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NEURAL NETWORKS BASED DATA MINING TECHNIQUES

الشبكات العصبيه المعتمده على تقنيه استنباط المعلومات

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الملخص العربي

نتيجة للزيادة المضطردة في أعداد المواقع الموجودة على شبكه الانترنيت و ضخامة حجم البيانات المرتبطة بهذه المواقع ظهرت مشكله كيفيه استنباط معرفه من خلال تلك البيانات و من ثم استخدامها في فهم و دراسة و التنبؤ بسلوك المستخدم لتلك المواقع من خلال تفاعله مع الموقع .

يقدم هذا البحث نوعين من الشبكات العصبية واحدة للتعرف على الزائرين للموقع من خلال نمط تصفحهم و الأخر لتصنيفهم إلى مجموعات حسب الصفحات التي يزورونها على الموقع،مما يسهل عمليه البحث و التصفح للمستخدم وتحسين أداء و فاعلية الشبكة من خلال توصيل هذه الشبكات العصبية مع قاعدة بيانات.

ABSTRACT

The rapid increase in web sites has created large volumes of data in web environment, which generates a problem of how to extract and gain useful knowledge from such data. Extracting such knowledge helps to discover, understand and predict user behaviors based on his interaction with the website.

This paper introduces two neural network based systems, one for web visitor recognition according to their web logs pattern, and the other for web visitor classification according to the visited pages. This will introduce rapid services and save user time with web through a database connected to these neural networks. Such system can be used to improve efficiency and effectiveness in searching for information on the web.
Complete architecture of the networks is given based on supervised and unsupervised learning paradigms. Experiments have been carried out in order to validate this approach.

Keywords Web mining, Machine learning, Artificial neural networks

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1. INTRODUCTION

With more than two billion pages contributed by millions of web page authors and organizations, the world wide web is a rich knowledge base. Such knowledge can be used to improve efficiency and effectiveness in searching for information.

The web size and its unstructured and dynamic content, as well as its multilingual nature make the extraction of useful knowledge a challenging research problem. The paper is organized as follows. Following this introduction data mining, data mining techniques, data sources, and machine learning for web mining are given in the introduction. Feature extraction is introduced in section 2. In section 3 the competitive neural networks is discussed. Results and discussion are given in section 4. Conclusion is presented in section 5.

1.1 Data Mining

Data mining deals with the discovery of hidden knowledge, unexpected pattern and new rules from large databases. Web mining is the application of innovative data analysis method. The concept of web mining is not limited to the data analysis task, but also includes collection, pre-processing and interpretation of data [1-8]. Web mining is divided into three categories: web content, web structure mining and web usage mining.

Web content mining refers to the discovery of useful information from web content. This usually consists of, but not limited to, text and graphics [9,10]. Web content mining aims at supporting the internet user in finding information from websites by filtering the relevant information.

Web structure mining aims at the generation of information concerning the structure of interesting web sites. It can be viewed as creating a model of the web organization by classifying web pages or creating similarity measure between documents [11]. Several web structure mining algorithms have been developed to address this issue as page rank and HITS algorithm [9, 12].

Web usage mining means using data mining techniques to analyze search logs or other activity logs to the discovery of usage patterns from web data and discover useful knowledge about the system usage characteristics and the user interests [9].

1.2 Data Mining Techniques

In this section, data mining algorithms that have been developed for large databases are briefly described. Pattern discovery draws upon methods and algorithms developed from several fields [9].

Statistical analysis techniques are the most common method to extract knowledge about visitors to web sites. By analyzing the session file, one can perform different kinds of descriptive statistical analysis (frequency, mean, median) [9].

Association rules refer to sets of pages that are accessed together with a support value exceeding some specified threshold [9]. Clustering is a technique to group together a set of items having similar characteristics. In the web usage domain, there are two types of clusters to be discovered: usage clusters and page clusters. Clustering of users tends to establish groups of users exhibiting similar browsing pattern. While clustering of pages will discover groups of pages having related contents. This information is useful for Internet search engines.

Classification is the task of mapping a data item into one of several classes [13, 14]. The extraction of the features that best describes the properties of a given class or category is required. Classification can be done by Bayesian classifiers, K-nearest neighbor classifiers or decision tree classifiers. Santosh K. Rangarajan, Vir V., and S. S. Lyengar have developed a clustering algorithm that groups users [15]. Their algorithm is based on adaptive resonance theory with accuracy of 97.78% .

