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A New Sentiment and Fuzzy Aware Product Recommendation System Using Weighted Aquila Optimization and GRNN in e-Commerce

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Customer reviews are playing an important role in e-commerce for increasing sales by knowing the customer's purchase pattern and expectations. The reviews that are collected after completing their purchase reflect the quality and services in e-commerce. The user's reviews are characterized and categorized through sentiment and semantic analysis. Moreover, the sentiment and semantic classification processes are also performed to predict the user's purchase patterns and liked products. However, the available classification is not able to predict the user's purchase patterns. This paper propose a new Product Recommendation System (PRS) to predict the appropriate product for users based on their purchase behavior and pattern. The proposed recommendation system incorporates the standard data preprocessing tasks like tokenization process, Parts of Speech (PoS) tagging process, and parsing, a new sentiment and semantic score calculation procedure, and a new feature optimization technique called the Weighted Aquila Optimization Method (WAOM). Moreover, the sentiment and semantic classification processes are performed by applying a General Regression Neural Network with the incorporation of fuzzy temporal features (FTGRNN) and obtaining better classification results. The novelty of this work is the introduction of new PRS with the incorporation of new feature optimizer and new fuzzy temporal neural classifier to predict the suitable products to the users. The experiments were conducted in this work to evaluate the proposed PRS and obtained superior performance than other systems available in this direction in terms of prediction accuracy, precision, recall, serendipity and nDCG.

KEYWORDS: Sentiment Analysis, Semantic Analysis, Data preprocessing, Feature Optimization, Fuzzy temporal rules and Convolutional Neural Network.

1. Introduction

E-commerce is necessary in this fast world due to the enormous development of technology and the growth of the population. Consumers can consume their favorite products from anywhere and anytime. Online shopping saves time and energy. In addition, customers can buy their favourite products from the place itself from the enormous variety of items. Even though, the customers are facing issues like low quality products, inconsistency, imperfect after purchasing, etc. while purchasing the products online with the help of e-commerce websites instead of offline shopping. The customer reviews are important in e-commerce platform and resolving the purchase issues by analyzing the customer reviews. Many e-commerce applications are concentrating on developing their own review systems. The review systems provide the opportunity to share their experience, and the related company can analyze the customer reviews and rectify the mistakes, improving the customer service by increasing the product quality. Apart from their own review system, the customers can freely reveal their opinions and experiences through suggestions and opinions about various products. In this scenario, the company needs to collect the review comments from various social media like Facebook, Twitter, Instagram, etc. and analyze them to know the current trends and customer purchase patterns and improve their sales.

Review comments on various products are helpful for making purchase decisions. In this scenario, the various review comments of customers are assumed to be trustworthy. Before initiating the online purchase, the user will collect the opinions of his / her friends about the product, solicit their suggestions, and then make a decision. Moreover, the review comments are to be analyzed by applying sentiment and semantic analysis. Sentiment analysis on review comments of the products is helpful for other customers and also useful for improving the business through their e-commerce platforms. Generally, sentiment analysis is helpful for determining the text orientation that refers to the customer's opinions on products effectively. The lexicon aware sentiment technique is used to develop a sentiment lexicon that selects the suitable sentiment terms, positive terms, negative terms, polarity, and degree adverbs that are marked for the development of a sentiment lexicon. Moreover, the terms in the review comments are matched with the sentiment terms in sentiment lexicon process. In addition, the sentiment terms are matched and arranged based on their weights and summed up for obtaining the sentiment score that determines the sentiment polarity value for the terms.

Data preprocessing is important in the processes of sentiment analysis and classification. The initial level of text processing is done by performing the tokenization, parts of speech (POS) tagging, and parsing that is helpful for performing sentiment classification. Apart from this basic text processing, the terms are to be identified as positive, negative, or neutral terms. Moreover, these terms are identified as attributes which are used to improve the accuracy. The features are to be optimized by applying the standard optimization methods. The optimized features or terms are capable of improving the sentiment classification accuracy.

Sentiment and semantic classifications are performed by applying the standard Machine Learning (ML) algorithms namely Naive Bayes (NB), etc. The classification accuracy is enhanced further by increasing the training process through Deep Learning (DL) algorithms. The traditional ML and DL algorithms are used for performing sentiment classification. Moreover, the fuzzy rules were applied to ML and DL algorithms for making effective decisions on prediction processes. In addition, the ML algorithms are incorporated into DL algorithms to enhance the classification accuracy. The hyper-parameter tuning process is also done on ML and DL algorithms to greatly improve the sentiment classification accuracy in a short span of time. Semantic analysis is also useful for predicting the purchase behaviour of customers. Finally, the sentiment and semantic scores are calculated and used for making final decisions on the prediction process.

In this work, a new PRS is developed with the incorporation of the data preprocessing, sentiment analysis, feature optimization and sentiment classification processes that are useful for predicting the user's liked products and recommending them to the customers according to their interests. The major contributions of this work as below:

1. To recommend a new product to customers based on their interests.
2. To identify useful terms, use data preprocessing tasks like POS tagging, parsing and tokenization.
3. To propose a new optimization algorithm called the Weighted Aquila Optimization Method (WAOM) for optimizing the features (terms) that are helpful for knowing the user's interests or liked products exactly.
4. To calculate the sentiment scores, which are useful for finalizing the key terms, positive, negative, and neutral terms.
5. To generate fuzzy temporal rules for making final decisions on sentiment classification processes by using GRNN along with fuzzy temporal rules effectively.
6. To obtain better in all the performance metrics considered in this work.

The novelty of this work is the proposal of a new PRS with the incorporation of new optimizer and new fuzzy temporal neural classifier to predict the suitable products to the users.

The remainder of this paper is presented as below: Section 2 describes the relevant research works in the areas of e-commerce, text pre-processing, sentiment and semantic classification processes, emphasizing the benefits and drawbacks. The workflow of the entire system is presented with necessary components in Section 3 through the overall architecture. The proposed PRS is explained with necessary details along with the required equations in Section 4. The results are demonstrated with justification for each significant number in Section 5. The proposed system is concluded by listing the achievement and the possible future work for further performance enhancement in the direction of Section 6.

