A New Fuzzy Lexicon Expansion and Sentiment Aware Recommendation System in e-Commerce

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***Abstract*—Customers' feedbacks are necessary for an online business to enrich themselves. The customers' feedback reflects the quality of the products and the e-commerce services. The companies are in a position to concentrate more and analyze the customers' feedback or reviews carefully by applying new techniques for predicting the current trends, customers' expectations, and the quality of their services. The e-business will succeed when one accurately predicts customer purchase patterns and expectations. For this purpose, we propose a new fuzzy logic incorporated sentiment analysis-based product recommendation system to predict the customers' needs and recommend suitable products successfully. The proposed system incorporates a newly developed sentiment analysis model which incorporates the classification through fuzzy temporal rules. Moreover, the basic level data preprocessing activities such as stemming, stop word removal, syntax analysis and tokenization are performed to enhance the sentiment classification accuracy. Finally, this product recommendation system recommends suitable products to the customers by predicting the customers' needs and expectations. The proposed system is evaluated using the Amazon dataset and proved better than the existing recommendation systems regarding precision, recall, serendipity and nDCG.**

***Keywords*—Classification; e-commerce; preprocessing; recommendation system; recurrent neural network; sentiment analysis**

I. Introduction

E-Commerce technology is growing fast due to rapid population development and technological adaptation. Most people are willing to complete their purchase from their place without visiting the shops online for an affordable cost. Today, people save their money and time with the help of e-commerce technology. They can purchase their items anytime online even though the e-commerce technology is in the position to fulfil the customers' requirements conveniently by providing good quality products. For this purpose, many e-commerce platforms are collecting feedback from their customers and trying to rectify the flaws, if there are any, by analyzing their feedback through sentiment analysis. This sentiment analysis can provide the customers' opinions on services and goods. Moreover, it is useful for enhancing service quality and fulfilling the customers' requirements as per their expectations. Moreover, the customers share their experiences, expectations, and comments about product quality. The sentiment analysis is applied to the review comments of the products and also predicts the customers' expectations and the current purchase trends [1].

Sentiment analysis is an important part of Natural Language Processing (NLP) which learns the exact meanings and the useful features of a review comment. The major objective of the sentiment analysis is to extract the sentiment entities and the features available in their review comments. Recently, social media usage has been drastically increasing daily, and people are sharing their purchase experiences by posting comments. Moreover, they spread their comments about their purchase experience and opinions to their friends and unknown circle through social media. So that every customer review comment also plays a role in the e-commerce platform, and if the specific product receives negative comments from a few customers, it also affects sales. Therefore, the e-commerce applications incorporated a sentiment analysis phase capable of categorizing the review comments such as an object, features of the object, meaning, holder and time of expression. Generally, the sentiment analysis finalizes the customer reviews as positive, negative, and neutral comments [2].

The sentiment analysis is categorized into three categories: statistics-based, knowledge-based, and hybrid. Among them, the knowledgebase-based method helps extract the features from the customer's reviews. Then the classification is performed over the reviews by applying the different Machine Learning (ML) algorithms such as the Naïve Bayes classifier, Support Vector Machine (SVM) and Maximum Entropy algorithm. Customers may have different sentiments over the various products using different entities and emotions. In this scenario, the system must apply multi-sentiment analysis to handle the different sentiments expressed in review comments and predict customer opinions on products. This kind of analysis is done by considering customer reviews collected from e-commerce websites, blogs, Facebook, Twitter, etc. Data preprocessing is also necessary before performing the sentiment classification. The basic data preprocessing [3] on review comments include syntax analysis, semantic analysis, tokenization etc. The data preprocessing steps can enhance the classification algorithm's performance.

Research Gaps*:* People are interested in purchasing products online. Here, people need help to choose their interests like products from the vast number of products.

To help society use e-commerce websites frequently, this paper proposes a new fuzzy aware sentiment classifier incorporated product recommendation system to recommend suitable products to the customers to satisfy their requirements. The contributions of this paper are listed below:

1) To propose a new product recommendation system to recommend suitable products to customers.

2) To apply basic level data preprocessing steps such as tokenization, syntax analysis and semantic analysis to extract the raw data from reviews.

3) To analyze the customers' reviews by applying the proposed sentiment analysis technique to know the customers' opinions on the products.

