THE EFFECT OF PRE-PROCESSING TECHNIQUES AND OPTIMAL PARAMETERS ON BPNN FOR DATA CLASSIFICATION

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ABSTRACT

The architecture of artificial neural network (ANN) laid the foundation as a powerful technique in handling problems such as pattern recognition and data analysis. It's data-driven, self-adaptive, and non-linear capabilities channel it for use in processing at high speed and ability to learn the solution to a problem from a set of examples. It has been adequately applied in areas such as medical, financial, economy, and engineering. Neural network training has been a dynamic area of research, with the Multi-Layer Perceptron (MLP) trained with back propagation (BP) mostly worked on by various researchers. However, this algorithm is prone to have difficulties such as local minimum which are caused by neuron saturation in the hidden layer. Most existing approaches modify the learning model in order to add a random factor to the model which can help to overcome the tendency to sink into local minima. However, the random perturbations of the search direction and various kinds of stochastic adjustment to the current set of weights are not effective in enabling a network to escape from local minimum within a reasonable number of iterations. In this research, a performance analysis based on different activation functions; gradient descent and gradient descent with momentum, for training the BP algorithm with pre-processing techniques was executed. The Min-Max, Z-Score, and Decimal Scaling Normalization pre-processing techniques were analyzed. Results generated from the simulations reveal that the pre-processing techniques greatly increased the ANN convergence with Z-Score producing the best performance on all datasets by reaching up to 97.99%, 95.41% and 96.36% accuracy.

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ABSTRAK

Reka bentuk rangkaian neural tiruan (ANN) menyediakan asas sebagai teknik yang berkesan dalam pengendalian masalah seperti pengecaman corak dan analisis data. Keupayaannya yang dipacu data, penyesuaian kendiri, dan bukan linear menjadikannya boleh digunakan dalam pemprosesan pada kelajuan yang tinggi dan keupayaan untuk mempelajari penyelesaian masalah daripada satu set contoh. Ia telah diaplikasikan dalam bidang seperti perubatan, kewangan, ekonomi, dan kejuruteraan. Latihan rangkaian neural menjadi satu bidang penyelidikan yang dinamik, dengan Perseptron Berbilang Lapisan (MLP) dilatih dengan rambatan balik (BP) yang kebanyakannya telah dijalankan oleh pelbagai penyelidik. Walau bagaimanapun, algoritma ini cenderung untuk mempunyai kesukaran seperti minimum setempat yang disebabkan oleh ketepuan neuron dalam lapisan tersembunyi. Kebanyakan pendekatan sedia ada mengubah suai model pembelajaran untuk menambah satu faktor rambang kepada model berkenaan yang boleh membantu bagi mengatasi kecenderungan untuk terdorong ke dalam minimum setempat. Walau bagaimanapun, pengusikan rawak terhadap arah carian dan pelbagai jenis pelarasan stokastik kepada set pemberat semasa tidak berkesan bagi membolehkan sesuatu rangkaian untuk menjauhi daripada minimum setempat dalam jumlah lelaran yang munasabah. Dalam kajian ini, analisis prestasi berdasarkan fungsi pengaktifan berbeza; turunan cerun dan turunan cerun dengan momentum, untuk latihan algoritma BP dengan teknik prapemprosesan telah dilaksanakan. Teknik-teknik prapemprosesan Min-Max, Skor-Z, dan Penormalan Skala Perpuluhan telah dianalisis. Hasil yang dijana daripada simulasi-simulasi tersebut menunjukkan bahawa teknik prapemprosesan banyak meningkatkan penumpuan ANN dengan Skor-Z menghasilkan prestasi yang terbaik pada semua set data yang menjangkau ketepatan sehingga 97.99%, 95.41% dan 96.36%.

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LIST OF SYMBOLS AND ABBREVIATIONS

AI	-	Artificial Intelligence
ANN	-	Artificial Neural Networks
BP	-	Back Propagation
MLP	-	Multi Layer Perceptron
Min-Max	-	Pre-processing Min-Max Normalization
Decimal Scaling	-	Pre-processing Decimal Scaling Normalization
Z-Score	-	Pre-processing Z-Score Normalization
Min-Max-Tansig	-	Min Max Normalization with sigmoid activation function
Min-Max –Logsig	-	Min Max Normalization with sigmoid activation function
Decimal Scaling-Tansig	-	Decimal Scaling Normalization with tangent activation function
Decimal Scaling-Logsig	-	Decimal Scaling Normalization with sigmoid activation function
Z-Score-Tansig	-	Z-Score Normalization with tangent activation function
Z-Score-Logsig	-	Z-Score Normalization with sigmoid activation Function
BPNN	-	Back-Propagation Neural Network
GD	-	Gradient Descent
GDM	-	Gradient Descent with Momentum
FFNN	-	Feed Forward Neural Network
ACC	-	Classification Accuracy
MSE	-	Mean Squared Error
CPU	-	Central Processing Unit
MATLAB	-	Matrix Laboratory

IEEE	-	Institute of Electrical and Electronics Engineering
UTHM	-	University Tun Hussein Onn Malaysia
η	-	Learning Rate
α	-	Momentum
Tanh	-	Hyperbolic Tangent Function
w	-	The weight vector
$f(.)$	-	Activation function
h_i	-	Hidden node
x_i	-	Inputs
t	-	The expected value
δ	-	Error term
Δw_{ij}	-	The delta/gradient of weights
max_p	-	The maximum value of attribute
min_p	-	The minimum value of attribute
mean (p)	-	Mean of attribute P
std (p)	-	Standard deviation of attribute P
m	-	Smallest integer number
A	-	The total number of instance
C	-	The corrected class
N	-	The number of instance
Pi	-	Vector of (n) predictions
Pi*	-	Vector of the true values
cm	-	Centi Meter

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CHAPTER 1

INTRODUCTION

1.1 Overview

Artificial Neural Network (ANN) is an information processing paradigm motivated by biological nervous systems. The human learning process may be partially automated with ANNs, which can be constructed for a specific application such as pattern recognition or data classification, through a learning process (Mokhlessi & Rad, 2010). ANNs and their techniques have become increasingly important for modeling and optimization in many areas of science and engineering, and this assertion is largely attributed to their ability to exploit the tolerance for imprecision and uncertainty in real-world problems, coupled with their robustness and parallelism (Nicoletti, 1999). Artificial Neural Networks (ANNs) have been implemented for a variety of classification and learning tasks (Bhuiyan, 2009). As such, the reason for using ANNs rest solely on its several inhibitory properties such as the generalization and the capability of learning from training data, even where the rules are not known *a*-priori (Penedo *et al.*, 1998).

