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ORIGINAL RESEARCH ARTICLE

An automatic product recommendation system in e-commerce using Flamingo Search Optimizer and Fuzzy Temporal Multi Neural Classifier

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ABSTRACT

In this paper, a new automatic product recommendation system (APRS) is proposed to recommend the suitable products to the customer in e-commerce by analyzing the customers' reviews. This recommendation system applies semantic aware data preprocessing, feature selection and extraction and classification. The initial level data preprocessing including blank space and stop word removal. Moreover, we use a Flamingo Search Optimizer (FSO) for optimizing the features that are extracted in the initial level data preprocessing. In addition, a new Fuzzy Temporal Multi Neural Classification Algorithm (FTMNCA) is proposed for performing effective classification that is helpful to make effective decision on prediction process. In addition, the proposed automatic product recommendation system recommends the suitable products to the customers according to the classification result. Finally, the proposed system is evaluated by conducting various experiments and proved as superior than the available systems in terms of prediction accuracy, precision, recall and f-measure.

Keywords: automatic product recommendation system; flamingo search optimizer; Multi Neural Classifier; fuzzy logic and temporal constraints

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1. Introduction

Electronic Commerce is shortly called e-commerce where the buying and selling are happening through internet. The online buyers and sellers are required enough knowledge about the products to do their activities successfully. In e-commerce web applications, the webmasters are available for examining the customers queries and also provided the suggestion to perform their tasks with less cost and effort on time. For this purpose, many search engines are available and also helping the customers by providing better suggestions. Here, the set of key terms are identified as useful to perform preprocessing. The major role of administrator is to handle the products according to the quality. The quality of the products is finalized according to the customers satisfaction and their rating over the products. The product is to be listed and displayed in the e-commerce websites when the product ratings is good and the items may be removed from the list of items in website when the rating becomes poor later on. The quality of the products is necessary to predict the customers interests.

In the last decade, the sentiment analysis is playing a major role to predict the users' interests over the products and also influence the business success in e-commerce websites[1]. So that the sentiment analysis is the analysis of the customers' perceptions and services. The automatic review analysis about the products for extracting the natural text and applications[2]. The major challenge in e-commerce sector is to succeed with the sentimental data that is a chance for mining the huge volume of social network data and stored that are not regulated and depends on the machine learning (ML), deep learning (DL) and natural language processing (NLP) techniques for categorizing the sentiment values.

The various methods are available for performing the sentiment analysis that incorporates the clustering, association, classification and prediction processes[3]. The different methods, tools and applications are used for resolving the customers' issues through many data items like prediction systems and expert systems. Even though, these methods are having drawbacks including the cost and time. Moreover, the prediction systems are different from various systems significantly that act as a major role to provide the required data to the customers[4]. The earlier methods that are available as recommendation system that has collaborative filtering and content-based filtering methods. Even though, these methods are specific boundaries like the customers need and also practice the characteristics for executing the recommendation. For reducing the dependencies and also required for developing a new system. The motivation of this research work is to help the customers to purchase their interested product easily without waste of their time. For this purpose, a new automatic product recommendation system is proposed to recommend the suitable products to the customers in e-commerce applications by applying the sentiment analysis, data preprocessing, feature optimization and classification. The important contributions of this work are listed below:

1) To develop a new automatic product recommendation system (APRS) to recommend the more suitable products to the customer in e-commerce by analyzing the customers reviews.
2) To perform semantic aware data preprocessing including blank space and stop word removal which are helpful to improve prediction accuracy.
3) To introduce a Flamingo Search Optimizer (FSO) for optimizing the features that are extracted in the initial level data preprocessing.
4) To develop a new Fuzzy Temporal Multi Neural Classification Algorithm (FTMNCA) for performing effective classification that is helpful for making effective decision on prediction process.
5) This proposed system is proved as better than the available product recommendation systems with respect to the prediction accuracy.

The entire paper is modeled as below: section 2 discusses the relevant works and also lists the advantages and disadvantages. Section 3 explains the workflow of the proposed recommendation system through an architecture. Section 4 describes in detail about the proposed automatic product recommendation system. Section 5 shows the performance of the proposed system and also evaluates by using the standard metrics. Section 6 provides the conclusion about the work and also mentions the performance and result obtained with suggestion to proceed further.

2. Related works

Many product recommendation systems were developed by the researchers in the earlier days by incorporating sentiment analysis, fuzzy logic, ontology and ML/DL classification algorithms. Among them, Islam and Alauddin[5] developed a new deep neural network framework to perform the classification process over the non-food e-commerce products. They also have designed a hierarchical neural structure which is capable of exploiting the earlier taxonomies for managing the complex task available in hardware. Their framework is achieved 61% as a highest accuracy. So that it is identified as a specific network for transferring the data successfully and also performed better than other models.