1.3 Data Sources

Data sources used for web mining analysis could be captured and collected from different sources. These sources can be classified as[11]:

1) Server-side collection (Web log files - Query data- Packet sniffing)
   A web Server log is an important source for performing Web Usage Mining. The data recorded in the server logs reflects the access of a Web site by multiple users. These log files can be stored in different formats.
2) Client-side collection (Cookies).
3) Client-side application (remote agents-browser (personal agents)).
4) Proxy servers.
   A Web proxy acts as an intermediate level of cashing between client browsers and Web servers.
5) Organization database.

1.4 Machine Learning for Web Mining

Machine learning algorithms can be classified as supervised or unsupervised learning. In supervised learning, training examples consisting of input/output pair patterns. The goal of learning algorithm is to predict the output values of new examples, based on their input values. In unsupervised learning, training examples contain only the input patterns and no explicit target output is associated with each input.

Many different types of neural networks have been developed among which the feed-forward /back-propagation model is the most widely used. Back-propagation networks are fully connected, layered, feed- forward network in which activation flow from input layer through the hidden layer and then to the output layer[16-19].

The network usually starts with a set of random weights and adjusts its weights according to each learning example. Other popular neural network models include Kohonen's self-organizing map and Hopfield network. Self-organizing maps have been widely used in unsupervised learning, clustering and pattern recognition [20-22].

2. FEATURE EXTRACTION

2.1 Data Collection

The experimental log file data has been captured by the sever of the Information System of Mansoura University Center as shown in Table 1.The total size of raw log files involved in the experiments was 104 MB. The total number of records (total number accessed the server) is 349183 records. The duration of experimental data collection was 45 days from 15/2/2001 to 30/3/2001.

2.2 Data Processing

The first stage of data analysis is data processing, which divided into two sub stages data filtering and Pattern identification.

2.2.1 Data Filtering

Data filtering aims at reducing the size of the row data (the web log files), hence extract and form pruning data files for the next sub stage of data processing. The original web log file f contains 11 fields (date / time/ c-ip / cs-username / s-ip s-port / cs-method / cs-uri-stem / cs-uri-query / sc-status /cs(User-Agent)) as shown in Table 1.Theses fields reduced to only (4) fields (date / time/ c-ip/ cs-uri-stem) as shown in Table 2.

Firstly, data is filtered according to Ips. Total number of distinct IPs (different users accessed server) is found to be 5475. The number of access of distinct IPs on server is in the range (1- 9564). The number of access of distinct IPs on server >700 times is found to be 107 IPs. The number of access of distinct IPs on server > 1000 access is found to be 52 IPs.

Secondly, data is filtered according to URLs. The total number of distinct URLs has been accessed on server is found to be 4630. Number of URLs with extensions (htm- html) after removing requested URLs with extensions (gif, jpeg, jpg, css, swf, exe, ect), characters (- , / , ++) and pages not belonging to server pages(www.pubmed.com ,www.google.com) is found to be 2996.

Number of request for different URLs on server range (1- 84973) . Number of request for different URLs on server >306 request is 1000 URLs. Number of access for different URLs on server > 1000 request is 41 URLs.
Number of URLs after removing requested URLs <10 request is 507 pages. Number of URLs after removing requested URLs <100 request is found to be72 pages. Number of URLs after removing requested 100<URLs <1000 request is 63.

The study will work on (52) distinct IPs which access server > 1000 time, and (63) URLs which requested between (100 < URLs <1000) request.

2.2.2 Pattern Identification

Pattern identification sub stage using extracted pruning data from data filtering sub stage is to identify, group and extract features of selected users and requested site pages(URLs) in a form of vectors, used at pattern discovery phase, which use (Supervised/Unsupervised) neural network to creates meaningful clusters for users and site pages(URLs) as shown in Table 3.

To get the feature of input pattern for classes of users, the data is analyzed and it is found that :
Numbers of IPs have Requested Different URLs > 90 request is 11 IPs and. numbers of IPs have Requested Different URLs > 50 request is : 20IPs.

Numbers of IPs have Requested same URLs = 1 request(defaut.asp) is 6 IPs.
Patterns identified for (20) IPs which have Requested URLs > 50 request are used to train the supervised neural network for visitor recognition.

