APPLICATION OF NEURAL NETWORK
IN
MALARIA PARASITES CLASSIFICATION

By

Lim Chia Li

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ABSTRACT

There are only a few researchers used artificial intelligence to classify malaria parasites. The purpose of this project is to classify malaria parasites into *Plasmodium falciparum, Plasmodium vivax* and *Plasmodium malariae* based on ratio of infected red blood cell's (RBC) size to normal RBC's size, shape of parasite, location of chromatin, number of chromatin, texture of infected RBC, and number of parasite per RBC using different types of neural network. Throughout the project, the suitability of the application of neural networks in malaria parasites classification will be investigated. The best neural network will be implemented to build an intelligent classifier for malaria parasites. The first stage of this project is to develop the neural network using MATLAB Neural Network Toolbox and Borland C++ Builder. Multilayer Perceptron (MLP) network and Radial Basis Function (RBF) network will be developed using MATLAB in which MLP network is trained with Back Propagation, Bayesian Rule and Levenberg-Marquardt learning algorithm and RBF network is trained with k-means clustering algorithm. Hybrid Multilayer Perceptron (HMLP) network with modified recursive prediction error algorithm will be developed using Borland C++ Builder. In the second stage, comparison will be done on the performance of neural networks developed to yield the best neural network and malaria parasites classification system will be developed using Borland C++ Builder. Result shows that HMLP network is the best neural network in classification of malaria parasites. It has a simple architecture, intelligent and accurate. The final product of this project is a software system that is capable to classify malaria parasites with high accuracy, high applicability, fast and cheap.

ABSTRAK

Aplikasi Rangkaian Neural untuk Pengkelasan Parasit Malaria

Hanya terdapat beberapa penyelidik yang menggunakan kecerdikan rekaan untuk pengkelasan parasit malaria. Tujuan projek ini ialah untuk mengkelaskan parasit malaria kepada *Plasmodium falciparum*, *Plasmodium vivax* dan *Plasmodium malariae* berdasarkan nisbah saiz sel darah merah terjangkit kepada saiz sel darah merah normal, bentuk parasit, kedudukan kromatin, bilangan kromatin, tekstur sel darah merah terjangkit dan bilangan parasit dalam sel darah merah dengan menggunakan pelbagai jenis rangkaian neural. Dalam projek ini, kesesuaian aplikasi rangkaian neural dalam pengkelasan parasit malaria akan dikaji. Rangkaian neural yang terbaik akan diimplemenkan untuk pembinaan sistem pengkelasan parasit malaria. Peringkat pertama ialah membina rangkaian neural menggunakan 'MATLAB Neural Network Toolbox' dan 'Borland C++ Builder'. Rangkaian Perceptron Lapisan Berbilang (MLP) dan Rangkaian Fungsi Asas Jejarian (RBF) akan dibina dalam MATLAB di mana rangkaian MLP dilatih dengan algoritma perambatan balik, Levenberg-Marquardt dan aturan Bayesian manakala rangkaian RBF dilatih dengan algoritma pengelompokan purata-k. Rangkaian Perceptron Lapisan Berbilang Hibrid (HMLP) dengan algortitma ralat ramalan rekursif ubahsuai akan dibina menggunakan 'Borland C++ Builder'. Perinkat kedua melibatkan perbandingan antara prestasi pelbagai rangkaian neural yang dibina untuk mendapatkan rangkaian neural terbaik dan sistem pengkelasan akan dibina dalam 'Borland C++ Builder'. Keputusan menunjukkan rangkaian HMLP adalah rangkaian neural terbaik dalam pengkelasan parasit malaria. Produk akhir adalah sebuah sisitem perisian yang dapat mengklasifikasikan parasit malaria dengan jitu, mempunyai kebolehgunaan yang tinggi, cepat dan murah.

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Abbreviation List

Abbreviation	Explanation
ANN	Artificial Neural Network
BP	Back Propagation
BR	Bayesian Rule
FF network	Feedforward network
GUI	Graphical User Interface
HMLP	Hybrid Multilayer Perceptron
LM	Levenberg-Marquardt
MIMD	Multiple Instruction Multiple Data
MLP	Multilayer Perceptron
MRPE	Modified Recursive Prediction Error
P.falciparum	*Plasmodium falciparum*
P.malariae	*Plasmodium malariae*
P.ovale	*Plasmodium ovale*
PU	Processing Unit
P.vivax	*Plasmodium vivax*
RBC	Red Blood Cell
RBF	Radial Basis Function
RNN	Recurrent Neural Network
RPE	Recursive Prediction Error

CHAPTER 1

INTRODUCTION

1.1 Introduction

Nowadays, the global burden of malaria is enormous and the development of better laboratory diagnostic tools is a key step in malaria control recommended by the WHO. Our objective is to classify the malaria parasites based on their specific characteristics into three different types using neural network. This is because neural network can provide variety solution for different problem areas since it can learn, auto organization, tolerance to faults, flexibility and scalability.

In this chapter, discussion will be focused on malaria parasites and classification of malaria parasites. Besides that, the objective and scope of the project will also be mentioned. Lastly, the repot draft will be discussed shortly.