4) To introduce fuzzy temporal rules for making effective decisions on product recommendation.

5) Proved as better than the available systems regarding the precision value, recall value, f-measure value and prediction accuracy by conducting various experiments.

The remainder of this paper is formulated below: Section II explains the available works in the direction of sentiment analysis and recommendation systems. Section III provides an overall architecture of the system for understanding the entire system. Section IV explains the proposed model by providing the necessary backgrounds, data preprocessing, fuzzy rules and classification. Section V demonstrates the effectiveness and efficiency of the proposed product recommendation system. Section VI concludes the work with future direction.

II. Related Works

Sentiment analysis, content recommendation systems, product recommendation systems, feature selection and classification incorporated systems in the past by many researchers. Among them, Li and Feng [4] developed a new clustering algorithm using the Latent Class Regression method capable of considering product ratings and opinions for identifying the reviewer's choice. They have enhanced their method by considering the products' weighted features and proved them as better through experimental results. Jawa and Hasija [5] designed a new model that works according to the interest-aware graphs with the sentiment analysis to calculate the correlation value of different entities, and it also supplies suitable and relevant products in e-commerce.

Zhang et al. [6] built an aspect-based sentiment collaborative filtering model that combines sentiment analysis with fuzzy Kano. They have obtained the various attitudes of the customers according to the results of sentiment scores. Moreover, they have incorporated a new similarity measure technique with user choices for a collaborative filtering method. Ultimately, their model is proved better than other models by conducting experiments by applying the Amazon datasets. Karthik et al. [7] proposed a novel Feature aware Product Ranking and Recommendation Algorithm to provide suggestions for customers interested in purchasing good quality products. Their algorithm analyses the various products and their ranks based on the review comments provided by the customers who purchased and used the product. Ultimately, the algorithm suggests the products that are more suitable for the customers. It evaluates through experimental results and is also proven superior to the classical ML algorithms, including random forest and SVM.

Irfan et al. [8] proposed a hybrid framework that uses context-aware recommendation based on product ratings and customer reviews. They have used text mining methods over large-scale user item feedback to calculate the sentiment scores. Moreover, they have proposed a greedy heuristic method for producing the item ranks according to the customers' similarities. The major advantage of their framework is the consideration of purchase similarities and the greedy search method. Dau and Salim [9] developed a new sentiment analysis incorporating deep learning technique-based recommendation system that considers the various aspects of products and the customer's sentiments that are used to improve the recommendation accuracy. They have mainly designed a semi-supervised topic modelling model for extracting product aspects associated with lexicons from customer reviews. They also have used long short-term memory (LSTM) encoder to achieve better product recommendation performance than other models.

Wang et al. [10] proposed sentiment matrix factors, sentiment scores and the reviews-based recommendation model to predict suitable content. Initially, they analyzed various topics and reviewed comments by applying the lexicon construction and Latent Dirichlet Allocation (LDA) methods. Then, they combined the user consistency computed using their review comments on products and the ratings. Next, they have integrated the reliability measurement of topics and sentiment analysis on review comments. Finally, they proved that their model is superior to other product recommendation systems. Hu et al. [11] proposed an enhanced recommendation model that considers the interests, credibility and sentiment scores. Their model consists of five different modules for performing the recommendation process, feature sentiment assignment, user interests, credibility analysis and feature extraction process. They have considered the customer's opinions on their liked products and the trust scores of the customer's review comments. Finally, they have made product decisions using weighted sentiment scores and features.

Mohammad et al. [12] developed two new lexicon generation approaches to handle aspect-based issues that use statistical methods and genetic algorithms. They have proved that their models as better than the existing approaches. Karthik and Ganapathy [13] developed a new approach called Multi scenario demographic hybrid with necessary and useful features, including users' ages and locations. Moreover, they have ranked the available products according to age group and purchase locations. Finally, their system is proven superior based on prediction accuracy.