To, get the feature of input pattern for classes of URLs according to visitors, the data is analyzed and it is found that:

numbers of IPs have Distinct Requested URLs > 30 request is 12 IPs.
numbers of IPs have Distinct Requested URLs ≥ 20 request is 25 IPs.
numbers of IPs have Distinct Requested URLs 0<URLs< 10 request is 7 IPs.
numbers of IPs have Distinct Requested URLs = 0 request is 7 IPs.

Patterns identified for Distinct Requested URLs from (63) URLs accessed by each distinct 25 IPs is used to extracted input pattern for unsupervised neural network. If the IP access the page, it will be coded as 1 in the input vector while if IP does not access the page, it will be coded as 0 in the input vector.

3. COMPETITIVE NETWORKS

When presented with a pattern $\underline{\mathbf{X}}$ with binary-valued features, MAXNET [23, 24] classifies that pattern as belonging to class C_j on the basis of the Hamming distance between the class exemplar and the input pattern $\underline{\mathbf{X}}$; that is, decide $\mathbf{X} \in C_j$. if Hamming distance ($\mathbf{U}_j$, $\mathbf{X}$) < Hamming distance ($\mathbf{U}_k$, $\mathbf{X}$)
for all k=1,2,...,M K≠j (1)
where U_j is the exemplar for class j.
In other words, X is classified as belonging to class j if the Hamming distance between $\underline{\mathbf{X}}$ and the class exemplar for class Cj is smaller than the distance from $\underline{\mathbf{X}}$ to any of the other class exemplars.
The Hamming distance between $\underline{\mathbf{X}}$ and exemplar $\mathbf{U}_j$ is simply N minus the sum of the product of the corresponding pairs of feature values; that is [23]:
Hamming distance :

$$(\underline{\mathbf{X}}, \underline{\mathbf{U}_j}) = N - \sum_i U_{ji} X_i \quad (2)$$

Where N is the number of features in the pattern. This quantity is precisely the number of instances in which the corresponding feature values in $\underline{\mathbf{U}_j}$ and $\underline{\mathbf{X}}$ do not agree.
The architecture of a MAX NET is shown in Fig.1. The feature values of the class exemplars are encoded in the weights $\mathbf{U}_{ji}$. For any pattern $\underline{\mathbf{X}}$, the feature values X_i are made available to the input nodes. These values are weighted and summed, and the net input to the node j at next layer is simply the numerical value of the number instance for which the input value agreed with value of the weight on the connecting link. These matching scores are presented as input to the MAXNET subnet nodes. Each of these nodes is weighted and interconnected so as to maintain its own value and to attempt to suppress the other. That is, MAXNET eventually picks that node for which the matching score is the largest. This action is equivalent to MAXNET picking that node for which the Hamming distance between $\underline{\mathbf{X}}$ and the class exemplar is least.

The activation function for the MAXNET is

$$f(x) = x \quad \text{if } x>0$$
$$= 0 \quad \text{otherwise} \quad (3)$$

Let W_{jk} be the connection weight from node j to node k.

The procedure is as follows:

Step 0:

Initialize activations and weight, (set $0 < \varepsilon < 1/M$ is the no. of possible classes

$a_k(o)$ input to node Y_K

$$W_{jk} = 1 \quad \text{if } j=k \quad (4)$$
$$= -\varepsilon \quad j \neq k \quad K = 1,2, \ldots\ldots M$$

Step 1:

while stopping condition is false, do step 2-4

Step 2:

Update activation of each node for k=1, 2, ….,M

$$a_K(new) = f[a_k(old) - \varepsilon \sum_M a_M(old)]$$

$$M \neq j \quad (5)$$

Step 3:

Save activation for use in next iterations

$a_k(old) = a_k(new), \quad K=1,2,\ldots..M$

Step 4:

Test stopping condition.

If more than one node has a nonzero activation, Continue otherwise, Stop.

4. RESULTS AND DISCUSSION

4.1 Visitor Recognition

The architecture of the neural network for visitor recognition is given in Fig.2 The feature vector of the visitor has (6) elements. So the neural network has (6) input nodes. The number of visitors is 20 because the patterns identified for (20) IPs. This number can be coded in 5 bits, so the neural network must have (5) output nodes. Different numbers of hidden layers with different number of nodes have been investigated to obtain the proper numbers. One hidden layer is found to be sufficient to reduce the error. The second hidden layer did not reduce the error significantly. The neural network with 6, 12, 3o, 60, 90 nodes in the first hidden layer has been investigated. The proper of number nodes of the first hidden layer is found to be (60).

