB akan menghasilkan keputusan Rangkaian Fungsi Asas Jejari (RBFN) yang lebih baik dan tepat. Nilai R^2 untuk Regresi Linear Berganda ialah 0.7450, manakala hasil keputusan R^2 untuk Rangkaian Fungsi Asas Jejari (RBFN) ialah 0.9702. Oleh itu, dapat disimpulkan terdapat lebih kebolehubahan dijelaskan oleh kaedah Fungsi Asas Jejari (RBFN).

Kata kunci: Rangkaian Fungsi Asas Jejari (RBFN), data Parkinson, R^2

1.0 INTRODUCTION

Neural networks are the tools that should be recalled for any job classification. They are developed enormously since the first attempts made modeling the perceptron architecture, six decades ago [1]. The neural network is a processing system sample which is inspired by the biological neural system in human brain. It is an interconnected group of artificial neurons, which may share some properties of biological neural networks. The key member of this novel structure is an information processing system or numerous numbers of them, working interactively like as brain hormones in order to solve some special problems like pattern reorganization or data classification through this training process [2].

In the human brain, a typical neuron collects signals from others through a host of fine structures called dendrites. The neuron sends out spikes of electrical activity through a long and thin stand known as axon, which splits into thousands of branches. At the end of each branch, a structure called a synapse converts the activity from the axon into electrical effects and sends a spike of electrical activity to an axon. Learning occurs by changing the effectiveness of the synapses thus it will influence of a neuron on other changes. The neural network has the ability to learn from experiences, improving its performance and adapting to the changes in the environment [3]. Besides that, the neural network has an efficient manipulation of the large size of data and able to generalize the results.

From an architecture point of view, a neural network can be divided into two groups; feed-forward and recurrent networks. For feed-forward networks, the flow of data is strictly from input to output cells that may be grouped into many layers but no feedback interconnections will exist. However, recurrent networks contain feedback loops and their dynamical properties are very important. The most popularly used type of neural networks employed in pattern classification tasks is the feed forward networks, which are constructed from layers and possesses unidirectional weighted connections between neurons. The examples of this category are Multilayer Perceptron (MLP) and Radial Basis Function Networks (RBFN) [1].

Multilayer Perceptron networks have been applied to distinct areas, performing tasks such as function fitting and pattern recognition problems. Most of them are using supervised training with an error algorithm known as back propagation. Typically, the MLP is organized as a set of interconnected layers of artificial neural networks [3]. There is input layer, hidden layer and output layer. The neurons in the first layer of MLP will propagate the weighted data and randomly selected bias through the hidden layers when data are provided in the input layer. Once the net sum at hidden node is determined, an output response is provided in the node by using a transfer function [4,5]. Meanwhile, RBFN topic will be discussed in the next section.

One of the principal differences between RBFN and MLP is the neuron transfer function inside the hidden and output layer [2]. Besides that, hidden notes in RBFN are operating differently with other nodes and have a different purposes while processing nodes in different layers shares a common neural model in MLP. Even though MLP and RBFN have the similarity of network topologies, RBFN are much simpler than MLP networks which usually have more complex architectures. Next, RBFN are often easier to train compared to MLP because of the fixed three layer architecture of RBFN. Lastly, the mechanisms of classification for RBFN and MLP networks works differently as RBFN clusters are separated by hyper spheres. Meanwhile, in MLP arbitrarily shaped hyper surface are used for separation [6]. Figure 1 will shows the different classification mechanisms for pattern classification in two-dimension space.

Neural networks was proved to be sufficiently good approach and useful to many problems, especially in biomedical classification tasks [1]. At present, the research is mostly on modeling parts of the human body and recognizing diseases from various scan [7]. This statement is supported by the research done by Brause, R. W where he made a medical analysis and diagnosis by neural networks while comparing the MLP and RBFN methods [8]. There is a long list of successful applications of neural networks in medicine reviewed by him. Furthermore, neural networks appear to be more popular methods of classification due to their promising performance over the other methods [9].

