APPLICATION OF ARTIFICIAL NEURAL NETWORKS IN THE CLASSIFICATION OF CERVICAL CELLS BASED ON THE BETHESDA SYSTEM

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ABSTRACT

Neural networks have been used in the medical field in various applications such as medical imaging processing and disease diagnostic technique. In this paper, we investigate the capability of two conventional neural networks as an intelligent diagnostic system. In particular, the radial basis function (RBF) and multilayered perceptron (MLP) neural networks were used to classify the type of cervical cancer in its early stage. The study is divided into two stages. In the first stage, we investigate the applicability of neural networks to classify cervical cells into normal and abnormal cells. In the second stage, we classify cervical cells abnormality into three classes based on The

Bethesda Classification System; normal, low-grade squamous intraepithelial lesion (LSIL) and high-grade squamous intraepithelial lesion (HSIL). Diagnosis obtained using RBF and MLP neural networks gave promising results. Nevertheless, classification of abnormal cells into LSIL and HSIL yielded unsatisfactory results. In order to address this problem, this study adopted two hybrid neural networks namely hybrid radial basis function (HRBF) and hybrid multilayered perceptron (HMLP) networks in order to improve the performances of conventional neural networks. The overall diagnostic performance was measured using accuracy, sensitivity, specificity, false negative and false positive analysis by comparing to the diagnoses made by pathologists. This study indicates that HMLP network produces better overall diagnostic performance than the MLP, RBF and HRBF networks.

Key words: RBF neural network, HRBF neural network, MLP neural network, HMLP neural network, cervical cancer, diagnostic system.

1.0 INTRODUCTION

Cervical cancer is one of the most common cancers among Malaysian women. Unlike other cancers that have early symptoms, most early cervical cancers (or cervical precancerous stage) have no telltale symptoms until they are advanced, which by then, they are often usually unresponsive to treatment. In most cases, cervical cancer takes many years to develop from normal to the advanced stage (WebMD, 2005). Cancer is a term for diseases in which abnormal cells divide without control. For cervical cancer, it refers to a rapid and uncontrolled growth of severely abnormal cells on the cervix. Abnormal cervical cell changes are caused by infection with certain types of human papillomavirus (HPV), and when abnormal cell changes persist over time and become severe, these cells can develop into cancer cells (WebMD, 2005). Over a long period of time, cervical cancer cells can invade nearby tissues and can spread through the bloodstream and lymphatic system to other parts of the body.

The mortality related to cervical cancer can be substantially reduced through early detection. To date, Papanicolaou test or better known as Pap test is the most popular screening technique for this cancer. Several previous studies (Kuie, 1996, Framer, 2001, Breen et al., 2001, Adami et al., 1994) showed that routine screening by Pap test has been proven to be effective in reducing the chances for a woman acquiring cervical cancer. However, the determination of abnormal cervical cells can sometimes be missed in certain situations (Hislop et al., 1994, Othman et al., 1995, Kuie, 1996, Othman et al., 1997). The major reasons contributing to the decrease in the accuracy of Pap test include technical and detection (human) errors. This is further enhanced by poor diagnostic skills of the cytotechnicians and cytopathologists.

The task of examining cervical smears for abnormal cervical cells requires an experienced cytopathologist. The human error could be reduced if alternative diagnostic techniques or systems could be used to interpret or diagnose Pap smears. The role of cytopathologists is never taken over nor replaced by these 'machines'; however, the diagnostic burden could be substantially reduced if 'assistance' from these diagnostic tools is available. One of the popular diagnostic tools for cervical cancer screening system is artificial neural networks (McKenna et al., 1992, Ricketts et al., 1992, Bazoon et al., 1994, Balasubramaniam et al., 1998, Tumer et al., 1998, Mitra et al, 2000, Li & Najarian, 2001).

