

# Classification of Acute Leukaemia Cells Using Multilayer Perceptron and Simplified Fuzzy ARTMAP Neural Networks

Aimi Abdul Nasir<sup>1</sup>, Mohd Yusoff Mashor<sup>1</sup>, and Rosline Hassan<sup>2</sup>

<sup>1</sup>Electronic & Biomedical Intelligent Systems Research Group, Universiti Malaysia Perlis, Malaysia

<sup>2</sup>Department of Haematology, Universiti Sains Malaysia, Malaysia

**Abstract:** *Leukaemia is a cancer of blood that causes more death than any other cancers among children and young adults under the age of 20. This disease can be cured if it is detected and treated at the early stage. Based on this argument, the requirement for fast analysis of blood cells for leukaemia is of paramount importance in the healthcare industry. This paper presents the classification of white blood cells (WBC) inside the Acute Lymphoblastic Leukaemia (ALL) and Acute Myelogenous Leukaemia blood samples by using the Multilayer Perceptron (MLP) and Simplified Fuzzy ARTMAP (SFAM) neural networks. Here, the WBC will be classified as lymphoblast, myeloblast and normal cell for the purpose of categorization of acute leukaemia types. Two different training algorithms namely Levenberg-Marquardt and Bayesian Regulation algorithms have been employed to train the MLP network. There are a total of 42 input features that consist of the size, shape and colour based features, have been extracted from the segmented WBCs, and used as the neural network inputs for the classification process. The classification results indicating that all networks have produced good classification performance for the overall proposed features. However, the MLP network trained by Bayesian Regulation algorithm has produced the best classification performance with testing accuracy of 95.70% for the overall proposed features. Thus, the results significantly demonstrate the suitability of the proposed features and classification using MLP and SFAM networks for classifying the acute leukaemia cells in blood sample.*

**Keywords:** *Acute leukaemia cells, feature extraction, classification, multilayer perceptron neural network, simplified fuzzy ARTMAP neural network.*

Received September 19, 2011; accepted December 30, 2011

## 1. Introduction

Cancer is one of the major health problems in Malaysia. Cancer constitutes 10.3% of medically certified deaths, which is the fourth leading cause of death after disease of the circulatory system, accidents and disease of the respiratory system [12]. There are over 100 different types of cancer and one of them is leukaemia. Leukaemia is a cancer of the marrow and blood. In leukaemia, the bone marrow produces a large number of abnormal white blood cells. These cells are immature and they do not function properly [8]. Without treatment, leukaemia can be a deadly disease. In Malaysia, leukaemia was reported to be the 5<sup>th</sup> out of 10 most frequent cancers in male and female between 2003 until 2005 [13]. In addition, leukaemia causes more death than any other cancers among children and young adults under the age of 20 [13]. Based on these arguments, the requirement for fast analysis of blood cells for leukaemia is of paramount importance in the healthcare industry.

Leukaemia can be cured if it is detected and treated at the early stage. In general, doctors often detect leukaemia by performing the complete blood count process [18]. If there are abnormalities in this count, a

study of morphological bone marrow smear is done to confirm the present of leukaemia cells [20]. The confirmation for the types of acute leukaemia required the observation of WBC. Specific morphological features will be observed in order to classify the acute leukaemia as either Acute Lymphoblastic Leukaemia (ALL) or Acute Myelogenous Leukaemia (AML). During this observation, there are three types of WBC that need to be considered, namely the lymphoblast, myeloblast and normal WBC [10]. Both lymphoblast and myeloblast are the abnormal WBCs. The presence of lymphoblast in the blood sample will relate to the type of ALL. On the other hand, the presence of the myeloblast in the blood sample will relate to the type of AML. Currently, the microscopic investigation is performed manually by haematologists through visual identification under the light microscope. This classification is very important in order to provide the best treatment. However, the manual recognition method has an error rate between 30% and 40% depending on the haematologists experience and difficulties to distinguish the types of leukaemia [20].

Artificial neural network (ANN) is a promising alternative utilized exclusively for complex data

analysis. The field of ANN was born in order to overcome the limitation of the ability of computer to perform certain tasks. ANN has been applied for solving problems such as speech recognition [21] and diagnosis of several types of cancer such as breast cancer [2, 6], cervical cancer [15] and blood disorder [1]. A number of useful researches on analyzing and classifying the blood cells using neural network have been carried out. For instance, Ongun *et al.* [17] proposed a fully automated classification of blood and bone marrow smears using various approaches including neural network based classifiers and Support Vector Machine (SVM), presented together with the features used in the classification. In order to conduct an automated counting of blood cells, the combination between segmentation, feature extraction and classification are needed. The segmentation process was done by morphological pre-processing followed by the snake-balloon algorithm. Several types of features based on intensity, colour, shape and texture have been used to robustly represent the object. In classification, SVM produced the best performance with 91.03% accuracy as compared to Multilayer Perceptron (MLP) network trained using Conjugate Gradient Descent, Linear Vector Quantization (LVQ) and k-Nearest Neighbor classifier which produced 89.74%, 83.33% and 80.76% of accuracy, respectively.

