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A Naïve Hopfield Neural Network based Approach for Multiclass Classification of Customer Loyalty

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ABSTRACT
Customer classification is an area of utmost interest for all businesses. For any organization retaining customer is more important than making new customers. In this paper, a simple idea based on Hopfield Neural Network (HNN) is proposed for multiclass classification of customer loyalty. Initially, transformation and k-medoid clustering algorithm preprocesses the training example dataset. Then, classifier model (HNN) learns patterns from this training set. After training is done, patterns are stored and classifier is ready to classify the unclassified examples using weighted matrices and Euclidean norm. It learns from its environment and does not need to be reprogrammed. The proposed classifier is tested over a real dataset collected through an online survey and it is 87.5% accurate, which is an encouraging result.

General Terms
Neural Networks, Clustering, Multiclass Classification, Training Dataset, Learning Algorithm

Keywords
Classification, Customer Loyalty, K-medoid clustering, Hopfield Neural Network, Normalization, Matrix similarity, Euclidean Norm

1. INTRODUCTION
In the present e-generation, customer retention is indispensible for an organization's growth [1, 2]. Thus, for maintaining a good relationship with the customer, analyzing his loyalty plays a imperative role. A loyal customer can prove very fruitful for an organization as he can bring many more customers for it [3]. The goal of Customer Relationship Management (CRM) is to recuperate the services provided to customers and using their information for planning effective marketing strategies [1]. The main application of this project is in retail industry, where they can identify different types of customers clearly and can take decisions appropriately. The companies can use the customer information for planning effective marketing strategies. In this paper, a framework has been proposed to identify their potential customers more accurately. The purpose of developing this classifier is to serve the best interests of customer relationship management. By making the software automate, it saves lots of time as compared to manual calculation.

Customer Loyalty is one of the major aspects of Customer Relationship Management (CRM). The relationship of a customer with the company terminates, if the customer moves away from the company's services when alternative providers become available. The customer no longer has a need for the company's products or services. For retaining customers, customers must be classified into various categories accurately, so that each category of customers is dealt by different marketing strategies.

Classification is a process in which classifier learns from the training data set and it will identify the class label for unseen pattern or record. Customer classification is a two-step process. The two steps are:

Learning: In the first step a classifier is built describing a predetermined set of classes. Because the class label of each training tuple is provided, this step is also known as supervised learning. In this training step classifier model learns from the training data set.

Classification: In the second step, the model is used for classification of unseen patterns. As model is already intelligent because of learning from training data set, so it is set to classify unlabelled data. To measure the accuracy of the classifier, test set is used which is made up of test tuples and associated class labels. Then the accuracy of the classifier is estimated. If the accuracy is acceptable, then the classifier can be used to classify any unseen patterns.

Mathematically, let $X=\{X_1, X_2,\ldots,X_n\}$ be n data objects , where each data object is further characterized by m attributes namely $\{x_1,x_2,\ldots,x_m\}$ and $Y=\{Y_1, Y_2,\ldots,Y_k\}$ be k target variables such that $f:X \rightarrow Y$ is defined as $f(X)=Y$. f is a many to one function.

Decision trees, Neural Network, Rule based classifier, Support vector machine, Bayesian classifiers are most commonly used classifiers. In this paper, Hopfield neural network is implemented for classification. The building block of a neural network is the neuron and its working is similar to the human brain. Hopfield neural network is represented by set of interconnected neurons, which asynchronously keep-on updating their weights and reducing the value of energy function in subsequent iterations, until a stable state of the system is achieved [4].

Hopfield network has the feedback connections to the network i.e. the outputs are fed back in to the network till network stabilizes. The Hopfield Neural Network's content addressable memory property helps in identifying the patterns for which it is not even trained. This type of networks is called feedback or recurrent networks [5].

The Energy function E makes the neural network to converge to a stable state. Energy function must decrease (or remain unchanged) with each iteration step and ultimately should remain unchanged; otherwise the network will never reach a stable state. In actually training of a network is adjustment or modification in the weights so that the actual output can match the desired output of the network.