The most common neural network employed in the computer-aided screening system for cervical cancer is the multilayered perceptron (MLP). Currently, the MLP network is used in one of cervical cancer diagnosis systems called Papnet (WebMD, 2005). Papnet System has been approved by the Food and Drug Administration (FDA) and has been used in United States of America. Research by (Ashfaq et al., 1996, Cabaniss et al., 1997) proved that the Papnet System produced a promising performance with the accuracy between 73% and 85%. Besides the Papnet System, few previous studies also showed their interest in using the MLP network as a diagnosis tool for cervical cancer networks (McKenna et al., 1992, Ricketts et al., 1992, Balasubramaniam et al., 1998, Mitra et al, 2000, Li & Najarian, 2001). Basically, those researches used features of cervical cells, which are extracted by human experts, as the MLP network's inputs and the classification of cervical cells type, i. e. normal and abnormal cervical cells, could be the MLP network's output. Besides the MLP network, other types of neural networks, radial basis function (RBF) (Tumer et al., 1998, Mat-Isa et al., 2002), adaptive resonance theory (ART) (Bazoon et al., 1994) and Hopfield (Brouwer, 1993, 1995) have also been used.

Although the computer-aided screening system based on neural networks has been studied over the last two decades, most of the previous studies focused on conventional methods and neural network architectures. These include:

(i) Classification of cervical precancerous cells based on normal and abnormal cells. The Bethesda Classification System (Cotran et al., 1994, WebMD, 2005) that classified cervical precancerous cells into normal, *low-grade squamous intraepithelial lesion* (LSIL) and *high-grade squamous intraepithelial lesion* (HSIL) cells is widely used nowadays. Therefore, the conventional classification is no longer significant.

(ii) Two conventional neural networks, namely radial basis function (RBF) and multilayered perceptron (MLP) neural networks were commonly used in cervical precancerous screening system. Rapid development in neural network architectures and training algorithms proved that the modified version of those neural networks architecture, such as hybrid architecture, produces better performances (Mashor, 2000a, 2000b).

(iii) Both the RBF and the MLP neural networks were trained using conventional training algorithm. The MLP neural network was commonly trained using back propagation (BP) algorithm. The BP algorithm provides slow convergence rate (McLoone et al., 1998, Rughooputh & Rughooputh, 1999), thus requiring a lot of training data, up to 10000. As for the RBF neural network, *k*-means clustering algorithm has stimulated much interest in training the RBF neural network due to its simplicity of implementation. However, due to dead centre, centre redundancy and trapped centre at local minima problems, the RBF neural network performance could be reduced most of the time (Mashor, 2000a).

(iv) In order to obtain better diagnostic performance, most of the previous studies used big number of cervical cell features as input data of neural networks such as 80 features by McKenna *et al.* (1992), 15 features by Balasubramaniam *et al.* (1998) and 21 features by Mitra *et al.* (2000), and many more (Ricketts et al., 1992, Bazoon et al., 1994, Tumer et al., 1998). This increases the complexity of neural networks' architecture, thus, increasing the processing time of the neural networks.

In this study, we showed how modification of conventional neural networks could achieve better diagnostic performance for cervical precancerous screening.

2.0 THE METHODOLOGY

The methodology consists of 5 major steps; The first step involves investigating the capability of both conventional neural networks in classifying cervical precancerous cells. The conventional categorization that classifies the cells into normal and abnormal cells was used. Based on the promising results described in (Mashor, 2000a, 2000b), this study employs a hybrid architecture of the conventional MLP and RBF neural networks, called hybrid MLP (HMLP) and hybrid RBF (HRBF) respectively.

In step 2, this study analysed the diagnostic performance by the neural networks used. Five (5) conventional analysis terms, namely accuracy, specificity, sensitivity, false negative and false positive, were analysed. This study further classified the abnormal cells into LSIL and HSIL cells as in The Bethesda Classification.

In Step 3, this study applied the same data input as in Step 1 to the same MLP, RBF, HMLP and HRBF neural networks, as used in Step 1, to investigate their capability in performing further differentiation of abnormal cells into the various degrees of abnormality, LSIL and HSIL. The proposed categorization that classifies the cells into normal, LSIL and HSIL cells is based on the Bethesda System. This was followed by diagnosis performance analysis as in Step 4. Finally, in Step 5, this paper compared the performance between the conventional and the proposed classification techniques. A schematic diagram of the methodology is shown in Figure 1.

