Assemble Intelligent Multi Agent System Based Feed-Forward Neural Network clustering

Roya Asadi, Sameem Abdul Kareem, Shokoofeh Asadi

Abstract*— One of the greatest potential of applying intelligent multi agent systems is the support of machine learning in order to reflect the whole complexity of the real and virtual world. However, a critical deficiency is a gap between two applicable streams of intelligent multi agent technology and learning models. In order to solve this problem, we developed a framework of intelligent multi agent based on the efficient feed-forward neural network clustering method. A feed-forward neural network is a software version of the brain and a popular tool for statistical decision making. The framework is applicable to different domains successfully and for the potential case study, the clinical domain and the breast cancer database from the University of Malaya Medical Center is considered to predict the survival time. *(Abstract)

Keywords*— Artificial intelligence, Multi agent systems, Feed-Forward Neural networks, Training, Clustering *(key words)

I. Intelligent Multi Agent Based System

Artificial intelligence (AI) includes learning in virtual environments and rule-based systems such as expert systems and neural network models can help to implement intelligent agent (IA) [1, 2]. Some features of IA on the basis of flexible independent action to set up their design objectives are as follows [3, 4]:

- Reactivity: IA receives information from the environment by its sensors, transforms domestic design objectives of its structure and deems suitable actions with feedback from time to time.
- Pro–activeness: IA is able to demonstrate the actions to achieve the goal through the plan; and to react for changing its environment in order to satisfy their design objectives.
- Sociability: IA is able to interact with other agents for negotiation and/or cooperation to satisfy their design objectives.

Other features of IA are self-analysis, learning, adapting and improving through communication with its environment.

Padghan and Winikopff (2004) enlightened the expression of agent refers to an entity that acts on behalf of other entities or organizations; and multi agent system (MAS) consists of several agents with capable of common communication with self-organization [5, 6]. The organization of multi agent system is often as follows:

- Actions: Answering to environmental events and changes,
- Percepts: Collecting information from its environment,
- Events: Updating beliefs and operating actions,
- Goals: Having the ability to achieve and update the goals of the system,
- Beliefs: Managing accumulated information about the environment,
- Plans: Utilizing the plan library to handle events and achieve goals,
- Messages: Communicating and interacting together,
- Protocols: Interacting through the rules.

Yoav and Kevin (2009) and Macy (2002) gave details about two relevant streams of agent based system (ABS) and IA; and the lack of a unified framework [7, 8]. Intelligent multi agent systems have great potentials to be applied in different research areas especially in virtual environments to support learning models with the whole complexity of the real world [9-12].

Bobek and Perko (2006) demonstrated the intelligent agents are able to be applied in [3]:

Roya Asadi,
Department of Artificial Intelligence, Faculty of Computer Science and Information Technology, University of Malaya, Kuala Lumpur, Selangor, 50603, Malaysia,
.

Sameem Abdul Kareem,
Department of Artificial Intelligence, Faculty of Computer Science and Information Technology, University of Malaya, Kuala Lumpur, Selangor, 50603, Malaysia.

Shokoofeh Asadi,
Department of Agricultural Management Engineering, Faculty of Ebne-Sina, University of Science and Research Branch, Tehran, 930277941, Iran,

- Intelligent Acquisition: To accumulate vague data from the environment of the system and transform to the suitable input data.
- Intelligent modeling: To create intelligent agent based system frameworks with prediction and management of data, future events and intelligent rules and plans.
- Intelligent delivery: To proactive relief of selected appropriate information and advanced report to approach special strategies.