1.2 Malaria Parasites

Malaria is a protozoa disease which infects human and insect hosts alternatively. It is a very old disease and prehistoric man is thought to have suffered from malaria. It probably originated in Africa and accompanied human migration to the Mediterranean shores, India and South East Asia. In the past it used to be common in the marshy areas around Rome and the name is derived from the Italian, (mal-aria) or "bad air"; it was also known as Roman fever. Today some 500 hundred million people in Africa, India, South East Asia and South America are exposed to endemic malaria and it is estimated to cause two and a half million deaths annually, one million of which are children (McConnell, 2002).

Malaria is caused by protozoan parasites belonging to the genus *Plasmodium*. The parasite is spread to people by the female Anopheles mosquito, which feeds on human blood. Female mosquitoes take blood meals to carry out egg production and such blood meals are the link between the human and the mosquito hosts in the parasite life cycle. Of approximately 430 known species of Anopheles, only 30-50 transmit malaria in nature. These species of female anopheline mosquitoes are differ in behaviour. This contributes to the varying epidemiological patterns of the disease seen worldwide (Greenwood et. al., 2005).

The malaria parasite requires specific human and mosquito tissues to complete its life cycle (refer Figure 1.1). In nature, malaria parasites spread by infecting successively two types of hosts: humans and female *Anopheles* mosquitoes. The phase in *Anopheles* is know as extrinsic phase, in which sexual reproduction occurs, is referred to as "definitive" while the phase in humans is know as intrinsic phase, in which asexual reproduction occurs, is referred to as "intermediate".

During a blood meal, a malaria-infected female *Anopheles* mosquito inoculates sporozoites into the human host ❶. Sporozoites infect liver cells ❷ and mature into schizonts ❸, which rupture and release merozoites ❹. After this initial replication in the liver (exo-erythrocytic schizogony A), the parasites undergo asexual multiplication in the erythrocytes (erythrocytic schizogony B). Merozoites infect red blood cells ❺. The ring stage trophozoites mature into schizonts, which rupture releasing merozoites ❻. Some parasites differentiate into sexual erythrocytic stages (gametocytes) ❼. Blood stage parasites are responsible for the clinical manifestations of the disease.