In order to increase the diagnosis performance, improved training using latest algorithms was applied to both conventional and hybrid neural networks. Although MLP neural network was trained using BP algorithm, slow convergence rate could be its limitation factor as noted by others before (McLoone et al., 1998, Rughooputh & Rughooputh, 1999, Mashor, 2000b). This problem was remedied by proposing modified recursive prediction error (MRPE) algorithm (Mashor, 2000b). This study trained the MLP and the HMLP neural networks using the MRPE algorithm.

In both RBF and HRBF neural networks they should have sufficient numbers and value of centres to represent the identified input data. Dead centres, redundant centres and trapped centres at local minima are three major problems which could cause poor performance. Conventional clustering algorithms, such as *k*-means and fuzzy *c*-means, are highly dependent on proper initialisation of centres. Therefore, bad initialisation process may generate a set of poor final centres due to the above problems (Xu et al., 1993, Kamel & Selim, 1994, Mashor, 2000a). This study used moving *k*-means clustering algorithm to train the RBF and the HRBF neural networks. Mashor (2000a) proved that the overall performance of the RBF and the HRBF neural networks was increased while simulation results revealed that the algorithm was not sensitive to initial centres.

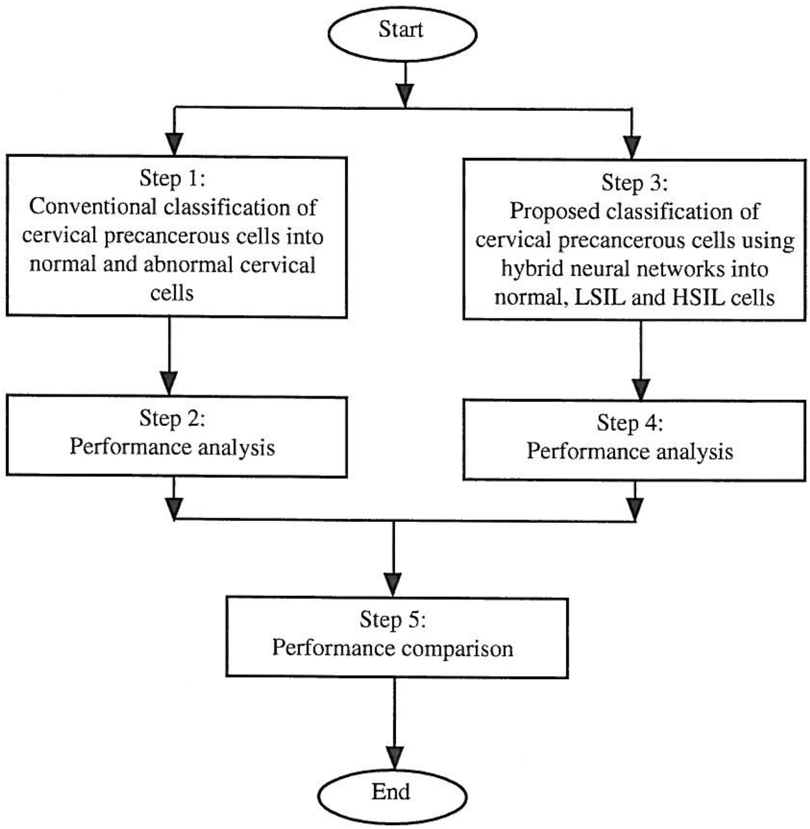

Figure 1: Schematic Diagram of the Methodology

In order for neural networks to be used as cervical precancerous diagnostic techniques, features of cervical cells need to be extracted by human experts and used as neural network inputs and their classification of cervical cells type could be the output. Most previous studies used this approach (McKenna et al., 1992, Ricketts et al., 1992, Bazoon et al., 1994, Balasubramaniam et al., 1998, Tumer et al., 1998, Mitra et al, 2000, Li & Najarian, 2001). As the aim of this study is to apply neural networks to classify precancerous cervical cells, Pap smear images taken from Pap tests are the only data sources. Several important features on Pap smear images were then extracted manually by cytopathologists using image analyser. Unlike previous studies, this study used smaller number of cervical cell features as input data of neural networks. Four features of Pap smear images were identified as major features which are significant in determining the type of cervical precancerous cells: size of the nucleus, size of the cytoplasm, the grey level of the nucleus and the grey level of the cytoplasm.