After training the neural network using back-propagation algorithm, the network parameters have been adjusted and calculated. Fig. 3 shows training error of neural network. Data is divided into two set. The first set is used for training the network to adjust the network parameters. The other set is used to test the neural network. After testing the network, it has recognized the users with accuracy of 90%.

4.2 Visitor URLs Classifier

The architecture of the unsupervised neural network for user URLs classifier is given in Fig.1. The Maxnet algorithm given in section 3 is used to train the network. Number of input nodes is (63) because patterns identified for distinct requested URLs from 63 URLs accessed by each distinct 25 IPs. 25 IPs can be coded into 5 bits. So, the unsupervised neural network has (5) output nodes. After training the network, it classified the user URLs into classes. Each class contains some users. This classification helps to load these URLs pages just the system recognizes the user which improves the efficiency of the web. Fig. 4 illustrates the numbers of classes with the numbers of user in each class. Neural networks can be connected to database system to improve and facilitate the web search just it recognizes the users without errors.

A proposed system is developed to improve and enhance the web searching using the unsupervised neural network as shown in Figure5. When an old user requests a web site (home page), the Proxy server extracts the user pattern from web log files which is fed to the neural network to recognize the user. Using this information, database server can prepare and load the URL pages for this user. If a new user requests the web, proxy server extracts its URLs and can predict its cluster using the unsupervised neural network to introduce a fast service in the next time using the web.

Figure 6 illustrates a proposed system for updating the clusters of old users based on its new input pattern. The database server extracts the user pattern. This pattern is fed to the unsupervised neural network which classifies its class.

For new user, database server extracts features and the supervised neural network recognizes the user to load its URLs and save to database.

5. Conclusion

This paper presents an approach for using neural network to analysis web logs files. Such analysis could be useful for many application like prediction and enhancement search for user sites. A proposed system based on neural network is introduced to improve and enhance the web searching tool.

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Table 1. Raw data format

```
#Software: Microsoft Internet Information Services 5.0
#Version: 1.0
#Date: 2001-02-04 21:02:57
#Fields: date time c-ip cs-username s-ip s-port cs-method cs-uri-stem cs-uri-query sc-
2001-02-04 21:02:57 193.227.50.11 - 193.227.50.6 80 GET /iisstart.asp - 200 Mozilla/4.
2001-02-04 21:02:59 193.227.50.11 - 193.227.50.6 80 GET /pagerror.gif - 200 Mozilla/4.
2001-02-04 21:03:24 193.227.50.11 - 193.227.50.6 80 GET /iisstart.asp - 200 Mozilla/4.
2001-02-04 21:03:26 193.227.50.11 - 193.227.50.6 80 GET /iisstart.asp - 200 Mozilla/4
2001-02-04 21:03:30 193.227.50.11 - 193.227.50.6 80 GET /iisstart.asp - 200 Mozilla/4.
2001-02-04 21:04:14 209.202.148.24 - 193.227.50.6 80 GET /FacMed/library/per/nl.htm -
2001-02-04 21:04:18 198.3.103.59 - 193.227.50.6 80 GET /univ/hospitals.html - 404 Arch
2001-02-04 21:04:53 193.227.50.205 - 193.227.50.6 80 GET /iisstart.asp - 200 Mozilla/4
2001-02-04 21:04:54 193.227.50.205 - 193.227.50.6 80 GET /pagerror.gif - 200 Mozilla/4
2001-02-04 21:07:28 209.202.148.24 - 193.227.50.6 80 GET /FacMed/library/per/ql.htm -
2001-02-04 21:07:47 208.219.77.29 - 193.227.50.6 80 GET /robots.txt - 404 Gulliver/1.3
2001-02-04 21:08:18 208.219.77.29 - 193.227.50.6 80 HEAD /facagr/zoology/cv/20796.htm
2001-02-04 21:08:22 193.227.50.6 - 193.227.50.6 80 GET /Default.asp - 200 Mozilla/4.0
2001-02-04 21:08:22 193.227.50.6 - 193.227.50.6 80 GET /Images/mans_bridge.jpg - 200 M
2001-02-04 21:08:45 193.227.50.6 - 193.227.50.6 80 GET /Default.asp - 200 Mozilla/4.0
2001-02-04 21:08:45 193.227.50.6 - 193.227.50.6 80 GET /Images/mans_bridge.jpg - 200 M
2001-02-04 21:09:52 209.202.148.24 - 193.227.50.6 80 GET /FacMed/library/per/b7.htm -
2001-02-04 21:11:32 195.219.86.35 - 193.227.50.6 80 GET /Default.asp - 200 Mozilla/4.0
2001-02-04 21:11:33 195.219.86.35 - 193.227.50.6 80 GET /Default.asp - 200 Mozilla/4.0
2001-02-04 21:11:44 195.219.86.35 - 193.227.50.6 80 GET /univ_indexa.asp - 200 Mozilla
2001-02-04 21:11:44 195.219.86.35 - 193.227.50.6 80 GET /Images/mans_bridge.jpg - 200
2001-02-04 21:11:46 195.219.86.35 - 193.227.50.6 80 GET /Default.asp - 200 Mozilla/4.0
2001-02-04 21:11:57 195.219.86.35 - 193.227.50.6 80 GET /Images/univ_sym.gif - 200 Moz
2001-02-04 21:11:57 193.227.50.11 - 193.227.50.6 80 GET /Default.asp - 200 Mozilla/4.0
2001-02-04 21:11:58 195.219.86.35 - 193.227.50.6 80 GET /Images/explorer.gif - 200 Moz
2001-02-04 21:12:00 195.219.86.35 - 193.227.50.6 80 GET /Images/NewClr.gif - 200 Mozil
2001-02-04 21:12:27 216.34.42.38 - 193.227.50.6 80 GET /faccsl/facindex.html - 200 Zyb
2001-02-04 21:12:29 195.219.86.35 - 193.227.50.6 80 GET /Default.asp - 200 Mozilla/4.0
```