Zarzour et al. [14] designed an architecture incorporating deep learning technique-based sentiment analysis to predict review comments. Their architecture has two major components: LSTM and Gated Recurrent Unit (GRU) methods. Finally, they evaluated their architecture by conducting experiments using the actual purchase and Amazon datasets and achieving better prediction accuracy. Munuswamy et al. [15] developed a novel rating and sentiment-aware content prediction method to build a recommendation system to mine valuable data from customer reviews or product feedback. Their algorithm helps predict the people who liked products by considering the ratings. Their algorithm uses a dictionary to calculate the sentiment scores to recommend the exact items. In the end, their method obtained superior prediction accuracy than available methods. Karthik and Ganapathy [1] developed a fuzzy aware product recommendation system capable of predicting the suitable products for the customers based on their interests in e-commerce. They calculated the sentimental score for each product, used them to form fuzzy rules, and stored them in an ontological table for making final decisions. Finally, they have proved that their system is superior by achieving better results in the majority of experiments on various sizes of datasets.

Wenxiong et al. [16] built a novel multi-level graph-based neural classifier for performing the sentiment analysis over their review comments. They have applied node connection windows to consider local and global features. Specifically, they have integrated a message-passing system that considers the scaled dot-product attention to fuse the features. Huiliang et al. [17] proposed a new neural classifier that applies an improved Bat Algorithm and Elman Neural Network to analyze the reviews of the products. Their method consists of four important steps: data collection, feature selection and sentimental classification. In their work, they have used Web Scrapping Tool to extract customer reviews about the products from e-commerce websites. The preprocessed data is categorized as positive, negative and neutral. Finally, they have achieved superior prediction accuracy than the available systems.

Abolfazl et al. [18] designed an automated model for performing effective sentiment analysis of customer review comments. They have considered the feature extraction process by incorporating the Term frequency, Inverse document frequency. They also speed up robust and local binary patterns to extract the features from pre-processed data. Finally, they have integrated the Deep Belief Network and Whale Optimization Method to perform feature optimization and sentiment classification. They have obtained around 97% classification accuracy, which is superior to other classifiers. Antony et al. [19] proposed a novel product recommender to predict suitable customer products. Their recommendation system incorporates the bidirectional encoder and the attention-based sequential recommendation system for effective classification. They have compared their system with other models and proved it superior.

Yao et al. [20] proposed a deep product recommender that considers the sentiment analysis of review comments and the product ranking. They applied the deep learning technique to map the extracted features and the ranking-based latent factor. Many experiments have been conducted using Amazon datasets and obtained higher accuracy than the available models in this direction. Rosewelt and Renjith [21] built a new method for enhancing the product recommendation systems' performance by deeply analyzing product reviews and the customer’s purchase behaviours. They have considered the product features, feedback, and not-liked product features to improve prediction accuracy.

III. System Architecture

Fig. 1 demonstrates that the proposed product recommendation system's workflow consists of four important components: Amazon Dataset, User Interaction Module, Decision Manager and Product Recommendation System, which has three different phases Sentiment Analyzer, Data Preprocessing and Sentiment Classification Module.

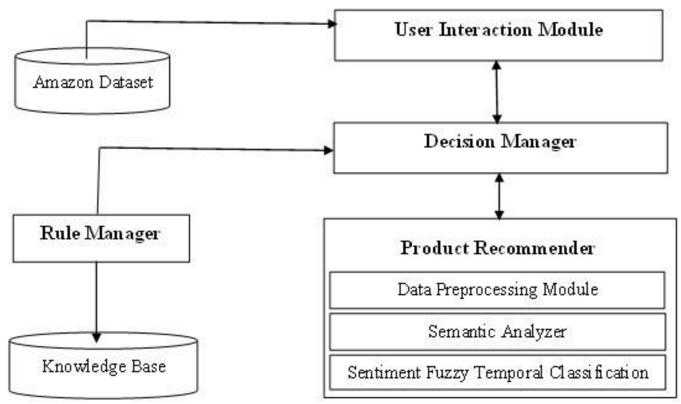

Fig. 1. System architecture.

The user interaction module extracts the necessary data from the Amazon dataset. The decision manager receives the extracted data and forwards them to the product recommender. The product recommender has three important phases: data preprocessing, sentiment analyzer and sentiment classification. The data preprocessing module performs the data preprocessing tasks, including stemming, stop word removal, tokenization and syntax analysis. Finally, the preprocessed data is to be moved to the sentiment analyzer capable of analyzing the data as per sentiments. The sentiment analyzer performs the sentiment analysis and forwards it to the sentiment classification by applying the classifier and considering fuzzy temporal rules. The decision manager makes effective decisions on the sentiment classification process by applying the fuzzy temporal rules stored in the knowledge base through the rule manager. Generally, the knowledge base contains the rules and facts. The rule manager is used to manage the rules available in the knowledge base based on the suggestions of the decision manager. The Amazon dataset contains the customers' purchase history and feedback as review comments.