In the final stage, this study compared the capability of the neural networks in classifying cervical precancerous cells based on the broad normal-abnormal category of the conventional classification and the Bethesda Classification.

3.0 HYBRID RADIAL BASIS FUNCTION NEURAL NETWORK

In 1985, radial basis functions were first introduced in the solution of the real multivariable interpolation problem by Powell (1988). It is now one of the main fields of research in numerical analysis. Broomhead and Lowe (1988) were the first to exploit the use of radial basis functions in the design of neural networks. To date, several previous researches (Achmitz & Aldrich, 1999, Zhu et al., 1999) gave major contributions to the theory, design and application of the RBF neural network.

A RBF neural network with m outputs and n_h hidden nodes can be expressed as follows:

$$y_i(t) = w_{i0} + \sum_{j=1}^{nh} w_{ij}\, \phi\,(\|v(t) - c_j(t)\|);\ i = 1,\ldots,m \tag{1}$$

where w_{ij}, $v(t)$ and $c_j(t)$ are the connection weights, bias connection weights, input vector and RBF centres respectively. $\phi\,(\bullet)$ is a non-linear basis function, while $\|\bullet\|$ denotes a distance measure that is normally taken to be the Euclidean distance.

RBF neural network is highly nonlinear. By using the RBF neural network, a linear system has to be approximated using the nonlinear neural network model. However, modelling a linear system using a nonlinear model can never be better than using a linear model. Therefore, the RBF neural network with additional linear input connections may be used. This modified version of RBF is called the hybrid radial basis function (HRBF) neural network. As shown in Figure 2, the HRBF neural network allows the network inputs to be connected directly to the output nodes via weighted connections to form a linear model, which is in parallel with the nonlinear original RBF model. The HRBF neural network with m outputs, n_h hidden nodes and n_l linear input connections can be expressed as follows (Mashor, 2000a):

$$y_i(t) = w_{i0} + \sum_{j=1}^{nh} w_{ij}\, \phi\,(\|v(t) - c_j(t)\|) + \sum \lambda_{ik} vl(t),\ i = 1,2..,m \tag{2}$$

where the l's and vl's are the weights and the input vector for the linear connections respectively.

Based on Equations (1) and (2), in the training phase, the training algorithms for RBF and HRBF neural networks are normally split into two part; positioning the network centres, $c_j(t)$ and estimating the weights, w_{ij}. In HRBF neural network, since λ's appear to be linear within the original RBF neural network, the λ's can be estimated using the same algorithm as for the w's. In our study, exponential weighted least squares was used to estimate w's and λ's. Many solutions have been suggested to solve the weighted least squares problem such as recursive modified Gram Schemit, fast recursive least squares, fast Kalman algorithm and Given least squares. In our study, Given least squares without square roots was used. The application of the Given least squares algorithm to adaptive filtering and estimation have stimulated much interest due to the superior numerical stability and accuracy (Ling, 1991). The implementation of Given least squares algorithm to estimate RBF weights can be found in reference by Chen *et al.* (1992).

The performance of RBF neural network is highly influenced by the centre locations of radial basis function. Clustering algorithm is most suitable and is widely used to position the RBF centres. This is due to research by Poggio and Girosi (1990), who showed that the updating rule for RBF centres derived from a gradient descent approach makes the centres move towards the majority of the input data. In adaptive k-means, non-adaptive k-means and fuzzy c-means clustering algorithm, there are three basic problems that normally arise during clustering; dead centres, centre redundancy and trapped centre in local minima. These problems degrade the performance of the RBF and HRBF neural networks. In 2000, Mashor proposed a non-adaptive clustering algorithm to minimise the first two problems and indirectly reduces the effect of the third problem. The algorithm is called moving k-means clustering algorithm. In that study, simulation results on modelling two systems revealed that the overall performance of the RBF neural network that used the proposed algorithm is much better than the ones that used other clustering algorithms. Therefore, in the current study, the moving k-means clustering algorithm is proposed to position the RBF centres. The implementation of moving k-means clustering algorithm can be found in reference by Mashor (2000a).