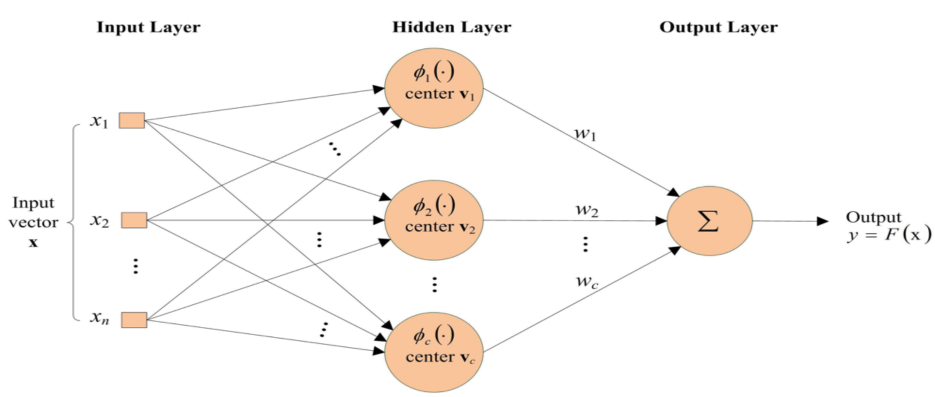


Figure 1 (a) Structure of radial basis function

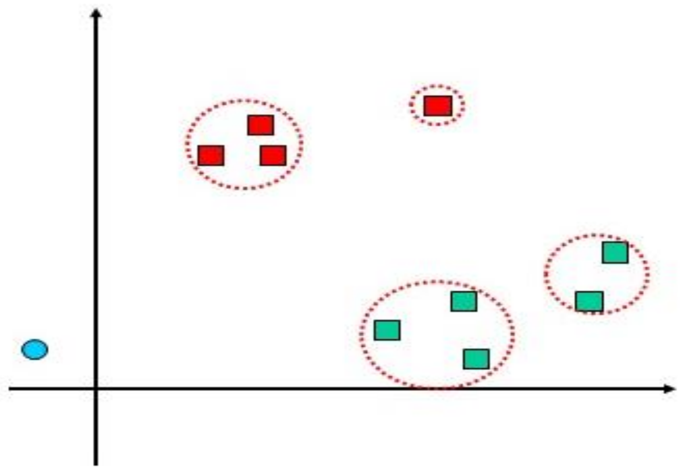


Figure 1 (b) Separation result of radial basis function

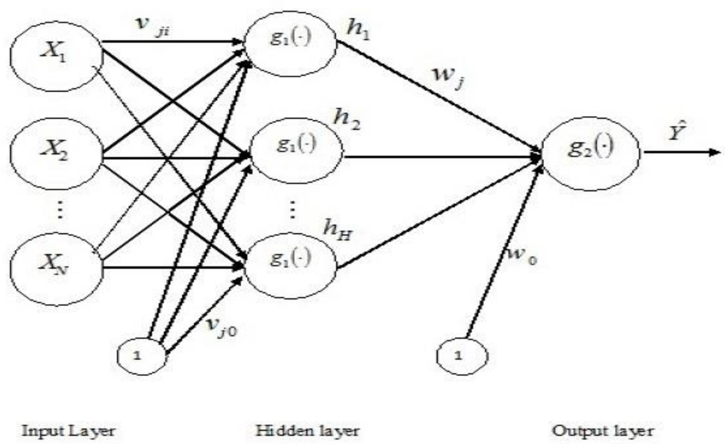


Figure 1 (c) Structure of multilayer perceptron

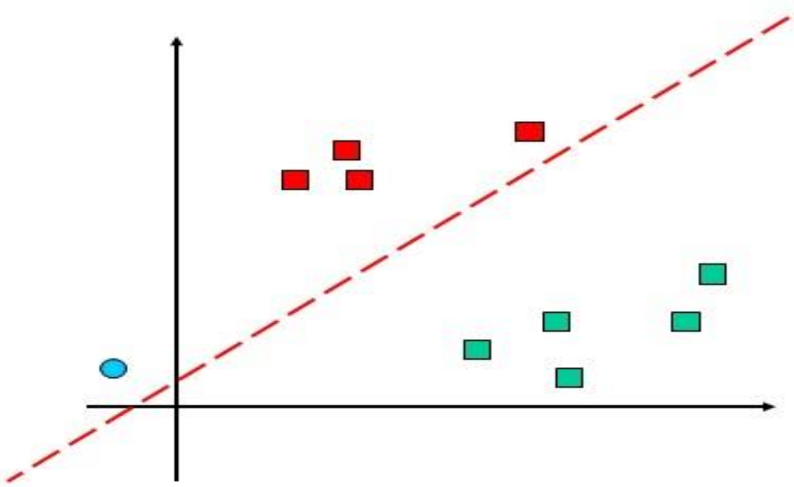


Figure 1 (d) Separation result of multilayer perceptron

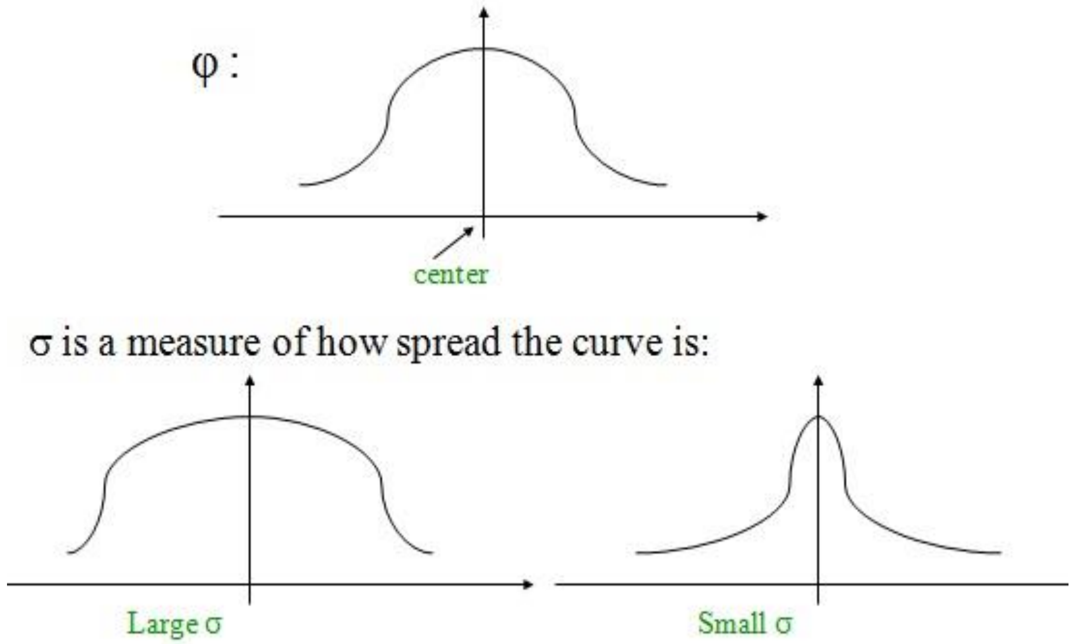


Figure 2 Euclidean distance

2.0 RADIAL BASIS FUNCTION NETWORK

RBFN emerged as a variant of artificial neural network in late 80's. However, their roots are entrenched in older pattern recognition techniques as examples are potential functions, clustering, functional approximation, spline interpolation and mixture models [10].

RBFN is an alternative to the more widely used MLP network and is less computer time consuming for network training. This function consists of three layers: an input layer, a hidden layer and an output layer. The nodes within each layer are fully connected to the previous layer and they have fixed architecture with only three layers [11]. The input layer serves only as input distributor to the hidden layer without any weights and can be trained by using any one of several possible unsupervised learning techniques [12]. Whereas each node in the hidden layer is a radial function.

A RBFN is a symmetrical about a given mean or center point in a multidimensional space. RBFN mainly consisting of two aspects based on the structure of RBFN in Figure 1. The first aspect is the determination of the parameters of the RBFN, namely the centres of the neurons and the Gaussian function widths. The second one is the calculation of the connection weights between the hidden and output layers [13].

The patterns in the input space will form a cluster when propagate to hidden layer. If the center of these clusters is known, then the distance from the cluster center can be measured. The most commonly used RBFN is a Gaussian function and *r* is the distance from the cluster centre. The distance from the cluster centre is usually known as Euclidean distance as shown in Figure 2. For every neuron in the hidden layer, the weights represent the coordinates from the centre of the cluster and the distance were calculated by using equation 1,