Artificial neural network (ANN) is inspired by attempts to simulate biological neural systems. The human brain consists primarily of nerve cells called *neurons* linked together with other neurons via stand of fibre called *axons*. Axons are used to transmit nerve impulses from one neuron to another whenever the neurons are stimulated. A neuron is connected to the axons of other neurons via dendrites which are extensions from the cell body of the neurons. The contact point between a dendrite and an axon is called a *synapse* (Khemphila & Boonjing, 2011). When natural neurons receive signals through synapses located on the dendrites or membrane of the neuron, and the signals received are strong enough (surpass a certain threshold), the neuron is activated and emits a signal though the axon. This signal might be sent to another synapse and might activate other neurons.

The number of types of ANNs and their uses is very high. Since the first neural model by McCulloch and Pitts (1943), there have been hundreds of different models developed considered as ANNs. The differences in them might be the functions, the accepted values, the topology, the learning algorithms, etc. Also, there are many hybrid models where each neuron has more properties but focus is directed at an ANN which learns using the back-propagation algorithm (Psichogios & Ungar, 1992) for learning the appropriate weights. Furthermore, Back-Propagation (BP) is one of the most common models used in ANNs (Vogl *et al*., 1988).

Back-Propagation (BP), the most commonly used neural network learning technique, is one of the most effective algorithms accepted currently, and also the basis of pattern identification of BP neural network. Gradient based methods are one of the most commonly used error minimization methods used to train back-propagation networks. Despite its popularity, there exist some shortcomings such as the defects of local optimal and slow convergence speed, etc. (Tongli *et al*., 2013). There are many researches aimed at improving the traditional Back-Propagation Neural Network (BPNN) since 1986 such as the addition of learning rate, and momentum parameters, or use of different activation function etc. This research is trying to avoid some shortcomings in BPNN algorithm. The problem statement will be discussed in the next section.

1.2 Problem Statement

The Back-Propagation (BP) algorithm is a gradient descent method minimizing the mean square error between the actual and target outputs of a multilayer perceptron. The BP network is based on the supervised procedure. The structure of BP network algorithm is composed of input layer, output layer and hidden layer, and the training procedures are divided into two parts: a forward propagation of information and a backward propagation of error. The features of standard BP algorithm are based on simple principles and offer easier implementation. Despite offering much flexibility, BP is known to have difficulties with local minima particularly caused by the neuron saturation in the hidden layer. Most existing approaches modified the learning in BP to add a random factor to the model, which can overcome the tendency to sink into local minima. However, the random perturbations of the search direction and various kinds of stochastic adjustments to the current set of weights are not effective in enabling a network to escape from local minima to converge to global minimum within a reasonable number of iterations (Vogl *et al*., 1988). There are many techniques used for improving training efficiency of back-propagation algorithm such as data pre-processing techniques that are considered the important steps in the data mining process. This research will investigate the following issues which affect the performance of BP algorithm:

i. *Data is not properly pre-processed*

Real-life data rarely complies with the requirements of various data mining tools. It is often inconsistent, noisy, contains redundant attributes and has unsuitable format, etc. That is why it has to be prepared carefully before the process of data mining can be started. It is well known that the success of every data mining algorithm strongly depends on the quality of data processing (Singh & Sane, 2014). In this context, it is natural that data pre-processing can be a very complicated task. Sometimes, data pre-processing takes more than half of the total time spent by solving the data mining problem. It is well known that data preparation is a key to the success of data mining tasks (Miksovskj *et al*., 2002). There are many techniques in pre-process data such as; Min-Max, Z-Score and Decimal Scaling Normalization preprocessing techniques. It is important to be able to identify which of the preprocessing methods will be adequately suitable in influencing and enhancing BP training.

ii. Some parameters that influence on the performance of BP

There are a number of different parameters that must be checked when designing a neural network because they can directly affect the performance of BP algorithm. The most important parameters involved during training are learning rate, momentum, number of hidden nodes in the MLP network and the selection of activation functions (logarithmic or Tangent Hyperbolic etc.). The proper selection of activation functions plays a vital role in the network performance and can effectively enable a network to escape from local minima and thus stops a network from failure within a reasonable amount of iterations (Isa *et al*., 2010). The research aims and objectives will be highlighted in the sections below.

1.3 Aim of the Study

The aim of this study is to classify benchmarked data using Artificial Neural Networks technique by focusing on the effect of pre-processing techniques and different ANN algorithms.

1.4 Research Objectives

This research intends to do the following objectives;

i. To study the effects of some parameters in back propagation algorithm namely; learning rate η, momentum α, activation function with different pre-processing techniques namely; Min-Max, Z-Score and Decimal Scaling Normalization preprocessing techniques; in improving the classification accuracy on some classification problems.
ii. To apply a combination of data pre-processing technique with optimal parameters in BP training algorithm.
iii. To compare the performance of the combined techniques in (ii) with other (GD, GDM) traditional techniques in classifying some benchmarked problems.

1.5 Scope of Study

This research focuses on the use of ANN namely; the Backpropagation (BP) as data classifier. Three pre-processing techniques are employed namely; Min-Max Normalization, Z-Score Normalization, and Decimal Scaling Normalization. Also, the introduction of two different training algorithms which are, the gradient descent (GD), and the gradient descent with momentum learning rate (GDM) are used for training the network. Furthermore, two activation functions are adopted which are the Sigmoid and Tangent activation functions. Dataset are taken from UCI Machine Learning Repository *(http://archive.ics.uci.edu/ml/)*, and results from the MLP for the classification task will be compared for different training algorithms. The next section of this Chapter will discuss the significance of the research.

1.6 Significance of Study

The importance of this research is to increase the classification accuracy by using ANN model for classification problems. Classification technique is a complex and fuzzy cognitive process. Hence, soft computing methods such as artificial neural networks have shown great reliable potentials and power when applied to these problems. The use of technology especially ANN techniques in classifying application can reduce the cost time, human expertise and error. Therefore, the research significance will be focusing on improving BP training by integrating or combining the optimal data pre-processing technique with optimal parameters such as types of the activation function, learning rate, momentum term, number of hidden nodes in achieving good accuracy for classification problem on some benchmark dataset. The outline of the thesis will be discussed in the next section.