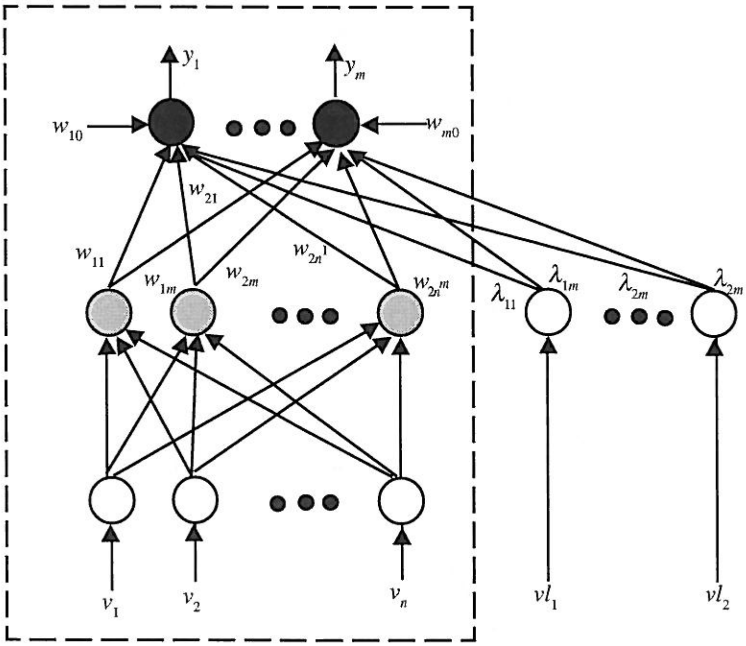

Figure 2: The HRBF Neural Network

4.0 HYBRID MULTILAYERED PERCEPTRON NEURAL NETWORK

Like the RBF neural network, MLP neural network is also a highly nonlinear neural network. Thus, a linear system has to approximate using the nonlinear MLP neural network model. A MLP neural network with m outputs and n_h hidden nodes can be expressed as:

$$\hat{y}_k(t) = \sum_{j=1}^{n_h} w^2_{jk} F\left(\sum_{i=1}^{n_i} w^1_{ij} x^0_i(t) + b^1_j\right) \text{ for } 1 \le k \le m \tag{3}$$

where w^1_{ij} and w^2_{jk} denote the weights of the connection between input and hidden layer, and weights of the connection between hidden and output layer respectively. b^1_j and x_i denote the thresholds in hidden nodes and inputs that are supplied to the input layer respectively. $F(\bullet)$ is an activation function and is normally selected as sigmoid function.

Based on the superior performance produced by HRBF neural network as compared to RBF neural network, Mashor (2000b) proposed additional linear input connections to the MLP neural network, which allows the network inputs to be connected directly to the output nodes via weighted connections to form a linear model as shown in Figure 3. The modified version of MLP is called hybrid multilayered perceptron (HMLP) neural network.

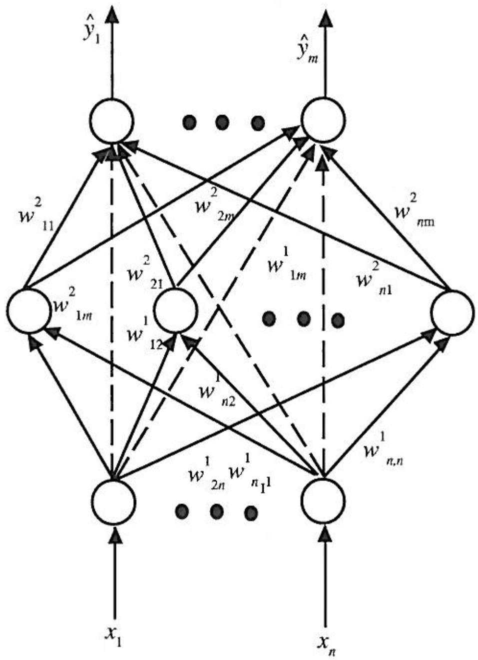

Figure 3: One-Hidden Layer HMLP Neural Network

As shown in Figure 3, for the HMLP neural network with m output nodes, n_h hidden nodes and n_i input nodes, the output of the kth neuron, y_k, in the output layer is given by:

$$\hat{y}_k(t) = \sum_{j=1}^{n_h} w^2_{jk} F\left(\sum_{i=1}^{n_i} w^1_{ij} x^0_i(t) + b^1_j\right) + \sum_{i=1}^{n_i} w^1_{ik} x^0_i(t) \quad 1 \le k \le m \tag{4}$$

where w^1_{ik} denote weights of the linear connection between input and output layer respectively.

