


Effective Selection of Entities From Heterogeneous and Large Resources Using a Cooperative Neuro-Fuzzy System: A Case of Fast Moving Consumer Goods

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ABSTRACT

This paper focuses on using the cooperative neuro-fuzzy system for the effective and customised selection of entities from large and heterogeneous resources by presenting a general architecture. An experiment is carried out with the fast-moving consumer goods to prove the utility of the architecture. It is observed that most consumers go for the frequent purchase of fast-moving consumer items. Further, various brands, costs, discounts, schemes, quantities, and reviews might make it challenging. Hence, such decisions need to be intelligent and practically feasible in terms of time and effort. The paper discusses neural networks to categorise the entities, type-1 & 2 fuzzy membership functions with rules, training sets, and graphical views of the fuzzy rules and the experiment details. Besides the generic approach and experiment, the paper also discusses the work done so far with their limitations and applications in other domains. At the end, the paper presents the limitations and possible future enhancements.

KEYWORDS

Artificial Neural Networks, Fast Moving Consumer Goods, Hybrid Intelligent Systems, Type 2 Fuzzy Logic

1. INTRODUCTION

In the modern world, tremendous data are generated in every business. Having a lot of data related to a concerning decision making and problem solving domain is a highly appealing situation. However, the data are generated in a collaborative form via multiple means, multiple approaches, and heterogeneous formats. Obviously, these data come in large volume too. To effectively utilize the data, there is a need for an intelligent process. The application of Artificial Intelligence (AI) can offer some help in this direction. However, traditional artificial intelligence methods such as expert systems can not be of great help because of many reasons. As conventional artificial intelligence based systems are based on knowledge, they are hard to characterize, voluminous, and dynamic in nature.

Further, when the domain is dynamic and undergoes frequent adaption, stored knowledge is quickly absolute. In this case, modern machine learning techniques might be useful. Some examples of such modern machine learning techniques are artificial neural networks, fuzzy logic and genetic algorithms. Such methods overcome the limitations of the conventional artificial intelligence based

DOI: 10.4018/IJSDA.302633

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systems. Each modern machine learning methods has its pros and cons. Fuzzy logic is good at uncertainty handling and approximate reasoning. The artificial neural network approach enables the storage of knowledge in implicit ways and offers advantages of self learning from a large amount of data. Hybrid intelligent methods based on modern machine learning techniques offer advantages of integrated techniques and overcome limitations associated with a standalone machine learning method. This paper discusses the use of hybrid neuro-fuzzy systems in the selection of fast moving consumer goods.

Humans generally and subconsciously categorize and classify things into classes without specific boundaries. For this, linguistic words are being used often. Some examples of these are expensive products, rich people, and luxury cars. Generally, a non-algorithmic way is used to select entities such as fast moving consumer products, documents, jobs, matrimonial profiles, mobiles, garments, finding beneficiaries of loan, Government schemes, etc. Consider a scenario where a fast moving consumer product such as a shampoo bottle needs to be purchased from a superstore. Varieties of products are available in this category with several schemes, plenty of subcategories, multiple brands, and different prices. Similar products are available online too, maybe with handsome discounts. ‘*Buy one get one free*’ offer on a shampoo bottle may have a special effect on the consumer. However, if the product is close to its expiry date, those two shampoo bottles bought under the scheme may not be used fully. It is very tedious to read all the labels, compare the product with other products in the same store and other marketplaces to make an effective decision as it involves multiple criteria. Above this, such criteria vary for each product. Such scenarios are classic examples of multi-criteria decisions from large and heterogeneous data sources.

Instead of applying the traditional models for the multi criteria based decision making, it is proposed to use the hybrid intelligent technology to offer more human-like decision making and approximate reasoning. To handle vagueness, uncertainty and provide approximate reasoning and inference, fuzzy logic is proposed. Some criteria cannot be mapped from fuzzy to crisp but require fuzzy to fuzzy mapping. In this situation, the use of type 2 fuzzy logic is proposed. To learn the trend of decision making and to know about consumer purchase patterns, the use of an artificial neural network is proposed. Both fuzzy logic and the artificial neural network are supposed to work in a cooperative manner. The hybridization, membership functions, and other technical details are presented in detail in this paper’s subsequent sections.

The paper is organized as follows. Section 2 of the paper discusses the literature survey presenting state of the art in the domain to make such recommendations using various intelligent approaches. The section also enlists observations and common limitations to identify the research gap. Section 3 presents a generic approach for effective and intelligent decision making by using a hybrid type 2 neuro-fuzzy architecture. Section 4 discusses an experiment based on the proposed architecture to recommend fast moving consumer goods, considering multiple criteria to analyze the results. Section 5 presents the conclusion by giving benefits, applications of the proposed approach in other areas with research possibilities ahead.

2. LITERATURE SURVEY

As the objective of the research work is to design and develop a neuro-fuzzy system that considers linguistic input as well as outputs and intelligently evaluates an entity from the large heterogeneous data sets, similar solutions and research papers were surveyed from the standard journals and other resources. The literature survey presented in this section is organized into three basic categories. These categories are namely (i) Traditional artificial intelligence based solutions, (ii) Modern stand alone machine learning applications and (iii) Hybrid machine learning applications.