2. Related Works

Many PRSs have been developed by many academicians and researchers in the past for enhancing business through e-commerce by collecting and analyzing customer feedback ([4], [12], [15-17], [33-34]). Among them, Shariaty and Moghaddam [33] designed a new technique to mine the user's opinions according to their perceptions. They have incorporated the conditional random fields for resolving the issues to define and filter the attributes to improve the accuracy. Finally, they have proved that their technique is more effective than other techniques through the incorporation of optimization techniques and experiments. Song et al. [34] proposed a technique to extract the implicit and explicit terms from review comments. Agarwal et al. [3] extracted the sentiment rich phrases by applying the POS tagging awareness rules from the input document. Then the semantic level is measured by using the point wise mutual information technique and also categorized the documents according to the semantic relevancy.

Yongzheng et al. [41] investigated those two extraction methods, such as Automatic Concept Extractor and Automatic Keyphrase Extraction. They have enhanced the automatic concept extractor with the necessary changes. The Automatic Keyphrase Extraction works as a supervised learning system. They have evaluated their methods and found them to be better. Efstratios et al. [11] developed an ontological table incorporating a method for enhancing the sentiment analysis of tweets. The novelty of their method is to post the characteristics through sentiment score, as is the case with the ML aware classification algorithms. Finally, their method was shown to be more accurate than existing methods in terms of prediction. Aravindan and Ekbal [7] extracted the most relevant features from review comments as positive and negative. They have performed association rule mining over the text and also considered the polarity value of the terms. Finally, they have obtained 80% success rate, which is greater than other ML classifiers in this direction.

Hu et al. [17] extracted the relevant data from review comments by applying sentiment analysis and also identified the potential terms which are used to make decisions in the content recommendation process. They used a deep neural classifier to analyze high-dimensional data. The experiments have been conducted for the purpose of resolving the high dimensional issues and of obtaining better results. Kumar and Vadlamani [26] presented a detailed review of sentiment analysis by considering the various techniques available in the years between 2002 and 2015. They have analyzed the various NLP and ML techniques that are used for sentiment analysis. Finally, they have compared the various works and provided the justification. Susana et al. [37] used probabilistic topic modelling to evaluate the LDA based models that considers the mono-lingual, bilingual and multi-idiomatic. They have obtained the highest stability and the highest precision. Milagros et al. [24] developed a new technique to predict the sentiment score through online based on the dependency parsing.

Sagheon and Wooju [31] developed a learning technique that is semi-supervised model which predicts the data to train the model for enriching the initial classification in the process of training. In the end, they have achieved better result which is better than other works. Cagatay and Mehmet [9] developed a new classification method that incorporates a new voting method that consists of three classifiers namely Bagging, SVM, and Naive Bayes. In the end of their work, they have achieved better performance that is better than other classifiers. Vinodhini and Chandrasekaran [39] developed a new ensemble approach that incorporates the ML algorithms for performing sentiment classification.

Karthik et al. [19] developed a novel method called product ranking algorithm which considers the features to suggest the most liked products according to their interests. Their method analyzes the reviews and ranks the products. According to the product ranking, the product is recommended to customers. At the end, their analysis and recommendations are evaluated and proved as superior. Antony and Arokia [29] conducted a detailed survey on sentiment analysis. They have considered various techniques for analyzing the tweets and other review comments. By applying POS and classifiers, Vanaja and Belwal [38] applied sentiment analysis to identify the positive, neutral, and negative terms from review comments. They have used the standard Amazon dataset to evaluate the models through experiments and also proved the effectiveness.

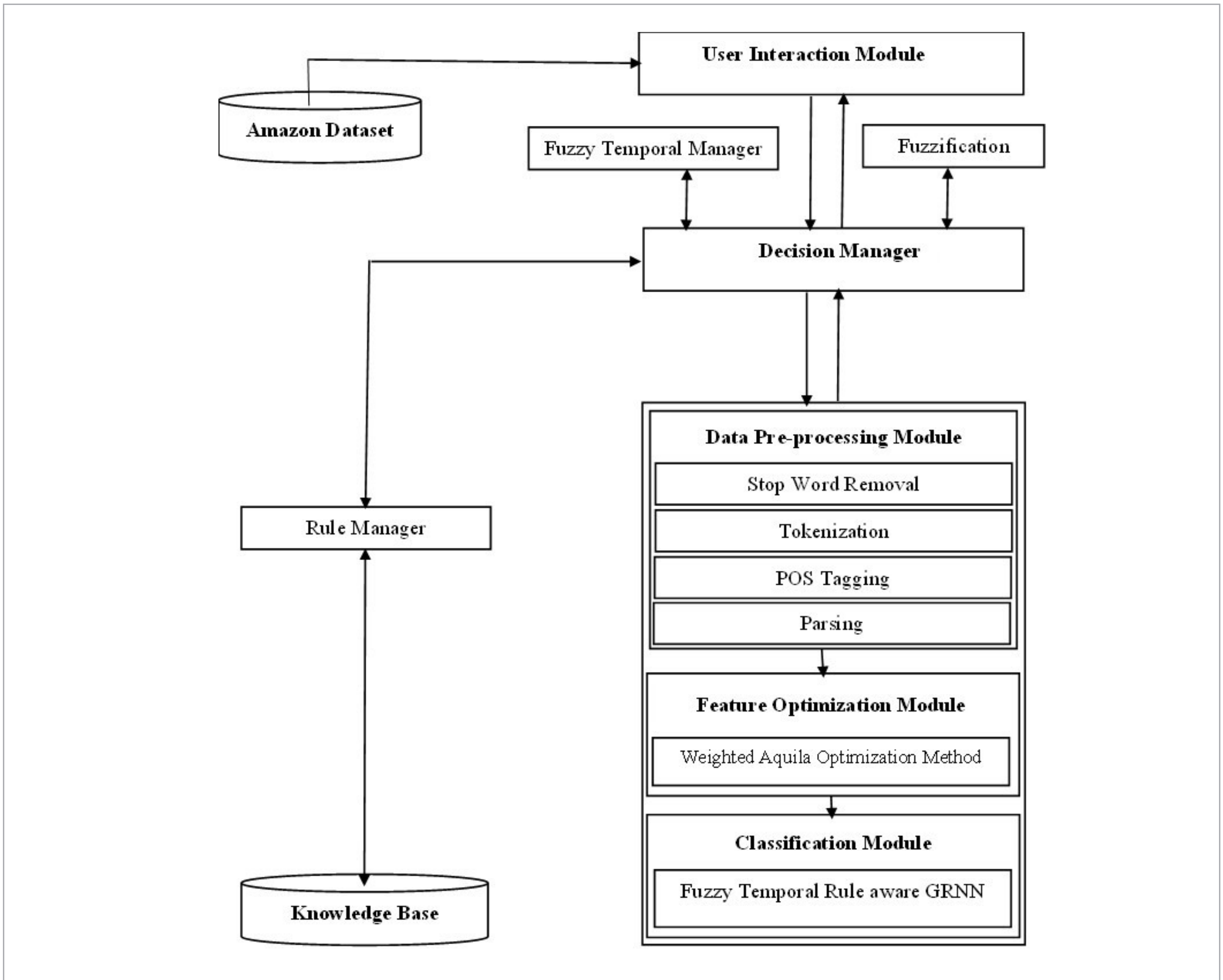
Dau and Salim [5] developed a new system which incorporates sentiment analysis algorithm and deep learning algorithm for capturing product aspects and user sentiments. Rosewelt and Renjit [30] developed an intelligent fuzzy clustering aware data retrieval method to perform the classification. Their method uses the fuzzy clustering method and classification. They have used mutual information aware preprocessing and also need to be done to improve the performance. In the end of their work, their work is achieved good prediction accuracy than other works.