1.7 Thesis Outline

The thesis is subdivided into six chapters, including the introduction and conclusion chapters. The following is the synopsis of each chapter:

Chapter 1: *Introduction.* Apart from providing an outline of the thesis, this chapter contains an overview of the background to research work, research problem, objectives, research scope and methodologies in conducting this research.

Chapter 2: *Literature Review***.** Backpropagation (BP) networks are the most commonly used network because they offer good generalization abilities and are relatively straightforward to implement. Although it may be difficult to determine the optimal network configuration and network parameters, researchers have tried to improve its computational efficiency by adjusting parameters such as learning rate, momentum, gain of activation function, network topology and different learning algorithms. Moreover, the proper choices of pre-process techniques also play a big role in improving the BP learning process. This chapter reviews the research contribution made by various researchers to improve the training efficiency of BP. It also demonstrates the effect of using pre-process technique to the BP learning process. At the end of this chapter, some of the advantages posed by the proper choice of pre-process technique are outlined. This chapter lays a foundation for introducing a proper technique for improving the learning efficiency as described in Chapter Three.

Chapter 3: *Research Methodology*. This chapter extends the work by using pre-process technique as proposed in Chapter Two. It was discovered that the use of pre-process technique influences the BP performance. The descriptions of the steps on how to use the ANN models for classification of datasets are presented, starting from the variable and data selection, data pre-processing and data partition, and performance comparison of the different training algorithms and different activation functions. The rationale of selecting parameters for each algorithm, the evaluation covering all the network parameters: the hidden nodes higher order terms, the learning factors and momentum factor, also the number of output nodes in the output layer. The proposed workflow is programmed in MATLAB toolbox programming language and is tested for its correctness on selected benchmark data sets. The results of the proposed workflow were compared to facilitate further testing and validation in the next chapter.

Chapter 4: *Results and Discussions.* The simulation results of the pre-processing techniques with each training algorithm is discussed and presented in this section. The efficient workflow proposed in Chapter Three is further evaluated for its efficiency and accuracy on a variety of benchmark data sets. Each model is then presented graphically in the last chapter.

Chapter 5: *Conclusion and future work.* The research contributions are summarized and recommendations are made for further continuation of work and improve the performance of the proposed network models.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

Over five decades, during which Artificial Intelligence (AI) has been a defined and active field, in several literature surveys. However, the field is extraordinarily difficult to encapsulate either chronologically or thematically (Brunette *et al.*, 2009). Artificial Neural Networks (ANNs) are a form of artificial computer intelligence which are the mathematical algorithms, generated by computers (Lei & Xing-Cheng, 2010). The Artificial Neural Networks (ANNs) has become popular recently and is one of the most effective computational intelligence techniques applied in Pattern Recognition Data Mining and Machine Learning (Nawi *et al*, 2013).

Recent technological advances in life facilitated the development of sophisticated equipment enabled to solve complex problems. In parallel, artificial neural networks emerged as promising tools for the application and implementation of intelligent systems (Pattichis & Pattichis, 2001). The Artificial Neural Network also offers great advantages over conventional modeling, including the neural structure of the brain that mimics the learning capability from experiences, and the ability to handle large amounts of noisy data from dynamic and nonlinear processes where nonlinearities and variable interactions play a vital role. Also, ANN is a powerful technique for several problems. Therefore, in order to be more certain in this field, this chapter provides the theoretical perspectives of a wide range of ANN which partly reveals the applications and techniques that have been used in ANN. However, despite the wide interest in the application of neural networks, there are a number of limitations that make the introduction of these tools daily practice difficult. Firstly, the presence of the black box nature of neural networks makes it difficult to explain. The second problem is how to validate a trained neural network

(Khemphila & Boonjing, 2010). Interestingly, the errors and undesirable results are reasons for a need for unconventional computer-based systems, which in turn reduces the errors, increases the reliability and safety (Ghwanmeh *et al*., 2013).

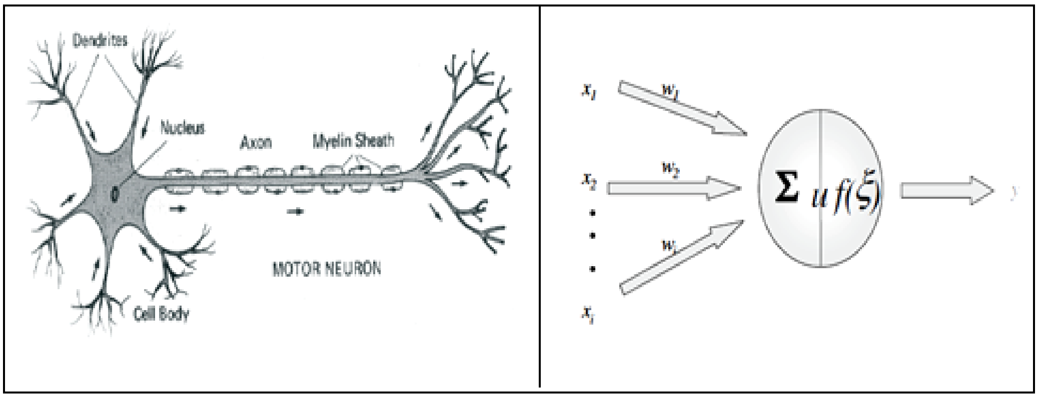
On the other hand, during the past few years, there have been significant researches on data mining particularly neural networks because it is heavily used in many fields. Most of these applications have used the back-propagation algorithm as the learning algorithm. The back-propagation algorithm requires the weights of each unit be adjusted so that the total quadratic error between the actual output and the desired output is reduced. A big problem with back-propagation networks is that its convergence time is usually very long. Selecting good parameters such as learning rate and momentum can reduce the training time but can require a lot of trial and error. Trying to find a universal learning rate or momentum which fits all needs is unrealistic (Hamid *et al*., 2011).

Therefore, this chapter focuses on the previous literature work that suggested certain improvements on BPNN model together with the effect of using pre-processing techniques for classification problems. The data mining processes and concepts constitute the section below.

2.2 Biological Neuron Transformation to Artificial Neuron (Perceptron)

The human brain which contains approximately 100 billion neurons - with 100 trillion connections, is an open complex giant system of self-organization and has two basic principles of organization: functional differentiation and functional integration (Huang & Feng, 2011).