- (i) **Use of Traditional Artificial Intelligent Methods:** Traditional artificial intelligence based solution includes the use of expert systems in market analysis, consumer behavior pattern, and

product promotion. An expert system for data analysis in marketing (Bockenho, Both, & Gaul, 1988) developed in the year 1988 is an example of the same. Similar work is done by (Courtney, Paradise, & Nassar, 1987) in the year 1987, which discusses a knowledge based decision support system for managerial problems analysis and solutions. The latest work in the use of traditional artificial intelligence based systems category can be seen in the work of (Dwivedi & McDonald, 2018) and (Krishnakumar, 2021). Both the papers talk about applications of marketing intelligence for the fast moving consumer goods.

- (ii) **Application of Modern Machine Learning Methods:** Benefits of machine learning methods are described in the work of (Icio, Getúlio, Camilo, Jose, & Douglas, 2019), (Pereira & Frazzon, 2021), (Joanna & Marek, 2020), and (Arvan, Fahimnia., Reisi, & Siemsen, 2018). The paper (Icio, Getúlio, Camilo, Jose, & Douglas, 2019) discusses the use of machine learning techniques in predicting demand for various fast moving consumer goods. The product categories such as fashion, technology, and fresh food are considered in their work with the primary aim of predicting the demand in line with the shelf life of such products. In the work of (Joanna & Marek, 2020), the researchers talk about the application of the gradient boosting technique in order to forecast the indicators of performance for measuring the product promotion efficiency, particularly for the fast moving consumer goods. A brief review is presented in the paper by (Arvan, Fahimnia., Reisi, & Siemsen, 2018), which discusses how human based judgments and heuristics can be used in quantitative forecasting methods in the retail industry as well as other sectors.

Stand alone machine learning systems without any hybridization are also used in item evaluation and tracking in the food industry (Lukyamuzi, Ngubiri, & Okori, 2020), agricultural products (Ray, 2021), marble industries (Shukla, Jangid, Soni, & Kumar, 2019), evaluation of students performance (Aggarwal, Mittal, & Bali, 2021), smart cities for multi criteria decisions (Juneja, Juneja, Bali, & Mahajan, 2021), and customer value generation (Herrera, Carvajal-Prieto, Uriona Maldonado, & Ojeda, 2019), etc. Various other applications in the context of developing nations are discussed in (Omamo, Rodrigues, & Muliaro, 2020) that utilize the systems dynamics model.

- (iii) **Application of Hybrid Machine Learning Methods:** As seen in the literature, hybridization of the fuzzy logic and neural network has become popular, as illustrated in the work of Lin & Lee (1991) and Jang (1992). Later such hybridization is seen in many researchers' work (Sulzberge, Tschichol-g-Gurman, & Vestli, 1993; Tano, Oyama, & Arnould, 1996; Abraham, 2001).

Besides the generic hybridization, many researchers have provided domain specific solutions also.

The work presented by Burke R (Burke, 2002) documents various experiments discussing the use of a fuzzy neural network to rate the food in restaurants based on fuzzy inputs like varieties, taste, and cost. Another application of the fuzzy input is seen in the work of Lamie (Lamei, 2005) for the fire alarm system. Fuzzy linguistic words are also used in other researchers' work such as (Nahla & Jabbar, 2008; George, Atsalakis, & Valavanis, 2009).

In software engineering, the use of a fuzzy neural network is seen in the work of Souza (Souza, 2018) to estimate the time and effort needed to develop software. Neuro fuzzy systems are extensively used in the area of text summarization (Sayed & Sajja, 2018), employee evaluation (Macwan & Sajja, 2014), web mining (Sajja, 2013), and other web based advisory systems (Trivedi & Sajja, 2011). A tool for the automatic development of such a system is also designed in the work of Sajja (2017). Other uses of fuzzy neural networks are seen in the recruitment systems at various places too (Krichevsky, 2017; Chen, Zhang, Chen, & Gan, 2015; Das, Naik, & Behera, 2020; Yen, Wang, & Cuong, 2018).

Observations from the Literature Survey: The traditional artificial intelligence based solutions such as expert systems do not offer advantages of modern machine learning techniques. When it comes to selecting suitable entities from large and heterogeneous data sets, use of traditional artificial intelligence based methods is not advisable. Solutions mentioned in the first category in the literature

survey have these limitations. Further, in the domain of fast moving consumer goods, where products, price, discounts, categories, etc., undergo continuous change. In this scenario, stored knowledge in the knowledge base has limited application, and the system can easily become obsolete.

The solutions that use stand alone modern machine learning techniques also do not provide effective solutions in comparison with the solutions that use hybrid machine learning techniques. The solutions referred to in the second category offer limited advantages. This is the main reason to adopt the hybrid neuro-fuzzy machine learning approach in this paper.

The solutions mentioned in the literature survey are either a state of the art survey or domain-specific applications except for a few generic tools. A little work facilitates the vague and uncertain inputs to the neural network that deals with heterogeneous and voluminous resources such as Web or big data. Following are some limitations of the existing solutions.