IV. Proposed Work

This work proposes a new product recommendation system that incorporates the data preprocessing technique and classification. The data preprocessing technique incorporates the newly developed weighted topic-aware lexicon expansion for performing effective preprocessing. The sentiment classification is also adopted for enhancing the data preprocessing processes capable of identifying the effective features to enhance the classification accuracy. The classification adopts the newly developed Fuzzy Temporal Product Recommendation Algorithm to identify suitable liked products for customers according to their interests.

A. Data Preprocessing

Data preprocessing consists of two important preprocessing tasks: lexicon expansion and sentiment classification. Before that, the basic data preprocessing,, including tokenization, POS (Parts of Speech) tagging and parsing, are useful for performing effective data preprocessing tasks in this work. Here, a new data preprocessing method called Fuzzy Weighted Product based Lexicon Expansion Method (FWP-LPM) is finalizing the preprocessed content. First, it explains this work's fuzzy logic and rules for performing data preprocessing and classification tasks.

1) Fuzzy logic and fuzzy rules: The fuzzy set theory was proposed by Zadeh [22]. Many applications in the real world cannot make decisions with certainty. This is because many phenomena in this world are fuzzy in nature. The crisp sets make decisions by manipulating formulas that can hold values of 1 and 0 only. Therefore, the logic, such as propositional logic and the first order predicate logic can only manipulate the formulas to make a true or false decision. However, the world consists of facts that are probabilistic in nature. Hence, it is necessary to perform the gradation of truth values. This type of gradation can help to perform qualitative reasoning as well as quantitative reasoning. Fuzzy logic provides operators and membership functions for converting the crisp set values into fuzzy linguistic values so that it is possible to perform reasoning under uncertainty.

A fuzzy inference system is capable of performing qualitative reasoning through the effective application of fuzzy rules. The fuzzy rules are formed according to the fuzzy membership functions like triangular, trapezoidal and Gaussian membership functions. Moreover, the fuzzy rules are represented in the form of IF…. THEN rules. The other type of format used for representing rules are Event, Condition and Action rules which are also represented using ON Event, IF (Cond) THEN rules and both these types of rules can be used for making inferences. In a fuzzy inference system, there are two modules in which the first module performs the fuzzification process. Here, the quantitative values are converted into qualitative and linguistic variables. In the de-fuzzification process, the qualitative rules and values are converted into quantitative values. The fuzzy rules can be used to adjust weight in the neural network-based classification algorithms to increase classification accuracy. In other classifiers, fuzzy rules can aid in decision-making by handling the uncertainty in the classification process.

2) Basic data preprocessing tasks: This subsection explains the tokenization, POS Tagging and Parsing in detail. These preprocessing tasks help perform effective classification.

a) Tokenization: The feedback is categorized into various tokens or words or terms. The sequence is identified and grouped as meaningful content according to the term relevancy. The review comments contain the terms "fantastic product", "good", "liked products" and "Worthy products" to perform the processes of morphological analysis and tokenization. Here, the tokenization is done and you get the terms like good, fantastic, like, and worthy. In addition, the stop words are also removed from the feedback or comments on products.

b) POS tagging: It provides the data on how the terms are applied in a sentence and also identifies the "Nouns", "Pronouns", "Adjectives" and "Verbs" are tagged on tokens. Moreover, it labels the terms over the POS tagging. Every token is identified and tagged with POS, which is used for identifying the suitable terms to predict the user's interest.

*c) Parsing: I*t provides a standard grammatical structure for any input sentence. Here, the parsing model groups the words according to their relevancy. In this work, the parsing model constructs a parse tree by considering the words relevancy in terms of subject or object.

3) Weighted topic (product) based lexicon expansion: The lexicon analysis is used to find the difference between the input content and the common opinion or meaning of the term. This work considers the relevancy between two terms with closure sentiment scores and relevant meaning. In this work, the polarity of the expression with less emotion is also calculated as the value of Weighted Point based Mutual Information (WPMI) simply between any two input terms using the formula given in (1).

$$WPMI\ (t1, t2) = log_2\left(\frac{p(t1,t2)}{p(t1)p(t2)}\right) * WT \quad (1)$$

Where, t1 and t2 are the different input terms or words, p indicates the probability, and WT represents the weight that is the common difference between the two terms.