II. Artificial Neural Networks and Learning

The artificial neural network has its roots in mathematics, statistics, numerical analysis, biology and psychology, and is one of the numerous algorithms used in machine learning and data mining. Neural networks are flexible algorithms that allow users to encode nonlinear relationships between input and desirable outputs [13-17]. The neural networks are suitable for extracting rules, quantitative evaluation of these rules, classification, clustering, and regression feature evaluation [18, 19]. Learning is an imperative feature of the artificial neural network in machine learning. There are numerous types of learning rules categorized broadly under supervised learning, unsupervised learning, and reinforcement learning [17-20]. Supervised training is similar to unsupervised training in the sense that training sets are provided. Back propagation network (BPN) is introduced by Werbos (1974) and can be used as a supervised multi-layer perceptrons in feed forward network [21]. BPN compares each output value with its sigmoid function of inputs in forward, and computes its error in backward. The algorithm employs weights of each connection in order to reduce the value of the error function. This cycle is repeated until the error becomes much smaller. The standard BPN method as a supervised FFNN classification method uses gradient-based optimization methods in two basic steps: to calculate the gradient of the error function, and to employ the gradient. The difference between two is that in supervised training, desired output is provided and weight matrix is adjusted to reduce the difference between predicted output and actual output of the neural network. Most approaches to unsupervised learning in machine learning are statistical modeling, compression, filtering, blind source separation, and clustering. Unsupervised learning or self-organized learning finds symmetries in the data represented by unlabeled input data. However to assess the performance of unsupervised learning, there is no error or reward signal [16, 17, 20]. In reinforcement learning, the model is capable of generating certain effects and interactions with dynamic environment for recognizing an unknown attribute value. At each point in time, the environment generates an observation for this unknown attribute value which is the reward or reinforcement for the model. Consequently, the model can select and use suitable rule and interacts with environment for more rewards. The environment is dynamic, hence the long-run cost is unknown, but it can be estimated. Neural networks are frequently used in reinforcement learning as part of the overall algorithm. The tasks include control problems and sequential decision making tasks [22]. The main advantage of neural networks is abilities of scaling and learning as in the machine learning algorithms. The neural networks are useful especially for analysing unknown data [23]. A feed forward neural network is a fashionable tool for statistical decision making and simulates the human brain learning. In this network, processing of data has only one forward direction from the input layer to the output layer without any cycles or backward [18, 23, 24].

III. Real Semi-supervised Feed-Forward Neural Network Clustering

Unsupervised FFNN (UFFNN) clustering methods are often on the basis of Hebbian learning, competitive learning, or competitive Hebbian learning. Hebb [25] developed the meaning of the first learning rule and proposed the Hebbian learning. Hebb explained a synaptic elasticity mechanism. The law of Hebbian learning is: "if neuron *i* is close enough to stimulate neuron *j* at the same time and takes part in its activation repeatedly, the synaptic connection between these two neurons is strengthened and neuron *j* will be more sensitive to the action of neuron *i*". The competitive learning network is an UFFNN clustering based on learning the nearest weight vector to the input vector as the winner node according to the computing distance, such as Euclidean. In the case of competitive Hebbian learning, the neural network clustering method applies some properties of both competitive learning and Hebbian learning [26-28]. Competitive learning can apply vector quantization (VQ) [29] during clustering. VQ [29] is generally considered as the fundamental patternand for some UFFNN clustering methods such as Kohonen's self-organizing map (SOM) [30] and growing neural gas (GNG) [31]. Linde et al. [29] introduced an algorithm for VQ design to earn a suitable code book of weights for input data nodes clustering. VQ is based on probability density functions by distribution of vectors of the weights. The GNG method is an example which uses the competitive Hebbian learning, in which the connection between the winner node and the second nearest node is created or updated in each training cycle. The GNG method can follow dynamic distributions by adding nodes and deleting them in the network during clustering by using the utility parameters. The disadvantages of the GNG include the increase in the number of nodes to obtain the input probability density and requirement for predetermining the maximum number of nodes and thresholds [32-34]. SOM maps multi-dimensional data onto lower dimensional subspaces, with the geometric relationships between points indicates their similarity. SOM generates subspaces with unsupervised learning neural network training through a competitive learning algorithm. The weights are adjusted based on their proximity to the "winning" nodes, that is, the nodes that most closely resembles a sample input [35-39]. The RUFFNN clustering method [40] computes a code book of real weights by using input data directly without using any random values. The best weight match vector is mined by using the codebook of weights. Consequently, the threshold of each input data was computed based on the best weight match vector. Finally, the input data are clustered based on the threshold. Some literatures devoted to improving the UFFNN methods by using constraints such as class labels. The constraints of class labels are based on the knowledge of experts and the user guide as partial supervision for better controlling the tasks of clustering and desired results [41-43]. The real semi-supervised feed-forward neural network (RSFFNN) clustering [44] is developed on the basis of the RUFFNN clustering method. The RSFFNN method has data dimension reduction ability and can solve the serious problems of speed, accuracy and memory complexity of the clusters. The RSFFNN can learn real weights and thresholds without using any random values and arbitrary parameters. The learning of the RSFFNN model does not require computing any error function, such as the mean square errors and updating weights in any training cycle, therefore the approach results in a reduced training time. The main goal of the RSFFNN model is learning of the standard weight *SW* vector as the criterion weight vector. Fig. 1 shows the RSFFNN clusterin method.