Toure and Basu [24] applied the MLP network trained by Back Propagation (BP) algorithm to predict the types of leukaemia either ALL or AML and the results gave 58% accuracy on test data. Hsieh *et al.* [9] proposed a leukaemia cancer model that utilizes Information Gain based on SVM technique and enhancement to evaluate and interpret the classification of two types of leukaemia which are ALL and AML. Here, the Information Gain technique has been used for feature selection. Given entropy,  $E$  to calculate the correlation in a training dataset, it has been used for estimating the usefulness of a feature while classifying the training data. The experimental results indicated that the SVM model has produced the highest result for classification of leukaemia cancer with accuracy of 98.10%. Due to the requirement for analysis of blood cells for leukaemia, the current study proposes to apply the artificial neural network for classification the individual WBC. In order to differentiate with other previous approaches, the current study will utilize the potential use of MLP and SFAM networks for classifying the individual WBC as lymphoblast, myeloblast and normal cell based on the extracted features from both ALL and AML blood samples.

## 2. Methodology

In order to perform the classification of acute leukaemia cells, the actions to be taken will include 4 main steps, starting with the image acquisition, image segmentation, feature extraction and end with the

classification using artificial neural network at the final step. In this research, there are a total of 500 images (200 ALL and 300 AML) were captured from acute leukaemia blood samples by using the Leica microscope and captured at 40X magnification. Further details for image segmentation, feature extraction and classification of acute leukaemia cells using artificial neural network are discussed in the following section.

## 3. Image Segmentation

A typical blood sample consists of three main regions: white blood cells or blast (abnormal WBC), red blood cells (RBC) and background areas. Nucleus and cytoplasm regions form a fully WBC and contain important information to be observed by haematologists. However, the RBC and background regions contain no information and can be eliminated from the image. To utilise the colour contents in an image, the colour image segmentation for WBC is performed based on the HSI (Hue, Saturation, Intensity) colour space. Here, the features have been extracted based on the fully segmented WBC and nucleus that have been obtained by applying the combination of contrast enhancement technique and colour image segmentation based on HSI colour space, and the procedures can be referred in [22]. Figure 1-a and b represent the original images for ALL and AML, respectively. Meanwhile, Figures 2 and 3 represent the resultant segmented WBC and nucleus, respectively. Based on Figure 1-a and b, the black, blue and red arrows indicate the appearance of lymphoblast, myeloblast and lymphocytes (normal WBC), respectively.

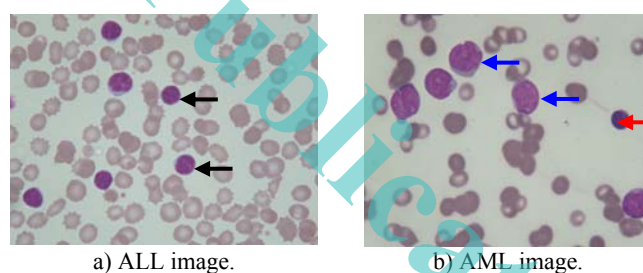


Figure 1. Original images.

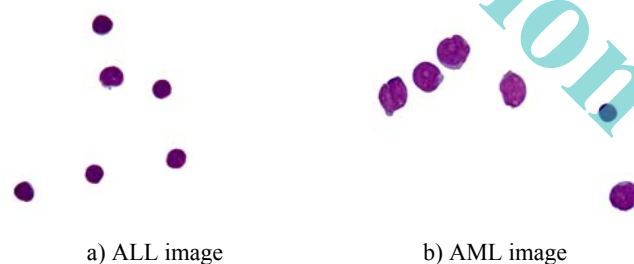


Figure 2. Resultant images of segmented WBC.

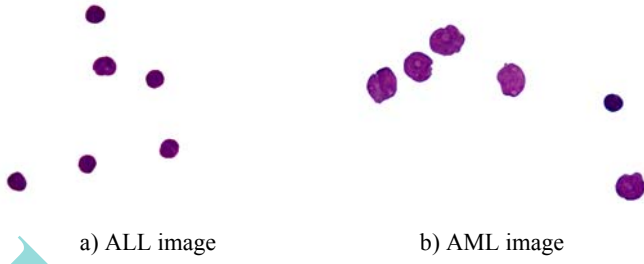


Figure 3. Resultant images of segmented nucleus.

#### 4. Feature Extraction of Size, Shape and Colour Based Features

After the segmented WBC and nucleus have been obtained, the next step is to perform the feature extraction. The extracted features will provide useful information for classification of WBC into lymphoblast, myeloblast and normal cell. Here, the features can be classified into three main types:

- Size based features: Area of fully segmented WBC, nucleus and cytoplasm; ratio of area between nucleus and cytoplasm (N/C); and perimeter of fully segmented WBC and nucleus.
- Shape based features: Roundness, compactness, central moment and affine invariant moment of nucleus.
- Colour based features: Mean and standard deviation of intensity and RGB colour space for nucleus and cytoplasm.