$$r_j = \sqrt{\sum_{i=1}^{n}(x_i - w_{ij})^2} \tag{1}$$

Next, the output is calculated by a linear combination of weighted radial basis function [8].

$$Y_k = \sum_j^N Wjk\ \phi j\ (\,|x - \mu j|) + Wok \tag{2}$$

where *N* is the number of neurons in the hidden layer, *k* is the number of outputs, X_i is the number of inputs in the input layer and *μ* is a prototype vector. However, in this case the equation was modified as the output consider is one. The modified equation was shown in equation 3.

$$Y_1 = \sum_{j=1}^N Wj1\ \phi j\ (\,|x - \mu j1|) + Wo1 \tag{3}$$

The basis functions are usually chosen as Gaussian and the number of hidden units is fixed a priori based on the properties of input data. The weights connecting the hidden and the output units are estimated by a linear least square method, as in the least mean square (LMS) method [15].

The advantages of RBFN are well suited for function approximation and pattern recognition due to their simple topological structure and their ability to reveal how learning proceeds in an explicit manner [16]. Besides that, the possibility of choosing suitable hidden basis function parameters without having to perform non-linear optimization of the whole network is one of the major advantages of RBFN [12].

3.0 LITERATURE REVIEW

With the improvement of people's living standards and industrialization in recent years, cancer incidence and mortality are significantly higher. Research showed that cancer prediction can greatly reduce cancer incidence and mortality. Thus, Yan. X et al., (2014) used the RBFN for predicting the cancer incidence by filtering the data attributes with feature selection algorithms firstly [17]. The data used was the breast cancer data from Wisconsin database of 255 patients with 11 attributes. Next, the network with selected data was trained. When the training meets certain conditions, the neural network can be used for prediction as it is essential in nonlinear mapping. The results showed that this method can improve accuracy, reliability and stability of cancer prediction greatly and effectively.