Artificial neural networks got inspired by the attempts to simulate biological neural systems. The human brain consists primarily of nerve cells called *neurons*, linked together with other neurons via stands of fibre called *axons*. Axons are used to transmit nerve impulses from one neuron to another whenever the neurons are stimulated. A neuron is connected to the axons of other neurons via *dendrites* which are extensions from the cell body of the neurons. The contact point between a dendrite and an axon is called a *synapse*. The biological neuron (Khemphila & Boonjing, 2010) is shown in Figure 2.1(a) below. The neurons of the Artificial Neural Network are a number of processing units that communicate by sending information to each other. The link between two neurons is done via weighted connections (Lei & Xing-Cheng, 2010) and is depicted in Figure 2.1(b).



(a): Biological Neuron (Dohnal *et al*., 2005)

(b): Artificial Neuron (Dohnal *et al*., 2005)

Figure 2.1: Biological and Artificial Neuron

2.3 Artificial Neural Network (ANN)

The artificial neural networks are a branch of artificial intelligence and also a research domain of neuron informatics. They are made of simple processing units (artificial neurons) that are strongly interconnected and work in parallel. The artificial neurons are a conceptual model of biological neurons that are part of human nervous system. Therefore, these networks can be considered a simplified form of a human brain. Their aim is to interact with the environment the same way a biological brain would do this. They have some properties that bring them very close to this aim: the ability to perform distributed computations, to tolerate noisy inputs and to learn (Filimon & Albu, 2014).

Artificial neural network can be most adequately characterized as 'computational model' with particular properties such as the ability to adapt or learn, to generalize or to cluster or organize data and which operation is based on parallel processing. The concept of artificial neural network is based upon the design of the brain and central nervous system. The neural network structure consists of several layers of processing units called neurons or nodes. Each neuron has its own memory and ability to process information. These results are stored within synaptic connections between neurons and existing network layers.

The main structure of the artificial neural network (ANN) is made up of the input layer, hidden layer, and the output layer (Li *et al*., 2014). Hence , Over the last few years, the artificial neural network (ANN) methodology has been accepted widely to solve problems such as prediction, classification, and ANN has become one of the most highly parameterized models that have attracted considerable attention in recent years (Isa *et al*., 2010). Because of the self-learning and self-organizing ability to adapt, artificial neural network (ANN) has the characteristics that can be trained. It can absorb experience by learning from the historical data and previous project information which can be used in the new prediction period. Back-propagation algorithm (BP) and feed-forward network are two widely applied ANN estimation technologies. ANN is constituted with active layers and hidden layers, and lots of nodes are connected inside each layer. One connection between two nodes represents a weight and each node represents a special activation function in which sigmoid function is widely used. ANN has the ability of self-learning process, modifying each layer's weight by training samples. The widely used algorithm is Back-propagation (Dan, 2013).

2.4 Components of Neural Network

As the name suggests, an artificial neural network is a system that consists of a network of interconnected unit called artificial neurons. The units are called artificial neurons because of a certain resemblance to the neurons in the human brain (Dohnal *et al*., 2005). An ANN consists of an enormous number of massively interconnected nonlinear computational element (neurons). Each neuron receives inputs from other neurons, performs a weighted summation, applies an activation function to the weighted sum, and outputs its results to other neurons in the network. Simulation of an ANN comprises simulation of the learning phase and the recall phase. Parallel processing of neural network simulations has attracted much interest during the past years (Richiardi *et al*., 2013). Neural Network can therefore be thought of as a black box that accept certain inputs and produces certain outputs. The functionality of the black box depends on the Neural Network structure and the model of every neuron in this structure.

2.4.1 Neuron

The artificial neuron model is a kind of artificial information processing model to extract, simplify, and imitate the creature neuron which is based on research for nerve science over the years (Lv *et al*., 2007). The artificial neuron is an information processing unit that is fundamental to the operation of a neural network, where it receives one or more inputs (representing the one or more dendrites) and sums them to produce an output (representing a biological neuron's axon). Usually the sums of each node are weighted, and the sum is passed through a non-linear function known as an *activation function* or *transfer function*. The transfer functions usually have a sigmoid shape, but they may also take the form of other non-linear functions.

2.4.2 Weight

Neural networks often have a large number of parameters (weights) (Leung *et al*., 2003). Typically, a neuron has more than one input. A neuron with R inputs and the individual input $\sum x_R$ are each weighted by corresponding elements $\sum w_{1R}$ of the weight matrix *W*. A set of synapses or connecting links, each of which is characterized by a weight or strength of its own specifically a single (x_j) at the input of synapses *j* connected to neuron K is multiplied by the synaptic weight (w_{kj}). It is important to make note of the manner in which the subscripts of the synaptic weight (w_{kj}) are written, where the first subscripts refers to the neuron in question and the second subscripts refers to the input end of the synapse to which the weight refers. Unlike a synapse in the brain, the synaptic weight of an artificial neuron may lie in a range that includes negative as well as positive values (Ozcan *et al*., 2006). On the other hand, the neurons are joined by directed arcs-connections. The neurons and arcs constitute the neural network topology. Each arc has numerical weight that specifies the influence between two neurons.

2.4.3 Hidden layer

Multi-layer network consists of one or more layers of neurons called hidden layer between input and output layer (Svozil *et al*., 1997). Hence, the hidden layer units can be any number (normally decided from trial and error) and the accuracy of the approximation depends on the number of nodes in the hidden layers of multi-layered network. Meanwhile, number of hidden nodes equals half the sum of the number of input and output nodes (Nawi, 2014). Also, many researchers have used five hidden nodes and got good results with BP for different classification problems (Nawi *et al*., 2013; Isa *et al*., 2010; Hamid *et al*., 2011).

2.4.4 Activation Function

The activation function (also called a transfer function) shown in Figure 2.2, can be a linear or nonlinear function. There are different types of activation functions (Sibi *et al*., 2013). The activation function *f(.)* is also known as a squashing function. It keeps the cell's output between certain limits as is the case in the biological neuron (Chandra & Singh, 2004). On the other hand, the relationship between the net inputs and the output is called the activation function of the Artificial Neuron. There could be different function or relationships that determine the value of output that would be produced for given net inputs.