Wahyudi and Kusumanigrum [42] aimed to measure the performance of the various sentiment analysis on e-commerce through customer review comments by applying the LDA. Finally, they have proved their model is superior than others by them through classification accuracy on specific review comments and general review comments. Ji et al. [18] constructed a new decision support system that considers the review comments and also applies the probability neutrosophic linguistic numbers for characterizing the online review comments. They have incorporated fuzzy logic into the characterization process and also found the negative comments. The negative comments are neglected and they perform the classification. In the end, their system obtained better service than other systems. Zhang and Zhong [47] presented an entity aware sentiment word pair mining technique to extract similar features. They have calculated their trust value based on their transitivity features.

Zhang et al. [46] proposed a new multi-classification technique which considers the sentiment analysis with weights. Yang et al. [44] built a model which incorporates their sentiment analysis that has a sentiment lexicon with CNN. Then, they use it for extracting the most important features and context reviews and applying the attention method to weight. In the

Figure 1

Proposed System Architecture



end of their work, their system is proved as efficient by achieving good prediction accuracy in short time. A new hybrid method was developed by Kumar et al. [22] to recommend movies which incorporate the collaborative filtering along with sentiment analysis on tweets. They have analyzed the tweets and identified the current trends. Finally, they have proved as superior than other movie recommendation systems with respect to accuracy. Sankar et al. [32] developed a new fuzzy recommendation system that combines the rating procedure and similarity measurement technique. They have improved the recommendation speed and accuracy in a better manner than the existing systems.

Rosewelt and Renjit [28] developed a new semantically aware data summarization technique for extracting the related data by applying the text categorization process through an effective classifier. Their model contains a semantically aware feature selection method, enrichment method, text summarization method and deep classifier. Antony and Arokia [6] developed a new RS to recommend the right content to the users based on their interests and learning capability. They have incorporated the Fuzzy Temporal Logic and Decision Tree incorporated CNN. Moreover, they have introduced a weighted Gini-Index aware feature selection method to identify the most relevant data from online and local repositories. Finally, they have recommended the suitable study materials alone to the learners with the help of the pre-processed text successfully.

Karthik and Ganapathy [20] proposed a new PRS using fuzzy rules to predict the more relevant products according to the customer's expectations and taste. They have developed a new method to calculate sentiment scores for every product and also applied fuzzy rules and ontological databases that are helpful for making effective decisions. Rong et al. [27] constructed a sentiment aware deep learning model to analyze product reviews in e-commerce. In their model, the review comments are categorized into two: positive and negative. They have conducted training and testing for the categorized terms by using a neural classifier. Then, the CNN is applied to identify the association between the terms by considering the emotions and the training result of those emotions. Zhu [48] developed a new hybrid deep neural classifier that combines the standard DL algorithms such as Bi-LSTM and CNN. They have incorporated the feature engineering process for performing normalization processes. In their model, the CNN is used for the prediction process, and before that, the Bi-LSTM is used for analyzing the review comments. Finally, they have predicted the sales by analyzing the review comments.

Boumhidi et al. [8] presented a new method which is used to perform the review popularity, spam filtering, and posting time calculations for generating accurate values. Their model calculates the reputation value according to the opinions collected from different sources and environments. They also designed a visualization tool to show the output in detail. They have conducted experiments using the comments taken from Facebook and Amazon. Li et al. [40] proposed a novel fusion model that incorporates the Bi-LSTM to perform sentiment classification. Abolfazl et al. [23] proposed a model which works automatically over online products that incorporates sentiment analysis. They have proposed a new preprocessing algorithm using latent semantic analysis. In addition, they have combined a whale optimization method with a random evolutionary and a DBN classifier to perform feature optimization and classification. Finally, they have achieved around 97% sentiment classification accuracy that is better than other systems.

Guixian et al. [43] proposed a sentiment classifier that considers the aspects and also incorporating the attention-aware Bi-LSTM and transfer learning technique. Their classifier performs effective sentiment classification. Yong et al. [10] proposed a novel Graph Fusion Network (GFN) that is capable of overcoming the disadvantages and also enhancing the classification accuracy. They have introduced a new text graph for transforming knowledge with different views. Moreover, they have divided it into three steps, such as learning, convolution, and fusion processes on graphs. They have handled the texts in these three steps and proved that their graph fusion is superior to other techniques. Faisal et al. [2] conducted a brief survey about the usage of deep learning algorithms in sentiment classification. Their survey shows the better deep classifier from the standard deep classifiers.

Gao et al [13] addressed the issue of cross-platform recommendation method for e-commerce in social media to recommend the suitable products to the customers for purchasing through social media. Solairaj et al [34] proposed a neural classifier to perform collaborative filtering process and also to predict the best products.

3. Proposed System Architecture

The workflow of the newly developed PRS is explained in a newly designed architecture that is shown in Figure 1 and it has ten components like Amazon dataset, User Interaction Module, Decision Manager (DM), Data Preprocessing Module, Feature Optimization Module, Sentiment and Semantic Classification Module, Rule Manager (RM), Knowledge Base (KB), Temporal Manager, and Fuzzification.