Gülbaş et al.[6] extracted the necessary features from the apparel datasets by using the deep classifiers such as CNN and extreme learning machine for performing effective apparel classification. They have used the various network models such as VGGNet, AlexNet and ResNet models to perform effective feature extraction process. Finally, their model achieved 60% as apparel classification accuracy. Perumal et al.[7] developed a new fuzzy recommendation system to suggest useful content to the learners based on their interests and history. They have taken decision in analysis on data by applying fuzzy rules and achieved better performance than other available systems with respect to the accuracy.

Perumal et al.[7] developed a new model called REFERS which is a short form of the proposed fuzzy logic aware recommendation system to recommend the suitable products to the customers by analyzing the review comments and the users' queries. At the end, they have proved that their system is superior than available systems with respect to the accuracy. Jin et al.[8] developed a new hybrid depth neural classifier to recognize the emotions through their text while giving medical reviews. They have used Bi-LSTM and CNN for obtaining the necessary semantic features that are useful for performing effective classification. Finally, they have done various experiments as three different models such as ML model, DL model and Attention model for providing 99% as classification accuracy and also proved as superior than available systems. Zhang[9] proposed a new method to perform the annotation process that depends on emotional and artificial lexicons. They have adopted a mixed lexicon method that adopts the lexicons with the combination of artificial and emotional to annotate and enhance the accuracy on annotation process in short span of time. Moreover, they have entered the comments with labels into DL and ML models and achieved higher accuracy for DL model than ML model.

Ayyub et al.[10] explored that the diversification on various feature sets and classifiers to perform the quantification according to the sentiment score. The feature sets are tested with the standard ML and DL classifiers. They have identified that the diversification between the features is capable of affecting the performance of the sentiment quantification. Finally, they proved that the DL techniques are performed well than the ML techniques. Xie et al.[11] proposed a new e-commerce review system which incorporates the BERT aware sentiment analysis method for Chinese people in their own language. They have applied pretraining model and also applied a new labelling pattern for the entities and also performed the sentiment analysis by adopting the data annotation. The experiments have been conducted for proving the effectiveness of their method and proved as better by considering the prediction accuracy.

Karthik and Ganapathy[12] proposed a new fuzzy logic aware system to predict the suitable products to the users according to the users interests by performing the sentiment analysis using ontological table in e-commerce applications. At the end, they have proved that their system is performed well than the existing systems. Munuswamy et al.[13] proposed a new system by incorporating the sentiment analysis techniques to recommend the products according to their interests and their requests. The decision is taken in the process of prediction using sentiment analysis and also proven as superior than other systems.

Rong et al.[14] built a new sentiment and deep learning aware model to conduct a review process in e-commerce platform to improve the performance. Their model was categorized into two such as negative and positive types. The input sentences or text can be divided into various number of words and the word vector that is the combination of words according to their frequency for performing training process. In their work, they have used CNN for performing effective classification. At the end, they proved that their system is superior than other systems which are available in the literature. Nguyen et al.[15] introduced different techniques to use DL in the process of identifying various aspects of the customers. The standard datasets were used for evaluating the new DL technique. Moreover, the words and sentences are considered as vectors. Finally, the CNN and MLP are used to learn the various aspects and also obtained better result in terms of accuracy.

Eke et al.[16] proposed a new context aware attribute selection approach to perform the sarcasm identification process by applying the bidirectional encoder representation and transformer (BERT), ML and DL models. Here, the algorithms including RNN, Bi-LSTM and BERT are used to evaluate the effectiveness of their attribute selection method. Finally, they have achieved 98.5% as maximum classification accuracy for twitter benchmark datasets. Rui[17] developed a new technique for performing the relevant feature extraction from a product image and product classification to improve the feature expression. At the end, the efficiency and applicability of the relevant works compared with their work by conducting the experiments and functional tests. Their technique is useful for enhancing the rationality of the functional designs and also improve the efficiency.

Gope et al.[18] developed a new sentiment analysis incorporated product rating and text review model that uses Amazon's dataset. They have applied RF, SVM, LSVM, NB and Logistic Regression to perform effective training and testing process and also achieved 97.5% accuracy as maximum for their deep learning technique called RNN with LSTM. Alzate et al.[19] developed a unified and unique structure for analyzing the reviews in online based on an ultimate goal. The text mining analysis is also a lexicon aware technique to create an emotional association between the different researchers. Shrivastava et al.[20] built a new opinion mining technique to learn the user's personalization from their review comments and also incorporates both the product rating and reviews for enhancing the quality of the recommended product list. Moreover, they have designed a new two-fold algorithmic aware objective method for mitigating the popularity bias by grouping the uncertainty according to the item's similarity, popularity and user preferences. In addition, they have designed an evolutionary method aware serendipity objective optimized recommender system for optimizing the serendipity's conflicting components. Finally, they have proved that their system is proved as better than the existing systems in terms of precision, recall and serendipity.