The area are described based on Equation 1 and can be obtained by performing the Seeded Region Growing Area Extraction (SRGAE) algorithm [7] on the segmented WBC and nucleus. Here,  $(x,y)$  is defined as the image pixel location, while  $f(x,y)$  is the corresponding image pixel value.

$$\text{Area, } A = \sum_{x=1}^X \sum_{y=1}^Y f(x,y) \quad (1)$$

In general, haematologists will classify the WBC by examining the shape of the cells and nucleus. In order to reflect the information of shape in feature vector, several measures such as roundness, compactness and moment have been used to represent the shape information. The roundness and compactness [3] are described based on Equation 2 and 3, respectively.

$$\text{Roundness} = \frac{(\text{Perimeter})^2}{4\pi * \text{Area}} \quad (2)$$

$$\text{Compactness} = \frac{(\text{Perimeter})^2}{\text{Area}} \quad (3)$$

Moment is a sequence of numbers used for characterizing the shape of an object. Here, the position of centroid  $(x_c, y_c)$  is used to determine the central moment by identifying the position of the object [5]. The position of  $x_c$  and  $y_c$  can be obtained based on Equation 4.

$$x_c = \frac{1}{A} \sum_{x=1}^X \sum_{y=1}^Y x f(x,y) \text{ and } y_c = \frac{1}{A} \sum_{x=1}^X \sum_{y=1}^Y y f(x,y) \quad (4)$$

Since the object is balanced at the centroid, the first order central moment is zero. Meanwhile, the 2nd till 5th order central moment can be obtained by using the Equation 5 [5]. Here, the sum of power  $(p + q)$  is the order of the moment.

$$\mu_{pq} = \sum_{x=1}^X \sum_{y=1}^Y (x - x_c)^p (y - y_c)^q f(x,y) \quad p \geq 0, q \geq 0 \quad (5)$$

The first and second affine invariant moments are defined in Equation 7 and 8, respectively [24].

$$\mu_{00} = A = \sum_{x=1}^X \sum_{y=1}^Y f(x,y) \quad (6)$$

$$L_1 = \frac{1}{\mu_{00}^2} (\mu_{02} \mu_{20} - \mu_{11}^2) \quad (7)$$

$$L_2 = \frac{1}{\mu_{00}^3} (\mu_{03} \mu_{30}^2 - 6 \mu_{03} \mu_{12} \mu_{21} \mu_{30} + 4 \mu_{12}^2 \mu_{30} + 4 \mu_{03} \mu_{21}^3 - 3 \mu_{12}^2 \mu_{21}^2) \quad (8)$$

Since colour is an important feature that human perceives while observing the WBC, identification of blood cells based on colour has been proposed. Here, the colour features are derived from the red, green, blue and intensity components. There are a total of 12 colour features that have been extracted from the nucleus and cytoplasm of the WBC. In order to perform the colour based feature extraction, the equation for both mean and standard deviation of colour can be referred in [5].

#### 5. Artificial Neural Network

##### 5.1 Multilayer Perceptron Neural Network

The Multilayer Perceptron neural network is a feed forward neural network with one or more hidden layers. Cybenko and Funahashi have proven that the MLP network with one hidden layer has the capability to approximate any continuous function up to certain accuracy. The classification performance of the MLP network will highly depend on the structure of the network and training algorithm. Here, two different training algorithms namely Levenberg-Marquardt (LM) and Bayesian Regulation (BR) have been used in order to determine the applicability of the MLP network. The main architecture of MLP network is illustrated in Figure 4.

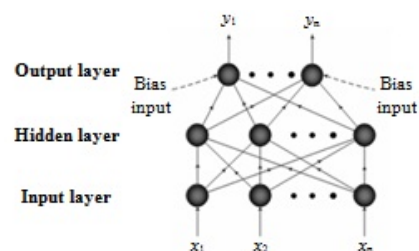


Figure 4. A Multilayer Perceptron neural network.

### 5.1.1. The Levenberg-Marquardt Algorithm

The Levenberg-Marquardt algorithm is used to train the MLP network because it has been proven that the LM algorithm has much better learning rate and can keep the relative stability compare to the famous Back Propagation (BP) algorithm [11]. LM algorithm is an approximation of Gauss-Newton algorithm, which generally provides much faster learning rate than the BP algorithm that is based on steepest descent algorithm [11]. The LM modification to the Gauss-Newton algorithm is shown as below:

$$\Delta x = [J^T(x)J(x) + \mu I]^{-1} J^T(x)e(x) \quad (9)$$

Based on Equation 9,  $\mu$  is the Marquardt adjustment parameter and  $I$  is an identity matrix. When  $\mu$  is small, the LM algorithm approximates the Gauss-Newton algorithm. Since the Gauss-Newton algorithm converges faster and more accurate near an error minimum, so the goal is to shift towards the Gauss-Newton algorithm as quickly as possible. Thus, the value of  $\mu$  is decreased after each step unless the change in error is positive. On the other hand, when  $\mu$  is large, the LM algorithm will approximate the steepest descent algorithm [11].