Peripheral arterial disease (PAD) is a common pathologic disease that affects more than 30 million people nationwide. It is difficult to decide whether surgical or medical treatment is the best option for PAD depends on many factors. In this paper, Yurtkuran et al., (2013) present a clinical treatment decision support system using RBFN and MLP to make an accurate decision for doctors [18]. The data set has been obtained from discharge patients dated from 2008 to 2012 within 186 people with 16 variables. The results clearly indicate that the difference between RBFN and MLP networks are statistically significant for all the indicators except the H-L statistics (H-L <12.0). Therefore, it is evident that the proposed RBFN is a better classifier for identifying the treatment type of PAD's compared to MLP networks.

Gengaje et al., (2012) develop a biomedical expert system by using RBFN for prediction of survival of burn patients and evaluate the performance of the system by varying the spread constant of RBFN [19]. Later, the use of this model will help the clinical people to better identify the risk group and provide treatment accordingly. To obtain the best result, 23 influencing factors were considered with the help of medical expert advices. Retrospective data of 306 patients are used for an RBFN system training and testing by using MATLAB platform. The result showed that the performance of the system is evaluated by varying the spread constant of RBFN. The researchers conclude that the spread constant of RBFN architecture plays an important role as the spread constant of RBFN larger than the distance between adjacent input vectors to gain the good generalization, but smaller than the distance across the whole input space. For proposed work that would mean picking a spread constant greater than 0.9 and less than 1.4.

High-resolution (1) H NMR spectroscopy of biofluids is a good representation of metabolic patterns and may offer a high potential technique for pathological diagnosis. Diagnosis of thalassemia and quantification of blood parameters can be performed by using this technique in parallel with chemo metric techniques. Spectra of 28 samples were collected from 13 healthy volunteers as control set and 15 adult male and female who suffered the thalassemia illnesses as experimental set. Principal component analysis (PCA) and linear discriminant analysis (LDA) were used as reduction tool and to establish an adequate model for discrimination of healthy and unhealthy samples. Besides that, these abstract factors used for calibration of blood parameters using RBFN as an artificial intelligence modeling method as proposed by Arimand et al., (2012) [20]. The researchers concluded that (1) H NMR, LDA and RBFN assisted by PCA provide a powerful and accurate analysis for thalassemia diagnosis and prediction of blood variants.

Saeed Mehrabi et al., (2009) were discussing the application of multilayer perceptron and radial basis function networks in differentiating between chronic obstructive pulmonary and congestive heart failure diseases in their own research [9]. Both methods of artificial neural network were used to differentiate between patients suffering one of these diseases by using 42 clinical variables. Data was collected based on medical records of 266 patients admitted at the Tehran IK Hospital during 1999 to 2005 with the help of cardiologists. A total of 42 variables was collected. However, some of the patient records were missing and it is replaced with the normal values assuming that if the readings were abnormal they would have been recorded. The result of this research record that the MLP led to a sensitivity of 83.9%, whereas the RBFN resulted in sensitivity of 81.8%. In summary, the authors showed that the variables of data can be differentiated using a multilayer perceptron and radial basis function neural networks.

The possibility of using a RBFN is to accurately recognize and predict the onset of Parkinson's disease tremors in human subject was discussed by Wu. D, et al., (2010) [13]. The number of Parkinson's patients is estimated to be 120 to 180 out every 100,000 although the percentage is increasing as life expectancies increase. The data used were recorded from a Parkinson's disease patient at the John Radcliffe Hospital, Oxford to find out a method which can accurately predict the tremor onset of Parkinson Disease from a wide range of patients. The training target of the RBFN is defined as -1 or 1, where -1 denotes a tremor onset pattern. If the output is close to the value of 1, it can be interpreted as the detection signal of tremor onset. In summary, the authors concluded that RBFN have been successfully designed to detect the tremor onset with only a small Number of spikes if more attention over the frequency range of 1-31 Hz given.

Two types of artificial neural network, Generalized Regression Neural Network (GRNN) and Radial Basis Function (RBFN) have been used for heart disease research. Hannan, S. A. et al., (2010) collected data from 300 patients with the supervision of a doctor from Sahara Hospital, Aurangabad to prescribe medicine for the patients [11]. This study includes the detailed information about the patient and preprocessing. The GRNN and RBFN have been applied after the data for the outcome. This research is important because based on statistics heart disease is one of the leading causes of deaths all over the world. Thus, significant life saving can be achieved by an accurate diagnostic decision. The result shows that medicines prescribed by the RBFN are satisfactory as the result verified by the doctor. However, for medicine prescribed by GRNN is vice versa.

Thalassemia is exist all over the world, especially in areas affected by malaria. This disease is a genetic disease that may cause a reduction in the life span. Abnormalities in the genes that regulates the formulation of blood cells is a sign of thalassemia disease. Thus, Masala, G. L, et al., (2013) is discussed on how to differentiate persons with thalassemia trait and normal subjects by inspecting characteristics of haemochromocytometri [21]. Clinical records consist of 304 patients is applied in radial basis function methods. The clinical records were carried out by the Ozieri Hospital on public school students based on thalassemia screening. The test is divided into two steps. The first step is recognizing the carriers of β-thalassemia, which resulting 14 hidden neurons with a Gaussian spread value of 25 and one output. The input considered in these steps is RBC, MCV, Ht, Hb and HDA_2. In the second step, RBF classifier discriminates normals with respect to α-carriers. The RBFN will have six hidden neurons, with a Gaussian spread of 42.5 and one input.