Table 2. Result of data pruning

Pruning web logs			
Date	Time	IPs	URLs
04 02	23 46 57	163.121.36.46	/images/univ_sym.gif
04 02	23 47 01	163.121.36.46	/images/explorer.gif
04 02	23 52 14	212.138.47.12	/univ_indexa.htm
04 02	23 52 17	212.138.47.14	/univ_indexa.htm
04 02	23 52 43	212.138.47.14	/univ_indexa.htm
05 02	00 03 52	62.114.66.144	/Default.asp
05 02	00 03 58	62.114.66.144	/images/mans_bridge.jpg
05 02	00 04 22	62.114.66.144	/univ_indexa.asp
05 02	00 04 29	62.114.66.144	/images/Newclr.gif
05 02	00 05 19	62.114.66.144	/images/univ_sym.gif
05 02	00 05 19	62.114.66.144	/images/explorer.gif

Table 3. Results of Data Filtering

No	IP	No IP Accesses	No of All Requested URLs	No of Distinct Requested URLs	No	IP	No IP Accesses	No of All Requested URLs	No of Distinct Requested URLs
1	193.227.50.11	9564	336	55	27	206.169.242.44	1502	51	50
2	195.149.20.62	4230	-	-	28	172.16.8.2	1498	25	11
3	212.138.47.24	4228	401	56	29	172.16.5.90	1472	61	22
4	195.7.144.102	4172	-	-	30	172.16.2.104	1415	25	15
5	134.222.247.30	4143	-	-	31	172.20.1.24	1399	47	21
6	208.219.77.29	4126	188	47	32	209.202.148.24	1392	58	37
7	212.138.47.22	3729	273	46	33	172.16.4.2	1364	63	28
8	212.19.192.206	3540	-	-	34	172.16.5.67	1358	55	17
9	193.227.50.112	3283	126	33	35	193.227.50.201	1331	24	17
10	212.138.47.23	3250	269	50	36	172.21.1.4	1298	-	-
11	193.227.50.110	2578	26	21	37	172.16.12.25	1283	-	-
12	193.227.50.104	2433	24	19	38	172.21.1.2	1260	3	2
13	212.138.47.21	2257	236	44	39	172.16.6.34	1219	2	1
14	172.20.1.23	2256	91	28	40	172.16.5.9	1186	45	15
15	172.16.30.2	2218	195	48	41	193.227.50.113	1185	31	20
16	217.52.17.133	2069	213	56	42	172.16.2.105	1179	42	25
17	172.19.1.4	1811	61	21	43	172.16.4.45	1152	39	25
18	172.16.8.7	1794	9	6	44	172.16.6.21	1149	2	1
19	172.16.2.109	1792	16	9	45	172.16.3.17	1142	2	2
20	193.227.50.100	1732	54	21	46	172.16.6.13	1125	11	4
21	172.16.2.107	1719	18	15	47	172.20.1.12	1100	17	9
22	172.16.2.110	1713	36	28	48	172.16.4.34	1084	46	25
23	172.20.1.2	1691	29	7	49	172.16.9.3	1079	7	5
24	172.22.1.3	1571	51	16	50	217.8.96.50	1058	-	-
25	193.227.50.200	1539	92	20	51	172.21.1.3	1051	4	3
26	172.16.2.102	1515	37	14	52	216.34.42.38	1013	62	45