The Amazon dataset supplies the necessary inputs to the proposed product recommendation system through its user interaction module. The user interaction module is used to collect the data from the Amazon dataset and it forward to the decision manager. It transmits the feature optimization module. The data preprocessing modules consist of five basic tasks such as tokenization, stop word removal, POS tagging, and parsing. The initial level preprocessing is done and it forwards to the feature optimization module. The feature optimization module applies a newly developed optimization algorithm called the Weighted Aquila Optimization Method for optimizing the features (terms) which are used to achieve better prediction accuracy. The optimized features are to be sent to the classification module with the help of decision manager. The classification module uses the newly developed Fuzzy Temporal Aware GRNN for categorizing the terms effectively. The decision manager will act as an overall controller of the entire system. The DM is helpful for generating fuzzy logic incorporated rules and also managing them using a rule manager. The RM manages the rules available in KB. The temporal features are to be referred to by the decision manager and they apply to the fuzzy rule generation process.

4. Proposed Model

A new PRS is developed that consists of data preprocessing, feature optimization and sentiment classification for predicting the suitable products for users according to their interests. First, this system performs the data preprocessing tasks such as stop word removal, tokenization, POS tagging, and parsing. Second, the system calculates the sentiment score and performs the feature optimization process. Third, the system applies the newly proposed enhanced version of GRNN with fuzzy temporal rules and sentiment score to perform the effective sentiment classification. In this work, the proposal of a new PRS with the incorporation of new feature optimizer and new fuzzy temporal neural classifier is a novelty to predict the suitable products to the users. This section explains the necessary background information about the Aquila Optimizer, Fuzzy Temporal Logic, and GRNN in the first subsection.

4.1. Background

This subsection explains the background information about the standard Aquila Optimization Method (AOM) [1] and Generalized Neural Network (GNN) [14]. First, it explains the standard AOM with the necessary formulae and steps. Second, it explains the fuzzy temporal logic and it explains the structure and functionalities of the standard GRNN.

4.1.1. Aquila Optimization Method

This section explains the standard Aquila Optimization Method (AOM), which is a nature-inspired method. The workflow of the standard AOM is presented as below:

- **Inspiration and Behaviour**

This section explains the inspiration and behaviour while performing the hunting process. The Aquila is a famous bird's prey in a hemisphere that is located in northern area. The Aquila is a very common endemic species. It is also one among the Accipitridae, like other birds and it is a dark brown with the combination of golden brown over the back of its neck. Generally, it has a white tail and minor white marks over wings. Moreover, it applies speed and agility together with large, hares, marmots, prey, deeps and sturdy feet [36]. In addition, the Aquila and their distinctive characteristics are captured. Finally, the Aquila is an intelligent and skillful hunter, and the major inspiration for AOM is derived.

- **Initialize the Solutions**

The AOM is a population-based method, and the optimizer starts as a candidate solution with the population of (X) that is described in Equation (1). This equation is created stochastically from lower bound to upper bound for the assigned problem. Moreover, the solution is finalized as a solution that is optimal in every execution.

$$X = \begin{pmatrix} x_{1,1} & \cdots & x_{1,Dim} \\ \vdots & \ddots & \vdots \\ x_{N,1} & \cdots & x_{N,Dim} \end{pmatrix}, \qquad (1)$$

where, X indicates the group of solutions that are randomly generated by applying Equation (2), X_i represents the location of i^{th} solution, population is represented by N and dimension size is represented by the variable Dim.

$$X_{ij} = RND \times (UB_j - LB_j), i = 1, 2, \ldots.., N, \\ j = 1, 2, \ldots.., Dim. \qquad (2)$$

where, the RND indicates the random number, the LB_j indicates the j^{th} lower bound and j^{th} upper bound is indicated by UB_j.

- **Mathematical Model**

The AOM is constructed according to the characteristics of the Aquila while hunting. The optimization procedure of AOM is explained in four techniques including search space selection, explore the diverge search space, exploits a diverge search space and walk and prey are performing the swoop. The AOM is transferred from exploration to exploitation with the necessary steps by considering the various characteristics according to the condition if the value of $t \leq \left(\frac{2}{3}\right) * T$. Here, the exploration steps are excited and the exploitation steps are executed. The mathematical model of AOM is shown below:

– **Expanded Exploration (X_1)**

Recognize the prey area and also choose the best area that is suitable for performing the hunting process. The AOM explored widely to determine the search space area. The characteristics of the Aquila (X_1) are described in Equation (3).

$$X_1(t+1) = X_{best}(t) \times \left(1 - \frac{t}{T}\right) + (X_M(t) - X_{best}(t) * RND), \tag{3}$$

where, the variable $X_1(t \quad 1)$ represents the next iteration of t that is developed in the initial search process of X_1. The variable $X_{best}(t)$ indicates the best solution in t^{th} iteration and it reflects the prey. The variable $\left(1 - \frac{t}{T}\right)$ is applied in this equation for controlling the exploration process through repeated execution. The mean value of the location is indicated by the variable $X_M(t)$ that is connected with current best solution at t^{th} iteration that is computed by using Equation (4). The variable RND is a random value between the value 0 and 1, the present execution and the highest number of executions are indicated by the variables such as t and T.

$$X_M(t) = \frac{1}{N} \sum_{i=1}^{N} X_i(t), \forall_j = 1, 2, \ldots, Dim, \tag{4}$$

where, Dim represents the dimension size and the variable N indicates the population size.