In this paper a simple Hopfield Neural Network (HNN) based framework to identify the type of customer loyalty as Super Premium Loyal customer (SPL), Premium Loyal customers (PL), valued customers (VC), Normal customers (NC) is proposed. Class label NC is assigned to a customer who is not a very regular customer and SPL is of utmost value to the organization, whereas other two loyalty class labels lies in between them. When classification involves more than two class labels to be assigned to the examples, it is termed as multiclass classification. In this paper, wherever term classification is used, it means multiclass classification. The main motivation behind selecting Hopfield Neural Networks for classification is its associative memory property, because of which it can classify incomplete or even noisy input pattern to the nearest class label.

The rest of the paper has been organized as follows: Section 2 provides the details of literature survey in the related area. Section 3, 4 and 5 explains the motivation behind the current work, preprocessing of the data and proposed method respectively. In Section 6, proposed method has been tested and experimental results are presented to classify customer loyalty. In section 7, the paper discusses the conclusion and future research direction of the current work.

2. RELATED WORK

The classification of a customer as 'loyal' or 'not loyal' cannot be considered in rigid sense. There are various factors that influence the loyalty of a customer towards an organization [1]. Crisp classification of customer loyalty towards a brand may not be fruitful for future prospective customer [2]. It is very important for an organization to identify its loyal customers, so that the organization can provide better and special services to these customers in order to retain such customers and enhance their business. So, for various reasons, it necessitates the need of appropriate classification of customers on the basis of their loyalty. Finally, the proposed framework is trained and tested over the real data set that is collected through an online survey (https://goo.gl/p4LZjK). The collection of data currently is restricted to the residents of Bangalore.

In literature, researchers have used various classifier models such as decision trees [6], fuzzy decision trees [7, 2], Bayes Classifier [8], Rough set theory [9] and Neural Networks [10, 11, 12, 13] for classifying customer loyalty.

Classifiers are the classification rules [14, 15] or models used for predicting the class of an unclassified record. One of the most popular and widely used strategies for generating classifiers is Decision Tree (DT) Induction [14,15]. Decision tree is constructed from training (sample) data set by splitting the dataset recursively [14, 15, 16]. Decision trees are used where one takes crisp decisions and Fuzzy Decision Trees (FDT) are used where boundaries of classification are not very rigid [2, 17]. In Fuzzy Decision Trees, one data object may belong to two classes at the same time. Fuzzy decision tree [17] keeps the boundary of the result soft. Soft boundaries help in classifying a customer, where he can belong to two classes at the same time.

Simha et al. [7] have used fuzzy context model that assigns customers to segments (segments of interest) based on some criteria. For this segmentation to produce the intended result, the context model classifies customers based on meta knowledge provided by domain expert and allows partial membership to multiple classes thereby giving a better description of classified elements and finds the potential or possible weakness of the element.

Cristina et al. [17] have explained the complete fuzzy decision tree technique, which is based on the concept of crisp and soft boundary values. They have given the exact comparison of the crisp and soft decision tree and the building technique of fuzzy decision tree.

According to Andreas et al. [18], the attributes for measuring customer loyalty are:

(a) Turnover

(b) Payment behavior

They have designed a fuzzy Classification Query Language (fCQL) toolkit. They have proposed a fuzzy classification model for online customers that extend and promote e-shops by analyzing e-customer's loyalty. Fuzzy classification query leads the customer loyalty to be either of the given four classes or the overlapping of any two.

Chen et al. [19] has explained a customer intelligence system using Life Time Value (LTV) model and the concepts of data mining [14, 15]. The LTV, has been computed as an aggregate revenues gained from a customer throughout his lifetime transactions. The system also provides various factors such as potential customer identification, customer loyalty analysis, profitable customers etc. They have divided the customers in 8 segments. They have employed fuzzy decision trees and self organizing maps for the development of the entire system.