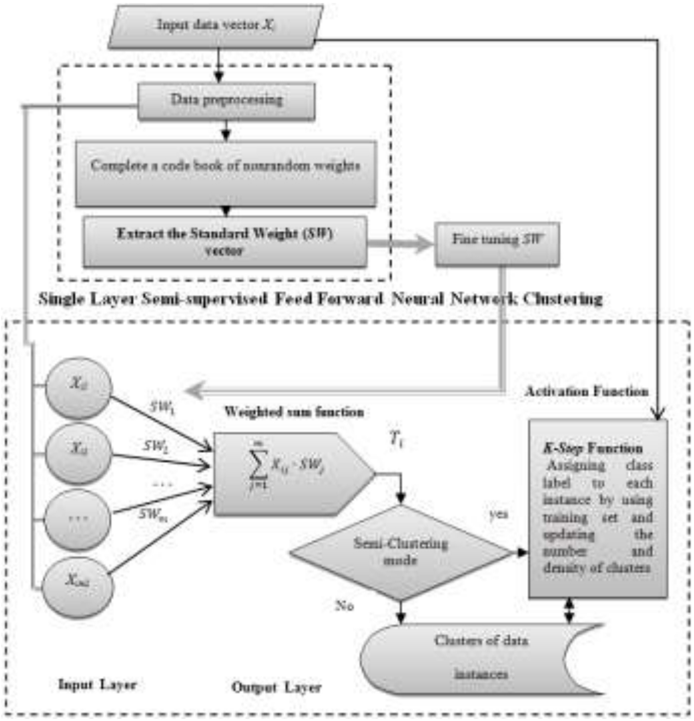

Fig. 1. The design of the RSFFNN clustering method [44]

First, a code book of nonrandom weights was trained by feeding input instances directly to the network. In order to adjust the weights precisely in order to achieve better results of clustering the data points, two phases of smoothing the weights and pruning the weak weights in the RSFFNN are considered. A single layer feed-forward neural network earns its normalized data values and real weights. Then, a unique and exclusive threshold of each input instance was computed. The input instances were clustered based on their exclusive thresholds. In order to improve the results of clustering by semi-clustering, the class label of each unlabeled input instance, were predicted by considering a *K-step* activation function and the exclusive threshold. Finally, the number of clusters and density of each cluster were updated. The model can be applied for clustering or semi-clustering. The time and memory complexities of the RSFFNN were *O(n.m)* and *O(n.m.sm)* based on the number of nodes, attributes and size of the attribute. The RSFFNN clustering model demonstrates high speed and accuracy in performance with low time usage of training in just one epoch and efficient memory complexity of networks [44].

IV. A Framework for Intelligent MAS Based on the RSFFNN

In order to solve the critical deficiency in a united framework of combination of two applicable flows intelligent multi agent systems in the real world and learning systems [45], we developed the framework of the intelligent multi agent system based on the RSFFNN clustering [44]. For illustration of the framework, we selected the clinical organization and its environment. There are several issues in this system such as intelligent acquisition, intelligent modeling and intelligent delivery. Fig. 2 shows an outline of the system.

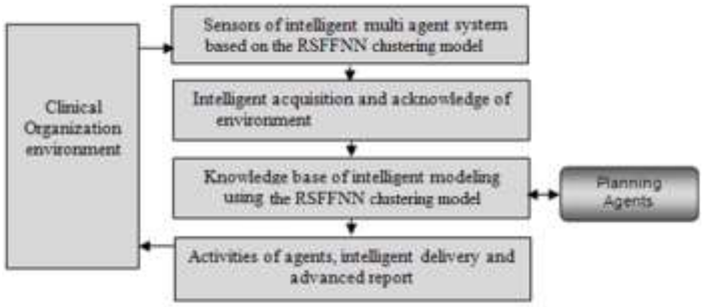

Fig. 2. Outline of intelligent multi agent system based on the RSFFNN clustering

- Intelligent acquisition in order to collect knowledge based on the data of population, clinical information and other data.
- Intelligent modeling in order to manage data, rules, plans, predict future. In this paper, a framework using the RSFFNN model is proposed. The intelligent multi agent framework has several agents which apply the outputs of preprocessing technique and the output of the RSFFNN clustering model. The intelligent model is able: to handle structured and unstructured data from various and distributed sources, to investigate the records and plans, and etc.
- Intelligent delivery in order to report based on managers' views. The framework can proactively answer to exceptional events; and it is able to determine and upgrade the rules and plans. The output of the framework will be intelligent results and advanced report through MIS, DSS and so on that they assist managers to act with best rules in front of events of the environment. This intelligent agent system has feedback for updating beliefs and rules too. The Fig. 3 shows the pyramid of clinical organization which is one simple purposed chart with several agents and one head.