The term's or word's orientation value semantically is demonstrated by using (2).

$$SOT(T) = WPMI(T, Pos) - WPMI(T, Neg) \quad (2)$$

Where, Pos means positive (+ve) and Neg means negative (−ve), T represents the token.

Generally, two different assumptions are considered in this work. First, the sentiment orientation of emotions such as ":)" and ":(" is stable relatively throughout the entire comments. Here, the positive and negative signs and comments on products are useful for knowing the two extreme statuses of the product in the market. Second, the comment on a product is not valid over the products with negations. For example, "I don't like this product". This comment is a negative comment about a product. Now, the polarity value of their opinion is measured by computing the relevancy score between the terms. The sentiment orientation on a product is calculated using (3).

$$SO(T) = log_2\left(\frac{H(T,Pos)\times H(Neg)}{H(T,Neg)\times H(Pos)}\right) \quad (3)$$

Where, H indicates the hits. The sentiment may not be applicable to some terms in comments. In this scenario, the POS tags of the terms can be applied for identifying the potential and useful terms that include "Adjectives", "Nouns", "Pronouns", "Verb" and "Intersections". This set of tags was identified and selected after conducting the experiments with various combinations of tag sets and applying this set to perform the classification effectively.

Fuzzy Weighted Product based Lexicon Expansion Method (FWP-LPM)

Input: Feedback or Review Comments and sales data

Output: Preprocessed Content

Step 1: Read the feedback about a specific product {FBp1, FBp2. . . .FBPn}

Step 2: Perform the tokenization process and extracts the terms as tokens.

Step 3: Perform the POS Tagging process and extracts the terms with parts of speech.

Step 4: Perform the Parsing process and construct the parse tree to provide the useful terms.

Step 5: Find the value of Weighted Point based Mutual Information (WPMI) for the two adjacent terms of the input terms using (1).

Step 6: Find the orientation of the sentiment score for the input term of a product by using (2) and (3), and also consider the sales history of the input data.

Step 7: Apply the Fuzzy Rules to finalize the terms.

Step 8: Return the preprocessed terms/contents.

The newly developed FWP-LPM is applied for performing the data preprocessing and is useful for extracting the preprocessed content.

4) Sentiment classification: This section describes the sentiment score calculation procedure used in this work to identify users' interest in the products through their comments/feedback. The product rating is calculated using the relevant feedback by applying the newly developed product ranking algorithm (PRA). Here, the sentiment polarity and product rank in the form of a score is summed up as a sentiment score. First, the product ranking process is explained in this section.

a) Product ranking: The average product score (PS_(p,u)) is computed by applying (4).Fuzzy Weighted Product based Lexicon Expansion Method (FWP-LPM)

$$PS_{p,u} = \sum_{i=1}^{TP_{p,u}} (SSi_{p,u}) \tag{4}$$

Where, $TP_{p,u}$ represents the number of feedbacks received and considered for the respective product. The overall ranking of the product is computed by applying (5).

$$POR_{p,u} = \frac{OR_p * NOF}{PS_{p,u}} \tag{5}$$

Where, the variable OR_p indicates the overall rank of the specific product and the variable NOF indicates the number of feedbacks considered for the specific product in this work.

In this way, the rank is to be identified for each product according to the feedback and also consider the current purchase behaviour of the users. Moreover, the similarity between the products is also considered in this work by applying the Cosine similarity formula that is given in (6).

$$CosineSim(p_i, p_j) = \frac{p_i . p_j^T}{\|p_i\| * \|p_j\|} \tag{6}$$

The cosine similarity value between the two products is useful for finalizing the specific product rank and product classification processes. This cosine similarity also plays an important role in the decision-making process in the various recommendation systems. In this work, the similarity value of each product must be below the threshold. The average cosine similarity value is considered a threshold value.