Daniel et al.[20] has explained the comparison between the capability of crisp and fuzzy decision trees. According to Daniel et al. fuzzy decision tree has the soft boundary range. Crisp decision tree produces the crisp decision from uncertainty that shows the unfairness of the decision. For the classification problem of numerical attributes, the fuzzy decision trees have the stronger generalization capability than crisp decision trees [20, 21].

Qiaohong Zu et al. [8] constructed a simple and intuitive extended Bayes model, which gives a better classification effect. The customer classification model uses these three factors to classify customers: Customer lifetime value, Customer credit, Customer loyalty, The customers were first clustered in k-means algorithm [15], then this cluster was used in customer classification prediction by weighted Bayes algorithm thereby improving the accuracy of the classification.

The rough set theory is used to find the weights to be assigned to the attributes [8, 9]. The extended Bayes algorithm [8] was constrained under both rough set attribute importance theory and expert prior knowledge and it also combined cluster preprocessing with classification prediction to effectively and efficiently classify the customers with multifactor based on customer value and customer behavior.

According to Ue-Pyng et. al [22], Neural networks have been characterized in various categories according to many relevant features. Generally, neural network have two kinds of structures. Both the structures have to be configured such that, the application of a set of input produces the desire set of outputs. Various methods exist to strengthen the weighted connections. One way is to place the weights explicitly using a priori knowledge and other way is to train the network by giving input

patterns and continuously changing the weights according to some learning rule.
Wan I-lee and Bih-Yaw Shih [11] confirms that neural network model is useful in recognizing existing patterns of customer's data. They developed a HNN model to recognize level of profitable customers for dental services.

Shouhong Wang [12] used discrete data for input units in network, with few exemptions. Also any continuous data can be approximately represented by discrete data for the classification purpose, without loss of generality.

For updating the neurons [23], two general ways are:

Asynchronous – Choose one neuron, calculate the weighted input sum and the neuron gets updated immediately. Neurons can be chosen in a fixed or random order.

Synchronous – The weighted input sum of all neurons are computed without updating the neurons.

In Hopfield neural network, pattern is entered in the network by setting all the nodes to a specific value. Synaptic weight matrix is calculated from the input neuron values, so the input patterns are stored in weight matrix.

3. MOTIVATION FOR THE WORK

The proposed work is aimed at classifying the customer loyalty by using Hopfield Neural Network (HNN) as it tries to get fairly accurate results as compared to other classification techniques [22, 24]. Finding customer loyalty is an important aspect of today's retail industries. Knowing the level of loyalty of customer can help in concentrating on retaining an old customer or can help converting a customer to higher category of class label by different marketing strategies. Also, the customers that belong to more than one class label (multi-label classification) can be future prospective customers. The main idea behind this proposed approach is to identify customers belonging to four different categories and thus the services (or offers) to be offered to them. The organizations can use the customer information for planning effective marketing techniques. Some of the features of Hopfield Neural Network (HNN) that motivated the work are [20, 22, 24, 25]:

- Hopfield Neural Network is fairly accurate and more robust to noise as compared to other classification techniques.
- It can infer for an unknown combination of input variables or in other words, for an incomplete or noisy input, it classifies the example to the nearest class label.
- If a neuron fails to be trained by Hopfield Neural Network, it still has a capability of processing, because it follows parallel and recurrent processing. If any neuron fails then the computation is allocated to another neuron [24].

In HNN each neuron is fully connected with remaining neurons by weights but is not connected to itself (that is no self feedback is provided).

4. PREPROCESSING OF THE DATA

As the customer data is collected through a survey, which is available online through Google forms. This collected data is used as training and testing dataset for Hopfield Neural Network (HNN).

The data collected is unsupervised because no class label is associated with examples. In order to associate class labels with the training dataset, k-medoid clustering algorithm is used. The reason for choosing k-medoid clustering algorithm over k-means is that, it works better and faster than k-means [14, 15].

Some examples of the dataset are used as training dataset and remaining as test dataset.