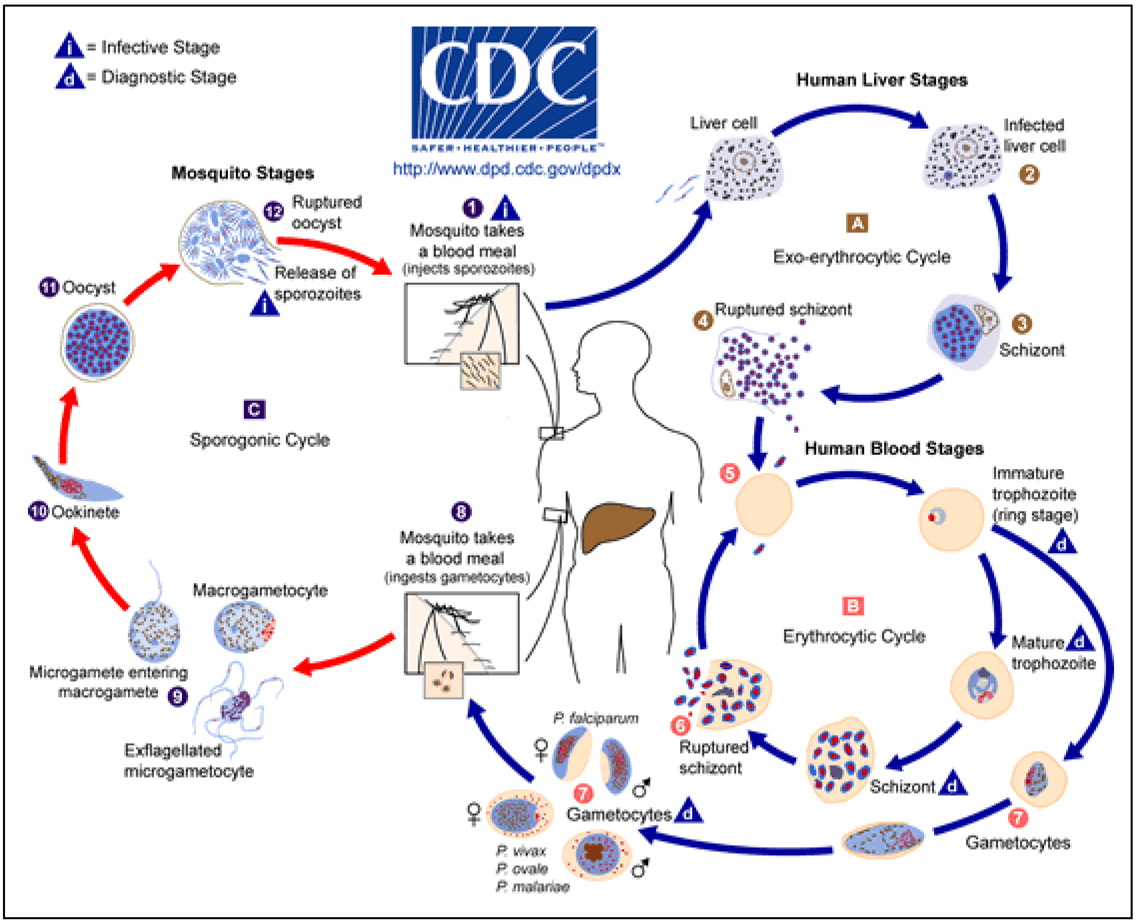

Figure 1.1 Schema of the Life Cycle of Malaria

The gametocytes, male (microgametocytes) and female (macrogametocytes), are ingested by an *Anopheles* mosquito during a blood meal ❽. The parasites' multiplication in the mosquito is known as the sporogonic cycle C. While in the mosquito's stomach, the microgametes penetrate the macrogametes generating zygotes ❾. The zygotes in turn become motile and elongated (ookinetes) ❿ which invade the midgut wall of the mosquito where they develop into oocysts ⓫. The oocysts grow, rupture, and release sporozoites ⓬, which make their way to the mosquito's salivary glands. Inoculation of the sporozoites ❶ into a new human host perpetuates the malaria life cycle. This information is cited from internet sources. URL:http://www.cdc.gov/malaria/biology/life_cycle.htm.

There are more than 100 species of *Plasmodium*, which can infect many animal species such as reptiles, birds and various mammals. Only four species account for almost all human infections, which are *Plasmodium falciparum* (*P.falciparum*), *Plasmodium vivax* (*P.vivax*), *Plasmodium ovale* (*P.ovale*) and *Plasmodium malariae* (*P.malariae*). The first two species cause the most infections worldwide. The latter two have dormant liver stage parasites which can reactivate and cause malaria several months or years after the infecting mosquito bite.

P. falciparum, which is found worldwide in tropical and subtropical areas are the most dangerous of these infections as *P. falciparum* malaria has the highest rates of complications and mortality. In addition it accounts for 80% of all human malarial infections and 90% of the deaths. *P. falciparum* can cause severe malaria because it multiples rapidly in the blood and can thus cause severe blood loss (anemia). Furthermore, the infected parasites can clog small blood vessels.

P.vivax, which is found mostly in Asia, Latin America and in some parts of Africa, is less prevalent than *P. falciparum*. While *P. vivax* only exceptionally cause death (most often due to rupture of an enlarged spleen), it can cause symptoms that are incapacitating. Thus, it contributes substantially to the disease burden of malaria, with a resulting social and economic impact. *P.vivax* has dormant liver stages that can activate and invade the blood several months or years after the infecting mosquito bite.

P.ovale is found mostly in Africa, especially West Africa and the islands of the western Pacific. It is biologically and morphologically very similar to *P.vivax*. *P.ovale* also has dormant liver stages that can activate and invade the blood several months or years after the infecting mosquito bite. However, differently from *P.Vivax*, it can infect individuals who are negatively for the Duffy blood group, which is the case for many residents of sub Saharan Africa.

P.malariae, found worldwide, is the only human malaria parasite species that has a quartan cycle. Quartan cycle means that this parasite has a three-day cycle. The three other species stated above have a tertian cycle, which means two-day cycle. Quartan malaria is so-called "benign malaria" and is not nearly as dangerous as that produced by *P. vivax*. *P.malariae* causes a long-lasting, chronic infection that in some cases can last a lifetime. In some patients *P.malariae* can cause serious complications such as the nephrotic syndrome.

Although four species of malaria parasites can infect humans and cause illness, only malaria caused by *P. falciparum* is potentially life-threatening. *P. falciparum* is the agent of severe, potentially fatal malaria, causing an estimated 700,000 to 2.7 million deaths annually. Furthermore, only three types of parasite are found in Malaysia which is *P.falciparum, P.vivax* and *P.malariae*. Since only three types of parasite are found in Malaysia, this pilot study will be focused on a system which is capable to classify these three types of parasite.

1.3 Classification of Malaria Parasites

- **Functional Classification**

  A functional catalogue of all current *Plasmodium* protein sequences based on the MIPS yeast headings as modified by the parasite genome community.

- **Biochemical Pathways**

  A catalogue of all current Plasmodium protein sequences placed in key biochemical pathways (KEGG).

- **Proteome Search Facility**

  Search the proteome data for any string of letters and/or numbers (e.g. kinase, KMP-11).

- **Motif Search**

  Search the database of all current *Plasmodium* protein sequences for a user defined protein motif.

- **Pfam Domain Distribution**

  A catalogue of Pfam domains found in *Plasmodium* ordered by domain frequency.

- **Plasmodium Reconstructed Sequence Database**

  This database is the result of a Bioinformatics project that attempts to understand the biology of the malaria parasite through genome analysis. The data consist of reconstructed and assembled *Plasmodium* sequences from three species of the malaria parasite, *Plasmodium falciparum, Plasmodium vivax* and *Plasmodium berghei*.

1.4 Objective and Scope of the Project

The main purpose of this pilot study is to develop an artificial intelligence system using neural networks to classify malaria parasites into three different types based on selected characteristics. The performance of several neural networks using different types of learning algorithm will be compared to yield the best network with the highest accuracy. Finally, the suitability of the application of neural networks in the malaria parasites classification will be examined.