### 5.1.2. The Bayesian Regulation Algorithm

The Bayesian Regulation algorithm can be recognized as a smoothen version of the Levenberg-Marquardt algorithm. It is a training algorithm that updates the weight and bias values according to the Levenberg-Marquardt optimization. Here, the BR algorithm is applied for optimizing the generalization quality of network training by minimizing a combination of squared errors and weights [4]. By the virtue of its generalization quality, it should be less prone to overfitting the input data, given from the same architecture or set of inputs. The basic weight adjustment step of BR iteration is [23]:

$$x_{k+1} = x_k - [J^T J + \mu I]^{-1} J^T e \quad (10)$$

Based on Equation 10,  $J$  is the Jacobian matrix that contains first derivatives of the network errors with respect to the weight and bias values,  $\mu$  is the Marquardt adjustment parameter and  $e$  is a vector of network errors. The performance function in BR algorithm involves modifying the mean square error,  $mse$  to improve the generalization capability of the network.

$$mse = \frac{1}{n} \sum_{i=1}^n e_i^2 \quad (11)$$

$$msw = \frac{1}{n} \sum_{j=1}^n w_j^2 \quad (12)$$

The function in Equation 11 is expanded with the addition of the mean square weights,  $msw$ . Thus the mean square error for the BR algorithm becomes [23]:

$$mse_{br} = mse(\beta) + msw(\alpha) \quad (13)$$

where,  $\alpha$  and  $\beta$  are the parameters which are to be optimized in Bayesian framework of Mackay [14]. The advantage of using the BR algorithm is to overcome the overfitting problems by taking into account the goodness-of-fit as well as the network architecture [4].

## 5.2. Simplified Fuzzy ARTMAP Neural Network

Simplified Fuzzy ARTMAP neural network is a fast, incremental, supervised learning system for analog inputs. In 1993, Kasuba proposed the SFAM network which is a simplification of Fuzzy ARTMAP [25]. The network is a step ahead of Fuzzy ARTMAP in reducing the computational and architectural redundancy of Fuzzy ARTMAP [25]. Thus, the current study will utilize the potential use of SFAM network for the classification process. The SFAM network has a simplified architecture when compared to the original Fuzzy ARTMAP [19]. The main architectures of SFAM network for classification of three categories or classes ( $C_1$ ,  $C_2$  and  $C_3$ ) are illustrated by the diagrams in Figure 5 [19][25].

The network contains two layers, input and output. During learning, input data are presented to the SFAM network together with their respective categories to learn. The raw inputs flow through a complement coder, which involves normalization and complementation of the input. The expanded input vector,  $x$  is then passes to the input layer. During the initial state of SFAM network, there is no node represented in the output layer until the network has its first opportunity to learn a pattern. Once an input pattern is presented, an output node is formed to represent it. Weights,  $w$  from each node of the output layer reach down to sample the input layer.

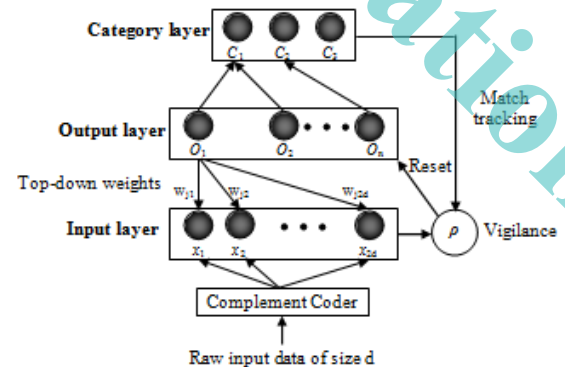


Figure 5. A SFAM network after a number of learning steps.

During the learning phase, these weights form the associations between the input patterns and their

associated category based on a number of adaptation steps. The category layer is an area that holds the categories or classes that the network has to learn. If a node in the output layer does not match with the teaching category described in the category layer, a reset signal is generated at the output layer, forcing the input to be re-classified into an appropriate node in the output layer. If the expected output node does not exist, a new output node is created to classify the input as shown in Figure 5. The fast learning capability of SFAM network involves two main processing stages namely the input preparation and output node activation [19].

### 5.3. Methodology for Classification of White Blood Cells

There are several analyses that will be conducted during the classification of WBC in order to compare the classification performance between MLP and SFAM networks. The analyses to be conducted are:

- Analysis of classification performance based on the size, shape and colour based features for MLP and SFAM networks.
- Analysis of optimum numbers of training epoch and hidden node for MLP network.
- Analysis of optimum numbers of training epoch and vigilance parameter for SFAM network.

The number of input node,  $I$  depends directly to the number of input features to be placed. The inputs will be normalized within the range of 0 and 1 to avoid features dominating during the training phase. For MLP network, the output nodes for the three categories will be set as lymphoblast (00), myeloblast (01) and normal cell (10). Meanwhile, in SFAM network, the three category nodes will be set as lymphoblast (0), myeloblast (1) and normal cell (2). Here, there are a total of 1683 WBC that have been segmented from 500 acute leukaemia images. 1009 cells are used for training, while the remaining of 674 cells are used for testing. 42 input features have been extracted from the fully segmented WBC and nucleus and will be fed as inputs to both MLP and SFAM networks. The total number of input features are 42 because certain features such as the 2nd, 3rd, 4th and 5th order central moment consists of 3, 4, 5 and 6 input features, respectively.