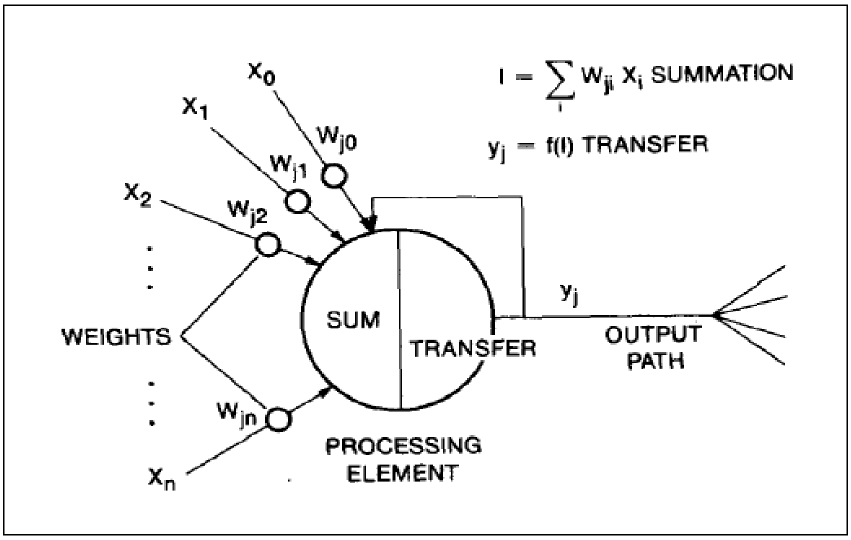


Figure 2.2: Activation function (Illingworth, 1989)

There are various types of activation functions such as; Threshold Function (hard-limiter), Piecewise Linear Function (Linear Function), Uni-Polar Sigmoidal Function (S-shape function) and Hyperbolic Tangent Function etc. Sigmoid and hyperbolic tangent are the most widely used because their differentiable nature makes them compatible with back propagation algorithm (BP). Both activation functions have an s-shaped curve while their output range varies.

The selection of activation function might significantly affect the performance of a training algorithm. Some researchers have investigated to find special activation function to simplify the network structure and to accelerate convergence time (Isa *et al.*, 2010). Hence, in designing neural networks, fast learning with a high possibility of convergence and small network size are very important. They are highly dependent on network models, learning algorithms and problems to be solved. They are also highly related to activation functions (Nakayama & Ohsugi, 1998).

In Lee and Moraga (1996), a Cosine-Modulated Gaussian activation function for Hyper-Hill neural networks has been proposed. The study compared the Cosine-Modulated Gaussian, hyperbolic tangent, sigmoid and sym-sigmoid function in cascade correlation network to solve sonar benchmark problem. Joarder and Aziz (2002) proved that logarithmic function is able to accelerate back propagation learning or network convergence. The study has solved XOR problem, character recognition, machine learning database and encoder problem using MLP network with back propagation learning. Wong *et al.* (2002) investigated the neuronal function for network convergence and pruning performance. Periodic and monotonic activation functions were chosen for the analyses of multilayer feed forward neural networks trained by Extended Kalman Filter (EKF) algorithm. The study has solved multi-cluster classification and identification problem of XOR logic function, parity generation, handwritten digit recognition, piecewise linear function approximation and sunspot series prediction. Piekniewski and Tybicki (2004) employed different activation functions in MLP networks to determine the visual comparison performance.

Some of the basic types of activation functions used in the literature are discussed as follows.

2.4.4.1 Threshold Function

Threshold function for this type of activation function is depicted in Figure 2.3(a). Say there exists:

$$g(net) = \begin{cases} 1: & if\ net \geq 0 \\ 0: & if\ net < 0 \end{cases} \tag{2.1}$$

Correspondingly, the output of the neuron *j* employing such threshold function is expressed as:

$$y_j = \begin{cases} 1: & if\ \ net_j \geq 0 \\ 0: & if\ \ net_j < 0 \end{cases} \tag{2.2}$$

where net *j* is the net input applied to neuron *j*; that translates to:

$$net_j = \sum_{j=0}^{k} w_{jk} x_k \tag{2.3}$$

Such a neuron is referred to in literature as the McCullocb-Pitts model which is in recognition of the pioneering work done by McCulloch and Pitts. In this model, the output of the neuron takes the value 1 if the total internal activity level at that neuron is nonnegative and 0 otherwise. This statement describes the all - or - none property of the McCullocb-Pitts model (Biol, 2011).

2.4.4.2 Piecewise Linear Function

For Piecewise Linear Function depicted in Figure 2.3(b), there exists:

$$g(net) = \begin{cases} 1: & if\ net \geq \frac{1}{2} \\ net: & if\ \frac{1}{2} > net > -\frac{1}{2} \\ 0: & if\ net \leq -\frac{1}{2} \end{cases} \tag{2.4}$$

By varying the domain of the net input values over which the above function exhibits linear characteristics, the two extremes of this activation function can be derived.

The one extreme happens when the domain of the net input values for which this function is linear is infinite; then an activation function that is linear everywhere is being dealt with. The other extreme occurs when the domain of the net values for which activation function is linear shrinks to zero; in that case, threshold activation function comes into play (Sibi *et al*., 2013).

2.4.4.3 Uni-Polar Sigmoidal Function

Sigmoid function is by far the most common form of an activation function used in the construction of artificial neural networks (Xie, 2012). Activation function of Uni-polar sigmoid function is given as follows:

$$g(x) = \frac{1}{1+e^{(-x)}} \tag{2.5}$$

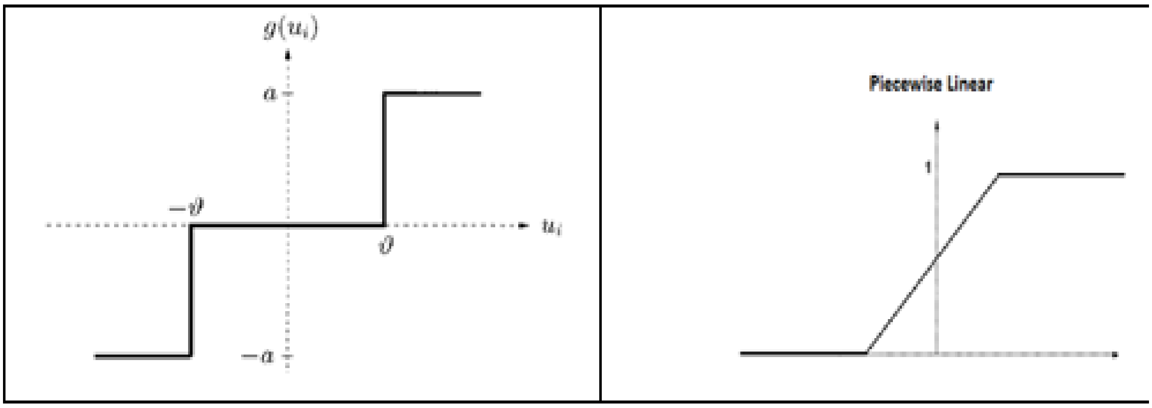
This function is especially advantageous to use in neural networks trained by back-propagation algorithms. This is because it can be easily distinguished, and this can interestingly minimize the computation capacity for training. The term sigmoid means 'S-shaped', and logistic form of the sigmoid maps where the interval (-∞, ∞) onto (0, 1) as seen in Figure 2.3(c) (Pierrehumbert *et al*., 2014).