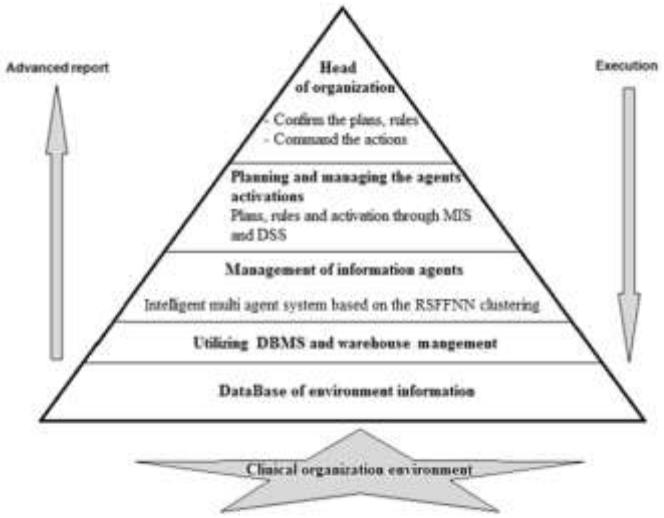

Fig. 3. The Pyramid of clinical organization

The traditional organization chart has several problems in managing, especially in the management of information and earning desired outputs such as: redundancy of data, multiple updating of database management system (DBMS). The traditional chart can be changed to an intelligent multi agent system based neural network. The management information agent collects the distributed information from the clinical environment. Therefore, there are several different sub-agents in this system such as agent of intelligent RSFFNN clustering, agent of clinical service management and etc. Fig. 4 shows details of the information management agent of clinical organization.

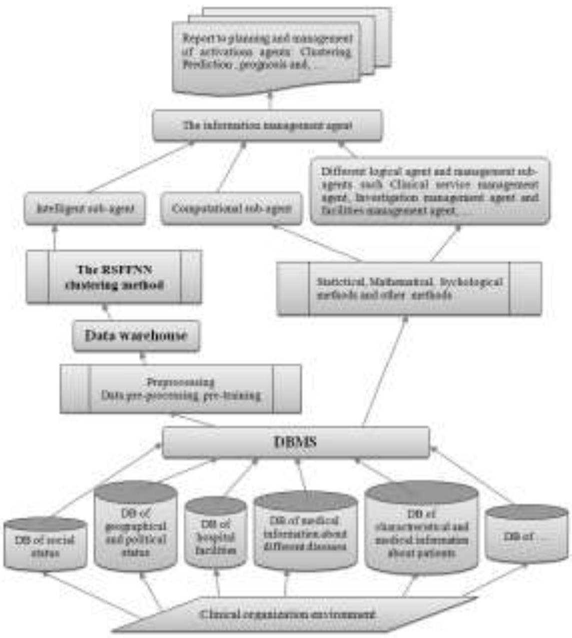

Fig. 4. Details of the information management agent of clinical organization

Fig. 5 shows a design to predict the survival time, which is extracted from the framework of the intelligent multi agent system based on the RSFFNN clustering. The phases of proposed framework are as follows:

- Collecting the information from clinical environment such as medical information of patients and save them in different databases. To illustrate the proposed framework we considered the breast cancer data set from the university of Malaya medical center (UMMC). The dataset was collected from 1992 until 2002 [46].