## 6. Results and Discussion

The white blood cells have been classified as lymphoblast, myeloblast and normal cell by using two classifiers namely Multilayer Perceptron and Simplified Fuzzy ARTMAP neural networks. For each category of analysis, the result and discussion will start with the analysis using MLP network trained by LM algorithm (MLP\_LM), followed by MLP network trained by BR algorithm (MLP\_BR) and end with the analysis using

SFAM network. The first category of classification is the classification of WBC based on size, shape and colour based features using the MLP and SFAM networks. Here, there are a total numbers of 6, 24 and 12 input features that have been extracted which represent the size, shape and colour based features of the WBC, respectively.

For the classification using MLP\_LM and MLP\_BR networks, the structure of the network is set to I:H:2 (input node: hidden node: output node). The selected training parameters are training algorithm = Levenberg-Marquardt (trainlm) and Bayesian Regulation (trainbr), number of training epochs = 150 and goal = 0.001. For the classification using SFAM network, the structure of the network is set to I:O:3 (input node: output node: category). The selected training parameter is vigilance parameter = 0.75. Tables 1, 2 and 3 represent the results for the classification performance based on size, shape and colour based features using MLP\_LM, MLP\_BR and SFAM networks, respectively. Based on Tables 1, 2 and 3, the results show that the classifications of WBC using both MLP and SFAM networks have given promising results with testing accuracy more than 80% for the three categories of features.

Table 1. Classification performance using size, shape and colour based features for MLP\_LM network.

Analysis	Features		
	Size	Shape	Colour
Number of inputs	6	24	12
Number of hidden nodes	6	10	4
Number of training epochs	150	150	150
Training accuracy (%)	92.47	88.90	95.94
Testing accuracy (%)	92.14	86.20	92.28
Overall accuracy (%)	92.34	87.82	94.47

Table 2. Classification performance using size, shape and colour based features for MLP\_BR network.

Analysis	Features		
	Size	Shape	Colour
Number of inputs	6	24	12
Number of hidden nodes	4	7	4
Number of training epochs	150	150	150
Training accuracy (%)	92.17	88.40	94.75
Testing accuracy (%)	92.14	87.69	92.43
Overall accuracy (%)	92.16	88.12	93.82

Table 3. Classification performance using size, shape and colour based features for SFAM network.

Analysis	Features		
	Size	Shape	Colour
Number of inputs	6	24	12
Number of training epochs	2	4	3
Vigilance parameter	0.75	0.75	0.75
Training accuracy (%)	98.81	99.41	100.00
Testing accuracy (%)	87.24	80.71	86.80
Overall accuracy (%)	94.18	91.91	94.71

Based on the results in Table 1, it is discovered that the colour based feature produces the highest testing accuracy with 92.28%. This is followed by the size and shape based features with testing accuracy of 92.14% and 86.20%, respectively. Based on the results in Table 2, the colour based feature is still producing the highest testing accuracy with 92.43%. This is

followed by the size and shape based features with testing accuracy of 92.14% and 87.69%, respectively. For the classification using SFAM network, it is discovered that the size based feature produces the highest testing accuracy with 87.24%. This is followed by the colour and shape based features with testing accuracy of 86.80% and 80.71%, respectively. Based on the resultant testing accuracy from these three tables, it is discovered that both size and colour based features are capable of providing the similar classification performance with high testing accuracy. Meanwhile, the shape based feature has provided the lowest classification performance compared to the size and colour based features.

Next is the classification of WBC based on the overall proposed features using the MLP and SFAM networks. In order to obtain the classification performance for MLP network, the actions that have been taken consist of 2 main steps namely analysis of number of training epochs and analysis of number of hidden nodes. Here, the optimum number of training epochs and hidden nodes are obtained when the MLP network achieved the highest classification performance. The analysis started by finding the number of training epochs that can provide the best testing accuracy. For this purpose, the structure of MLP network is set to 42:10:2. Figure 6(a) and (b) show the classification performance for number of training epochs for MLP\_LM and MLP\_BR networks, respectively.

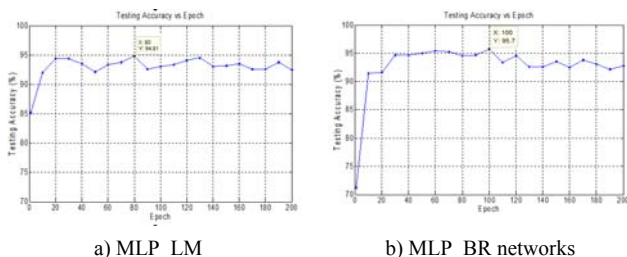


Figure 6. Testing accuracy versus training epoch for classification between lymphoblast, myeloblast and normal WBC, respectively.