2.4.4.4 Hyperbolic Tangent Function

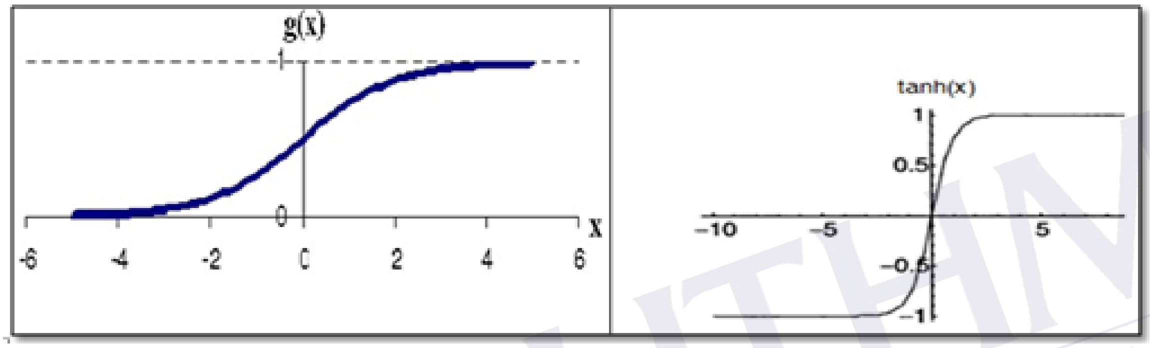
In many applications, the activation function is moved such that the output y is in the range from -1 to +1 rather than 0 to +1 (Özkan & Erbek, 2003). Hence, hyperbolic tangent function is defined as the ratio between the hyperbolic sine and the cosine functions or expanded as the ratio of the half difference and half sum of two exponential functions in the points x and –x as follows:

$$tanh(x) = \frac{\sinh(x)}{\cosh(x)} = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}} \tag{2.6}$$

Hyperbolic Tangent Function is similar to sigmoid function. Its output range is between -1 and 1 as seen in Figure 2.3(d).



(a) Threshold Function (Mathis *et al*., 2001). (b) Piecewise Linear Function



(c)Uni-Polar Sigmoidal Function (Özkan & Erbek, 2003) (d) Hyperbolic tangent Function (Özkan & Erbek, 2003)

Figure 2.3: Types of Activation Function

Generally, both the activation functions (tangent and Sigmoid) have an S-shaped curve while their output range varies. Previous researchers have investigated to find special activation function to simplify the network structure and to accelerate the convergence time (Isa et al., 2010; Sibi et al., 2013).

The section below highlights and discusses on algorithms which are used in training the Artificial Neural Network. This helps to determine the performance level of the ANN algorithms.

2.5 Multi-Layer Perceptron (MLP)

The extension of the single-layer feed-forward structure is the multilayer feed-forward structure depicted in Figure 2.4. As it can be observed, there still exists the input layer of nodes and the output layer of nodes as in the single-layer case. However, between these two layers are one or more layers of nodes designated as hidden layer. All these layers of nodes are denoted as layer 0 (input layer), layer 1 (first hidden layer), layer 2 (second hidden layer), and finally layer M (output layer) (Gunther & Fritsch, 2010). Multilayer feed-forward network has become the major and most widely used supervised learning neural network architecture (Basu *et al*., 2010). MLPs utilize computationally intensive training algorithms (such as the error back-propagation) and can get stuck in local minima. In addition, these networks have problems in dealing with large amounts of training data, while demonstrating poor interpolation properties, when using reduced training sets (Ghazali *et al*., 2009). Attention must be drawn to the use of biases. Neurons can be chosen with or without biases. The bias gives the network extra variable, which logically translates that the networks with biases would be more powerful (Badri, 2010).

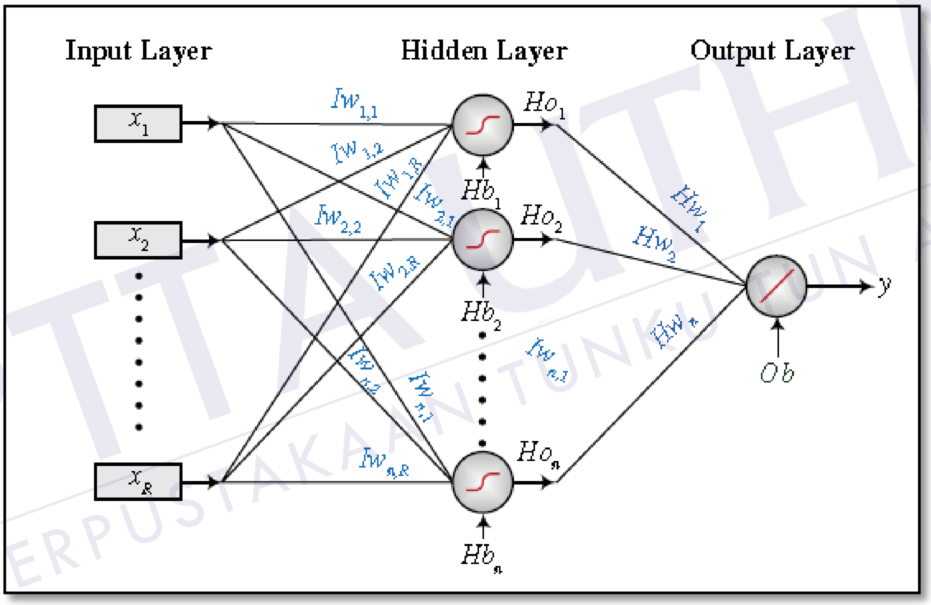


Figure 2.4: Fully connection feed-forward network with one hidden layer and one output layer (Razavi & Tolson, 2011)

2.6 Back-Propagation Algorithm (BP)

The back-propagation (BP) algorithm is one of the most common algorithms used in the training of artificial neural networks (Lahmir, 2011). The BP learning has become the standard method and process in adjusting weights and biases for training an ANN in many domains (Nawi *et al*, 2013). The back-propagation algorithm can be defined as follows:

For a test set, propagate one test through the MLP in order to calculate the output.

$$h_{i} = f \sum x_{i} w_{ij} \tag{2.7}$$

$$y_i = f \sum h_i w_{jk} \tag{2.8}$$

where $\boldsymbol{h}$ is the hidden node, $\boldsymbol{x}$ is the input need, $\boldsymbol{w}$ is the weight, and $\boldsymbol{y}$ is the output node.