Joseph et al.[21] applied the store item demand forecasting challenge dataset that is available in Kaggle for evaluating their model which is proposed by using the standard CNN and Bi-LSTM along with lazy adam optimizer for making accurate forecasting result of the product demands. At the end, they have proved that their system is superior than the available works by achieving better accuracy. Sharma and Sadagopan[22] presented a new system which consists of initial level of the data pre-processing, semantic word and feature extraction processes and classification to perform the data preprocessing include removal of stop words, stemming and removal of blank spaces, semantic aware feature selection and classification effectively. Finally, the selected features are used for enhancing the classification accuracy further by using deep belief network in which applies a tuned activation function with the help of an optimization method called Grey inked Chick update aware chicken swarm optimizer.

Mehbodniya et al.[23] designed a new automatic model to recommend the suitable products to the customers by analyzing the review comments and the user's requests. Moreover, they have done a normalization process to collect the better data and also perform the effective data preprocessing to extract the relevant features. At the end, a whale optimization method that works in evolutionary and random manner along with DBN to perform the feature optimization and classification. They have achieved 97% as product recommendation accuracy which is greater than the earlier recommendation system performance. All the available recommendation systems are useful for recommending the suitable products.

3. System architecture

The workflow of the newly developed APRS is shown in **Figure 1** that contains of ten important components namely Amazon data set, data collection agent, temporal agent, fuzzification, decision manager, rule manager, product recommendation system and knowledge base.

The Amazon dataset contains the various review comments including the Amazon review dataset that is extracted and collected by using the data collection module. Then, the collected data is forwarded to the semantic aware data preprocessing for performing initial level data preprocessing. The preprocessed data is moved to the feature selection and extraction module to extract the selected features. The selected features are optimized by applying the Flamingo Search Optimizer and it forwards them to classifier. The classification module applies the newly developed Fuzzy Temporal Multi Neural Classifier for performing effective classification that is used to predict the users purchase pattern and recommend the suitable products to the customers according to their requests. Finally, the products are to be recommended to the customers as "Excellent", "Very Good", "Good", "Average" and "Bad" by applying the newly generated fuzzy temporal rules.

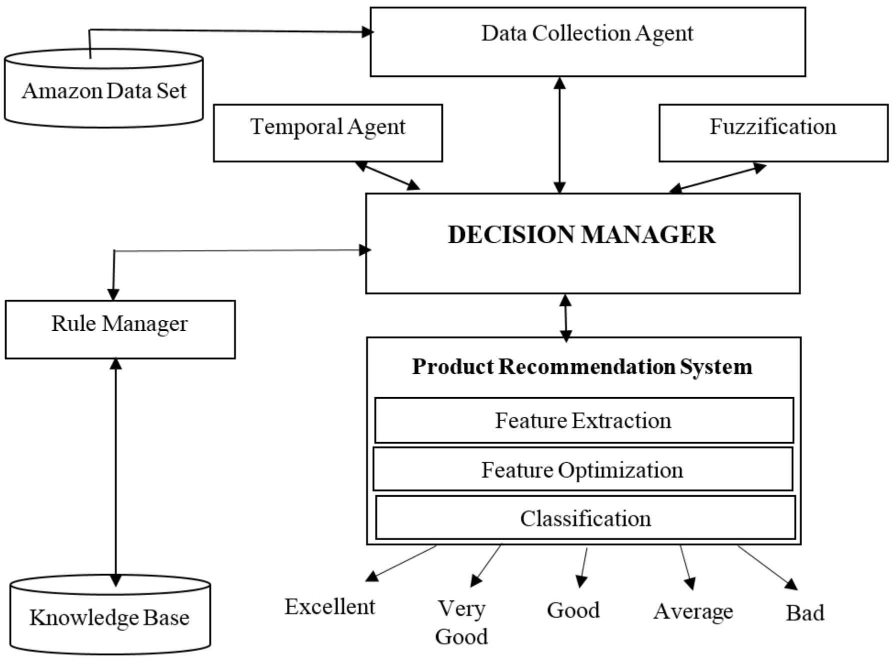

Figure 1. Overall architecture of the recommendation system.

4. Proposed system

This section described the newly developed automatic product recommendation system to recommend the suitable products to the customer in e-commerce applications by analyzing the customers reviews. The proposed recommendation system uses semantic aware data preprocessing, feature extraction and optimization, and classification. The initial level data preprocessing including blank space and stop word removal. The necessary features are selected and extracted. Moreover, this work applies Flamingo Search Optimizer (FSO) to optimize the extracted features. In addition, a new Fuzzy Temporal Multi Neural Classification Algorithm (FTMNCA) is also proposed to categorize the products effectively as "Excellent", "very Good", "Good", "Average" and "Bad" as prediction result. According to the product categorization, the system recommends the product to the customers. This section explains the data preprocessing.