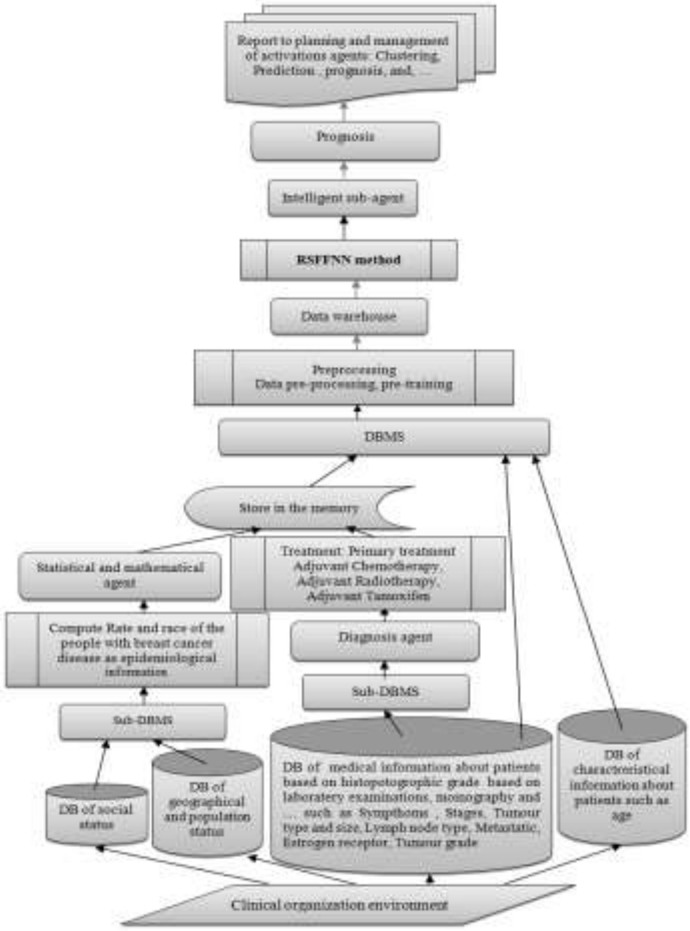

Fig. 5. Details of the prognosis agent of proposed framework

- Managing and controlling the data as rational database by the DBMS. As shown in Table I, the dataset was divided into 9 subsets based on the interval of survival time: 1_{st} year, 2_{nd} year, … , 9_{th} year.

TABLE I. THE 9 SUBSETS OF OBSERVED DATA OF THE BREAST CANCER FROM THE UMMC BASED ON THE INTERVAL OF SURVIVAL TIME [44]

Year Of treatment	1_{st} year	2_{nd} year	3_{rd} year	n_{th} year	8_{th} year	9_{th} year
1993	Data from 1993 to 1994	Data from 1993 to 1995	Data from 1993 to 1996	…	Data from 1993 to 2001	Data from 1993 to 2002
1994	Data from 1994 to 1995	Data from 1994 to 1996	Data from 1994 to 1997	…	Data from 1994 to 2002	
1995	Data from 1995 to 1996	Data from 1995 to 1997	Data from 1995 to 1998	….		
…	…	…	…			
2000	Data from 2000 to 2001	Data from 2000 to 2002				
2001	Data from 2001 to 2002					

Table II shows, the breast cancer dataset contains of 13 attributes. The number of input data instances in the dataset is 827, the number of attributes is 13 continuous and one attribute for showing the binary class in two cases of alive or dead. The used breast cancer dataset from the UMMC has class labels of ‘0’ for alive and ‘1’ for dead as constraints.

TABLE II. THE INFORMATION OF THE UMMC BREAST CANCER DATA SET ATTRIBUTES [44]

Attributes	Attribute Information
AGE	Patient’s age in year at time first diagnosis
RACE	Ethnicity (Chinese, Malay, Indian and Others)
STG	Phase (how far the cancer has spread anatomically)
T	Tumour type (the extent of the primary tumour)
N	Lymph node type (amount of regional lymph node involvement)
M	Metastatic (presence or absence)
LN	Number of nodes involved
ER	Estrogen receptor (negative or positive)
GD	Tumour grade
PT	Primary treatment (type of surgery performed)
AC	Adjuvant Chemotherapy
AR	Adjuvant Radiotherapy
AT	Adjuvant Tamoxifen

- Assisting the specialists by accessing to examinatinal, historical, theoretical and medical information about the disease for diagnosis.
- Preprocessing the data and preparing data warehouse in order to be used by the RSFFNN clustering method. After preprocessing, the data are collected as data warehouse in order to be used by the intelligent model.
- Computing statistical and mathematical information from raw data for assisting the physicians and researchers about situation of patients, their environments and risk factors. The collected dataset from UMMC and its interpretation showed that the high risk group and race of patients from Chinese, Indian and Malay people in Malaysia are between (40-50) and Chinese respectively.
- Intelligent RSFFNN clustering agent clusters the data based on different goals of system and selected attributes, by the information management agent and a computational agent.