- The traditional artificial intelligence based solution does not offer advantages related to the modern machine learning methods such as automatic and self learning to some extent, adaptability, avoiding hazards of knowledge acquisition and representations, etc.
- Most of the researchers have applied either fuzzy logic or neural network in the domain of the fast moving consumer goods (Kumar, Jarial, & Narwal, 2019; Chahal & Narwal, 2019; Okunade & Daodu, 2020). Hybridization of both the components has not been seen much in the selected domain.
- Some generic solutions are also available that use hybridization of neural networks and fuzzy logic in many ways. However, such solutions do not offer advantages of the higher level uncertainty handling such as type 2 fuzzy logic (Lin & Lee, 1991; Jang, 1992; Abraham, 2001; Chen, Zhang, Chen, & Gan, 2015; Sajja, 2017).
- Most of the solutions are application specific, such as fire alarm systems (Lamei, 2005), recruitment systems (Krichevsky, 2017), employee evaluation (Macwan & Sajja, 2014), and text summarization (Saiyed & Sajja, 2018).
- Applications of various mining and forecasting techniques are also popular for fast moving consumer goods recommendations (Dahl, 2020; Tao, Yang, & Feng, 2020).

The above mentioned limitations observed from the literature survey lead to the need for a user friendly architecture of a hybrid intelligence system to select entities from the heterogeneous and large data sets. Further, to increase the usability of the proposed architecture, it has to be domain independent. The architecture also enables users fuzzy inputs to select and evaluate the available entities. Such entities can be a product, document, web page, job profile, film, employee, or anything that needs evaluation. The paper presents a generic architecture and experiments it in the domain of fast moving consumer goods. The proposed research work uses a hybrid neuro-fuzzy approach for effective recommendations. Further, care is also taken to design the underlying architecture used in many other domains.

The next section discusses the generic architecture.

3. DESIGN OF NEURO-FUZZY SYSTEM

This section presents the architectural design of a neuro-fuzzy system. The design consists of three major components. The first component is the neural network along with the Web resources. The second component is the fuzzy logic based component. The third component is a bunch of repositories with user profiles and other databases. Figure 1 illustrates the general architecture of the neuro-fuzzy system. As stated, the architecture is used to select entities from voluminous and heterogeneous resources of the chosen domain in an effective and customized manner.

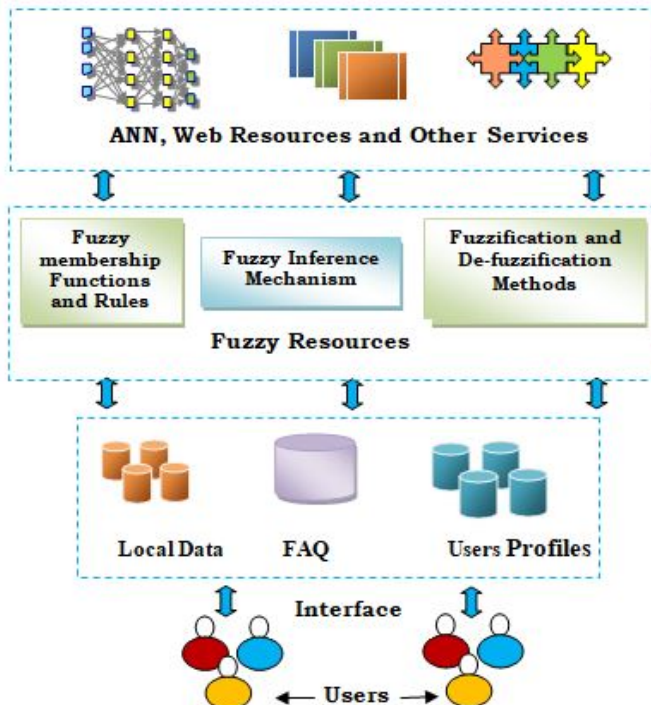
As demonstrated in Figure 1, the first component of the neuro-fuzzy system's architecture consists of repositories. The repositories include user profiles, local data, and frequently asked questions/data. The component also has a mechanism or interface to interact with users. The main stakeholders of the system

can be users, administrators, and domain experts. These users interact with the system through the interface. Such an interface can be in regional language or supported with any type of graphical interface to facilitate ease of use and operational level acceptability. The system remembers users' basic information, historical information about the last few transactions, and preferences related to the given domain. The storage of such users centric information enables the system to provide further customized results (Sajja, 2020).

The second component of the architecture provides a facility to handle vagueness and imprecision associated with the query and human-like approximate reasoning. It is to be noted that the neural network based systems do not document the knowledge as there is no utility like a knowledge base. Such a lack of knowledge base further restricts explanation and reasoning and limits future use and training using the stored knowledge. The incorporated fuzzy logic based component overcomes these limitations (Akerkar & Sajja, 2016). As the fuzzy logic can document the knowledge symbolically in the form of 'if then else' rules with fuzzy membership degrees, the above mentioned advantages can be achieved. The fuzzy logic based component includes the definitions of fuzzy membership functions, defuzzification methods, type reducer (in case of type 2 fuzzy logic), fuzzy rule base, and inference mechanism. The inference mechanism chosen here follows the standard backward chaining approach. The inference can also be developed using forward chaining or hybrid chaining techniques on need (Malik, Ahmad, Kim, Park, & Kim, 2019).