4.1. Data preprocessing

This subsection explains the data preprocessing tasks namely stop word removal process, removal of stemming process and the removal of blank space.

Process of stop word removal: the frequently occurred characteristics that are arises in every record and the pronunciation of the attributes like it, he, she, etc., and the conjunctions like and, but, or, etc. to be removed these all terms that are not able to affect the classification process.

Stemming process: this process is the removal of prefixes and suffixes from the features that are done to decrease the features to the process of stemming. This stemming process is incorporated to decrease the count of attributes which exists the attribute space and also improves the performance of the classifier. For example: “take”, “takes”, “taken” and “taking”.

Removal of blank space: the additional blank spaces are enlarged the terms size and the blank spaces are to be terminated. The whitespace is substituted for the tab spaces and the key terms are to be extracted from every review of the dataset and also categorized into “Positive”, “Negative” and “Neutral”.

Feature extraction: the feature extraction process is performed to extract the features. It performs the semantic aware word extraction process is highly matched with the extracted key terms. According to the semantic score of each key term, the features are extracted.

4.2. Feature optimization

This section describes the feature optimization process by applying the Flamingos Search Optimizer (FSO) with necessary detail. Generally, the FSO works by considering three different features such as Communicative character, Beak scanning character and Bipedal mobile character. These are all the attributes are playing an important role in the process of identifying the suitable features from the set of features in a dataset. First, the communicative behavior of flamingos is to give group call to other flamingos for food once find any food anywhere. The location of the food is also identified according to the presence of the various flamingos. The exact location is to be identified by each flamingo according to the origin of group call. This work considers the flamingo has food in the *j*-th dimension that is xb_j. Second, the beak scanning behavior is a forage for food, heads dip downward, turn upside the mouth, eat the food and also discharging the extra water and dregs. When the area swept by the concern flamingo’s beak is greater food and it is useful for observing the area carefully and stretch out the neck slowly causes of beak and also increase the scanning area. Then, the maximum distance of the flamingo’s beak scan is quantified as $\left|G_1 \times xb_j + \varepsilon_2 \times x_{ij}\right|$, where ε_2 indicates a random number which is a range between -1 and 1. G_1 represents the random number that follows a general distribution process. The distribution process is introduced for simulating the scanning range of flamingo’s scanning behavior and their curve variation is also ranged as $G_2 \times |G_1 \times xb_j + \varepsilon_1 \times x_{ij}|$, where G_2 indicates a random number which is capable of responding the as per the distribution process. Third, the bipedal mobile behavior is a process of scanning the beaks and move towards the food where the group of flamingos available. Here, the food location is rich in the people is xb_j and the distance moved is counted as $\varepsilon_1 \times x_{ij}$, where ε_1 indicates the random number that is ranged between -1 and 1.

The flamingo’s moving step is searching in *t*-th iteration is the range between the flamingo beak and move their distance of the feet that is demonstrated in the formula present in Equation (1).

$$b_{ij}^t = \varepsilon_1 \times xb_j^t + G_2 \times |G_1 \times xb_j^t + \varepsilon_2 \times x_{ij}^t| \tag{1}$$

The Equation (2) is used to update position of flamingo foraging characteristic is

$$x_{ij}^{t+1} = (x_{ij}^t + \ \varepsilon_1 \times xb_j^t + G_2 \times |G_1 \times xb_j^t + \varepsilon_2 \times x_{ij}^t|)/K \tag{2}$$

where, the variable x_{ij}^{t+1} indicates position of the *i*-th flamingo's in *j*-th dimension of the population in *(t+1)*-th iteration, x_{ij}^{t} indicates the *i*-th flamingo's location in *j*-th dimension of the population in *t*-th iteration, xb_j^t indicates the *j*-th flamingo's position in *j*-th dimension of the population in *t*-th iteration. $K = K(n)$ means that the dispersion factor that is a random number that is followed the chi-square distribution of n degrees of freedom.

In the migration behavior of flamingo's, the population is migrating through the next area where the food is abundant. Let considers the food location in the *j*-th dimension is xb_j, the flamingo population is presented in in Equation (3).

$$x_{ij}^{t+1} = x_{ij}^{t} + \omega \times (xb_j^t + x_{ij}^t) \tag{3}$$

where, the variable x_{ij}^{t+1} indicates the *i*-th flamingo's position and the *j*-th dimension of the population in $(t + 1)$ iteration, x_{ij}^{t} indicates the *i*-th flamingo's position and the *j*-th dimension of the population in t iteration, xb_j^t indicates the *j*-th dimension flamingo's position with best fitness over the population in *t*-th iteration. $\omega = N(0, n)$ means that the Gaussian random number with n degrees of freedom that is applied for increasing search area while migrating the flamingos and also simulate each flamingo's characteristic in the process of migration.