B. Classification

The classification is performed by applying a newly developed Fuzzy Temporal and Sentiment awareness Product Recommendation Algorithm (FTS-PRA) in their work to predict the user's interests and to recommend suitable products. The fuzzy logic is applied in this work for making effective decisions over the product recommendation process. Moreover, this paper uses the standard triangular fuzzy membership function to generate the fuzzy rules. In the process of fuzzy rule generation, time is also considered an important parameter. The reason is for considering the temporal feature for enhancing the prediction accuracy. The steps of the FTS-PRA are as follows:

Fuzzy Temporal and Sentiment aware Product Recommendation Algorithm (FTS-PRA):

Input: Feedback or Review Comments, sales data

Output: Recommended product

Step 1: Read the feedback about a specific product {FBp1, FBp2. . . .FBPn}

Step 2: Apply basic preprocessing tasks

Step 3: Apply Weighted Product based Lexicon Expansion along with sentiment score.

Step 4: Check whether the specific product similarity value is below the threshold and sold out reasonable numbers.

Step 5: Calculate the product ranking score for the product by applying (3) and (4).

Step 6: Apply the Fuzzy Temporal Rules

Step 7: Perform the sentiment classification and initiate the product recommendation process

Step 8: Recommend a suitable product to the customer/user.

The newly developed FTS-PRA is used to predict the user purchase pattern and the suitable products by analyzing the feedback of the customers who purchased the product early. First, it reads the product's feedback and performs the preprocessing tasks including Tokenization process, POS Tagging process and Parsing. Moreover, this algorithm applies the newly developed weighted product-based Lexicon expansion with a semantic score method to retrieve the most useful contents from feedback. Next, the product similarity is calculated by considering the feedback analysis. Then, based on the sentiment classification result, find the product score for the products and also recommend the product to the users. Finally, it recommends the product to the customer.

V. Result and Discussion

This section demonstrates the experimental results for evaluating the proposed system and the relevant discussion. First, it explains the dataset used in this work.

A. Dataset

The proposed system is evaluated using the famous benchmark dataset, the Amazon dataset. The Amazon 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.

Amazon Sales Dataset 2023*:* The Amazon sales dataset 2023 [25] has sales records. The sales records contain the details about the products, sales time and date and the frequency of sales with the number of items sold out for the specific time duration [25].

B. Performance Metrics

The proposed system is evaluated by considering the standard evaluation metrics including Precision and Recall metrics shown in (7) and (8).

$$Precision = \frac{Relevant\ Recomended\ Products}{Total\ Recomended\ Products} \tag{7}$$

$$Recall = \frac{Relevant\ Recomended\ Products}{Total\ no.of\ relevanted\ products\ to\ be\ Recomended} \tag{8}$$

This work focuses on the precision value and recommends the same product repeatedly that may be different from what users liked. In this scenario, the product recommendation can be based on metrics such as Serendipity and nDCG.

a) Serendipity: This metric is very useful for recommending a suitable product to the user. Serendipity value is computed by applying the formula shown in (9).

$$P_x = \frac{no.-rank_x}{no.-1} \tag{9}$$

b) nDCG: This metric is useful for identifying the user's liked products and recommending them for purchase. The ncDCG value helps check the correctness of the recommended product described in (10).

$$nDCG(L,k) = \frac{1}{|L|}\sum_{x=1}^{|L|} Z_{kx} \sum_{m=1}^{k} \frac{2^{R(x,m)}-1}{log_2(1+m)'} \tag{10}$$

C. Experimental Results

The experiments are done with different sets of records as separate datasets such as DS1, DS2, DS3, DS4, DS5 and DS6. These datasets contain different products with various numbers of records. Fig. 2 demonstrates the precision value analysis between the proposed model and the existing models like the Fuzzy recommendation system (Sankar et al. [2]), MDH Approach (Karthik and Ganapathy [13]), Fuzzy Recommendation System (Karthik and Ganapathy [1]).

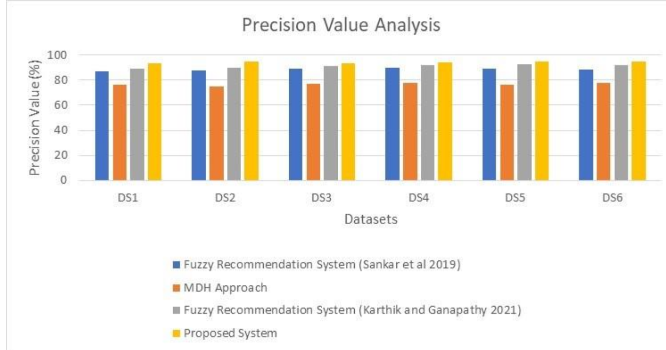

Fig. 2. Precision value analysis.