Here the use of type 2 fuzzy is suggested because of many reasons. The type 2 fuzzy systems extend the generalization in the traditional fuzzy systems in order to increase the level of the uncertainty handled by the system. It is observed that the type 1 fuzzy systems, which are known as the traditional fuzzy logic based systems work with a key component called membership function. The membership functions with the traditional fuzzy logic based system map crisp values to the

Figure 1. General architecture of the neuro-fuzzy system



fuzzy values and vice-versa. The membership functions with the type 2 fuzzy logic based system map fuzzy values with fuzzy values. In the year 1975, Lotfi A. Zadeh (Zadeh, 1975) invented the notion of type 2 fuzzy sets with more sophistication and enhanced uncertainty. The crisp set is a special case of a fuzzy set, where the uncertainty factor is reduced to zero. In a similar way, the type 1 fuzzy set is a special case of type 2 fuzzy set, where the uncertainty factor is reduced. The interval type 2 membership functions are commonly used. Such a membership function has an upper membership function and a lower membership function for a given linguistic variable. The upper membership function is abbreviated as UMF, and the lower membership function is abbreviated as LMF. Both the upper membership function and lower membership function can be of any shape and type. They can be triangular fuzzy membership function, normal (bell shaped) fuzzy membership function, trapezoidal fuzzy membership function, etc. The upper membership function is also considered as the traditional type 1 membership function on a linguistic variable. The distance/region between an upper membership function and a lower membership function is called the footprint of uncertainty, FOU. Type 2 fuzzy logic based system, additionally needs a type reducer too. As stated, the use of a type 2 fuzzy logic based system provides more uncertainty and behaves more naturally. According to Azar (Azar, 2012), by handling such a higher level of uncertainty, flexibility and applicability of the fuzzy logic based systems can be enhanced.

The third component is based on an artificial neural network. An artificial neural network is a collection of artificial neurons in a well organized topology. An artificial neuron is a simulation of biological neuron, which is a basic unit in a natural nervous system. Due to a large number of neurons, their ability to work in parallel, asynchronous, and distributed manner, and the fault tolerance (because of the large number of neurons in a network), the neural network based systems can exhibit an ability to think and intelligent decision making. Such artificial neural networks learn from large amount of data instead of the symbolic and stored knowledge in explicit form. The artificial neural network used in this architecture is a multi layered, feed forward, and fully connected neural network with perceptrons as nodes. The neural network learns in a supervised manner using lots of training data from the domain.

The artificial neural network takes inputs from user's queries, product labels, and other information from the web resources. The artificial neural network takes the crisp values generated from type 1 and type 2 fuzzy membership functions from the fuzzy logic based component. Additionally, some middleware services or readymade web services (such as services getting commodity price values) can also be considered here. The artificial neural network needs to be application specific.

The above mentioned components are working in a cooperative manner. As stated, the fuzzy logic based component takes the data from environment, which are fuzzy in nature, and using the type 1 and type 2 membership functions, they are converted into a crisp manner. The crisp values are considered by the trained neural network to output a crisp decision. Later the crisp decision is fine tuned by the fuzzy logic based component again. That is, the fuzzy component and the user interface facilitate ease of use and work with the fuzzy linguistic variable. The neural network focuses on self-learning and classification. In the next section, a detailed process flow of the fuzzy logic and artificial neural network based component is discussed.

4. EXPERIMENT BASED ON ARCHITECTURE

To prove the utility of the proposed general purpose architecture, a case of fast moving consumer product evaluation and selection is considered. Such products are also known as FMCGs (Fast Moving Consumer Goods). The FMCGs include baked goods, frozen foods, processed food, cleaning products, cosmetics, and toiletries such as soap, shampoos, stationery items such as ball pens and markers, over the counter drugs like pain relievers, aspirins, etc. People would generally not like to give conscious evaluation and comparison efforts for a product with a small to medium price range. Such products are rather casually selected. Though such products' prices are low, consumers' purchase

mainly consists of such small products and offers an excellent opportunity to be very effective in cost control. Further, such purchase happens frequently in one's life; almost every week or every month.

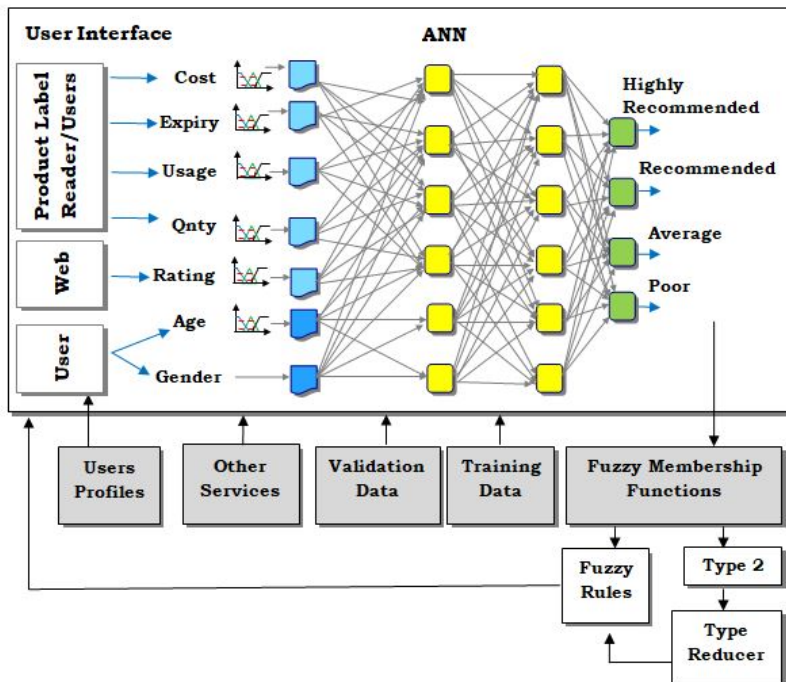
As suggested in the generic architecture in section 3 of the paper, such a system requires some essential components that need to be designed. These components are as follows.