The scope of this project is to develop Multilayer Perceptron (MLP) network and Radial Basis Function (RBF) network using the Matlab Neural Network toolbox. In addition, the scope of this project is also to develop Hybrid Multilayer Perceptron (HMLP) network and user interface using Borland C++ Builder. For RBF network, k-means clustering algorithm will be used to position the RBF centers and Givens Least Squares algorithm to estimate the weights. While for MLP network, three different types of learning algorithm will be used. They are Back Propagation (BP) learning algorithm, Bayesian Rule (BR) training algorithm and Levenberg-Marquardt (LM) learning algorithm. The HMLP network will be trained using the modified recursive prediction error (MRPE) algorithm.

There are total 603 data are used to classify the parasite malaria which 358 data are used in training phase and 245 data are used in testing phase. The neural network used in this pilot study consists of three layers: one input layer, one hidden layer and one output layer. There are six inputs to the neural network. These inputs are ratio of infected red blood cell's (RBC) size to normal RBC's size, shape of parasite which can be divided to long, ring shape and basket shape, location of chromatin, number of chromatin, texture of RBC, and number of parasite per RBC.

As predicted earlier, HMLP network will give the highest accuracy compared to the other networks. This means that HMLP network gives the best performance in classification of malaria parasites. So this project will be focused on the development of HMLP network together with the user interface. The user interface should contain some basic features such as input test box, results, exit button and help files. The final product of this project will be a software system that is capable to classify malaria parasites. This system should be user friendly, fast, accurate and with high applicability.

1.5 Report Draft

In overall, this report contains five chapters which each of the chapters will explain the progress of the project in details. The first chapter will focuses on malaria parasites and classification of malaria parasites. This chapter also explains the objective and scope of the project in details.

Chapter 2 is mainly focused on the fundamental of biological neural network and artificial neural networks. It also includes a short introduction about the various types of neural network, learning in the neural networks and application of neural network. A literature review regarding the application of neural networks in malaria parasites classification is also discussed here.

Chapter 3 discussed more on methodology used in this project. It focused on the theories of the neural network used in the project. Besides that, it also contained a detailed explanation for all the procedures throughout the development of the malaria parasites classification system: from the preparation of training data and testing data to the development of neural network.

Chapter 4 contained all the results which are obtained through the analysis performance being done on the system. The system interface being built in the project will be enclosed. Some discussion on the performance for the various type of neural network will be included. Furthermore performance comparison among the networks developed also included here. In this chapter, guide line to use the user interface will be also included.

Chapter 5 is the last chapter in this report. It contains the overall conclusion for the project. Future suggestion for the improvement and enhancement to the classification system will be discussed here too.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

Today neural networks are being applied to an increasing number of real-world problems of considerable complexity. They are good pattern recognition engines and robust classifiers, with the ability to generalize in making decisions about imprecise input data. They offer ideal solutions to a variety of classification problems such as speech, character and signal recognition, as well as functional prediction and system modeling where the physical processes are not understood or are highly complex (Hassoun, 2000).

In this chapter, discussion will be focused on biological neural network and artificial neural network. This chapter will also focus on the literature review of neural networks and application of neural network in malaria parasites classification.

2.2 Biological Neural Network

The neuron is the basic building block of the nervous system and most neurons are located in the brain. The human brain is estimated to contain an interconnected network of approximately 10^{11} neurons, each connected, on average, to 10^4 others. Neuron activity is typically excited or inhibited through connections to other neurons (Arbib, 1987).

Neurons can be classified into three main classes:

(i) **Sensory (Receptor) Neurons (Afferent)** – Carry impulses from the sense organs (receptors) to the brain and spinal cord. Receptors detect external or internal changes and send the information to the Central Nervous System in the form of impulses by way of the Afferent Neurons.

(ii) **Motor Neurons (Efferent)** - Carry impulses from the brain and spinal cord to muscles or glands. Muscles and glands are two types of effectors. In response to impulses, muscles contract and glands secrete.

(iii) **Interneurons** - Connect sensory neurons (brain) and motor neurons (effectors) and carry impulses between them. They are found entirely within the Central Nervous System (Jerry G. Johnson, 2006).