Discussion: Fig. 2 demonstrates that the performance of the proposed model is proved as better than the available models like the Fuzzy recommendation system (Sankar et al. [2]), MDH Approach (Karthik and Ganapathy [13]), Fuzzy Recommendation System (Karthik and Ganapathy [1]).

Reason for the Enhancement: The performance is using a weighted topic-based lexicon expansion method, sentiment analysis and fuzzy temporal rules.

Fig. 3 shows the recall value analysis between the proposed model and the existing models like the Fuzzy recommendation system (Sankar et al. [2], MDH Approach (Karthik and Ganapathy [13]), Fuzzy Recommendation System (Karthik and Ganapathy [1]).

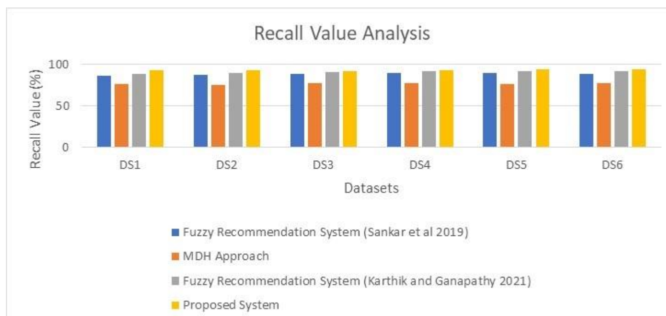

Fig. 3. Recall value analysis.

Discussion: Fig. 3 shows the performance of the proposed model that is proved as superior in terms of recall value than the available product recommendation systems such as Fuzzy recommendation system (Sankar et al. [2]), MDH Approach (Karthik and Ganapathy [13]), Fuzzy Recommendation System (Karthik and Ganapathy [1]).

Reason for the Enhancement: The reason for the enhancement here is the use of weighted topic-based lexicon expansion method, sentiment analysis and fuzzy temporal rules.

Fig. 4 shows the Serendipity value analysis between the proposed model and the available recommendation systems like Fuzzy recommendation system (Sankar et al. [2]), MDH Approach (Karthik and Ganapathy [13]), Fuzzy Recommendation System (Karthik and Ganapathy [1]).

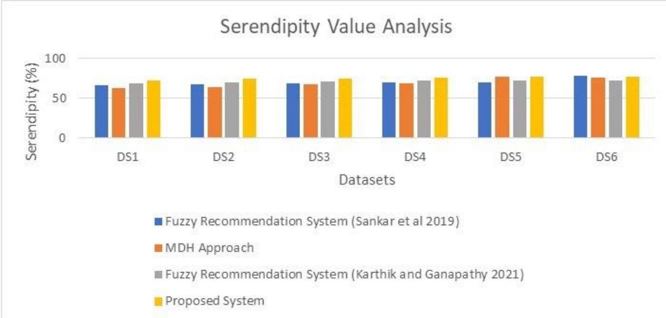

Fig. 4. Serendipity value analysis.

Discussion: Fig. 4 shows the serendipity value of the proposed model which achieves superior value than the available models like the Fuzzy recommendation system (Sankar et al. [2]), MDH Approach (Karthik and Ganapathy [13]), Fuzzy Recommendation System (Karthik and Ganapathy [1]).

Reason for the Enhancement: This better enhancement is applying weighted topic-based lexicon expansion method, sentiment analysis and fuzzy temporal rules.

Fig. 5 demonstrates the nDCG value analysis between the proposed model and the available models like the Fuzzy recommendation system (Sankar et al. [2]), MDH Approach (Karthik and Ganapathy [13]), Fuzzy Recommendation System (Karthik and Ganapathy [1]).

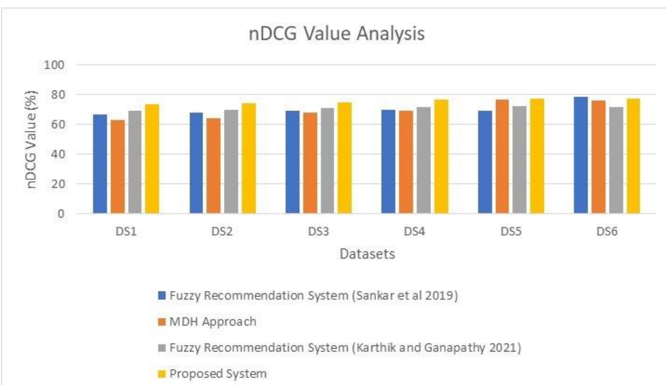

Fig. 5. nDCG value analysis.