Barr, W. (1990) diagnose 356 patients of a heart intensive care unit [22]. 120 of the patients were suffering from a disease called acute myocardial infarction The neural network was trained and the result shows a sensitivity of 92% and specificity of 96% for heart attack prediction. It shows that the neural network method is suited to medical data.

Bounds, D. (1988) use a questionnaire among 145 respondents to discussing the use of neural network for the diagnosis of low back pain [23]. They are a 4 possible diagnosis result, such as simple lower back pain (SLBP), root pain (RP), spinal pain (SP) and abnormal illness behavior (AIB). The result of the network shows the same success as the human, an experienced expert. However, for some cases with simple lower back pain the network, diagnose worse than a physician. Fortunately, the neural network in the average shows an accurate decision with 83%, For neurosurgeon, orthopedic surgeon and physicians the result shows an accuracy is 82%, 84% and 81% respectively.

A survival probability prediction in trauma care was discussed by Mc Gonigal, M. et al., (1994) [24]. A network was trained with 4800 examples resulting with 2 output variables which are life and death. The input variables that was studied is revised trauma score (RTS), injury severity score (ISS) and age. The study was comparing the percentage of sensitivity and specificity among three methods. The methods are TRISS, ASCOT and neural network. The result shows the percentage of neural network in sensitivity is 90.3%, whereas for TRISS and ASCOT is 83.3% and 80.6%, respectively, By comparing the percentage of specificity, neural networks shows 97.5% slightly higher percentage than TRISS and ASCOT. Both of this method recorded 97.2 % and 97.5% respectively.

Next, the case study of diagnosing septic shock patients was studied by Brause, R. W [8]. The event of septic shock is quite rare and there is neither a successful clinical therapy to deal with this problem, nor there are reliable early warning to avoid this situation. Due to this fact, there is no statistical basis were exist. The epidemiology of 656 intensive care unit patients was used in a study made between November 1995 and December 1977 at the clinic of J. W. Goethe University. The study in November 1995 showed that the sensitivity of this research is about 19.38% to 28.30%, while specificity is about 89.74% up to 94.49%. Meanwhile, the next study recorded the average specificity was 88% and the average of sensitivity was 18.15%.

Sarimveis, H. et al., (2008) investigates the potential of applying the RBFN method for the classification of biological miscrosopic images [25]. The image displays lung tissue sections with idiopathic pulmonary fibrosis. The new technique was applied in lung sections acquired using a microscope and captured by a digital camera, at a magnification of 4 times. The captured image was analyzed and correspond to 7, 15 and 23 days after bleomycin or saline injection has been performed to the mice sample. The images were analyzed and color features were extracted. The result shows the RBF neural network had a slightly better performance than SVM classifier. Both of these methods are performing well and matching to a great percentage of the experts scoring.

4.0 RESULTS AND DISCUSSION

4.1 Data Study

The data examined in this study are based on the estimated total of Unified Parkinson's Disease Rating Scale (UPDRS) in 500 Parkinson's patients. Radial Basis Function Network method was applied to data obtained from the UCI Machine Learning website. This dataset is used because it is very commonly used among the other reliable researcher. The dataset was created by researchers from the University of Oxford in collaboration with 10 medical centers in the US and Intel Corporation. The researchers who developed the telemonitoring device to record the speech signals to predict the clinician's Parkinson's symptom on the UPDRS scale [26]. Table 1 shows the list of variables that has been used throughout this research.

Table 1 List of variables

Code	Variables
Y	Total of Unified Parkinson's Disease Rating Scale (UPDRS)
X_1	Jitter (%)
X_2	Shimmer
X_3	Noise to harmonic ratio (NHR)
X_4	Harmonic to noise ratio (HNR)
X_5	Recurrence period density entropy (RPDE)
X_6	Detrended fluctuation analysis (DFA)
X_7	Pitch period entropy (PPE)

4.2 Results

Building a RBFN architecture needs a radial basis neuron number, approximation variance accuracy and radial layer's spread constant. Typically, the amount of the input vector number is same as the radial basis neuron number. The neural network toolbox in MATLAB provides an effective RBFN creation function –*newrb( ),* which are automatically increasing the neuron number until the mean square deviation's accuracy can meet the demand or reach the maximum value [18]. MATLAB code is listed as follows to produce a hidden number of neurons, mean squared error (MSSE) and the value of R^2.

net = newrb (P, T, 0.11, 1.0, 10, 1) (4)

The MATLAB code of *newrb* designs a radial basis network with zero error in the design factors. The code was used to create a precise function for the RBFN, which automatically chooses the number of the hidden layer, making predictions more accurate [27]. In the above code, P is the value of input vectors and the target class of vectors are assigned as a T. The value of 0.11 in this case is referring to a goal or the mean squared error (MSE), 1.0 is the default value of the spread in radial basis function's spread constant, the maximum number of neurons, we want to achieve is 10 whereas the value of 1 represents a number of neurons to add between displays.