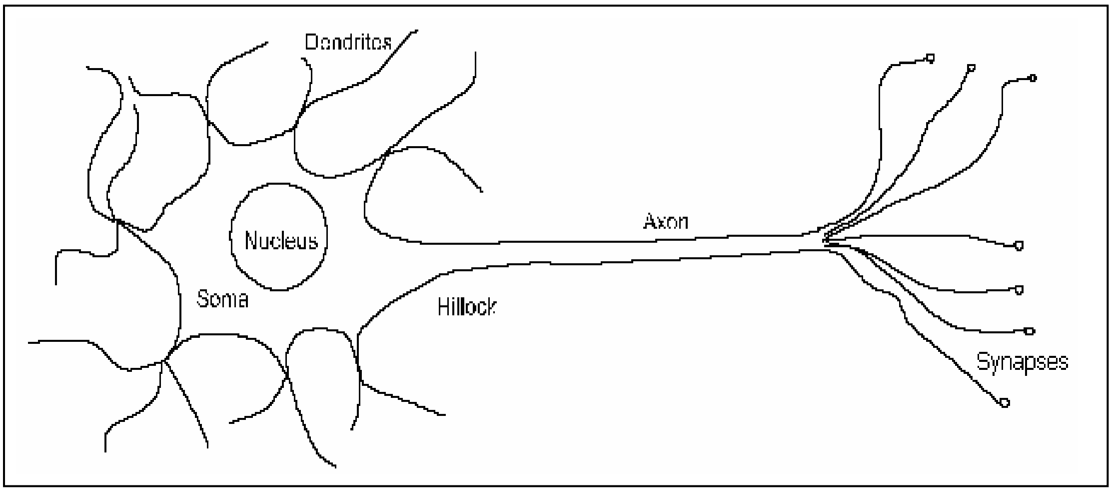

Figure 2.1 Biological Neuron

There are hundreds of neuron types, each with its characteristic function, shape and location, but the main features of a neuron of any type are its *cell body*, called *soma*, *dendrites, axon* and *synapse* as illustrated in Figure 2.1.

The cell body or *soma* is much like the body of any other cell. It contains the cell nucleus, various bio-chemical factories and other components that support ongoing activity. It is usually 5 to 100 µm in diameter and contains the normally large nucleus of the neuron. Surrounding the *soma* are *dendrites*. The *dendrites* are receptors for signals generated by other neurons. These signals may be excitatory or inhibitory. All signals present at the *dendrites* of a neuron are combined, in excess of a certain threshold or activation level, will determine whether or not that neuron will fire.

If a neuron fires, an electrical impulse that has been generated stimulates the boutons and results in electrochemical activity which transmits the signal across the synapses to the receiving dendrites. This impulse starts at the base, called the hillock, of a long cellular extension, called the axon, and proceeds down the axon to its ends. The end of the axon is actually split into multiple ends, called the boutons. The boutons are connected to the dendrites of other neurons. Such a connection is called a synapse (from the greek verb "to join"). Actually, the boutons do not touch the dendrites. There is a small gap between them and is known as synapse gap or synapse cleft. In short, the dendrites act as the input channels of external signals to the neuron and the axon acts as the output channel.

The human brain differs in another, extremely important, respect beyond speed; it is capable of "self-programming" or adaptation in response to changing external stimuli. In other words, it can learn. The brain has developed ways for neurons to change their response to new stimulus patterns so that similar events may affect future responses. Particularly the sensitivity to new patterns seems more extensive in proportion to their importance to survival or if they are reinforced by repetition (Berteig, 2003).

2.3 Artificial Neural Network

"An Artificial Neural Network is a parallel, distributed information processing structure consisting of processing units (which can possess a local memory and can carry out localized information processing operations) interconnected via unidirectional signal channels called connections. Each processing unit has a single output connection that branches into as many collateral connections as desired; each carries the same signal - the processing unit output signal. The processing unit output signal can be of any mathematical type desired. The information processing that goes on within each processing unit can be defined arbitrarily with the restriction that it must be completely local; that is, it must depend only on the current values of the input signals arriving at the processing element via impinging connections and on values stored in the processing unit's local memory." (Hecht-Nielsen, 1990)

From the above definition, ANN can be seen as a subclass of a general computing architecture known as Multiple Instruction Multiple Data (MIMD) parallel processing architecture. Hecht-Nielsen points out that maybe the general MIMD architectures are too general to be efficient and maybe ANN is a good compromise between an efficient structure with considerable information processing capability and a general-purpose implementation.

ANN is also known as simulated neural network or simply just a neural network. ANN is biologically inspired computer programs designed to simulate the way in which the human brain processes information. ANN gathers it knowledge by detecting the patterns and relationships in data and learn (or are trained) through experience, not from programming. An ANN is formed from hundreds of single units, artificial neurons or processing units (PU), connected with coefficients (weights), which constitute the neural structure and are organized in layers.