The newly developed improved FSO is explained with necessary steps below:

Step 1: Finalize the initializing parameters.

Step 2: Initialize the flamingo population and set as P.

Step 3: Finalize the number of iterations is ITM and direct proportional to migrated flamingo.

Step 4: Calculate the fitness value for every flamingo.

Step 5: The low fitness of the earlier flamingos and the greater fitness with flamingo are regarded as migratory flamingo and the other flamingos are considered as hunting flamingos.

Step 6: The migrated flamingos are updated by applying the Equation (3) and the flamingos foraging are reorganized by using the Equation (2).

Step 7: Check whether the flamingos are within the threshold or not.

Step 8: If the maximum number of times executed and reached the ITM then

Returns the optimal features

Else

Go to step 2.

The improved FSO is used in this work to optimize the relevant features which are extracted in the process of feature extraction. Moreover, the selected optimal features are considered for identifying the relevancy of the users according to their interests. The FSOA is used in this work for performing effective optimization than the existing optimization techniques. All the other optimizers are ten years old and also consume more time and space to complete the optimization process. But the FSA is taken less time to process the data and also consumed less memory space. For this purpose, this paper is incorporated the FSA to perform feature optimization process effectively and efficiently.

4.3. Classification

This section explains the newly developed Fuzzy Temporal Multi Neural Classifier (FTMNC) that works according to the backpropagation neural network (BPNN) to predict the users interests and also recommends the suitable products to the customers. The proposed FTMNC works by using the fuzzy temporal rules over the BPNN with four different layers such as input, output and hidden layers. Here, the input layer finds the soft-max method as a fitness function and it forward to the output layer which are used to perform the prediction process through classification. The newly developed FTMNC for learning the fuzzy temporal rule like gradient descent approach. Moreover, the weights and bias values are adjusted by applying the fuzzy temporal rules. The newly developed FTMNC is explained with the following steps:

Fuzzy Temporal Multi Neural Classifier (FTMNC):

Step 1: Assign the weights to each layer with other 0 metric as initial level value.

Step 2: Read the input value IP_i and it finds the result by applying the Equations (4) and (5) by considering the specific time duration.

$$NNI_j < t1, t2 >= \sum_{i=1}^{n} w_{ij} x_i - b_j \tag{4}$$

$$NNO_j < t1, t2 >= f\left(NNI_j\right) < t1, t2 >= \frac{1}{1 + exp\ (-NNI_j)} < t1, t2 > \tag{5}$$

where, w_{ij} indicates the weight difference from the value of input to hidden layer.

Step 3: Get the input value of j and it finds the output of the second layer by applying Equations (6) and (7) with the consideration of time constraints.

$$NNI_c < t1, t2 >= \sum_{j=1}^{p} w_{cj}\ NNO_j - b_c < t1, t2 > \tag{6}$$

$$NNO_j < t1, t2 >= f(NNI_c) < t1, t2 >= \frac{1}{1 + exp(-NNI_c)} < t1, t2 > \tag{7}$$

Step 4: Find the output of the neuron y_k by applying the Equations (8) and (9).

$$sum_k < t1, t2 >= \sum_{c=1}^{q} W_{ck} NNO_c - b_k < t1, t2 > \tag{8}$$

$$y_k < t1, t2 >= p(sum_k) < t1, t2 >= \frac{e^{sum_k}}{\sum_{k=1}^{m} e^{sum_k}} < t1, t2 > \tag{9}$$

The soft-max function is applied an activation method with the consideration of necessary weights.

Step 5: Find the total mean square error (MSE) values by using the formula presented in Equation (10).

$$MSE_{Tot} < t1, t2 >= \frac{1}{2} \sum_{k=1}^{m} (d_k - y_k)^2 < t1, t2 > \tag{10}$$

where, the variable d_k represents the estimated output that is present kth and the y_k is the output of the actual value in neural classifier.

Step 6: The formula shown in Equation (11) is used to find the suitable weight from the specific output layer to processing layer and also the Equation (12) is used to find the weight difference from output layer to the processing layer for the specific time duration.

$$\delta_k < t1, t2 >= |y_k - d_k| < t1, t2 > \tag{11}$$

$$\delta_c < t1, t2 >= \sum_{k=1}^{m} w_{ck} d_k < t1, t2 > \tag{12}$$

$$\delta_j < t1, t2 >= \sum_{c=1}^{q} w_{cj} d_c < t1, t2 > \tag{13}$$

$$\Delta w_{ij} < t1, t2 >= \mu \delta_j \frac{\tau f_j(NNI_j)}{\tau(NNI_j)} x_i < t1, t2 > \tag{14}$$

$$\Delta w_{jc} < t1, t2 >= \mu \delta_c \frac{\tau f_j(NNI_c)}{\tau(NNI_c)} NNI_j < t1, t2 > \quad (15)$$

$$\Delta w_{ck} < t1, t2 >= \mu \delta_k \frac{\tau f_k(NNI_k)}{\tau(NNI_k)} NNI_c < t1, t2 > \quad (16)$$