- User interface and various repositories regarding users, products, and other local databases. This is a tedious process. The users' data can also have fuzzy variable within their profiles. An interface might be needed in regional or graphical language to facilitate users. Product data, initially can be taken by various sites as mentioned later in this section;
- Fuzzy membership functions that map the users vague and imprecise linguistic words used in their queries need to be developed;
- For each type 2 fuzzy membership functions, an upper membership function (UMF) and a lower membership function (LMF) need to be defined;
- Type reducer is necessary for the type 2 fuzzy membership functions used in the system;
- Fuzzy rules to fine-tune the decisions taken by the underlying artificial neural network, and other utilities for fuzzy logic based systems;
- The data required to train and validate the artificial neural network can be collected with multiple domain experts and from various resources; and
- A pre-trained and validated artificial neural network which takes data about users, data about various resources, and products to be compared and evaluated.

The process flow of the experiment is demonstrated in Figure 2.

The neural network described in Figure 2 takes inputs regarding various aspects of product and consumer. For any type of evaluation and decision making, product parameters such as cost, expiry dates, usage, quantity

Figure 2. Process flow of the experiment



offered in a unit, and rating of the product are generally considered. The consumer related parameters, such as age and gender, can also be considered. There are many more parameters like user's shopping history, and the tendency for shopping can also be considered. The majority of these parameters are fuzzy. The neural network's main objective is to classify a given product into one of the four categories and to recommend the possible purchase. These four categories are: (i) Highly recommended, (ii) Recommended, (iii) Average, and (iv) Poor.

The products with an acceptable rate, handsome quantity per unit, high usability, and far (long or high) expiry date are definitely to be purchased. Such items are highly recommended for purchase. The available products at a very low rate with good usage and handsome quantity might be having low or nearer shelf lives. This is the reason why the products with nearer expiry date are sold with high discount and low rate. Such items are not going to be used but wasted because of the close expiry date. These types of items need not be recommended purchased if the user is not going to fully utilize the product within the expiry date limit. The items with a high rate with the minimum quantity and most minor usage are not at all to be recommended to purchase.

The above mentioned neural network is trained with data collected from domain experts and various consumers. As a part of the experiment, the dataset from the Flipkart¹ FMCG is used. The data set is available at Kaggle². The data set and help from a few users from different categories are also taken for the experiment. The Flipkart dataset contains 20,000 records in comma-separated values on various parameters of the FMCG products. A larger data set with approximately 5 million product data along with values on different parameters is also available at the above mentioned site. The data set consists of some costly products, which are avoided. The products under 1000 bucks are extracted here with some selected attributes for the experiment. This extraction yields approximately 500 training data sets, which are used for training and validation in the ratio of 70:30.

The data first undergoes pre-processing and formatting. Later various fuzzy membership functions map them into appropriate values if needed. This is required for the additional data provided by the users in fuzzy form. After the initial training, the neural network is also tested with fuzzy training data. Table 1 enlists some examples of training data sets.

As stated, the artificial neural network does not understand vague data, there is a need for suitable fuzzy membership functions that maps the fuzzy linguistic parameters used in input to their equivalent

Table 1. Training Data Sets

No.	X ₁	X ₂	X ₃	X ₄	X ₅	X ₆	X ₇	O ₁	O ₂	O ₃	O ₄
1	L	H	H	A	A	M	1	1	0	0	0
2	L	H	H	H	A	Y	0	1	0	0	0
3	L	VL	L	L	A	O	0	0	0	1	0
4	A	H	VH	H	H	M	1	0	1	0	0
5	H	H	VH	H	H	M	1	0	1	0	0
6	H	L	A	A	H	Y	0	0	0	0	1
7	L	H	L	L	A	M	1	0	0	0	1
8	A	VH	L	L	A	M	1	0	0	0	1
9	A	A	VH	L	A	M	0	0	1	0	0
10	L	L	L	L	L	O	1	0	0	0	1
11	H	VH	VH	H	H	Y	0	1	0	0	0
12	A	VH	VH	H	H	Y	1	0	0	0	0
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X₁: Cost, X₂: Expiry, X₃: Usage, X₄: Qnty, X₅: Rating, X₆: Age, X₇: Gender, O₁: Highly Recommended, O₂: Recommended, O₃: Average, O₄: Poor.
 Permissible fuzzy values are VL: Very Low, L: Low, A: Average, H: High, and VH: Very High

crisp and normalized values. The fuzzy membership functions used in the experiment are Cost, Expiry, Usage, Quantity, Rating, Age, and Recommendation. These fuzzy variables are described as follows.

The fuzzy variable 'Cost' considers the cost or price of a given product. Here, products in multiple categories are considered. Though the cost is measured in currency, it varies for different products and places. This makes it very difficult to measure cost. Considering the vagueness associated with the cost variable, it is considered as fuzzy. The possible values of the cost fuzzy variable are Very Low (VL), Low (L), Average (A), High (H), and Very High (VH).