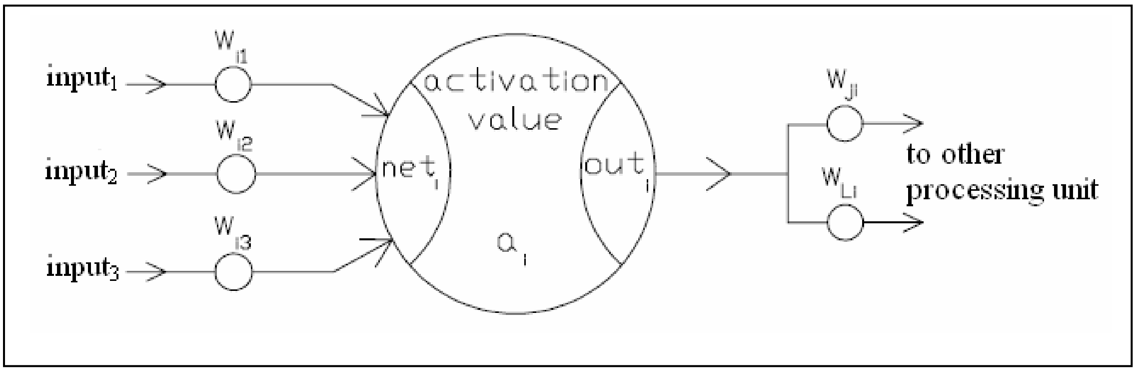

Figure 2.2 General Model of a Processing Unit

The starting point for most neural networks is a model neuron, as in Figure 2.3. This neuron consists of multiple inputs (X_1, X_2,….., X_i) and a single output (Y_j). Each input is modified by a weight, which multiplies with the input value. The neuron will combine these weighted inputs and, with reference to a threshold value and activation function (also known as a transfer function), use these to determine its output. This behavior follows closely how real neurons work. The weights are the adjustable parameters and, in that sense, a neural network is a parameterized system. The weighted sum of the inputs constitutes the activation of the neuron. The activation signal is passed through transfer function to produce a single output of the neuron. Transfer function introduces non-linearity to the network.

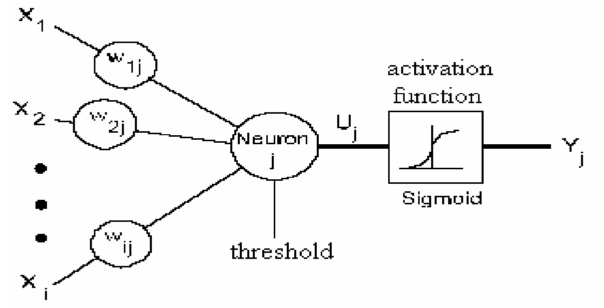

Figure 2.3 Model of a Neuron

During training, the inter-unit connections are optimized until the error in predictions is minimized and the network reaches the specified level of accuracy. Once the network is trained and tested it can be given new input information to predict the output. Many types of neural networks have been designed already and new ones are invented every week but all can be described by the transfer functions of their neurons, by the learning rule, and by the connection formula.

ANN represents a promising modeling technique, especially for data sets having non-linear relationships which are frequently encountered in pharmaceutical processes. In terms of model specification, artificial neural networks require no knowledge of the data source but, since they often contain many weights that must be estimated, they require large training sets. In addition, ANN can combine and incorporate both literature-based and experimental data to solve problems.

There are many different ANN models but each model can be precisely specified by the following eight major aspects (Haykin, 1994):

- A set of processing units
- A state of activation for each unit

- An output function for each unit
- A pattern of connectivity among units or topology of the network
- A propagation rule or combining function, to propagate the activities of the units through the network
- An activation rule to update the activities of each unit by using the current activation value and the inputs received from other units
- An external environment that provides information to the network and/or interacts with it.
- A learning rule to modify the pattern of connectivity by using information provided by the external environment.

2.3.1 Types of Artificial Neural Network

Network architecture is the arrangement of neurons into layers and the connection patterns within and between layers. Each of the neural networks is different from others in the form of their architecture and the algorithm being used to train the network. There are several types of ANN which are feedforward neural networks, recurrent neural networks, stochastic neural networks, modular neural networks and dynamic neural networks. The feedforward neural networks can further divided into five types which are Perceptron, ADALINE, MADALINE, Radial Basis Function (RBF) and Kohonen Self-Organizing Network. Only two types of neural network will be discussed here, that is feedfoward neural network and recurrent neural network.

(i) Feedforward Neural Network

The feedforward neural networks (FF networks) are the first and arguably simplest type of artificial neural networks devised. Beside that they are also the most popular and most widely used models in many practical applications. They are known by many different names, such as "multi-layer perceptrons." FF networks consist of a (possibly large) number of simple neuron-like processing *units*, organized in *layers*. Every unit in a layer is connected with all the units in the previous layer. These connections are not all equal; each connection may have a different strength or *weight*. The weights on these connections encode the knowledge of a network. Often the units in a neural network are also called nodes.

Data enters at the inputs and passes through the network, layer by layer, until it arrives at the outputs. During normal operation, that is when it acts as a classifier, there is no feedback between layers. This is why they are called FF networks. Figure 2.4 shows a 2-layered network with, from top to bottom: an output layer with 2 units, a *hidden* layer with 4 units, respectively. The 5 input units do not belong to any layer of the network (although the inputs sometimes are considered as a virtual layer with layer number 0). Any layer that is not an output layer is a *hidden* layer. This network therefore has 1 hidden layer and 1 output layer. Figure 2.4 also shows all the connections between the units in different layers. A layer only connects to the previous layer.

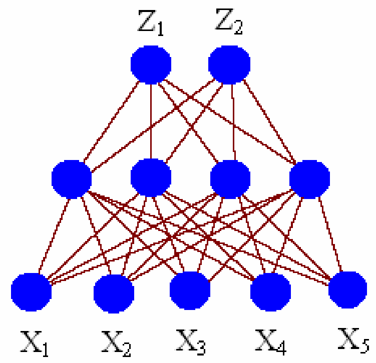

Figure 2.4 Feedforward Neural Network

The operation of this network can be divided into two phases:

(i) The learning phase

- During the learning phase, the weights in the neural network will be modified. All weights are modified in such a way that when a pattern is presented, the output unit with the correct category will have the largest output value.