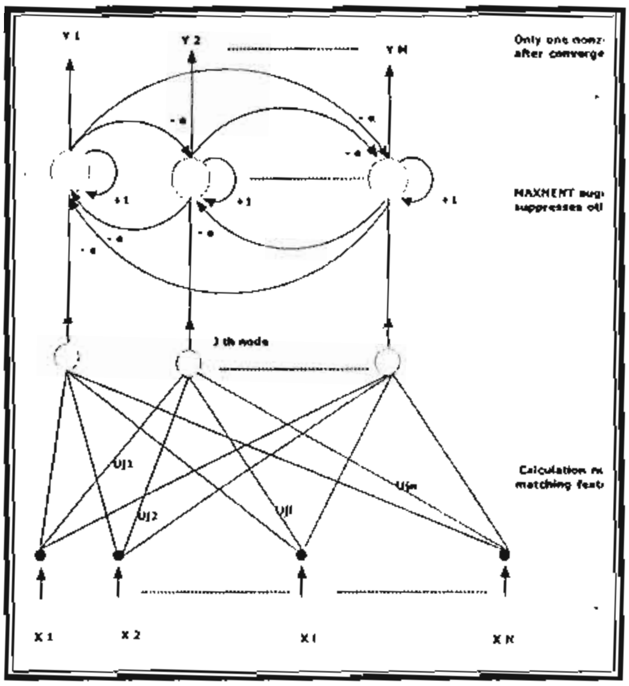

Fig.1. The architecture of a Maxnet network

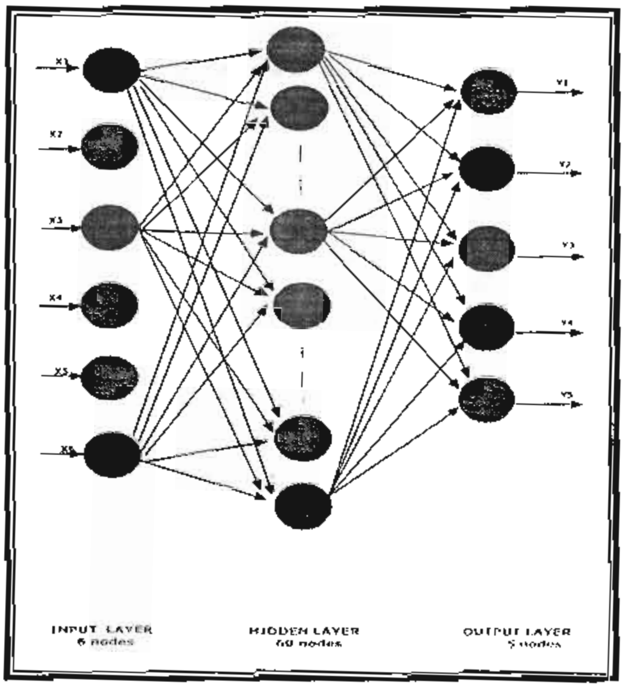

Fig.2 Neural network architecture for supervised learning

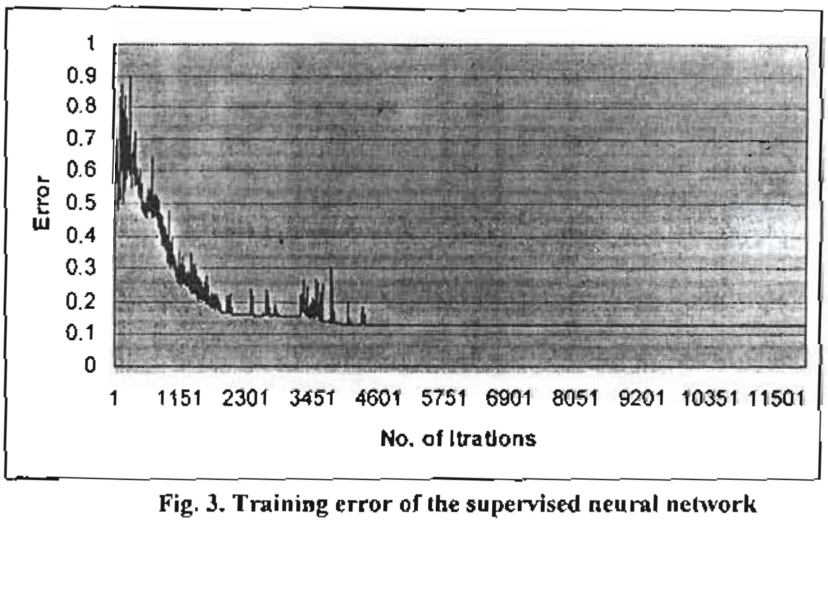

Fig. 3. Training error of the supervised neural network