Expiry of a product denoted by 'Expiry' is another important variable the needs to be considered while making the decision. The nature and type of a product determine the expiry of the product. For drugs, beverages, and other edible items expiry date is very important and short. For clothes, crockery, and stationery items, the expiry may be long. Here, the expiry is considered as a fuzzy variable. The expiry variable takes fuzzy values such as Very Low (VL), Low (L), Average (A), High (H), and Very High (VH).

In a similar way the fuzzy variable 'Usage' indicates the possible use of the given product. Some products have frequent and high usage with longer shelf lives. The products with nearer expiry date and less usage are not preferred to be purchased at a high cost. Here, type 2 fuzzy membership functions are used, which are later type reduced. Similarly, for the rating of a product also type 2 membership functions are used.

The quantity of the selected product in this experiment is denoted by 'Qty'. This variable has to be defined as fuzzy for obvious reasons. The quantity of a product is measured in different units. Depending on the type and nature of the product, one can determine whether the quantity is high or low. For example, a gold coin quantity is less, and biscuits and chocolate quantity may be high. Here, the fuzzy variable Qty deals with only four permissible values namely Very Low (VL), Low (L), Average (A), and High (H). Another variable called Age is also fuzzy and takes only three permissible values of such as Young (L), Medium (M), and Old (O).

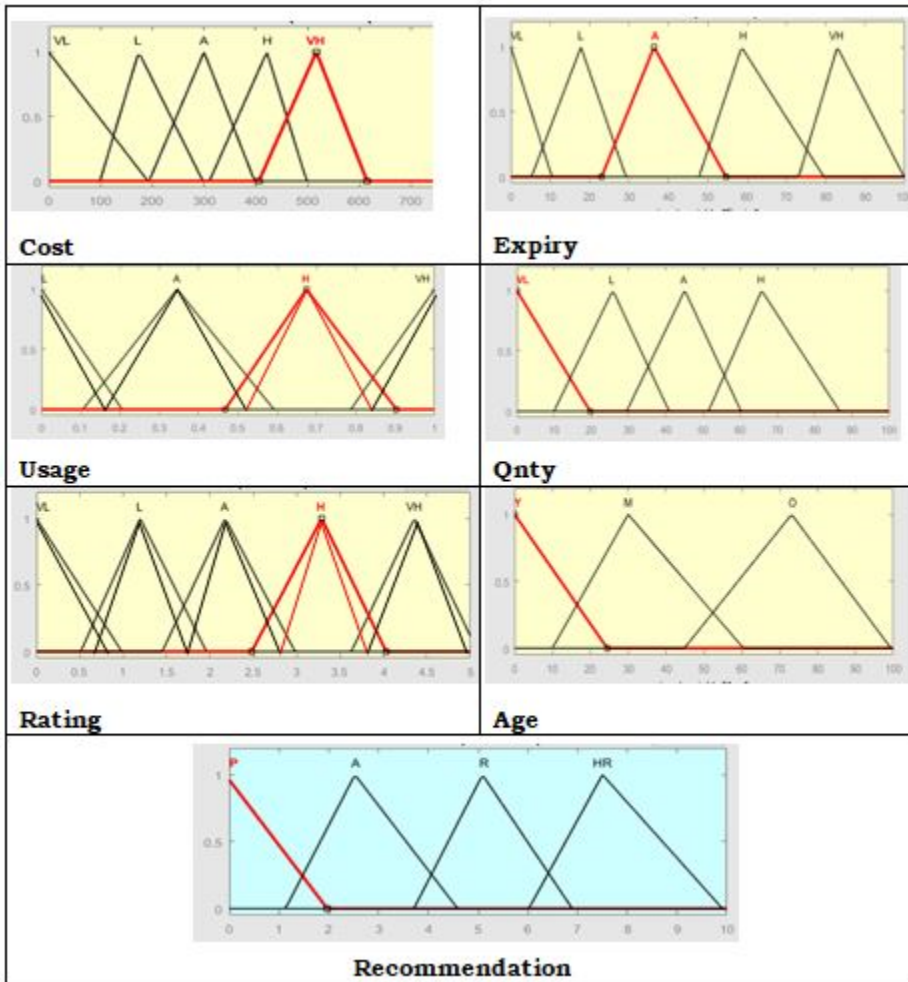
A few parameters such as cost, expiry, and quantity can be retrieved through the product. There are many applications available that reads product label automatically. The product's rating comes from the Web or any permissible third party services. In this experiment, these values are collected through surveys from users and domain experts. Other users' related information such as interests, age, job type, gender, etc., come from user profiles, which might be given by the user at the time of registration. One possibility is that the system might learn from consumers' behavior in an automatic way by a machine learning method. The neural network uses some of these values to classify the product into various categories. In this experiment, four categories are designed, namely, (i) 'Highly recommended', (ii) 'Recommended', (iii) 'Average', and (iv) 'Poor to buy'. Later, the fuzzy component considers more information from the user (user's interest, job type, etc.) and information available online for products (product category, price, brand, etc.) for comparison, evaluation, and final recommendation.

Type 1 and type 2 fuzzy membership functions used in the experiment are illustrated in Figure 3.

As stated, the neural network's output is in a crisp format, which can be further fine-tuned with fuzzy rules. Some examples of the fuzzy rules used in the experiment are given as follows.