(ii) The classification phase

- In the classification phase the weights of the network are fixed. A pattern, presented at the inputs, will be transformed from layer to layer until it reaches the output layer. Now classification can occur by selecting the category associated with the output unit that has the largest output value. In contrast to the learning phase, classification phase is very fast.

(ii) Recurrent Neural Network

A recurrent neural network (RNN) is a neural network where the connections between the units form a directed circle. A RNN is also known as feedback neural network. Contrary to feedforward networks, recurrent neural networks are models with bi-directional data flow. Recurrent neural networks also propagate data from later processing stages to earlier stages.

RNNs are used in situations when we have current information to give the network, but the sequence of inputs is important, and we need the neural network to somehow store a record of the prior inputs and factor them in with the current data to produce an answer. In RNNs, information about past inputs is fed back into and mixed with the inputs through recurrent or feedback connections for hidden or output units. In this way, the neural network contains a memory of the past inputs via the activations.

RNNs are biologically more plausible and computationally more powerful than other adaptive models such as Hidden Markov Models (no continuous internal states), feedforward networks and Support Vector Machines (no internal states at all). There are two types of recurrent neural network which are fully recurrent neural network and partial recurrent neural network.

Fully recurrent networks (refer Figure 2.5) provide two-way connections between all processors in the neural network. A subset of the units is designated as the input processors, and they are assigned or clamped to the specified input values. The data then flows to all adjacent connected units and circulates back and forth until the activation of the units stabilizes. Figure 2.5 shows the input units feeding into both the hidden units and the output units. The activations of the hidden and output units then are recomputed until the neural network stabilizes. At this point, the output values can be read from the output layer of processing units. Fully recurrent networks are complex, dynamical systems, and they exhibit all of the power and instability associated with limit cycles and chaotic behavior of such systems.

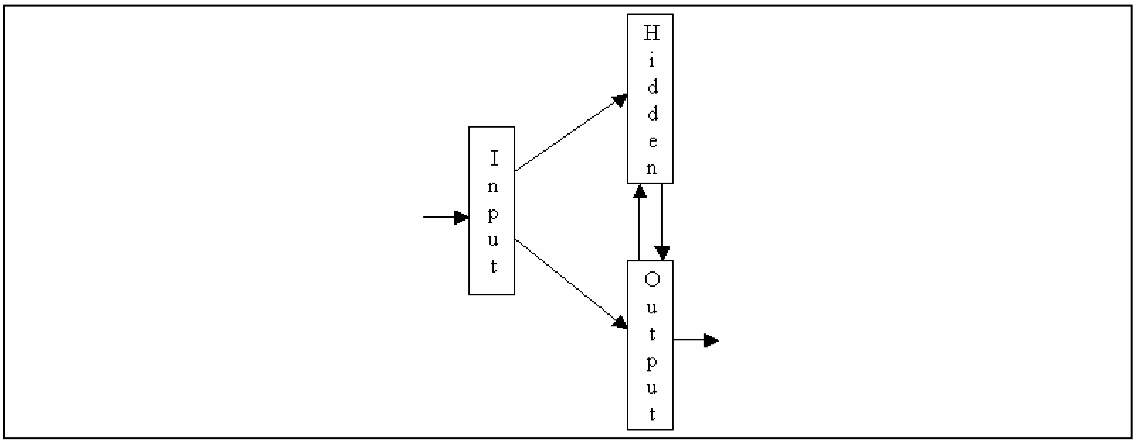

Figure 2.5 Fully Recurrent Neural Network

Two major architectures for partial recurrent networks are widely used as shown in Figure 2.6. Network with feedback from the hidden units to a set of additional inputs called context units (Elman, 1990) and network with feedback from the output units back to a set of context units (Jordan, 1986). This form of recurrence is a compromise between the simplicity of a feed-forward network and the complexity of a fully recurrent neural network because it still allows the popular back propagation training algorithm to be used.