Based on the results in Figure 6-a and b, the best classification performance is obtained at 80 and 100 training epochs with testing accuracy of 94.81% and 95.70%, respectively. Then, the 80 and 100 training epochs are used in order to find the number of hidden nodes that can provide the best testing accuracy. It is necessary to determine the optimum number of hidden nodes in order to avoid the problems of underfitting or overfitting. Figure 7-a and b show the classification performance for number of hidden nodes for MLP\_LM and MLP\_BR networks, respectively.

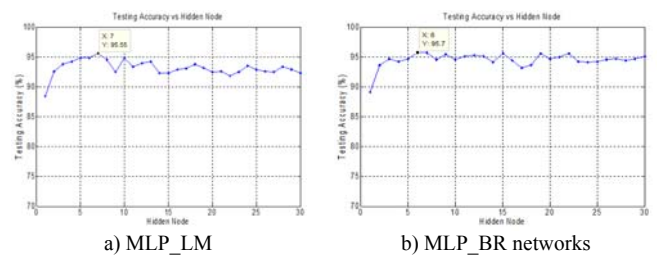


Figure 7. Testing accuracy versus hidden node for classification between lymphoblast, myeloblast and normal WBC, respectively.

Based on the results in Figure 8-a, the best classification performance is obtained at 7 hidden nodes with testing accuracy of 95.55%. Thus, the MLP\_LM network produces the best classification performance of 95.55% at 80 training epochs and 7 hidden nodes. Based on the results in Figure 7-b, the best classification performance is obtained at 6 hidden nodes with testing accuracy of 95.70%. The results also show that the testing accuracy above than 90% have been achieved when applying the hidden nodes within 2 and 50 with regular repetition of 100 training epochs. Thus, the MLP\_BR network produces the best classification performance of 95.70% at 100 training epochs and 6 hidden nodes.

The third classification for overall features that has been conducted is the classification using SFAM network. For SFAM network, there are two parameters that need to be considered namely the number of training epochs and the value of vigilance parameter. The analysis started by finding the number of training epochs that can provide the best testing accuracy. For this purpose, the structure of SFAM network is set to 42:0:3. The parameter for training that has been set is vigilance parameter = 0.75. Figure 8-a and b show the classification performance for number of training epochs and different values of vigilance parameter using SFAM network.

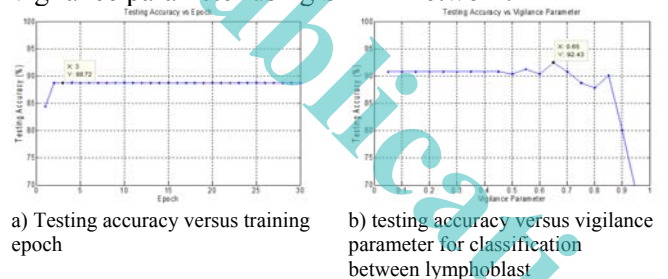


Figure 8. myeloblast and normal WBC using SFAM network

Based on the results in Figure 8(a), the best classification performance is obtained at 2 training epochs with testing accuracy of 88.72%. However, the training accuracy at 3 training epochs is higher compared to the training accuracy at 2 training epochs. Thus, the 3 training epochs is used in order to find optimum value of vigilance parameter that can provide the best testing accuracy. Figure 8(b) represents the results of analysis of different values of vigilance parameter for classification performance using SFAM

network. Here, the best classification performance is obtained when the vigilance parameter is set to 0.65 with testing accuracy of 92.43%. Thus, the SFAM network produces the best classification performance of 92.43% at 3 training epochs and 0.65 vigilance parameter. The classification performances based on overall proposed features for MLP network trained using LM and BR algorithms and SFAM network for the classification of lymphoblast, myeloblast and normal WBC are summarized in Table 4.

Table 4. The performance comparison between MLP and SFAM network for classification of lymphoblast, myeloblast and normal WBC.

Analysis	Multilayer Perceptron		Simplified Fuzzy ARTMAP
	Levenberg-Marquardt	Bayesian Regulation	
Training algorithm	Levenberg-Marquardt	Bayesian Regulation	-
Number of inputs	42	42	42
Number of hidden nodes	7	6	-
Number of training epochs	80	100	3
Vigilance parameter	-	-	0.65
Training accuracy (%)	98.91	98.12	99.90
Testing accuracy (%)	95.55	95.70	92.43
Overall accuracy (%)	97.56	97.15	96.91

Based on the results in Table 4, both MLP and SFAM networks provide good classification performance. The MLP network trained by BR algorithm has proved to be the best with testing accuracy of 95.70%. This is followed by MLP network trained by LM algorithm on the second place with testing accuracy of 95.55% and SFAM network on the third place with testing accuracy of 92.43%. In order to achieve the optimal classification performance, the number of hidden nodes required for MLP\_LM and MLP\_BR networks are 7 and 6, while the numbers of training epochs are 80 and 100, respectively. Here, the MLP\_BR network required less number of hidden nodes to provide a better generalization property. Thus, the BR algorithm has again proved to be the best training algorithm with high testing accuracy and required only 6 hidden nodes in order to achieve the optimal classification performance.