- If Cost is Low And Expiry is High And Usage is High And Qty is Average and Rating is Average And Age is Medium And Gender is True then Action is Highly Recommended.
- If Cost is Low And Expiry is High And Usage is High And Qty is High and Rating is Average And Age is Young And Gender is False then Action is Recommended.
- If Cost is Low And Expiry is Very Low And Usage is Low And Qty is Low and Rating is Average And Age is Old And Gender is False then Action is Average Recommended.
- If Cost is Average And Expiry is High And Usage is Very High And Qty is High and Rating is High And Age is Medium And Gender is True then Action is Recommended.

Figure 3. Example fuzzy membership functions



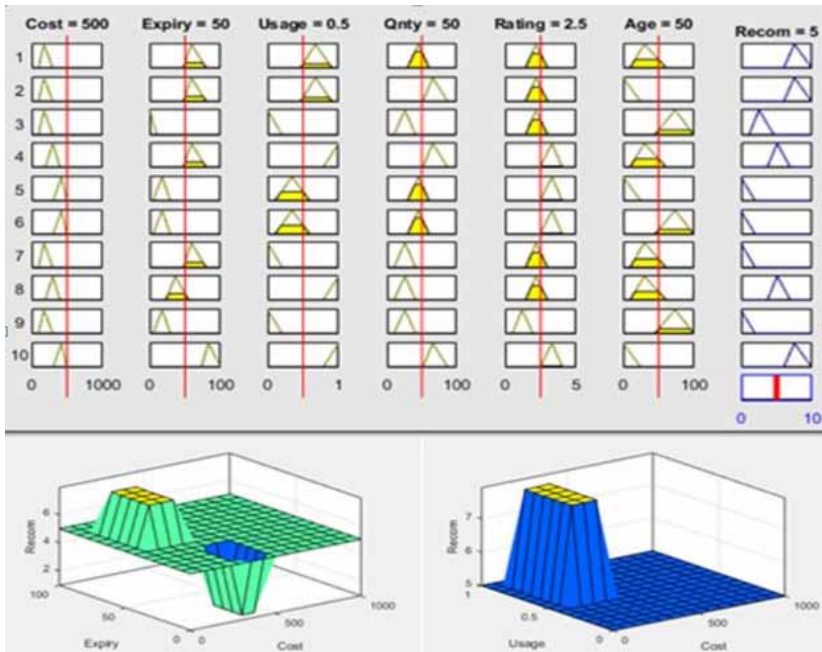
- If Cost is High And Expiry is High And Usage is Very High And Qnty is High and Rating is High And Age is Medium And Gender is True then Action is Recommended.
- If Cost is High And Expiry is Low And Usage is Average And Qnty is Average and Rating is High And Age is Young And Gender is False then Action is Poorly Recommended.
- If Cost is Low And Expiry is High And Usage is Low And Qnty is Low and Rating is Average And Age is Medium And Gender is False then Action is Poorly Recommended.
- If Cost is Average And Expiry is Very High And Usage is Low And Qnty is Low and Rating is Average And Age is Medium And Gender is True then Action is Poorly Recommended.
- If Cost is Average And Expiry is Average And Usage is Very High And Qnty is Low and Rating is Average And Age is Medium And Gender is False then Action is Recommended.
- If Cost is Low And Expiry is Low And Usage is Low And Qnty is Low and Rating is Low And Age is Old And Gender is True then Action is Poorly Recommended.
- If Cost is High And Expiry is Very High And Usage is Very High And Qnty is High and Rating is High And Age is Young And Gender is False then Action is Recommended.

- If Cost is Average And Expiry is Very High And Usage is Very High And Qnty is High and Rating is High And Age is Young And Gender is True then Action is Highly Recommended.
- Etc.

To evaluate the performance of the experiment carried out, parameters such as precision, sensitivity, specificity, and accuracy, etc., are measured. Such parameters are the standard parameters available in the literature and evaluate the quality of the results achieved in the absence of competitive solutions or other benchmarks.

A confusion matrix generated from the experiment shows a summary and performance of the architecture used in the experiment. The confusion matrix uses parameters such as true positive, false

Figure 4. Graphical view of example fuzzy rules



positive, true negative, false negative, recall, precision, sensitivity, specificity, and accuracy. True positive (TP) indicates the cases in which the recommendation is positive and which was the actual case. In this experiment, the confusion matrix gives TP values ranging from 33 to 310 in batch sizes 50 to 500. True negative (TN) indicates the cases in which the recommendation is negative and which was the actual case. In this experiment, the confusion matrix gives TN values ranging from 11 to 140 in batch sizes 50 to 500. The False Positive (FP) is the case where the system has recommended or highly recommended the product, however it should not be the case. Similarly, False Negative (FN) is the case where the system has not recommended the product, which should be recommended. Other confusion matrix parameters such as precision, accuracy, recall, and specificity can be obtained from the True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). The accuracy shows to what extent the architecture has given the correct result. The accuracy is defined as the total of True Positive (TP) and True Negative (TN) divided by the total cases. In the experiment conducted here, the accuracy is ranging from 88% to 90% for the batch size 50 to 500. In the case of the large batch size, the accuracy can be further improved.