From Equations (3) and (4), the values of w^1_{ij}, w^2_{jk}, w^1_{ik} and b^1_j must be determined using the appropriate algorithm. Back propagation (BP) algorithm is commonly used to find optimum values for those parameters. Although the algorithm is easy to implement and produces a good performance, its convergence rate is slow. To overcome the problem, Chen *et al.* (1990) proposed recursive prediction error (RPE) to replace the BP algorithm. The RPE algorithm provides a faster convergence rate and better final convergence values of weights and thresholds. In 2000, Mashor (2000b) proposed a modified version of RPE algorithm, known as modified recursive prediction error (MRPE). By optimising the way the momentum and the learning rates are assigned, the MRPE algorithm is able to improve the convergence rate of the RPE algorithm. Thus, the MRPE algorithm will be used to train the HMLP neural network in the current study. Refer to reference Mashor (2000b) for implementation of MRPE algorithm.

5.0 EXPERIMENTAL RESULTS

These neural networks were tested with 200 clinical samples of cervical precancerous cells collected from Hospital Universiti Sains Malaysia (HUSM), and Hospital Kota Bharu, Kelantan, Malaysia. The samples consisted of 50 normal cells, 50 LSIL cells and 100 HSIL cells. The samples were divided into training data set and testing data set. 128 cervical cells, which consist of 32 normal cells, 32 LSIL cells and 64 HSIL cells, were used to train the neural networks. The remaining 72 cervical cells, which consisted of 18 normal cells, 18 LSIL cells and 36 HSIL cells were used as testing data.

As discussed in Section 2, four cervical cell features were used as input data to the neural networks. Thus, each neural network needs 4 input nodes. In Step 1, these neural networks classified cervical precancerous cells into normal and abnormal cells, which require one output node. While, in the Step 3, cervical precancerous cells were classified into normal, LSIL and HSIL cells, which require 3 output nodes for each neural network.

Five analyses were used to determine the suitability and applicability of these neural networks as an intelligent diagnostic system. These are accuracy, sensitivity, specificity, false negative and false positive analysis. Accuracy refers to the ability of neural networks to produce correct screening test. Sensitivity is the ability of neural networks to produce positive screening test given that the person has the precancerous cervical cells (the LSIL and HSIL cells). Specificity is the ability of neural networks to produce negative screening test given that the person is clear from the precancerous cells (able to detect normal cells correctly). False negative refers to wrong determination of the HSIL cells as the LSIL or the normal cells, or wrong determination of the LSIL cells as the normal cells. False positive refers to wrong determination of normal cells as the HSIL or the LSIL cells, or wrong determination of the LSIL cells as the HSIL cells.

For the RBF and the HRBF neural networks, both neural networks were trained based on the following configuration:

$$\rho = 1000.0,\ \beta_0 = 0.00,\ \beta(0) = 0.95,\ \alpha_0 = \frac{1}{\textit{no. of hidden nodes}}$$

where ρ is a positive constant and β is an exponential forgetting factor, both parameters are in Given least square algorithm [32], while α is a constant value, $0 < \alpha < 1$, which is in moving k-means clustering algorithm [21].

For the MLP and the HMLP neural networks, both neural networks were trained based on the following configuration:

$$\alpha_m(0) = 0,\ \alpha_g(0) = 0.5,\ a = 0.01,\ b = 0.85,\ \lambda_0 = 0.99 = 0,\ \lambda(0) = 0.95$$

where α_m and α_g are constant values, which are close to 1 and 0 respectively, a is a small constant and λ is forgetting factor [22]. All parameters are in the MRPE algorithm.