The results also show that the SFAM network has obtained the optimal classification performance of 92.43% at 3 training epochs and 0.65 vigilance parameter. However, the classification results produced by SFAM network are not as higher as the MLP network. Even though the classification performance produced is less than the MLP network, the SFAM network required only 3 training epochs in order to achieve the optimal classification performance. Thus, the SFAM network has an advantage in producing high rate of convergence with less number of training epochs.

The researches in neural network implementation for analysis of blood cells for leukaemia have been done by several researchers. Table 5 reports the classification results provided by the current study and also several previous approaches for analysis of blood cells for leukaemia.

Table 5. The performance comparison between various classifiers for analysis of blood cells for leukaemia.

Reference	Classifier	Performance Accuracy
The proposed method	MLP_BR	95.70%
	MLP_LM	95.55%
	SFAM	92.43%
Ongun <i>et al.</i> [17]	SVM	91.03%
	MLP_CGD	89.74%
	LVQ	83.33%
	KNN	80.76%
Toure and Basu [24]	MLP_BP	58.00%
Hsieh <i>et al.</i> [9]	SVM	98.10%
Mohapatra and Patra [16]	SVM	95.00%

Based on the results in Table 5, it seems that the results provided by the current study using MLP\_LM, MLP\_BR and SFAM networks with testing accuracy of 95.55%, 95.70% and 92.43%, respectively are higher compare to the results provided by Ongun *et al.* [17], Toure and Basu [24], and Mohapatra and Patra [16]. Overall, by using the 42 input features, the MLP network trained by BR algorithm has proven to be better with a higher testing accuracy and required less number of hidden nodes in order to achieve the optimal performance.

## 7. Conclusions

The MLP network trained by LM and BR algorithms as well as the SFAM network have been used to classify the WBC into three categories namely lymphoblast, myeloblast and normal cell. Here, there are a total of 42 input features that represent the size, shape and colour based features have been extracted from a fully segmented WBC and nucleus, and be fed as inputs to the neural network. The results show that the proposed size, shape and colour based features have the capability to classify the WBC with good classification performance. In addition, both MLP and SFAM networks give good classification performance with testing accuracy of above 90% by using the overall features. However, the MLP network trained by BR algorithm has proven to be the best with classification performance of 95.70% by using the overall 42 input features. Thus, the result significantly demonstrates the suitability of the proposed features and classification using MLP and SFAM networks for classification of acute leukaemia cells in blood sample.

## Acknowledgements

The authors gratefully acknowledge and thank the team members of acute leukaemia research at Universiti Malaysia Perlis for making this research achievable and Universiti Sains Malaysia (USM) for providing the acute leukaemia blood samples. We also would like to acknowledge the Malaysian Government for providing the financial support through the Fundamental Research Grant Scheme under the Ministry of Higher Education, Malaysia.