In statistics, the coefficient of determination, R^2 is important to indicate the fit of the data. There is a natural appeal for a measure that can be computed for a fitted model, takes values between 0 and 1 [28]. When the value of R^2 is approaching the value of 1, it indicates the model fits better and providing a simple and clear interpretation. Thus, the formula of R^2 was written in MATLAB code to check whether the data is fitted or vice versa. The formula of R^2 in a general version as is written in equation 5,

$$R^2 = \frac{SS_R}{SS_t} \qquad (5)$$

In the above definitions,

$$SS_T = \sum (Y_i - \acute{y})^2 \qquad (6)$$

$$SS_R = \sum (\hat{Y}_i - \acute{y})^2 \qquad (7)$$

where Yi, $\hat{Y}_i$ are the original data values and modelled values respectively. SS_T is the total sum of squares and SS_R is the sum of squared errors. In this research, there are two conditions were applied to the data.

4.2.1 *Radial Basis Function Network with Significant Variables*

Previously Nur Farahana et al., (2014) develop a model of linear regression analysis based on Parkinson data [29]. The results show only 5 variables are significant from the total of 7 variables which are percentages of jitter, noise to harmonic ratio (NHR), harmonics to noise ratio (HNR), detrended fluctuation analysis (DFA) and pitch period entropy (PPE). The result was interpreted by using SPSS software and by using Multiple Linear Regression.

Table 2 List of significant variables in Multiple Linear Regression

Model	B	Std. error	Beta	t	Sig.
(Constant)	55.644	5.001		11.127	.000
X_1	954.029	220.534	.209	4.326	.000
X_3	-63.556	26.529	-.102	-2.396	.017
X_4	.939	.116	.347	8.122	.000
X_6	-89.626	4.191	-.753	-21.385	.000
X_7	25.260	6.232	.144	4.053	.000

By using the MATLAB code in equation 4 and significant variables in Table 2, two hidden neurons were produced by the mean squared value (MSE) is 0.100723 (see Figure 3). The value of the error and R^2 produced is 940.5518 and 0.9702 respectively.

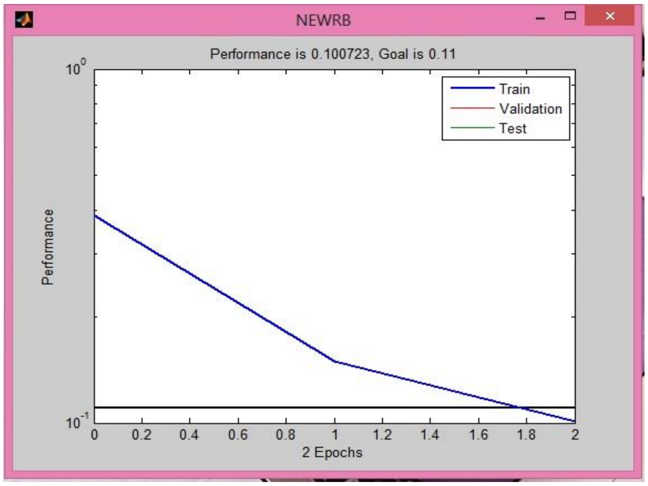


Figure 3 Training accuracy curve

4.2.2 Radial Basis Function Network with non-Significant Variables

In this part, all the significant variables from the original data was used, which are a percentage of jitter, noise to harmonic ratio (NHR), harmonics to noise ratio (HNR), detrended fluctuation analysis (DFA) and pitch period entropy (PPE). By using the MATLAB code in equation 4, two hidden neurons were produced with the mean squared error (MSE) is 0.100604 (see Figure 4). The value of the error and R^2 produced is 940.5820 and 0.9702 respectively.