Step 7: The learning rate is calculated by applying the Equations (17) to (19) for the specific time duration.

$$\Delta b_j < t1, t2 >= \mu \delta_j \frac{\tau f_j(NNI_j)}{\tau(NNI_j)} x_i < t1, t2 > \quad (17)$$

$$\Delta b_c < t1, t2 >= \mu \delta_c \frac{\tau f_j(NNI_c)}{\tau(NNI_c)} NNI_j < t1, t2 > \quad (18)$$

$$\Delta b_k < t1, t2 >= \mu \delta_k \frac{\tau f_k(NNI_k)}{\tau(NNI_k)} NNI_c < t1, t2 > \quad (19)$$

Step 8: Repeat the steps from step 1 to step 5 until get the less MSE value for the neural classifier.

Step 9: Call the fuzzy temporal rules to make effective decision over the inputs.

Step 10: Returns the result that are extracted from output layer.

The newly developed FTMNC performs the training process with enough times to find the best patterns for predicting the user interests and suitable products for the given input datasets that contains the various items and the relevant review comments. This work applies fuzzy temporal rules to make effective decision over the input datasets according to the time duration. The time is playing major role to recommend the suitable products to the customers according to their purchase interests shown over the specific products and also consider the feedbacks about the products over the specific time period. Generally, the Multi Neural Classifiers are capable of performing the effective multi-classification in effective manner. Moreover, the proposed FTMNCA is incorporated the fuzzy logic and temporal constraints that are useful for making effective decision on customers purchase history effectively and also recommends the exact likely product to the customers. For this purpose, this paper proposes and uses the FTMNCA.

5. Results and discussion

This section demonstrates the experimental results which are conducted for evaluating the proposed product recommendation system and the relevant discussion. The proposed APRS has been developed by using Python programming language and Kera's tensorflow in a personal computer with Intel i7 2.3 GHZ core processor with 16 GB RAM. The different levels and subjects of the contents are considered as input and the product review dataset which is available as Amazon dataset that has various users' feedback about the different products is also used for conducting various experiments and also to evaluate the proposed APRS. First, it explains the dataset used in this work.

5.1. Dataset description

The proposed APRS is evaluated by applying the famous benchmark dataset called Amazon dataset. Here, the Amazon dataset (https://www.kaggle.com/datasets/lokeshparab/amazon-products-dataset) is considered the kindle store items, books, magazines, CDs, toys, greeting cards, crafts and video games, grocery, office products, pantry, home and gourmet food. All these items are categorized into different datasets according to the type of products. The dataset is taken from online and categorized the customers' feedback according to the products purchased by them in various time periods in online. Here, we have considered 100 reviews for each product as sample and conducted experiments. In this work, we have considered the 70% as training dataset and 30% as testing dataset for conducting experiments.

5.2. Performance metrics

This section provides the three-evaluation metrics such as precision, recall and f-measure which are used to evaluate the proposed APRS. Here, the prediction accuracy of the proposed APRS is calculated by using the formulae given in Equations (20)–(22).

$$PV = \frac{No.of\ more\ relevant\ products}{Total\ no.of\ products\ considered} \tag{20}$$

where, the variable PV indicates the precision value.

$$RV = \frac{Total\ no.of\ relevant\ dproducts\ identified}{Total\ no.of\ products\ identified\ \ from\ repository} \tag{21}$$

where, the variable RV represents the recall value.

$$FV = 2 \times \frac{PV \times RV}{PV + RV} \tag{22}$$

where, the variable FV indicates the f-measure value.

Moreover, the prediction accuracy of the proposed APRS is calculated by using the Equation (23).

$$PA = \frac{PV + RV}{FV} \tag{23}$$

where, the variable PA indicates the precision accuracy.

5.3. Experimental results

First, the proposed APRS is proved as better than the existing systems that are developed by Islam and Alauddin[5], Perumal et al.[24], Karthik and Ganapathy[12], Shrivastava et al.[20] and Sharma and Sadagopan[22] based on the precision value that is demonstrated in **Figure 2**. Here, five experiments have been done by considering the various products according to the requests. In this work, all the kinds of products were considered to conduct the experiments.