Before using the neural networks to classify the cervical cells, the optimum structure for each neural network, i.e. number of hidden nodes and epochs of training data, should be determined during training phase. This procedure ensures the neural networks achieve optimum generalization, hence producing optimum classification performance. The determination was carried out by increasing the number of hidden nodes and training data epochs until the maximum or optimum classification was achieved. This procedure was commonly used in application of neural network as pattern classification (Mat-Isa et al., 2002, Mat-Sakim, 2004). Table 1 shows the results for optimum number of hidden nodes and training data epochs for each neural network used in this study.

Table 1: Optimum Structure for the RBF, HRBF, MLP and HMLP Networks for Normal/Abnormal Classification of Cervical Cells

Type of neural network	Optimum number of hidden nodes	Optimum number of training data epochs
RBF	1	26
HRBF	1	26
MLP	5	18
HMLP	5	10

5.1 RESULTS FOR CLASSIFICATION OF CERVICAL CELLS BASED ON THE CONVENTINAL SYSTEM

As described previously in Section 2, these neural networks were first applied to classify cervical cells into normal and abnormal cervical cells. After setting the above parameters into these neural networks and observing their outputs, it was discovered that the neural networks managed to achieve diagnostic performance as shown in Table 2. Table 2 shows the percentages of accuracy, sensitivity, specificity, false negative and false positive during testing phase.

Table 2: Diagnosis Performance of the RBF, HRBF, MLP and HMLP Networks for Normal/Abnormal Classification of Cervical Cells

Analysis	RBF	HRBF	MLP	HMLP
Accuracy	100.00	100.00	100.00	100.00
Sensitivity	100.00	100.00	100.00	100.00
Specificity	100.00	100.00	100.00	100.00
False negative	0.00	0.00	0.00	0.00
False positive	0.00	0.00	0.00	0.00

5.2 RESULTS FOR CLASSIFICATION OF CERVICAL CELLS BASED ON THE BETHESDA SYSTEM

The results for the proposed cervical cells classification methodology based on the Bethesda System as carried out in Step 3 and 4 of the current work are shown in Table 3. From the results in Table 3, this paper further analyses the performance of the proposed classification methodology by determining the correct determination of normal, LSIL and HSIL cells separately. The results are as shown in Table 4. This provides a better picture of the ability of these neural networks in classifying cervical cells separately based on the Bethesda Classification.

Table 3: Diagnosis Performance of the RBF, HRBF, MLP and HMLP Neural Networks Using the Proposed Classification Methodology Based on the Bethesda System

Analysis	RBF	HRBF	MLP	HMLP
Accuracy	75.00	75.00	75.00	94.44
Sensitivity	66.67	66.67	66.67	92.59
Specificity	100.00	100.00	100.00	100.00
False negative	0.00	0.00	0.00	5.55
False positive	50.00	50.00	50.00	2.78

Table 4: Percentage of Correct Determination of Cervical Cells Type Using the Proposed Classification Methodology Based on the Bethesda System

Type of neural network	Normal cell	LSIL cell	HSIL cell
RBF	100.00	0.00	100.00
HRBF	100.00	0.00	100.00
MLP	100.00	0.00	100.00
HMLP	100.00	94.44	91.67

6.0 DISCUSSION

There is no difference in the results between conventional and hybrid neural networks obtained in Section 5.1. All of the neural networks produced 100% accuracy, sensitivity and specificity. No false negative and false positive cases occurred. The superior diagnostic performance strongly suggests that all of the neural networks could be used in classifying cervical cancer into normal and abnormal cells as in conventional classification procedure.

For the proposed classification of cervical cells based on the Bethesda System, all neural networks were capable of determining all of the normal cells correctly as shown in Table 4. Thus, all neural networks produced 100% of specificity as shown in Table 3. Table 4 also indicates that the RBF, the HRBF and the MLP neural networks were capable of determining all the HSIL cells correctly, while the HMLP neural network determined 91.67% of the HSIL cells.