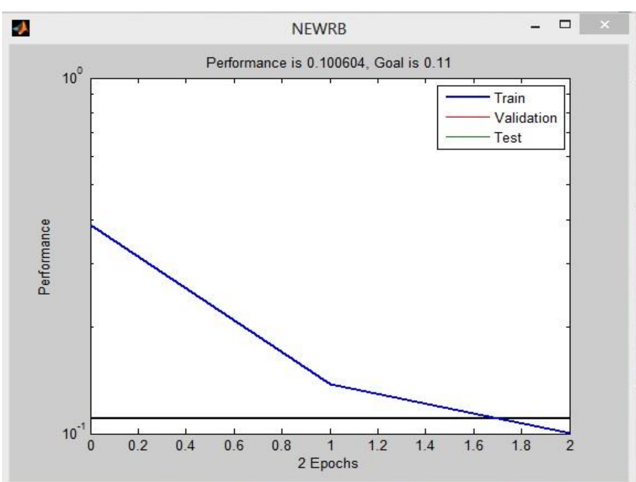


Figure 4 Training accuracy curve

Here, we can conclude from both methods that applying RBFN, the value of R^2 is exactly the same which is 0.9702. Hence, it shows that RBFN have a good ability to perform a good approximation for the conditions that are mostly encountered with this method. The real data set is used by inserting the significant and non-significant variables to see the effect of the variables in this type of the model. As a result, we can conclude that the RBFN architecture as seen in Figure 5. All of the variables in the data are selected in the input layer, producing two hidden layers and an output layer.

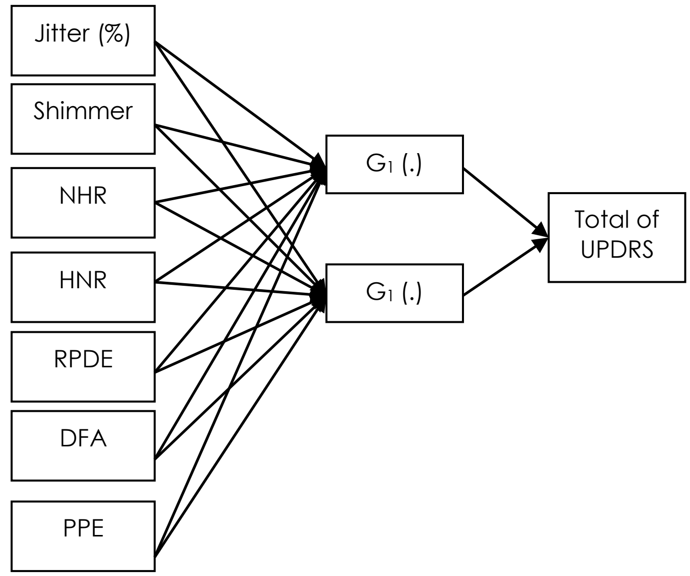


Figure 5 Radial Basis Function

5.0 CONCLUSION

Radial Basis Function Network (RBFN) has an increasingly attract interest many researchers due to the advantages over traditional multilayer perceptrons, namely faster convergence, smaller extrapolation errors and higher reliability. The purpose of this review paper was to study the literature review on Radial Basis Function Networks (RBFN) which applied to medical data. In addition, fundamental principles and the concept of RBFN theory were discussed. From the research that has been done, the medical data are producing the best model by comparing the value of R^2 in previous work by using Multiple Linear Regression method. This value will give the percentage of the variation that can be explained by the independent variable. If the value of R^2 closer to 1, it explained the strong relationship between independent and dependent variables. Hence, we can conclude that RBFN value that was generated by MATLAB producing the value of 0.9702 is strong and the independent and dependent variables are reliable for this research. The real data set is used by inserting the significant and non-significant variables to see the effect of the variables in this type of the model

Acknowledgement

We would like to thank the Fundamental Research Grant (FRGS) for funding this research under grant no 59266. The data presented, the statements made and the view expressed are solely the responsibility of the authors.

References

[1] Can, M. Neural Networks to Diagnose the Parkinson's Disease. *Southest Europe Journal of Soft Computing*. 68-73.

[2] Gharehchopogh, F. S. & Mohammadi, P. 2013. A Case Study Of Parkinson's Disease Diagnosis Using Artificial Neural Networks. *International Journal of Computer Application*. 975-8887.

[3] Santos, R. B., Markus, R., Santiago, J. B. and Ana, M. F. F. 2013. Comparison Between Multilayer Feedforward Neural Networks and a Radial Basis Function Network to Detect and Locate Leaks in Pipelines Transporting Gas. *The Italian Association of Chemical Engineering.* 32: 1375-1380.

[4] Kuo, J. T., Hsieh, M. H., Lung, W. S. and She, N. 2007. Using Artificial Neural Network for Reservoir Entrophication Prediction. *Ecological Modelling.* 200: 171-177.

[5] Kim, M. and Gilley, J. E. 2008. Artificial Neural Network Estimation of Soil Erosion and Nutrient Concentrations in Runoff from Land Application Areas. *Computers and Electronics in Agriculture.* 2: 268-275.

[6] Hao, Y., Xie, T. T., Stanislaw, P. and Bogdan, M. W. 2011. Advantages of Radial Basis Function Networks for Dynamic System Design. *IEEE Transactions on Industrial Electronics.* 58: 5438-5450.

[7] Wadhonkar, M., Tijare, P. A and Sawalkar, S. N. 2013. Classification of Heart Disease Dataset using Multilayer Feed Forward Backpropagation Algorithm. *International Journal of Application or Innovation in Engineering of Management.* 214-219.