Table 1: Customer Dataset collected through online survey

Cust. ID	TE	LT	FV	MP	Label
1	9000	4	7	1	PL
2	30000	6	7	1	SPL
3	12000	4	3	1	SPL
4	2000	4	1	1	VC
5	25000	6	3	1	SPL
6	15000	8	2	1	SPL
7	10000	3	5	1	SPL
8	8000	3	8	1	PL
9	6000	1	8	1	PL
10	159	1	3	1	VC
11	5000	2	2	1	VC
12	2000	1	5	0	NC
13	15000	2	5	1	SPL
14	8000	6	2	1	SPL
15	2000	2	4	1	VC
16	6000	1	6	1	PL
17	100	1	4	1	VC
18	4000	3	4	1	VC
19	8000	4	8	0	PL
20	3000	2	2	1	VC
21	15000	1	1	1	VC
22	6000	4	8	1	PL
23	6000	4	6	0	PL
24	3000	1	2	1	VC
25	30000	6	2	1	SPL
26	10000	2	2	1	VC
27	20000	8	8	1	SPL
28	3000	8	6	1	SPL
29	5000	6	4	1	SPL
30	7000	7	4	1	SPL
31	5000	4	8	1	PL
32	15000	6	5	1	SPL
33	30000	2	3	1	VC
34	5000	2	8	1	PL
35	200	1	8	0	NC
36	8000	4	2	0	NC
37	25000	7	5	0	SPL
38	15000	4	3	1	SPL
39	15000	4	4	1	SPL
40	10000	6	6	1	SPL
41	25000	1	5	1	SPL
42	18000	1	5	1	SPL

43	5000	3	3	0	NC
44	15000	1	3	0	NC

The attributes in the collected data for the classification of customer loyalty are:

i) Total Expenditure of customer (TE) – The amount in rupees spend by the customer in a particular duration.
ii) Life Time of a customer (LT) – Total number of years from the first visit of the customer to the last purchase.
iii) Frequency of visit (FV) – Total number of visits in a specific time interval.
iv) Mode of Payment (MP) – How a customer is making the payment. For payment by "Credit/Debit card" as 1 and "cash/others" as 0.

In order to understand the intrinsic nature of the data collected, correlation between the variables TE, LT and FV is computed. Mode of payment (MP) is not taken into consideration, as it is a binary variable.

To calculate correlation coefficient "r", Correlation Coefficient formula is used:

$$r(TE,FV)=\frac{\sum_{i=1}^{n}(TE_i-TE_{mean})(FV_i-FV_{mean})}{\sqrt{(\sum_{i=1}^{n}(TE_i-TE_{mean})^2\sum_{i=1}^{n}(FV_i-FV_{mean})^2)}}$$

where n is the number of training examples.

$TE_{mean}=9401.63$ $\quad r(TE,FV)=-0.0654$

$LT_{mean}=3.638$ $\quad r(TE,LT)=0.4042$

$FV_{mean}=4.472$ $\quad r(FV,LT)=0.0712$

So, The variables TE and FV are negatively correlated. It means the variables "total expenditure" and "frequency of visits" of the customers are negatively correlated (as number of visits (FV) of customer increases, expenditure (TE) by the customer decreases). Also, the variables TE, LT and FV, LT are positively correlated. This analysis gives a good insight into collected dataset about the behavior of customers based on the above attributes.

As a preprocessing step, the data so collected is transformed so that the values of the variables fall in [0, 1] range. For this purpose, Normalization technique is applied to avoid data loss [19], which is given as follows:

$$x_i=\frac{x_i\text{ - }\min\_x_i}{\max\_x_i\text{ - }\min\_x_i}.$$

where x_i is the values of different attributes of the dataset.

After normalization, value of attributes TE, LT, FV, MP will fall in the range [0, 1]. The transformed dataset is shown in Appendix Table 7.

Since the dataset obtained from online survey is unsupervised, so partitional clustering algorithm PAM(Partitioning around Medoids, a k-medoid algorithm) is applied. PAM algorithm provides four clusters 1, 2, 3, 4. Of which, 1 indicates class label PL, 2 is SPL, 3 represents VC and 4 is NC based on the behavior of each cluster. The four clusters so obtained are shown in Figure 1.