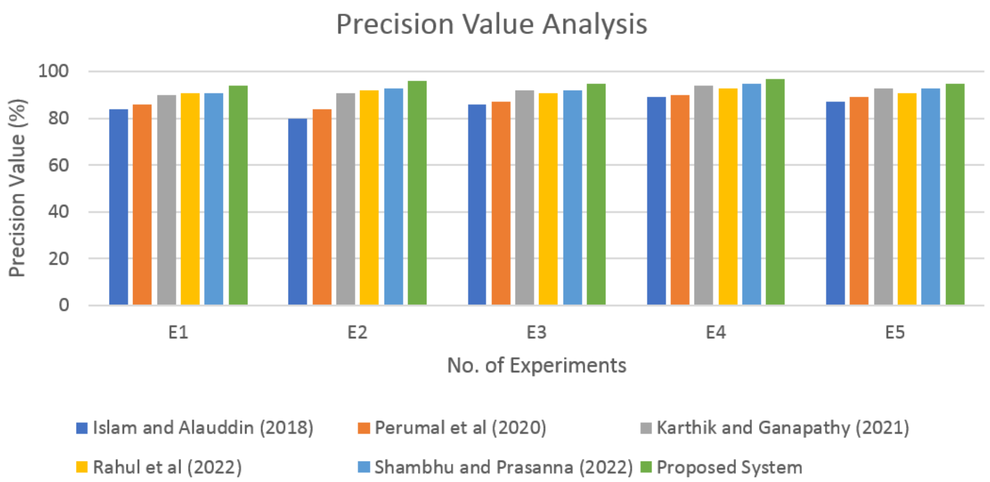

Figure 2. Performance analysis w.r.t precision value.

Figure 2 demonstrates the five experimental results with the consideration of various kinds of products and it shows that the proposed APRS is obtained better precision value than the available systems that are developed by Islam and Alauddin[5], Perumal et al.[24], Karthik and Ganapathy[12], Shrivastava et al.[20] and Sharma and Sadagopan[22]. This is due to the application of FSO, fuzzy temporal logic and Multi Neural Classifier.

The proposed APRS is proved as superior than the available systems that are developed by Islam and Alauddin[5], Perumal et al.[24], Karthik and Ganapathy[12], Shrivastava et al.[20] and Sharma and Sadagopan[22] based on the recall value that is demonstrated in **Figure 3**. Here, five experiments have been done by considering the various number of products for the users' requests. All these products are gathered from e-commerce websites and repositories for the various users. In this work, all kinds of products were considered for conducting experiments.

The proposed APRS is proved as superior than the available systems in **Figure 3** that considers five experimental results with the many reviews of different products. The proposed APRS is achieved better recall value than the available works that are developed by Islam and Alauddin[5], Perumal et al.[24], Karthik and Ganapathy[12], Shrivastava et al.[20] and Sharma and Sadagopan[22]. The reason for this better performance is the application of the Flamingos Search Optimizer, Fuzzy Temporal rules, Multi Neural Classifier.

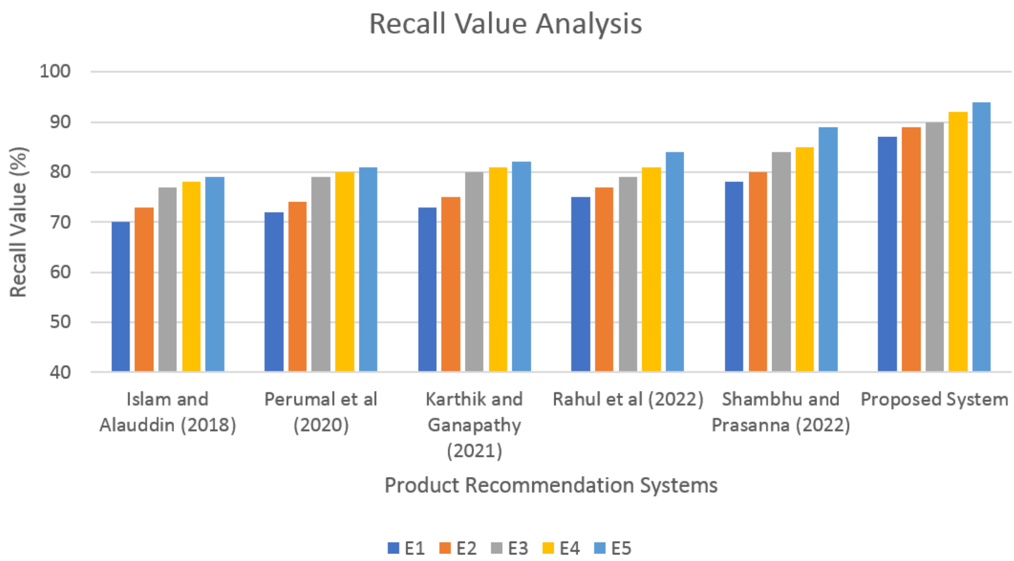

Figure 3. Recall value analysis.

The proposed APRS is proved as superior than the available systems that are developed by Islam and Alauddin[5], Perumal et al.[24], Karthik and Ganapathy[12], Shrivastava et al.[20] and Sharma and Sadagopan[22] based on the f-measure value that is demonstrated in **Figure 4**. Here, five experiments (E1, E2, E3, E4 and E5) are considered the different kinds of products. All these products details are collected from e-commerce websites and local repositories for the different kinds of users. In this work, all the kinds of products were considered for conducting experiments.