– **Narrowed Exploration (X_2)**

The second step of (X_2) is identifying the high soar and the circles of Aquila is greater than the target prey. The AOM explored the chosen search space area of the target prey. The characteristics of the AOM are described in Equation (5).

$$X_2(t+1) = X_{best}(t) \times Levy(D) + X_R(t) + (y - x) * RND, \tag{5}$$

where, the variable $X_2(t+1)$ represents the solution of the $t+1^{th}$ iteration for the search technique X_2, the variable D indicates the dimension space and $Levy(D)$ represents the levy flight distribution method that is computed by applying Equation (6), the variable $X_R(t)$ means that the random solution chosen from the range between 1 and N at i^{th} iteration.

$$Levy(D) = s \times \frac{u \times \sigma}{|v|^{\frac{1}{\beta}}}, \tag{6}$$

where, the variable s represents a fixed value as a constant, the variable u indicates the random number 0 and v represents the random number 1. The σ is computed by using the formula present in Equation (7).

$$\sigma = \left(\frac{r(1+\beta) \times \sin e\left(\frac{\pi\beta}{2}\right)}{r\left(\frac{1+\beta}{2}\right) \times \beta \times 2^{\left(\frac{\beta-1}{2}\right)}} \right), \tag{7}$$

where, the variable β holds a value from 0 to 1.5 as constant value. The variables x and y represent the spiral shape, and these are available in Equation (5) and also calculated their values by using Equations (8)-(9).

$$y = r \times \cos(\theta) \tag{8}$$

$$x = r \times \sin(\theta) \tag{9}$$

where,

$$r = r_1 + U \times D_1 \tag{10}$$

$$\theta = -\omega \times D + \theta_1 \tag{11}$$

$$\theta_1 = \frac{3 \times \pi}{2}. \tag{12}$$

The variable r_1 holds a value that is from 1 to 20, the variable U indicates a fixed value that holds 0.00565, the variable D_1 indicates the integer values start with 1 to the length of search space, and ω represents a fixed value as 0.005.

– **Expanded Exploration (X_3)**

The exploitation approach (X_3) that prey area is mentioned clearly. Moreover, it is also ready to attack and identify the prey reaction descends. The characteristics of this character are described in Equation (13).

$$X_3(t+1)=\left(X_{best}\left(t\right)-X_M\left(t\right)\right)\times\alpha-rand+\left(\left(UB-LB\right)\times rand+LB\right)\times\delta, \tag{13}$$

where, the variable $X_3(t+1)$ indicates the search function solution X_3, $X_{best}\left(t\right)$ represents the prey location until i^{th} iteration, and $X_M\left(t\right)$ represents the mean value that is computed by using Equation (4), RND is a random value that is range from 0 to 1, the variables α and δ are representing the exploitation parameters that are useful for performing adjustment to 0.1, the variable LB represent the lower bound and the variable UB indicates the upper bound.

– **Narrowed exploration (X_4)**

The narrowed exploitation method (X_4) is applied if the Aquila became closer with prey. Moreover, the Aquila is also capable of attacking the prey over the land space according to the movements that is known as grab prey and walk method. The characteristic is described in Equation (14).

$$X_4(t+1)=QF\times X_{best}\left(t\right)-(G_1\times X\left(t\right)\times rand)-G_2\times Levy(D)+rand\times G_1, \tag{14}$$

where, the variable $X_4(t+1)$ represents the solution for the fourth function $\left(X_4\right)$, the variable QF represents a quality method that is helpful for performing the equilibrium search that is computed by using Equation (15), the variable G_1 indicates the different motions of the AOM that are helpful for tracking the prey that is developed by using Equation (16), the variable G_2 indicates the values between 2 and 0 in deceasing value which is helpful to follow the prey from the first (1) to last (t) locations that are created by applying Equation (17) and the variable $X(t)$ indicates the current solution.

$$QF(t)=t^{\frac{2\times RND-1}{(1-T)^2}} \tag{15}$$

$$G_1=2\times RND-1 \tag{16}$$

$$G_2=2\times\left(1-\frac{t}{T}\right). \tag{17}$$

The variable $QF\left(t\right)$ indicates the quality functional value, RND represents a random value that is a range between 0 and 1, the variable t indicates the present iteration and the maximum number of iterations is mentioned by the variable T, the levy flight distribution is indicated by the variable $Levy\left(D\right)$ which is computed by using Equation (6).

4.1.2. Fuzzy Temporal Logic

Fuzzy sets [45] form a key technique to represent and process uncertain data. The uncertainty arises in various forms in the databases, such as imprecision, vagueness, non-specificity, inconsistency, etc. The fuzzy sets are exploiting the uncertainty to increase the system complexity. At the same time, fuzzy sets are created as a powerful method for considering incomplete data, noisy data, and imprecise data. These are useful in developing data uncertainty, which provides better performance traditionally. Here, two important tasks, such as fuzzification and defuzzification processes, are performed in this fuzzy theory. The fuzzy intervals are also varied according to the fuzzy membership functions, including triangular, trapezoidal, Mamdani, and Gaussian fuzzy membership functions. Here, generate the fuzzy rules according to the intervals that are fixed by the specific fuzzy membership function and the expected outcome for the specific problem.

This section deals with fuzzy rules and fuzzy logic that is applied in the generation of the necessary fuzzy rules according to the deadline of the user's interest and the available products. Here, the standard trapezoidal function is used to generate the rules. Generally, it contains four parameters, namely a,b,c and d that are demonstrated in Equations (18)-(19).

$$trapezoid(x;a,b,c,d)=\left\{\begin{array}{ll}0, & x\le a\\ \frac{x-a}{b-a}, & a\le x\le b\\ 1, & b\le x\le c\\ \frac{d-x}{d-c}, & c\le x\le d\\ 0, & d\le x\end{array}\right\} \tag{18}$$

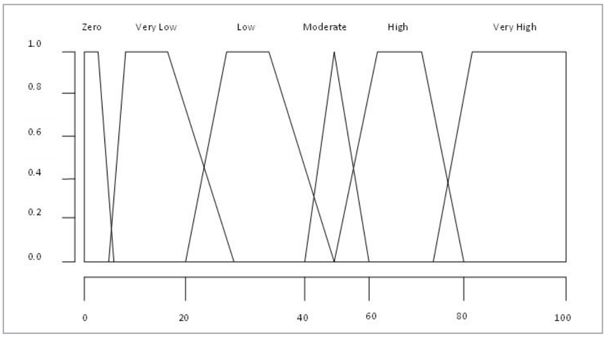
$$trapezoid(x;a,b,c,d)=\max\left(\min\left(\frac{x-a}{b-a},1,\frac{d-x}{d-c}\right),0\right). \tag{19}$$

Here, the values of the parameters such as a,b,c and d are lesser than the value of b, the value of b is less than or equal to the value of c, the c value is lesser than d that represents the x coordinate values. Here, the triangular membership function is shown in Figure 2 with six different intervals such as Very High, High, Moderate, Low, Very Low and Zero.

Fuzzy logic is used to make a decision on the products according to the customer's interests using the fuzzy rules. Here, the various rules are generated with fuzzification along with time to purchase the products by various customers and relevant products. Generally, the fuzzy rules are generated according to the fuzzy intervals for the input ranges through fuzzy membership function.