The four clusters are plotted with the plotcluster() function of R using package named "cluster". For plotting clusters in two dimensions this function reduces the dimension of the dataset using Principal Component Analysis(PCA)[15]. With the help of these clusters, training dataset is labeled with four class labels namely SPL, PL,VC, NC as described earlier.

Figure 1: Clusters obtained from real dataset using R

The real customer dataset shown in Table 1 gets the class labels with the help of PAM[15].The pam() function from R is used for this purpose that takes the dataset, number of clusters and distance metric as its arguments. Transformed dataset is now used as training and testing dataset for a Hopfield Neural Network (HNN) based classifier, so that HNN learns from this dataset and gets trained for classifying unclassified new examples.

5. PROPOSED FRAMEWORK

The proposed classification framework involves the following steps:

Step1: Customer dataset is collected through an online survey.

Step 2: The collected dataset is assigned class labels by applying PAM(k-medoids clustering) algorithm, as training dataset is unsupervised.

Step 3: After class labels are assigned to the training dataset, as per traditional approach of classification, each example from this labeled dataset is fed one by one to Hopfield Neural Network (HNN) so that it can learn these patterns.

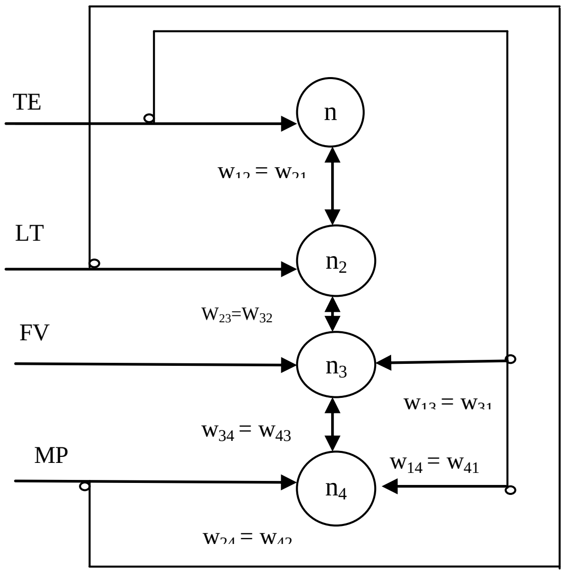

Figure 2: The Hopfield Neural Network Structure with four inputs TE, LT, FV, MP

(a) But instead of storing all the patterns, only four patterns corresponding to four class labels are stored.

(b)The HNN is trained (Figure 2) with 4 derived real training examples obtained by data aggregation each representing one class label respectively.

(c) Data Aggregation is done by computing the median value of each attribute corresponding to one class label and fed to HNN to get the stable weight matrix.

Eg, for class label "VC", there are 11 training examples belonging to this class label, so median of each attribute is calculated and the values are:

TE_{median}= 0.096, LT_{median}=0.142, FV_{median}=0.142, MP_{median}=1

Similarly, remaining training examples are treated and four examples are fed to HNN and four stable synaptic weight matrices are stored.

Step 4: For the process of learning, the following steps are followed by HNN:

(a) Computation of Synaptic weight matrix using Hebb's Rule [26]:

where η=1/N is the learning rate of the neural network, N is the number of examples in the training dataset.

(b) Activation Rule: Activation s_i of neuron i is given by:

$$s_i = \eta \sum_n w_{ij} x_j$$

where summation varies from j=1 to n over a specific i.

(c) Computation of Energy Function (E): A scalar value called Energy E is associated with each state of the network, which actually identifies its stable state and is computed as:

$$E = -\frac{1}{2} \sum_i \sum_j w_{ij} s_i s_j$$

when neurons are fired randomly, E is either further lowered or remains the same. Once local minimum for E is attained, the network state and the synaptic weight matrix is considered stable.

These stable weight matrices are obtained as learned patterns, which are retained by the network for future reference.