Discussion: Fig. 5 shows the achievement of better nDCG value than the available models like the Fuzzy recommendation system (Sankar et al. [2]), MDH Approach (Karthik and Ganapathy [13]), Fuzzy Recommendation System (Karthik and Ganapathy [1]).

Reason for the Enhancement: This betterment applies a weighted topic-based lexicon expansion method, sentiment analysis and fuzzy temporal rules.

Table 1 shows the comparative outcome analysis between the proposed and available product recommender models. The proposed product recommendation system considers the evaluation metrics such as precision, recall, serendipity and nDCG. It implies that a new product is recommended based on the context and relevant to current user interest. This improves user satisfaction as well. Table 1 shows the consolidated results with the conducted results. Both recommendation-specific metrics Serendipity and nDCG are improved without impacting or compromising the precision and recall.

TABLE I. COMPARATIVE OUTCOME ANALYSIS

Recommendation system	Precision	Recall	Serendipity	nDCG
FBPRR	0.32	0.15	0.022	0.23
Fuzzy rule	0.52	0.32	0.024	0.25
MDH	0.45	0.45	0.02	0.21
Fuzzy recommendation	0.49	0.49	0.04	0.34
Product Recommendation System	0.50	0.49	0.041	0.36
Personalized Recommendation System	0.51	0.51	0.042	0.37
Proposed System	0.52	0.52	0.045	0.38

Discussion: Table 1 shows the better achievement of the proposed recommender model according to the evaluation parameters such as precision value, recall value, serendipity value and nDCG value than the available recommenders like the Fuzzy recommendation system (Sankar et al. [2]), MDH Approach (Karthik and Ganapathy [13]), Fuzzy Recommendation System (Karthik and Ganapathy [1]), Product Recommendation System [23] and Personalized Product Recommendation System [24].

Reason for the Enhancement: This achievement applies a weighted topic-based lexicon expansion method, sentiment analysis and fuzzy temporal rules.

Table 2 shows the time analysis between the proposed and existing product recommendation systems. Here, the experiments have been done with randomly selected 700 records as training datasets and 300 records are given as testing datasets from the Amazon sales dataset 2023 and Amazon Product Review Dataset for this time analysis.

TABLE II. TIME ANALYSIS

Recommendation system	Training Time (sec)	Testing Time (sec)
FBPRR	0.41	0.19
Fuzzy rule	0.40	0.18
MDH	0.39	0.17
Fuzzy recommendation	0.39	0.17
Product Recommendation System	0.38	0.16
Personalized Recommendation System	0.37	0.15
Proposed System	0.34	0.14

Discussion: Table 2 shows the better achievement of the proposed recommender model with respect to the training and testing time than the available recommenders like the Fuzzy recommendation system (Sankar et al. [2]), MDH Approach (Karthik and Ganapathy [13]), Fuzzy Recommendation System (Karthik and Ganapathy [1]), Product Recommendation System [23] and Personalized Product Recommendation System [24].

Reason for the Enhancement: This efficiency betterment is considering time constraints and applying a weighted topic-based lexicon expansion method, sentiment analysis and fuzzy temporal rules.

VI. Conclusion and Future Works

In this work, a new fuzzy logic incorporated sentiment analysis-based product recommendation system is developed to predict the customer's need and recommend suitable products successfully. The proposed system incorporates a newly developed sentiment analysis model which incorporates the classification through fuzzy temporal rules. Moreover, the basic level data preprocessing activities such as stemming, stop word removal, syntax analysis and tokenization are performed to enhance the sentiment classification accuracy. Finally, the proposed product recommendation system recommends suitable products to the customers by predicting the customer's needs and expectations. The proposed system is evaluated using the Amazon dataset and proved superior to the existing recommendation systems in terms of precision, recall, serendipity and nDCG values. This work can be further enhanced by introducing a deep learning algorithm for classification instead of a normal machine learning classifier.

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