Figure 2

Diagram of Membership Function



4.1.3. Generalized Regression Neural Network

The GRNN is a local approximation network that is the improved Radial Basis Function (RBF). The development of GRNN has a basis in clear theoretical concepts and does not only perform the training but also performs the weight adjustment on neurons while performing the training process. So that it is robust with a high computation cost. The GRNN contains a strong and non-linear mapping capability and is also act as a flexi network. Finally, the GRNN has been identified as a tool to predict the output with various factors and complexity. In this work, the CRF is applied to identify the parameters of GRNN for improving the performance of GRNN. The steps of the GRNN are explained as below:

The GRNN is executed with a specific input value in the form of a new pattern and also the output layers. The relevant input vectors are denoted by $X = [X_1, X_2, ..., X_n]$ and the output vectors are represented by $h = [h_1, h_2, ..., h_m]$. The equal number of input layers are available as training samples that are transmits to input data. The input neurons are consistent and the transfer method of the RBF that is presented in Equation (20).

$$K_i = \exp\left(-\frac{(X - X_i)^T (X - X_i)}{2\sigma^2} \right), \tag{20}$$

where, the variable K_i represents the transfer method and the spread parameter is mentioned by the variable σ.

The two different formulae are demonstrated in Equations (21)-(22) that are capable of computing the weighted sum of each neuron and also calculate the arithmetic sum of the outputs on pattern layer.

$$S_{Nj} = \sum_{i=1}^{n} h_{ij} \exp\left(-\frac{(X - X_i)^T (X - X_i)}{2\sigma^2} \right), \tag{21}$$

$$S_D = \sum_{i=1}^{n} \exp\left(-\frac{(X - X_i)^T (X - X_i)}{2\sigma^2} \right), \tag{22}$$

where, the variable S_{Nj} indicates the weighted sum, the variable S_D represents the arithmetic sum, $j \quad 1,2,...m$ and h_{ij} is the j^{th} element in the i^{th} training record, and $j = 1$ while forecasting the PV output.

The output layer incorporates a linear method to the output layer, and the estimation of the corresponding neuron j is:

$$h_j = \frac{S_{Nj}}{S_D}. \tag{23}$$

The GRNN has a parameter that is required for determining the spread parameter (σ). If the symbol σ is too large, then the value is an estimated value of the average target value for training records. If the variable σ is very small, then the capability of predicting the target value in a generalized manner is very limited. In this work, σ represents the best value, the optimization process is incorporated for identifying the optimal value and it also enhance the prediction accuracy.

4.2. Proposed WAOM-FTGRNN

The newly proposed Weighted Aquila Optimization Method (WAOM) aware Fuzzy Temporal GRNN (FTGRNN) is described with necessary steps in this work. Here, the proposed algorithm is a combination of WAOM and FTGRNN that are helpful for performing an effective classification process. The proposed WAOM-FTGRNN contains three different phases like feature selection and optimization, training, and prediction, which are explained in this section. First, it explains the feature optimization process with five steps that are: i) identify the initial level features, ii) initialize the required parameters, iii) calculate the inconsistent rate, iv) find the optimal feature subset, and v) stop feature optimization and begin prediction.

Weighted Aquila Optimizer Method

Input: Pre-processed Comments on various products

Output: Reduced feature set

Algorithm 1: Feature Optimization

Step 1: Assign the population X to AO.

Step 2: Calculate the fitness values for all items.

Step 3: Best product is identified according to the fitness values of items.

Step 4: Update the average solution at a specific time duration.

Step 5: Update the values of $x, y, G_1, G_2, Levy(D)$

Step 6: IF the RND value is less than or equal to 0.05 then

1. Perform the expanded exploration of (X_1)
2. Find the weight for X_1 with respect to the fitness value of the same.
3. Updating the current solution using Equation (3) along with weights.
4. Comparing the fitness values at specific time period for the products.

Step 7: Else

1. Perform Narrowed exploration of (X_2)
2. Find the weight for X_2 with respect to the fitness value of the same.
3. Update the current solution using Equation (5) with weights.
4. Comparing the fitness values at specific time period for the products.

Step 8: Else if the random value is $1 \le 0.5$ then

1. Perform Expanded exploitation of (X_3)
2. Find the weight for X_3 with respect to the fitness value of the same.
3. Update the current solution using Equation (13) with weights.
4. Comparing the fitness values of X_3 at specific time period for the products.

Step 9: Else

1. Perform Expanded exploitation of (X_4)
2. Find the weight for X_4 with respect to the fitness value of the same.
3. Update the current solution using Equation (14) with weights.
4. Comparing the fitness values of X_4 at specific time period for the products.

Step 10: Return the best solution (X_{best}).

The proposed WAOM returns the best solutions as outputs that are considered and forwarded to the classifier for performing the prediction process by applying the effective classification. The best solutions have been identified by the newly proposed Weighted Aquila Optimization Method (WAOM) and also provided as important features that are helpful for predicting the most suitable products for the customer. Here, the sentiment score is calculated for the selected features that are related to the most frequently moving products. The sentiment score is computed by applying Equations (24)-(25).

The product rating as a sentiment score is explicitly shown for every product. Customers put their comments on products on social media platforms and company websites. Analyzing the review comments is helpful for categorizing the products and also calculating the product rating according to the customer's interests. It can also be recommended to other customers who have similar kinds of interests.

$$SC_{p,u} = \sum_{i=1}^{n_{p,u}} \left(SSi_{p,u} \right), \tag{24}$$

where, $n_{p,u}$ is the number of review comments for the relevant customers. Next, the product rating $PR_{p\,u}$ is also performed by considering the overall rating and the number of review comments.

Table 1
Amazon Dataset Description

Dataset	Product category	User reviews	Number of products
DS1	Books, kindle store, magazine subscriptions, CDs and vinyl	61,665,000	3,975,000
DS2	Gift cards, arts, crafts and sewing, toys and games, video Games	13,788,000	1,022,000
DS3	prime pantry, office products, home and kitchen, grocery and gourmet food	32,424,000	1,913,000
DS4	DS1 + DS2	75,453,000	4,997,000
DS5	DS1 + DS2 + DS3	107,877,000	6,910,000

$$PR_{p,u} = \frac{OR_p * NoR_p}{SC_{p,u}}, \quad (25)$$

where OR_p indicates the general review is score for the respective product and NoR represents the number of review comments considered in this work. By considering the sentiment score only, the decision is made in this work. The newly proposed Fuzzy Temporal Rules incorporated General Regression Neural Network (FTGRNN) is explained with necessary steps as below:

Algorithm 2: Fuzzy Temporal Rule aware GRNN

Input: Reduced feature subset

Output: Recommended products

Step 1: Read the reduced feature subset from Phase 1.