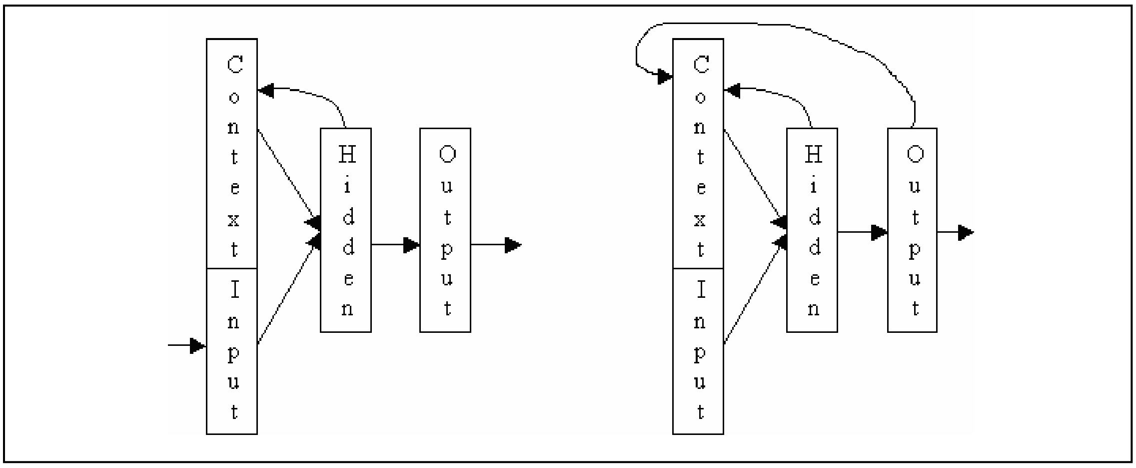

Figure 2.6 Partial Recurrent Neural Networks

2.3.2 Learning in Artificial Neural Network

Learning or known as training is essential to most of the neural network architectures. Therefore the choice of learning algorithm is a central issue in network development. In this phase a learning rule is used to change the elements of the weight matrix ***W*** and other adaptable parameters that the network may have. In this context "learning" and "adaptation" are seen as simply changes in the network parameters. In ANN models the external environment will normally provide a set of "training" input vectors. There are two main types of learning: supervised and unsupervised.

In supervised learning the external environment also provides a desired output for each one of the training input vectors and it is said that the external environment acts as a "teacher". A special case of supervised learning is reinforcement learning where the external environment only provides the information that the network output is "good" or "bad", instead of giving the correct output. In the case of reinforcement learning it is said that the external environment acts as a "critic". The reinforcement learning is a special case of supervised learning.

In unsupervised learning the external environment does not provide the desired network output nor classifies it as good or bad. This means that there is no external teacher is present. By using the correlation of the input vector the learning rule changes the network weights in order to group the input vector into "clusters" such that similar input vectors will produce similar network outputs since they will belong to the same cluster. Ideally, the learning rule finds the number of clusters and their respective centers, if they exist, for the training data. This learning method is also called self-organization. Sometimes, it is improperly said that in unsupervised learning the network learns without a teacher, but this is not absolutely correct. The teacher is not involved in every step but the teacher still has to set goals even in an unsupervised learning mode.

2.3.3 Application of Artificial Neural Network

Artificial Neural Networks have been applied to an increasing number of considerably complex real problems, as for example, the recognition of models, data classification, predictions, etc. Their most important advantage lies in solving problems which are too complex for conventional techniques: problems which do not have a specific algorithm for their solution, or whose algorithm is too complex to be found. This information is cited from internet sources.
URL: http://www.aernsoft.com/eng/ayuda/apendic11.htm

In general, ANNs have been clearly accepted as very efficient systems for the treatment of information in many fields. This has resulted in a variety of commercial applications (in products as well as in services) of this technology of neural networks.

For example, ANNs are widely used in investment analysis, signature analysis, process control, monitoring or marketing (Prof. Leslie Smith, 1996).

2.4 Application of Neural Network in Malaria Parasites Classification

Artificial Neural Networks (ANNs) have proven to be a promising paradigm for Intelligent Systems. Neural networks have been trained to perform complex functions in various fields of application including pattern recognition, identification, classification, control systems, speech and vision. ANNs have the advantage of learning by example and the ability to generalize from their training data to other data. They are fault tolerant in the sense that they can produce correct outputs from noisy and incomplete data. However, there is only one previous study on malaria parasites classification using neural network could be found.

The project was carried out by Premaratne et. al. from Faculty of Medicine, University of Colombo, Sri Lanka in 2003. The objective of this project is to develop an automated tool for the recognition of intracellular malaria parasites in stained blood films. Digital images of oil immersion views from microscopic slides captured though a capture card is used. They were preprocessed by segmentation and grayscale conversion to reduce their dimensionality and later fed into a feedforward back propagation neural network for training. Then a user interface was developed incorporating this trained neural network. In the final product, the tool allows a user to view the slide in a graphical user interface. When the user gives a command to analyze, a still image is captured and sent to the neural network for recognition after preprocessing.

This project was initially planned to be completed in 2 stages. In the first stage it was decided to develop a suitable ANN and train it with a data set to find out the feasibility of using ANN for this project. Feedforward back propagation neural network architecture developed by Paul Werbos was chosen as it was a simple and one of the most commonly used ANN's. Another reason to choose back propagation was its ability to perform pattern classification on data where the input and the output had no linear relationship, as in the case of this application.

In the second stage a software tool was developed incorporating the ANN that was trained, which could also capture the video stream coming from the camera mounted on the microscope and display it to the user in a graphical user interface(GUI). The same GUI could display the result on the analysis window after analyzing the captured image.

At last, the ANN will categorize images to two categories, i.e. images with parasites and without parasites. The user is also presented with information such as how many image segments have parasites and their coordinates on the analysis window.

2.5 Summary

Artificial Neural Network (ANN) is an interconnected group of artificial neurons that uses a mathematical or computational model for information processing based on a connectionist approach to computation. As discussed in Section 2.3, the original inspiration for ANN was from examination of bioelectrical networks in the brain formed by neurons and their synapses.