Step 5: (a) Now, Test Example is fed to HNN and it will generate the weight matrix corresponding to this example.

(b) Once weight matrix for test example is obtained, it's matched with the 4 stored patterns and identifies the class label of the test record.

(c) In order to find the similarity of the obtained weight matrix to the stored patterns, Euclidean norm is computed as follows:

$$Euc(A,B) = \sqrt{\sum_{i=1}^{n} \sum_{j=1}^{n} (a_{ij} - b_{ij})^2}$$

where A and B are two weight matrices, and Euc(A,B) identifies the closeness of two matrices. Of all the similarity values, whichever is minimum will be considered to identify the class label of the test record.

$$w_{ij} = \begin{cases} \eta \sum_i \sum_j x_i^{(n)} x_j^{(n)}, i \neq j \\ 0................, i = j \end{cases}$$

The above five steps explain the complete proposed multiclass classification for customer loyalty. The process of training of Hopfield Neural Network is implemented through C.

The Figure 3 depicts the entire framework of the Hopfield Neural Network classifier.

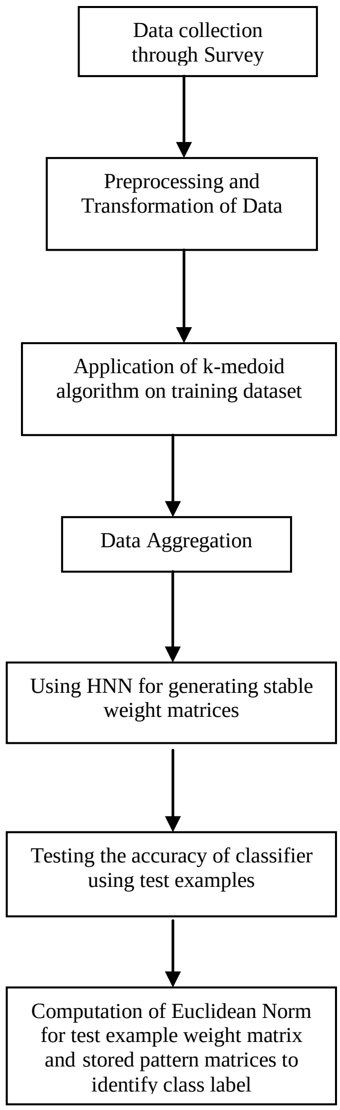

Figure 3: Proposed System Flow

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6. EXPERIMENTAL RESULTS AND SIMULATION

We provide an empirical evaluation of our methodology. Experiment is performed on AMD dual core processor 1.60 GHz and 2GB of RAM machine 32-bit operating system, to test the results over a dataset (Table 1).

Input to the HNN are the following four examples obtained from the preprocessed customer dataset (Table 2).

Table 2: Four Examples taken for training of HNN

S.no	TE	LT	FV	MP	Class Label
1.	0.49	0.714	0.42	1	SPL
2.	0.197	0.428	1	1	PL
3.	0.096	0.142	0.142	1	VC
4.	0.113	0.142	0.428	0	NC

Each training example is fed to HNN one by one and corresponding stable matrices are obtained. For better understanding, one such stable synaptic weight matrix(T_{SPL}) corresponding to class label SPL is given below:

$$T_{SPL}= \begin{bmatrix} 0 & 0.0096 & 0 & 0.01345 \\ 0.0096 & 0 & 0 & 0.01928 \\ 0 & 0 & 0 & 0 \\ 0.01345 & 0.01928 & 0 & 0 \end{bmatrix}$$

Similarly, the stable matrices for other three class labels is also obtained and stored. In order to make processing more efficient only upper triangular matrix elements are stored as $w_{ij}=w_{ji}$, for all i, j.