Step 2: Find the best valued feature from the reduced feature set.

Step 3: Perform the training process on input features by applying the activation function.

$$AF(j) = -\left(a + r(j) + b \times \frac{1}{NoF(j)}\right), \quad (26)$$

where, AF indicates the activation function, NoF represents the number of features.

Step 4: Find the sentiment score for the reduced feature subset.

Step 5: Generate Fuzzy Temporal Rules by considering the sentiment score of the product and purchase time.

Step 6: Apply Fuzzy Temporal Rules for making final decision on training process.

Step 7: Smoothing factors are considered to finalize the prediction process.

Step 8: Return the prediction result.

The newly proposed Fuzzy Temporal Rules incorporating GRNN consider the reduced feature subset as input and also produce the recommended products to the customer as output. First, this work applies the WAOM to identify the effective feature subset that is used to predict the products. Second, the Fuzzy Temporal Rule aware GRNN is applied to perform an effective training process and predict the products that are identified as liked products. The proposed algorithms are evaluated by conducting many experiments and proving that they are more efficient than the existing algorithms that are available in the literature in terms of prediction accuracy.

Case study of PRS: A customer wants to purchase a smart watch in online. In this scenario, the proposed PRS recommends the various company smart watches that are available in the market based on the following steps: i) the specific product (smart watch) related review comments and the user expected company watch and model are taken as input for the system, ii) the review comments are preprocessed by the proposed data preprocessing algorithm by identifying the suitable key terms, positive and negative feedback, iii) the preprocessed review comments are given to the classifier as input for categorizing the review comments by using the key terms, positive and negative terms to recommend the suitable product to the customer, iv) Before taking the final decision by decision manager, it refers the fuzzy rules that are constructed newly in this work. This is the way the products are recommended by the PRS to the customer.

5. Results and Discussion

This section demonstrates the performance of the PRS according to the experimental results and proved as superior with discussion. First, it explains the dataset used in this work.

5.1. DataSet

The standard Amazon dataset [25] is used to evaluate the newly developed PRS. The Amazon dataset description is given in Table 1. Moreover, two different kinds of datasets were applied to evaluate the newly developed PRS, which are famous e-commerce datasets. Here, the dataset 1 (DS1) contains the details of books, Kindle Store, magazine subscriptions, CDs, and vinyl category products. Moreover, it holds the customer reviews for every product and also the product meta data information. The dataset 2 (DS2) is derived from the Amazon dataset and includes gift cards, arts, crafts and sewing, toys and games, and video game category products. The motivation for selecting DS2 is to get more data towards the real target end users, like kids. The Dataset 3 (DS3) is prepared by referring to the prime pantry, office products, home and kitchen, and grocery and gourmet food Amazon datasets. Dataset 4 (DS4) is derived by combining DS1 and DS2. The dataset (DS5) was prepared by combining DS1, DS2 and DS3 Amazon datasets. The DS5 gives the complete coverage of all sequential, repeated and target user aspects in the evaluation.

5.2. Performance Metrics

The proposed CST framework is tested against the standard Amazon dataset using the Precision and Recall metrics described in Equations (27)-(28).

$$Precision = \frac{Relevant\ Recommended\ Products}{Total\ Recommended\ Products} \tag{27}$$

$$Recall = \frac{Relevant\ Recommended\ Products}{Tot.no.of\ relevented\ products\ to\ be\ Recommended} \tag{28}$$

Focusing more on precision may sometimes recommend same product repeatedly which may not interest the user. Recommendation specific metrics such as Serendipity and nDCG are considered for evaluating the proposed system.

Serendipity

It is important for a recommendation system to predict some new product that is interesting and relevant to the user. Serendipity helps to determine this check by using Equation (29).

$$P_x = \frac{no. - rank_x}{no.} \tag{29}$$

nDCG

It is important to put the product in top in the recommendation which is more relevant and more likely to buy. nDCG helps to check and correct the order as given in Equation (30).

$$nDCG(L,K) = \frac{1}{|L|}\sum_{x=1}^{|L|} Z_{kx} \sum_{m=1}^{k} \frac{2^{R(x,m)}-1}{\log_2(1+m)'}. \tag{30}$$

5.3. Experimental Results

The experiments are done with different sets of records as separate datasets, such as DS1, DS2, DS3, DS4 and DS5. These datasets contain the different products with varying numbers of records. Figure 3 demonstrates the precision value analysis between the available PRSs such as the Fuzzy recommendation system (Sankar et al. [32]), MDH Approach (Karthik and Ganapathy [21]), Fuzzy Recommendation System (Karthik and Ganapathy [20], the system developed by Abolfazl et al. [23] and the proposed PRS.

Figure 3 demonstrates that the performance of the newly developed PRS is proved as superior than other PRSs like Fuzzy recommendation system (Sankar et al. [32]), MDH Approach (Karthik and Ganapathy [21]), Fuzzy Recommendation System (Karthik and Ganapathy [20]), and the system developed by Abolfazl et al. [23]. The reason for the performance is the application of weighted AOM, sentiment score, and fuzzy temporal rules incorporated into GRNN.

The recall value of the new PRS and the available PRSs namely the Fuzzy recommendation system (Sankar et al. [32]), MDH Approach (Karthik and Ganapathy [21]), Fuzzy Recommendation System (Karthik and Ganapathy [20]), and the system developed by Abolfazl et al. [23] are demonstrated in figure 4.