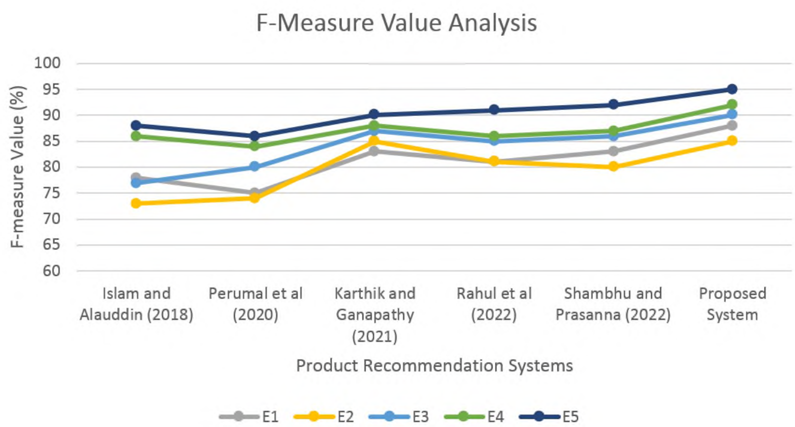

Figure 4. F-measure value analysis.

The proposed APRS is proved as superior than the available systems in **Figure 4** that has considered five experimental results by considering the different number of products. The proposed APRS is achieved better performance with respect to the recall value than the available systems that are developed by Islam and Alauddin[5], Perumal et al.[24], Karthik and Ganapathy[12], Shrivastava et al.[20] and Sharma and Sadagopan[22]. The reason for the achievement is the use of the Flamingos Search Optimizer, Fuzzy Temporal rules, Multi Neural Classifier.

Table 1 demonstrates the overall performance of the proposed APRS based on the evaluation metrics such as precision, recall, f-measure and accuracy. Islam and Alauddin[5], Perumal et al.[24], Karthik and Ganapathy[12], Shrivastava et al.[20] and Sharma and Sadagopan[22].

Table 1. Performance comparative analysis.

Content recommendation systems	Precision (%)	Recall (%)	F-measure (%)	Accuracy (%)
Islam and Alauddin[5]	90.29	93.17	94.07	93.52
Perumal et al.[7]	96.51	97.79	98.75	98.73
Karthik and Ganapathy[12]	97.42	98.31	98.84	98.78
Shrivastava et al.[20]	97.62	98.51	99.05	98.98
Sharma and Sadagopan[22]	98.72	98.42	98.87	98.65
Proposed APRS	99.54	99.73	99.75	99.61

Table 1 proved that the efficiency and effectiveness of the proposed content recommendation system based on the precision, recall, f-measure and the prediction accuracy. Here, the proposed system performance is superior than all the recommendation systems in all the performance metrics that are considered in this analysis. The reason for the enhancement is the incorporation of the Flamingos Search Optimizer, Fuzzy Temporal rules, and Multi Neural Classifier. This work uses the prediction accuracy as a final decision on every product recommendation. First, the relevant review comments are to be considered as input and processed by the proposed model. Second, it predicts the number of customers satisfied with the products when they purchased in a specific time duration and brand as well. It is calculated based on the number of positive comments appeared in the testing datasets. Finally, the proposed model recommends the suitable products to the customers and the number of products recommended by the system correctly is considered as prediction accuracy.

6. Conclusion and future works

In this work, a new APRS is developed to recommend the suitable products to the customer in e-commerce by analyzing the customers reviews. This recommendation system applies semantic aware data preprocessing, feature selection and extraction and classification. The initial level data preprocessing including blank space and stop word removal. Moreover, we use Flamingo Search Optimizer (FSO) for optimizing the features that are extracted in the initial level data preprocessing. In addition, a new Fuzzy Temporal Multi Neural Classification Algorithm (FTMNCA) is proposed for performing effective classification that is helpful for making effective decision on prediction process. The proposed automatic product recommendation system recommends the suitable products to the customers according to the classification result. Finally, the proposed system evaluates by conducting various experiments and proved as superior than the available systems in terms of accuracy. The limitation of this work is not considering the semantic analysis in feature selection and optimization process. Because, each word is capable of proving many meanings according to the places where used. For this purpose, the semantic analysis is necessary to predict the customers' interests exactly. So that this work can be enhanced further with the introduction of new semantic analysis aware feature selection method.

Author contributions

Conceptualization, BM and PR; methodology, BM; software, BM; validation, BM, PR and SC; formal analysis, BM; investigation, BM and SC; resources, BM; data curation, BM; writing—original draft preparation, BM; writing—review and editing, BM, PR and SC; visualization, BM; supervision, PR and SC; project administration, BM.

Conflict of interest

The authors declare no conflict of interests.

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