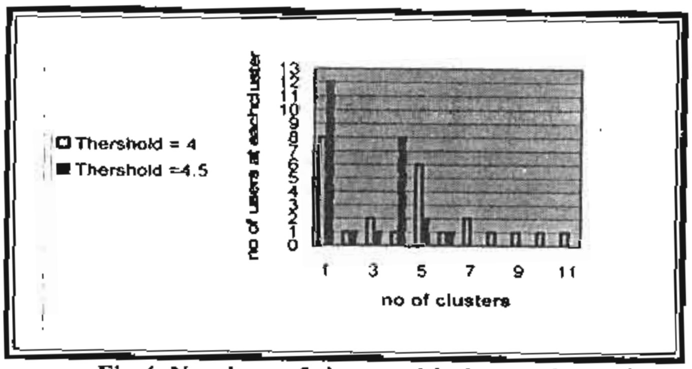

Fig.4 Numbers of classes with the numbers of users.

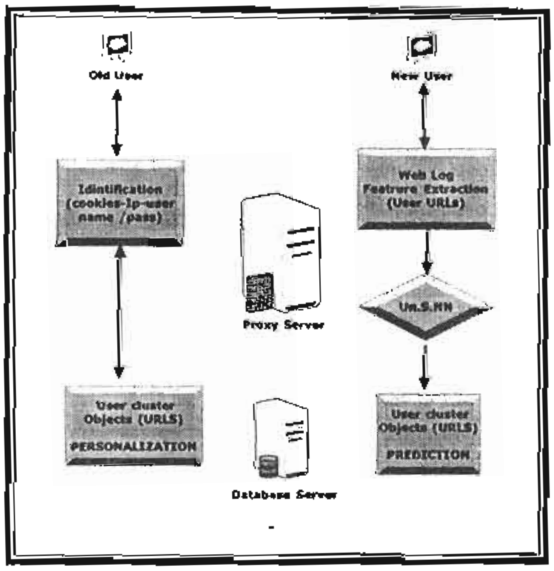

Fig.5 Proposed system using unsupervised ANN.

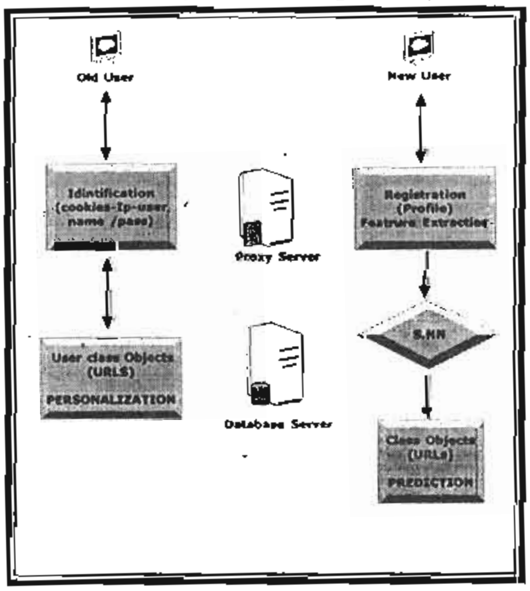

Fig.6 Proposed system using supervised ANN.