Then compute the error, which will be the difference of the expected value $\boldsymbol{t}$ and the actual value, and compute the error information term $\boldsymbol{\delta}$ for both the output and hidden nodes.

$$\delta y_i = y_i(1 - y_i).(t - y_i) \tag{2.9}$$

$$\delta h_i = h_i(1 - h_i) . \delta y_i . w_{jk} \tag{2.10}$$

$\boldsymbol{\delta_j}$ the information error of the nodes

Finally, back-propagate this error through the network by adjusting all of the weights; starting from the weights to the output layer and ending at the weights to the input layer. This is shown in Figure 2.5.

$$\Delta w_{jk} = \eta . \delta y_i . h_i \tag{2.11}$$

$$\Delta w_{ij} = \eta . \delta h_i . x_i \tag{2.12}$$

$$w_{new} = \Delta w + w_{old} \tag{2.13}$$

where $\boldsymbol{\eta}$ is the learning rate.

The back-propagation algorithm can be described as shown in Figure 2.5. The inputs are first applied from the training data set where the desired output for each input is known. Later, the actual output produced is compared to the desired output and used to calculate an error δ, then the weights w are adjusted to reduce the error by adding Δw values. Finally, repeat presenting the inputs and estimate the actual outputs. Also, adjust the weights until the required minimum error is obtained or a maximum number of epochs.

Hence, a BP network learns by example. That is, by providing a learning set that consists of some input examples and the known-correct output for each case. Therefore, these input-output examples are used to show the network what type of behavior is expected, and the BP algorithm allows the network to adapt. The BP learning process works in small iterative steps: one of the example cases is applied to the network, and the network produces some output based on the current state of its synaptic weights (initially, the output will be random). This output is compared to the known-good output, and a mean squared error signal is calculated. The error value is then propagated backwards through the network, and small changes are made to the weights in each layer. The weight changes are calculated to reduce the error signal for the case in question (Robinson & Fallside, 1988). There are various elements or components that make up the neural network, and they are enumerated in the following section.

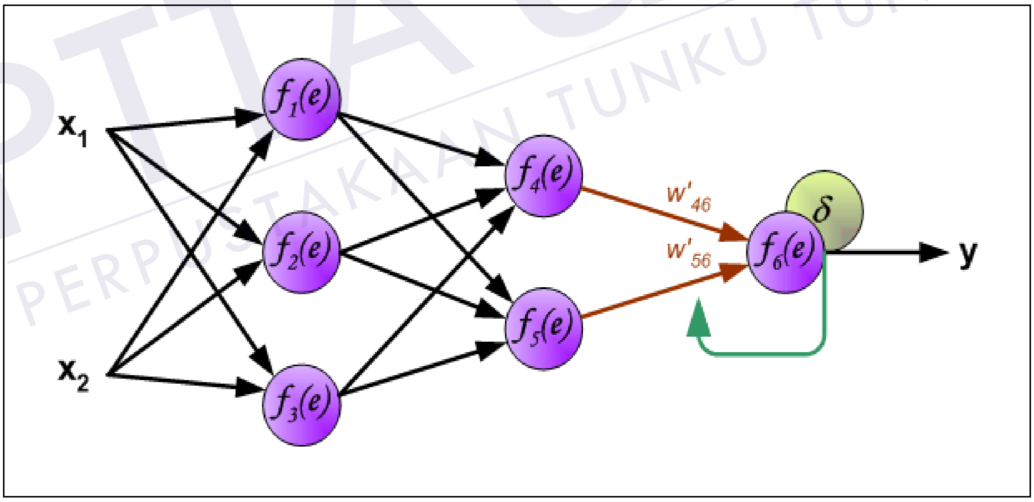


Figure 2.5: Back-propagation Neural Network

The applications of Artificial Neural Network with Back Propagation algorithm have gained immense popularity in different areas. Some of these areas include but not limited to: face detection, control systems, medical, time series prediction, and cryptosystems etc. In an effort to tackle the problems associated with BP algorithm, Magoulas and Vrahatis (1999) proposed Back Propagation algorithms that incorporates learning rate adaptation methods and apply the Goldstein-Armijo line search. The advantages of using these methods are because they provide stable learning, robustness to oscillations, and improved convergence rate. Experiments reveal that the algorithms proposed can ensure global convergence (that is avoiding local minima). The importance of activation function within the back propagation algorithm was emphasized in the work done by Sibi *et al.* (2005). They carried out a performance analysis using different activation functions, and confirmed that in as much as activation functions play a great role in the performance of neural network; other parameters come into play such as training algorithms, network sizing and learning parameters. The BP was improved by using adaptive gain which adequately causes a change in the momentum and learning rate (Hamid *et al.*, 2011). The simulation results show that the use of changing gain propels the convergence behavior and also slides the network through local minima. In the area of pattern recognition, the identification and recognition of complex patterns by the adjustment of weights were experimented upon (Kuar, 2012). Experimental results show that it yielded high accuracy and better tolerance factor, but may take a considerable amount of time. Nawi *et al.* (2013) proposed a cuckoo search optimized method for training the back propagation algorithm. The performance of the proposed method proved to be more effective based on the convergence rate, simplicity and accuracy.

2.7 Learning Algorithm for ANN

The property that is of primary significance for a neural network is the ability of the network to learn from its environment, and to improve performance through learning. The improvement in performance takes place over time in accordance with some prescribed measures. A neural network learns about its environment through an interactive process of adjustments applied to its synaptic weights and bias levels. The network becomes more knowledgeable about its environment after each iteration of the learning process (Kaur *et al*., 2012). Furthermore, the learning (or training) for a neural network is not simply a matter of memorizing the mapping relationship between the inputs and the outputs among the learning samples, but of extracting the internal rules about the environment which are hidden in the sample by learning the finite sample date (Houwer *et al*., 2013).