After this phase, HNN is now exposed to test examples in order to establish its accuracy. Of the collected customer dataset, some examples were kept for testing purpose(Appendix, Table 6). The synaptic weight matrix($Test_{34}$) corresponding to a test example 34(Appendix, Table 6) [0.498, 0.428, 0.285, 1] is

$$Test_{34}= \begin{bmatrix} 0 & 0 & 0.00001 & 0.00001 \\ 0 & 0 & 0.00383 & 0.00383 \\ 0.00001 & 0.00383 & 0 & 0.027 \\ 0.00001 & 0.00383 & 0.027 & 0 \end{bmatrix}$$

Then, the convergence of this test example synaptic weight matrix is patterned by defining similarity between the stored pattern matrices and this matrix using Euclidean norm. The label assigned to this customer is PL that is same as that of the expected label.

Similarly, synaptic weight matrix ($Test_{37}$) corresponding to the test example 37 [0.832, 0.857, 0.571, 0] is given in the below matrix.

The label assigned to this customer through classifier is NC, same as expected label.

$$Test_{37}= \begin{bmatrix} 0 & 0.01925 & 0.01283 & 0 \\ 0.01925 & 0 & 0.01321 & 0 \\ 0.01283 & 0.01321 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

In this way, unclassified test example is assigned one of the four class labels.

In order to compute the accuracy of the proposed classifier, the confusion matrix of the 8 test examples is computed, as shown in Table 3.

Table 3: Confusion matrix for four class labels

ACTUAL Class	PREDICTED Class			
	SPL	PL	VC	NC
SPL	3	0	0	0
PL	1	1	0	0
VC	1	0	0	0
NC	0	0	0	2

Accuracy of the prediction of four class labels is computed by identifying True Positives (TP), True Negatives(TN), False Positives(FP) and False Negatives(FN) as given in Table 4.

So, overall accuracy of the Hopfield Neural Network is given by computing the average of accuracy of all class labels.
Thus, accuracy of proposed approach is 87.5%, which is quite reasonable. Even in case of incomplete or noisy data, this approach gives best possible class labels.

Table 4: Accuracy of prediction of four class labels

	SPL	PL	VC	NC
TP	3	1	0	2
TN	3	6	7	6
FP	2	0	0	0
FN	0	1	1	0
Accuracy	75%	87.5%	87.5%	100%

Thus, any unclassified example having the four attributes can be assigned class labels for further decision-making purposes.

This approach has given similar results on the sample dataset [2].

7. CONCLUSIONS AND FUTURE SCOPE

The proposed automatic classifier categorizes the customers to various categories based on their purchase behavior into four specified class labels namely SPL, PL, VC and NC. The Hopfield Neural Network based classifier model predicts the class labels of the unclassified records efficiently. The dataset so collected, is preprocessed through transformation and aggregation and then HNN based classifier model learns patterns from this dataset. This is then tested for test examples and accuracy of the classifier is computed (87.5%). The online survey is still open and the data is pouring in. For further improving the accuracy of classifier, a bigger real dataset is under consideration. This proposed framework can help experts to take informed decisions. Further, investigations have revealed that there are few customers that fall into more than one category of class labels indicating towards multi-label classification. Such customers can be of great interest for decision makers as these customers can get converted to superior categories amongst the four class labels (like a customer who belongs to VC as well as PL). Although in this paper, such customers from the real dataset is removed but investigation including those customers is in progress. Further the data collected through survey contains many other attributes that are taken into consideration for their impact on customer loyalty.

Also, investigation on applying deep learning process on the customer dataset for the classification of customer loyalty is in pipeline.

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9. APPENDIX

Table 5: Test Dataset without transformation

Cust. ID	TE	LT	FV	MP	Label
34	5000	2	8	1	PL
37	25000	7	5	0	SPL
38	15000	4	3	1	SPL
39	15000	4	4	1	SPL
40	10000	6	6	1	SPL
41	25000	1	5	1	SPL
42	18000	1	5	1	SPL
44	15000	1	3	0	NC

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Table 6: Test Dataset after transformation

Cust. ID	TE	LT	FV	MP	Label
34	0.163	0.142	1	1	PL
37	0.832	0.857	0.571	0	SPL
38	0.498	0.428	0.285	1	SPL
39	0.498	0.428	0.428	1	SPL
40	0.331	0.714	0.714	1	SPL
41	0.832	0	0.571	1	SPL
42	0.598	0	0.571	1	SPL
44	0.498	0	0.285	0	NC