[8] Rudiger, W. B. 2001. Medical Analysis and Diagnosis by Neural Networks. *J. W. Goethe University, Computer Science Department.* Germany.

[9] Saeed, M., Mehran, M., Hossein, A., Rezvan, N. and Yones, N. 2009. Application of Multilayer Perceptron and Radial Basis Function Neural Networks in Differentiating between Chronic Obstructive Pulmonary and Congestive Heart Failure Diseases. *Expert Systems With Applications 3G.* 6956-6959.

[10] Tou, J. T. and Gonzalea, R. C. 1974. *Pattern Recognition*. Reading, MA: Addison-Wesley.

[11] Hannan, S. A., Manza, R. R. and Ramteke, R. J. 2010. Generalized Regression Neural Network and Radial Basis Function for Heart Disease Diagnosis. *International Journal of Computer Applications*. 7: 7-13.

[12] Bullinaria, J. A. 2014. Radial Basis Function Netwoks: Algorithms. *Neural Computation: Lecture 14.*

[13] Defeng, W., Kevin, W., Zi, M., Burgess, J. G., Song, P. and Aziz, T. Z. 2010. Prediction of Parkinson's Disease Tremor Onset using Radial Basis Function Neural Networks. *Expert Systems with Applications. 37:* 2923-2928.

[14] Moghaddam, M. J. and Zadeh, H. S. Medical Image Segmentation Using Artificial Neural Networks. *Methodological Advances and Biomedical Applications*. 121-138.

[15] Moody. J. and Darken, C. J. 1989. Fast Learning in Network of Locally-tuned Processing Units. *Neural Computation*. 1: 281-294.

[16] Tao, K. A. 1993. Closer Look at The Radial Basis Function Networks. *A. L. A Singh (Ed.). Conference Record of 27th Asilomar Conference on Signals, System and Computers*. New York. 401-405.

[17] Yan, X. B., Xiong, W. Q., Hu, L. and Zhao, K. 2014. Cancer Prediction Based On Radial Basis Function Neural Network With Particle Swarm Optimization. *Asian Pac. J. Cancer Prev*. 15: 7775-7780.

[18] Yurtkuran, A., Tok, M., and Emel, E. 2013. *A Clinical Decision Support System for Femoral Peripheral Arterial Disease Treatment*. Comput Math Methods Med. 898041.

[19] Gengaje, S. R. and Alandkar, L. S. 2012. Prediction of Survival of Burn Patient using Radial Basis Function Network. *Avishkar – Solapur University Research Journal*. 2: 1-6.

[20] Arjmand, M., Kompany-Zareh, M., Vasighi, M., Parvizzadeh, N., Zamani, Z., and Nazgooei, F. 2010. Nuclear Magnetic Resonance-based Screening of Thalassemia and Quantification of Some Hematological Parameters using Chemometric Methods. *Talanta*. 81: 1229-1236.

[21] Masala, G. L., Golosio, B., Cutzu, R. and Pola, R. 2013. A Two-layered Classifier Based on The Radial Basis Function for The Screening of Thalassemia. *Computers in Biology and Medicine.* 43: *1724-1731*.

[22] Baxt, W. 1990. Use of An Artificial Neural Network for Data Analysis in Clinical Decision Making: The Diagnosis of Acute Coronary Occlusion. *Neural Computation.* 2: 480-489.

[23] Bounds, D., and Llyod, P. J. 1988. A Multilayer Perceptron Network for The Diagnosis of Low Back Pain. *Proc. IEEE International Conference on Neural Networks.* II: 481-489.

[24] McGonigal, M. 1994. A New Technique for Survival Prediction In Trauma Care Using A Neural Network. *Proc. World Conference on Neural Networks.* 3495-3498.

[25] Sarimveis, H., Kiranoudis, C. T., Chatziioannou, A. A., Oikonomou, N. and Aidinis, V. 2008. Radial Basis Function Neural Networks Classification for The Recognition of Idiopathic Pulmonary Fibrosis in Microscopic Images. *Information Technology in Biomedicine, IEEE Transaction.* 12: 42-54.

[26] Tsanas, A., Little, M. A., McSharry, P. E. and Ramig, L.O. 2009. Parkinsons Telemonitoring Data Set. https://archive.ics.uci.edu/ml/datasets/Parkinsons+Telemonitoring

[27] Olanrewaju, A. O., Adisa, A. J. and Pule, A. K. 2012. Comparing Performance of MLP and RBF Neural Network Models for Predicting South Africa's Energy Consumption. *Journal of Energy in Southern Africa.* 23: 40-46.

[28] Zainudin, N. F., Mohamed, N., Aleng, N. A. and Ahmad Rusmili, S. H. 2014. Modeling Multiple Linear Regression on Parkinson Data. 2014. *The 10th IMT-GT International Conference on Mathematics, Statistics and its Application (ICSMA) 2014*. Kuala Terengganu, Malaysia. 14-16 October 2014. 577-584.