Hence, one of the main functions of neural network is about their excellent ability to model a complex multi-input multi-output system. Neural Networks have widely been considered and used as a kind of soft mathematical modeling. In a given high dimensional input-output dataset, neural networks are able to provide a promising modeling service (Mitrea *et al*., 2009). The learning process requires adaptation, and in fact, changes in the function that distinguish complex learning from simpler forms of adaptation are the ones that require a process of adaptation of the parameters that are sensitive to the environment. They are also conducive to self – organization (Roodposti & Rasi, 2011). There are two classifications of training algorithms for neural network namely, supervised and unsupervised. Within each classification, there exist many procedures and formula that may accomplish the learning objectives (Halder *et al*., 2011). Up till now, there are many learning algorithms of neural networks among which is the error back-propagation algorithm (BP algorithm) and its various improved patterns are most extensively and effectively applied. MLP model which adopts the BP algorithm is generally called a BP network. Ultimately, the back-propagation algorithm has emerged as the most widely used and successful algorithm for the design of multilayer feed-forward networks.

There are two distinct phases to the operation of back-propagation learning: the forward phase and backward phase. In the forward phase, the input signals propagate through the network layer by layer, and eventually producing some response at the output of the network. The actual response produced is compared with a desired (target) response, generating the error signals that are then propagated in a backward direction. In this backward phase of operation, the free parameters of the network are adjusted so as to minimize the sum squared errors. Back-propagation learning has been applied successfully to solve some difficult problems (Aljawfi *et al*., 2014). A learning algorithm for an artificial neural network is often related to a certain function approximation algorithms, especially to some iterative algorithms that make the approximation error gradually smaller. In fact, the above-mentioned BP algorithm corresponds to gradient descent algorithms; such as gradient descent, gradient descent with momentum and gradient descent with adaptive learning rate in function approximation. Once this principle is known, it can construct various learning algorithms for neural networks according to different function approximation algorithms. Two of the learning rate algorithms will be explained in the section below.

2.7.1 Gradient Descent Back-propagation (GD)

Nowadays, the Multilayer Perceptrons (MLP) trained with the back propagation (BP) is one of the most common methods used for classification purpose. This method has the capacity of organizing the representation of the data in the hidden layers with high power of generalization (Nawi *et al.*, 2013). Artificial Neural Networks are often trained using algorithms that approximate (gradient descent or steepest descent). This can be done using either a batch method or an on-line method. In the case of batch training, weight changes are accumulated over an entire presentation of the training data (an epoch) before being applied, while on-line training updates weights after the presentation of each training example (instance). Hence, Back Propagation Gradient Descent (GD) is probably the simplest of all learning algorithms usable for training multi-layered neural networks. It is not the most efficient, but converges fairly reliably. The technique is often attributed to Rumelhart, Hinton, and Williams (Seung, 2002).

The aim of BP is to reduce the error function by iteratively adjusting the network weight vectors. At each iteration, the weight vectors are adjusted one layer at a time from the output level towards the network inputs. In the gradient descent version of BP, the change in the network weight vector in each layer happens in the direction of negative gradient of the error function with respect to each weight itself. Hence, it can be noted that the learning rate η is multiplied by the negative of the gradient to conclude the changes to the weights and biases, as obtained in Equation 2.14.

$$\Delta w_{ij} = \eta \,.\delta_j.\ x_{ij} \tag{2.14}$$

where $\boldsymbol{\Delta w_{ij}}$ is the delta/gradient of weights

$\boldsymbol{\eta}$ is the learning rate parameter

$\boldsymbol{\delta_j}$ is the information error of the nodes

And $\boldsymbol{x_{ij}}$ is the value of the network nodes

Thus, it can be noted that if the learning rate becomes too large, the algorithm will be unstable. If the learning rate is fixed too small, the algorithm will take a long time to converge. Highlighted in Table 2.1 are the advantages and disadvantages of this method.

Table 2.1. Advantages and Disadvantages of Gradient Descent Back-propagation (Lahmiri, 2011; Tongli *et al.*, 2013)

Advantages	**Disadvantages**
Always downhill	Might zigzag down valleys
Avoids saddle points	Linear search may cause problems
Efficient further from the minimum	Slower close to minimum

2.7.2 Gradient Descent with Momentum (GDM)

The back-propagation with momentum algorithm (GDM) has been largely analyzed in the neural network literature and even compared with other methods which are often trained by the use of gradient descent with momentum. A momentum term is usually included in the simulations of connectionist learning algorithms. It is well known that such a term greatly improves the speed of learning, where the momentum is used to speed up and stabilize the training iteration procedure for the gradient method. A momentum term is often added to the increment formula for the weights, in which the present weight updating increment is a combination of the present gradient of the error function and the previous weight updating increment.

The momentum parameter is analogous to the mass of Newtonian particles that moves through a viscous medium in a conservative force field. GDM depends on two training parameters. The parameter learning rate is similar to the simple gradient descent. The parameter momentum is the momentum constant that defines the amount of momentum, as in Equation 2.15.

$$\Delta w_{ij}(r) = \eta \,.\, \delta_j \,.\, x_{ij} + \alpha \,.\, \Delta w_{ij}(r-1) \tag{2.15}$$

where α is the momentum parameter, and $\boldsymbol{r}$ is the of iteration.

The following section describes the importance of pre-processing technique selection for classification problem, as it affects the performance of learning in Neural Network.

2.8 Data Pre-processing

Data mining is one of the most important and useful technology in the world today for extracting useful knowledge in large collections of dataset. Most of the organizations are having a large number of dataset but to extract useful and important knowledge is very difficult, and extracting knowledge without violation such as privacy and non-discrimination is most difficult and challenging (Singh & Sane, 2014). On the other hand, datasets are often large, relational and dynamic. They contain many records, places, things, events and their interactions over time. Such datasets are rarely structured appropriately for knowledge discovery, and they often contain variables whose meanings change across different subsets of the data (Fast *et al*., 2007).

Data analysis is now an important component of any data mining task. It involves the basis for investigations in many areas of knowledge, from science to engineering (Baskar *et al*., 2013). Data pre-processing technique is a step to remove the irrelevant information and extract key features of the data to facilitate a recognized problem pattern without throwing away any important information. Hence, data pre-processing technique is a significant step in the data mining process. Mostly, data gathering methods are lightly controlled, resulting in outliers, impossible data combinations and missing values, etc. Analyzing data that have not been carefully separated can produce confusing results. Thus, the depiction and quality of data are the first and foremost factors considered before running any analysis. The quality, reliability and availability are some of the factors that may lead to a successful data interpretation by a neural network. If there is inappropriate information present or noisy and unreliable data, then knowledge discovery becomes very difficult during the training process. Data preparation and filtering steps can take considerable amount of processing time but once pre-processing is done the data become more reliable and robust results are achieved.

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