## References

- [1] Aeinfar V., Mazdarani H., Deregeh F., Hayati M., and Payandeh M., "Multilayer Perceptron Neural Network with Supervised Training Method for Diagnosis and Predicting Blood Disorder and Cancer," *IEEE International Symposium on Industrial Electronics (ISIE 2009)*, Seoul, Korea, pp. 2075-2080, 2009.
- [2] Almadani A., Diagnosing Breast Cancer Disease Using Fuzzy ARTMAP Technique, Master's thesis, University Utara Malaysia, Nov. 2007.
- [3] Demir C., and Yener B., "Automated cancer diagnosis based on histopathological images: a systematic survey," Tech. Rep., Rensselaer Polytechnic Institute, 2005.
- [4] Doan C. and Liong S., Generalization for Multilayer Neural Network Bayesian Regularization or Early Stopping, 2004.
- [5] Gonzalez R. and Woods R., *Digital Image Processing*, Prentice Hall, New Jersey, USA, 2007.
- [6] Hamdan H., The Application of Backpropagation Neural Network in the Prognosis of Breast Cancer, Master's thesis, Faculty of Computer Science and Information Technology, University Malaya, Malaysia, 2004.
- [7] Harun N., Mashor M., and Rosline H., "Calculation of Blast Area for Acute Leukemia Blood Cells Images," *Proceedings of the International Postgraduate Conference on Engineering*, Perlis, Malaysia, 2010.
- [8] Henry D., Latest News in Blood Cancer Research, 2010.
- [9] Hsieh S., Wang Z., Cheng P., Lee I., Hsieh S., and Lai F., "Leukemia Cancer Classification based on Support Vector Machine," *2010 8th IEEE International Conference on Industrial Informatics*, Osaka, Japan, pp. 819-824, 2010.
- [10] Kennedy J., Hematopathology V Acute Leukemia, Acute Lymphoblastic Leukemia, Chronic Lymphocytic Leukemia, and Hairy Cell Leukemia, 2002.
- [11] Kisi O., "Multi-layer perceptrons with Levenberg-Marquardt training algorithm for suspended sediment concentration prediction and estimation," *Hydrological Sciences-Journal-des Sciences Hydrologiques*, vol. 49, pp. 1025-1040, 2004.
- [12] Lim G., "Overview of Cancer in Malaysia," *Japanese Journal of Clinical Oncology*, vol. 32, pp. 37-42, 2002.
- [13] Lim G., Rampal S., and Yahaya H., Cancer Incidence in Peninsular Malaysia, The Third Report of the National Cancer Registry, Malaysia, 2008.
- [14] MacKay D., "A practical Bayesian framework for backpropagation networks," *Neural Computation*, vol. 4, pp. 448-472, 1992.
- [15] Mango L., "Computer-assisted cervical cancer screening using neural networks," *Cancer Letters*, vol. 77, pp. 155-162, 1994.
- [16] Mohapatra S. and Patra D., "Automated Cell Nucleus Segmentation and Acute Leukemia Detection in Blood Microscopic Images," *Proceedings of 2010 International Conference on Systems in Medicine and Biology*, India, pp. 49-54, 2001.
- [17] Ongun G., Halici U., Leblebicioglu K., Atalay V., Beksac M., and Beksac S., "Feature Extraction and Classification of Blood Cells for an Automated Differential Blood Count System," *Proceedings of the 2001 International Joint Conference on Neural Networks*, Washington, DC, USA, pp. 2461-2466, 2001.
- [18] Priyankara G., Seneviratne O., Silva R., Soysa W., and Silva C., An Extensible Computer Vision Application for Blood Cell Recognition and Analysis, 2006.
- [19] Rajasekaran S. and Pai G., "Image Recognition Using Simplified Fuzzy ARTMAP Augmented with a Moment Based Feature Extractor," *International Journal of Pattern Recognition and Artificial Intelligence*, vol. 14, pp. 1081-1095, 2000.
- [20] Reta C., Altamirano L., Gonzalez J., Diaz R., and Guichard J., "Segmentation of Bone Marrow Cell Images for Morphological Classification of Acute Leukemia," *Proceedings of the Twenty-Third International Florida Artificial Intelligence Research Society Conference*, Florida, USA, pp. 86-91, 2010.
- [21] Salam M., Mohamad D., and Salleh S., "Malay Isolated Speech Recognition Using Neural Network: A Work in Finding Number of Hidden Nodes and Learning Parameters," *The International Arab Journal of Information Technology*, vol. 8, pp. 364-371, 2011.
- [22] Salihah A., Mashor M., Harun N., Abdullah A., and Rosline H., "Improving Colour Image Segmentation on Acute Myelogenous Leukaemia Images Using Contrast Enhancement Techniques," *2010 IEEE EMBS Conference on Biomedical Engineering & Sciences*, Kuala Lumpur, Malaysia, pp. 246-251, 2010.
- [23] Saptoro A., Yao H., Tadé M., and Vuthaluru H., "Prediction of coal hydrogen content for combustion control in power utility using neural network approach," *Chemometrics and Intelligent Laboratory Systems*, vol. 94, pp. 149-159, 2008.

[24] Toure A. and Basu M., "Application of Neural Network to Gene Expression Data for Cancer Classification," *Proceedings of the 2001 International Joint Conference on Neural Networks*, Washington, DC, USA, pp. 583-587, 2001.

[25] Venkatesan P. and Suresh M., "Classification of Renal Failure Using Simplified Fuzzy Adaptive Resonance Theory Map," *International Journal of Computer Science and Network Security*, vol. 9, pp. 129-134, 2009.



**Aimi Salihah Abdul Nasir** was born in Malacca, Malaysia in 1986. She received her B.Eng (Hons) degree in Mechatronic Engineering from Universiti Malaysia Perlis (UniMAP) in 2009 and M.Sc in Biomedical Electronic Engineering from the same university in 2011. She is currently pursuing her PhD in Biomedical Electronic Engineering at UniMAP. Her research interests include image processing, medical image analysis, artificial neural network and medical diagnostic system.



**Prof. Dr. Mohd Yusoff Mashor** obtained his Bachelor of Engineering in Control and Computer Engineering from University of Westminster, London in 1990. Under Universiti Sains Malaysia (USM) RLKA scheme, he pursued his M.Sc in Control Engineering and Information Technology at University of Sheffield in 1991. In 1995, he obtained his PhD specialized in neural network from the same university. He started his service in USM in the School of Electrical and Electronic Engineering in December 1995. He is currently the Dean of Postgraduate Studies, Universiti Malaysia Perlis. Since his PhD time, he is actively involved in research. Over the years, he has developed his expertise in neural network, system identification, fuzzy logic, control system, intelligent forecasting/prediction, image processing and medical diagnostic systems. He has authored and co-authored for more than 100 research publications in the form of book chapters, refereed journals and conferences at the international and national levels.



**Assoc. Prof. Dr. Rosline Hassan** obtained her medical degree, MD from Universiti Kebangsaan Malaysia and MMed in Pathology from Universiti Sains Malaysia. She is currently the Head of Department of

Hematology, School of Medical Sciences, Universiti Sains Malaysia. Her research interests include haematopathology with special interest in molecular aspect of haematological disorders, leukaemias and myeloproliferative disorders, red cell disorders inclusive of thalassemia, cytogenetic of leukaemia, cell culture studies and stem cell studies. She has published numerous research articles in the international journals and conference proceedings.