Table 7: Customer dataset collected through online survey after transformation

Cust. ID	TE	LT	FV	MP	Label
1	0.297	0.428	0.857	1	PL
2	1	0.714	0.857	1	SPL
3	0.397	0.428	0.285	1	SPL
4	0.063	0.428	0	1	VC
5	0.832	0.714	0.285	1	SPL
6	0.498	1	0.142	1	SPL
7	0.331	0.285	0.571	1	SPL
8	0.264	0.285	1	1	PL
9	0.197	0	1	1	PL
10	0.001	0	0.285	1	VC
11	0.163	0.142	0.142	1	VC
12	0.063	0	0.571	0	NC
13	0.498	0.142	0.571	1	SPL
14	0.264	0.714	0.142	1	SPL
15	0.063	0.142	0.428	1	VC
16	0.197	0	0.714	1	PL
17	0	0	0.428	1	VC
18	0.13	0.285	0.428	1	VC
19	0.264	0.428	1	0	PL
20	0.096	0.142	0.142	1	VC
21	0.498	0	0	1	VC
22	0.197	0.428	1	1	PL
23	0.197	0.428	0.714	0	PL
24	0.096	0	0.142	1	VC
25	1	0.714	0.142	1	SPL
26	0.331	0.142	0.142	1	VC
27	0.665	1	1	1	SPL
28	0.096	1	0.714	1	SPL
29	0.163	0.714	0.428	1	SPL
30	0.23	0.857	0.428	1	SPL
31	0.163	0.428	1	1	PL
32	0.498	0.714	0.571	1	SPL
33	1	0.142	0.285	1	VC
34	0.163	0.142	1	1	PL
35	0.003	0	1	0	NC
36	0.264	0.428	0.142	0	NC
37	0.832	0.857	0.571	0	SPL
38	0.498	0.428	0.285	1	SPL
39	0.498	0.428	0.428	1	SPL
40	0.331	0.714	0.714	1	SPL
41	0.832	0	0.571	1	SPL
42	0.598	0	0.571	1	SPL
43	0.163	0.285	0.285	0	NC
44	0.498	0	0.285	0	NC

Table 8: Training Dataset after transformation

Cust. ID	TE	LT	FV	MP	Label
1	0.297	0.428	0.857	1	PL
2	1	0.714	0.857	1	SPL
3	0.397	0.428	0.285	1	SPL
4	0.063	0.428	0	1	VC
5	0.832	0.714	0.285	1	SPL
6	0.498	1	0.142	1	SPL
7	0.331	0.285	0.571	1	SPL
8	0.264	0.285	1	1	PL
9	0.197	0	1	1	PL
10	0.001	0	0.285	1	VC
11	0.163	0.142	0.142	1	VC
12	0.063	0	0.571	0	NC
13	0.498	0.142	0.571	1	SPL
14	0.264	0.714	0.142	1	SPL
15	0.063	0.142	0.428	1	VC
16	0.197	0	0.714	1	PL
17	0	0	0.428	1	VC
18	0.13	0.285	0.428	1	VC
19	0.264	0.428	1	0	PL
20	0.096	0.142	0.142	1	VC
21	0.498	0	0	1	VC
22	0.197	0.428	1	1	PL
23	0.197	0.428	0.714	0	PL
24	0.096	0	0.142	1	VC
25	1	0.714	0.142	1	SPL
26	0.331	0.142	0.142	1	VC
27	0.665	1	1	1	SPL
28	0.096	1	0.714	1	SPL
29	0.163	0.714	0.428	1	SPL
30	0.23	0.857	0.428	1	SPL
31	0.163	0.428	1	1	PL
32	0.498	0.714	0.571	1	SPL
33	1	0.142	0.285	1	VC
35	0.003	0	1	0	NC
36	0.264	0.428	0.142	0	NC
43	0.163	0.285	0.285	0	NC