The RSFFNN model was implemented on each subset of the breast cancer dataset by considering the class labels. Table III shows the results of the implementation of the RSFFNN method [44].

TABLE III. THE RESULTS OF IMPLEMENTATION OF THE RSFFNN FOR EACH SUBSET OF THE BREAST CANCER [44]

Year	*Correctly Classified Nodes (CCN)*	Density of *CCN* (%)	The number of data in each subset	CPU Time usage (Milliseconds)	F-measure Accuracy of the RSFFNN (%)
1st year	819	99.03	827	43	99.55
2nd year	666	98.96	673	34.5	98.85
3rd year	552	98.44	561	32.5	99.04
4th year	429	97.5	440	32	98.29
5th year	355	100	355	29.4	100
6th year	270	100	270	15.8	100
7th year	200	100	200	15	100
8th year	124	100	124	14.5	100
9th year	56	100	56	13.7	100

Table III shows the number of instances of each subset; CPU Time usage per second for training each subset during one epoch; and the accuracy of the semi-clustering of each subset of breast cancer dataset based on the F-measure with 10 folds of the test set by using the RSFFNN clustering model. Table III shows that the training process for each subset of the breast cancer dataset took one epoch between [13.7, 43] milliseconds of CPU time; and the F-measure accuracies of the RSFFNN in order to predict the survival time by using the breast cancer subsets were between [98.29% - 100%] [44]. Roya et al. [44] showed the RSFFNN has superior results in accuracies, CPU time usage and time and memory complexities.

- Advanced reports based on specialists' views. This intelligent agent system has feedback for updating beliefs and rules. The MAS based on the RSFFNN clustering method helps the physicians for better treatments and taking feedback for better prognosis and actions. The information management agent sends the reports of knowledge to planning and management of an activation agent for applying by DSS, MIS, statistical and scientific software, and other management systems. The plans and rules will be updated and advanced reports will be sent to organization head for confirmation and action permission.

V. Conclusions and Future Work

Applying the intelligent multi agent system based on a learning model instead of traditional system in different research areas illustrates relationships between components clearly and shows the whole complexity of the real and virtual world. However, there is the critical deficiency in a united framework of a combination of two applicable flows intelligent multi agent systems and learning systems. We developed the framework of the intelligent multi agent system based on the RSFFNN clustering. To illustrate the proposed framework, we selected the clinical environment and dataset of breast cancer from UMMC. Consequently, we extracted a design in order to predict the survival time from the framework of the intelligent multi agent system based on the RSFFNN clustering. For future work, we suggest developing this intelligent multi agent framework by using an online dynamic feed-forward clustering models in other purposes.

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Author biographies:

Roya Asadi was born in Tehran - Iran. She received the Bachelor degree in Computer Software engineering from Electronics and Computer Engineering Faculty, Shahid Beheshti University and Computer Faculty of Data Processing Iran Co. (IBM), Tehran, Iran. She obtained Master of Computer Science in Database System from UPM university in Malaysia. She is a research student of Ph.D. of Computer Science in Artificial Intelligence (Neural Network) in University of Malaya. Her professional working experience includes 12 years of service as Senior Planning Expert 1. Her interests include Artificial Neural Network modeling, Medical Informatics, Image Processing.

Shokoofeh Asadi received Bachelor Degree in English Language Translation (International Communications Engineering) from Islamic Azad University of Tehran–Iran and Master of Agricultural Management Engineering from University of Science and research in Tehran- Iran. Her interests are: English Language Translation, Biological and Agreecultural engineering, Management and leadership, Strategic Management and Operations Management.

Assoc. Prof. Datin. Dr. Sameem Abdul Kareem: received the B.Sc. in Mathematics (Hons) from University of Malaya, in 1986, the M.Sc. in Computing from the University of Wales, Cardiff, UK, in 1992, and the Ph.D. in computer science from University of Malaya, in 2002. She is currently an Associate Professor of the Department of Artificial Intelligence, Faculty of Computer Science and Information Technology, University Of Malaya. Her interests include Medical Informatics, Information Retrieval, Data Mining and Intelligent Techniques. She has published over 80 journal and conference papers.