The significant difference of diagnostic performances between these neural networks was in the analysis of correct determination of the LSIL cells. Results in Table 4 shows that the RBF, HRBF and MLP neural networks produced poor performance in diagnosing LSIL cells. Most of the LSIL cells were wrongly diagnosed as HSIL cells. This gives rise to false positive diagnosis, which lowers the sensitivity as shown in Table 3. However, the HMLP neural network produces better performance in determining the LSIL cells. From Table 4, 94.44% of the LSIL cells were correctly determined. As a result, the HMLP neural network produced high percentage of sensitivity as well as lowers the percentage of false positive as shown in Table 3. The reason for the better performance by the HMLP network could be due to the ability of the HMLP network to represent both linear and nonlinear models as compared to the MLP network that could only represent a nonlinear model [22].

As can be seen in Table 1, the MRPE algorithm has significant ability in producing a faster convergence rate. The HMLP network trained using the MRPE algorithm needed only 128 items of data with a small number of epochs, i.e. 5 epochs, to produce the optimum and promising performance. Hence, the HMLP network employed the simple architecture with 10 hidden nodes as compared to the RBF, HRBF and MLP networks with 18, 26 and 26 hidden nodes respectively.

Like the HMLP network, the HRBF network also has the capability to represent both linear and nonlinear models. However, the HRBF network produced almost the same performance as the conventional RBF network with no improvement. Theoretically, as mentioned in Section 3.0, the performance of the HRBF networks is highly influenced by centre locations of radial basis function. A good clustering algorithm should intelligently find the best centre locations to represent the data of normal, LSIL and HSIL cells separately. But, as shown in Table 4, the HRBF network wrongly classified all LSIL cells as HSIL cells, which increased the false positive rate as stated in Table 3. This shows that the moving *k*-means clustering algorithm still faces one of the common problems in conventional algorithm, i.e. dead centre, centre redundancy and trapped centre at local minima. This leads to failure of providing different centre locations to represent the data of LSIL and HSIL cells separately.

Overall, the results gave positive indication of the applicability of the HMLP neural network to classify cervical cells based on the Bethesda Classification. In our study, the HMLP network produces better diagnosis performance than other neural networks as it produces 94.44%, 92.59% and 100% of accuracy, specificity and sensitivity respectively. False negative and false positive diagnosis were low, 5.55% and 2.78% respectively. As discussed above, the diagnostic performance and correct determination of cervical cells abnormality favours the HMLP network as a suitable neural network for cervical cancer screening process. Furthermore, the HMLP network employs a straightforward architecture as well as requires small number of training data and epochs.

Good diagnostic performance produced by the HMLP neural networks also proved the following hypotheses of our study:

(i) Four features of cervical cells are enough to be used as input data. This prevents a complex architecture of the neural networks as compared to several previous studies [10]-[15], which used a bigger number of input. With four input nodes, this simpler neural network could produce faster screening results.

(ii) The hybrid architecture of neural network produced better diagnostic performance than conventional architecture. The ability of representing both linear and non-linear models could be the reason.

(iii) The results obtained also proved that the MRPE algorithm has high ability in producing a faster convergence rate. The HMLP neural network that was trained using the MRPE algorithm needed only 128 items of data with only 5 epochs to produce good performance up to 94.44% of accuracy.

7.0 CONCLUSION

In conclusion, this study demonstrates the classification of the cellular abnormality of the cervix based on the Bethesda Classification using artificial neural network. This study indicates that the HMLP neural network gives promising and significant diagnostic performance. The accuracy and sensitivity obtained by HMLP is much higher compared to the RBF, HRBF and MLP neural networks. The HMLP neural network is also capable of determining normal, LSIL and HSIL cells correctly better than other neural networks. It has low false negative and false positive diagnoses. The HMLP neural network has good generalisation, where the results for both testing and training data sets are equally good.

Although the current work is still in its early stage, the results suggest that the HMLP neural network provides useful predictions for cervical cancer cell abnormality. The HMLP neural network is intended to be used as a good computer assisted cervical cancer screening system. It can assist physicians in decision making and has the potential to enhance efficiency as results can be obtained faster. For these reasons, we foresee that the complete system would be welcomed by pathologists, physicians and health personnel who are involved in the screening process for cervical cancer.

8.0 ACKNOWLEDGEMENT

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