The confusion metrics generated from the above mentioned experiment are presented in Table 2. From Table 2, it can be observed that results are consistent and improved as the size of data sets increases.

The results achieved for the precision, accuracy, recall, and specificity are represented in Figure 5.

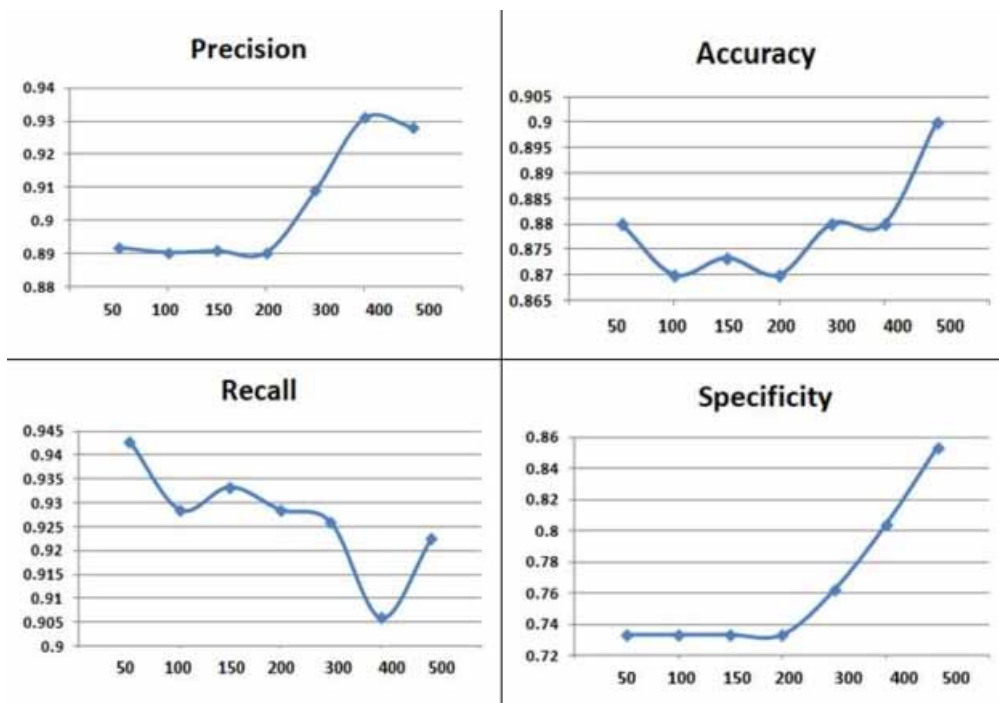
Besides the recommendation, the system also offers a feature to compare the prices. In this experiment, a comparison is made on the Flipkart data provided by the Kaggle. Once the neuro-fuzzy system suggests the product's possible purchase, a few other popular eCommerce websites are explored by providing the product details and price can be fetched. Using this facility, the consumer can have an added advantage of the lowest price for the product.

Table 2. Analysis of the results achieved with different batches

Batch Size	TP	FP	TN	FN	Recall	Precision	Sensitivity	Specificity	Accuracy
50	33	4	11	2	0.94286	0.89189	0.94286	0.73333	0.88
100	65	8	22	5	0.92857	0.89041	0.92857	0.73333	0.87
150	98	12	33	7	0.93333	0.89091	0.93333	0.73333	0.87333
200	130	16	44	10	0.92857	0.89041	0.92857	0.73333	0.87
300	200	20	64	16	0.92593	0.90909	0.92593	0.7619	0.88
400	270	20	82	28	0.90604	0.93103	0.90604	0.80392	0.88
500	310	24	140	26	0.92262	0.92814	0.92262	0.85366	0.9

TP: True Positive, FP: False Positive, TN: True Negative, FN: False Negative

Figure 5. Graphical analysis of the results for different batches



5. CONCLUSION

The neuro-fuzzy architecture discussed in the paper has experimented in the domain of Fast Moving Consumer Goods (FMCG). With minor modifications, the architecture can also be used for different domains such as medicine/drug selection, garment selection, course selection, employee evaluation, matrimonial and job profile evaluation, etc. The proposed architecture uses type 2 fuzzy logic based system in conjunction with an artificial neural network. Such hybridization of both these technologies offers dual advantages of neural network and fuzzy logic such as self-learning, extracting knowledge from the voluminous and heterogeneous data, handling vague and imprecise data, and approximate reasoning.

The generic architecture that works in multiple domains discussed in the paper can be enhanced by adding a user friendly interface. As stated in section 3 of the paper, such an interface can be in regional language or any type of graphical interface to increase its usability.

Such a system is the most suitable for the mobile platform. Most of the users have mobile instruments with an internet facility. The system can be further enhanced as a mobile application so that every consumer can use it handily. Further, instead of entering all the data related to the product, voice or image (label of the product) input can be thought. Such a mobile system can be compatible with other mobile applications, such as finding nearby stores, demonstration videos, and social media platforms for sharing and rating. The design of the generic architecture is flexible enough to accommodate the above mentioned future enhancements in multiple domains handling large, heterogeneous, and distributed resources.

FUNDING AGENCY

The publisher has waived the Open Access Processing fee for this article.

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ENDNOTES

- ¹ <https://www.flipkart.com/>
- ² https://www.kaggle.com/flipkart_com-ecommerce_sample.csv

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