Figure 3
Precision Value Analysis

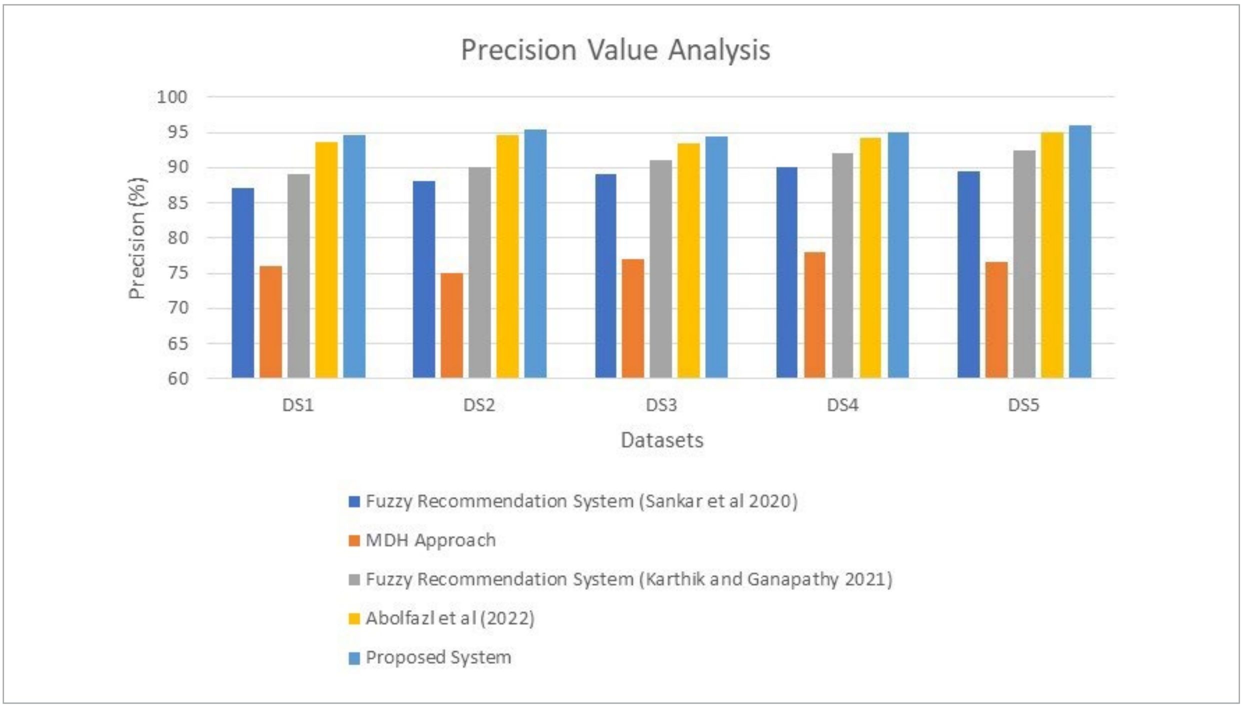


Figure 4
Recall Value Analysis

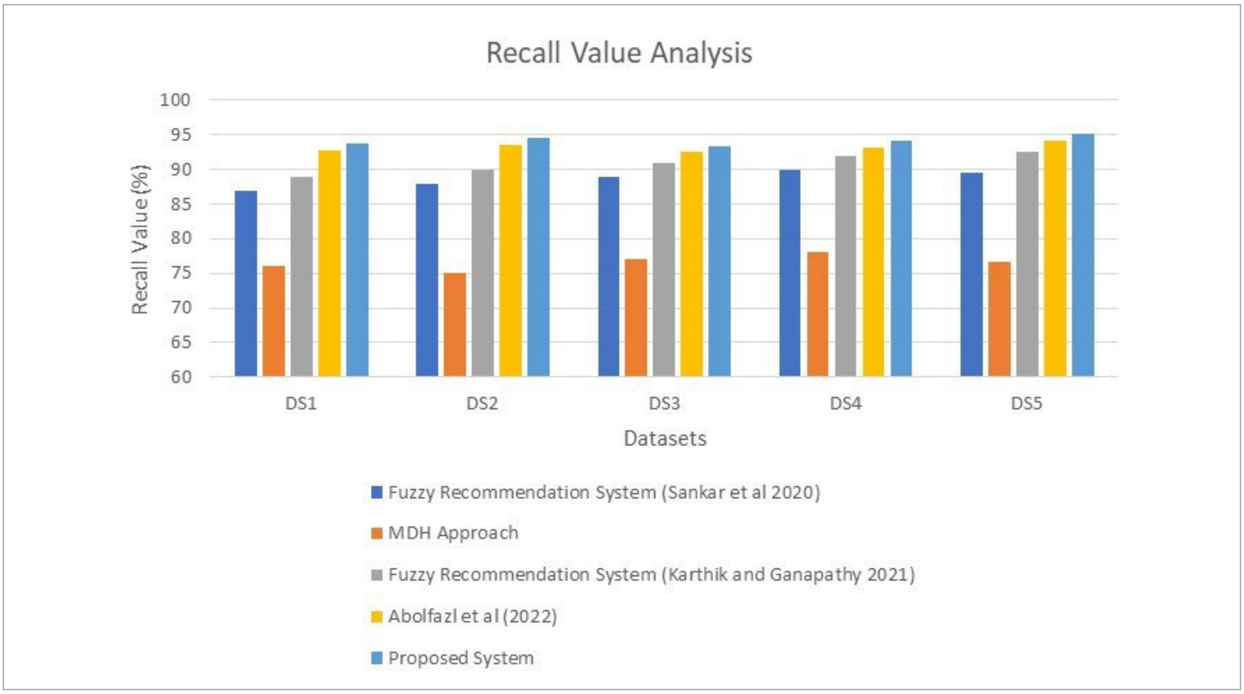


Figure 4 is proved the effectiveness of the new PRS through recall value as superior than the available Fuzzy RS (Sankar et al. [32]), MDH Approach (Karthik and Ganapathy [21]), Fuzzy RS (Karthik and Ganapathy [20]), and the system developed by Abolfazl et al. [23]. The application of weighted AOM, sentiment score, and fuzzy temporal rules incorporated into GRNN are the main reason for the enhancement.

Figure 5 demonstrates the Serendipity value analysis between the newly developed PRS and the available PRSs like the Fuzzy recommendation system (Sankar et al. [32]), MDH Approach (Karthik and Ganapathy [21]), the Fuzzy Recommendation System (Karthik and Ganapathy [20]) and the system developed by Abolfazl et al. [23].

From Figure 5, it is proved that the newly developed PRS is better than the available Fuzzy recommendation system (Sankar et al. [32]), MDH Approach (Karthik and Ganapathy [21]), Fuzzy Recommendation System (Karthik and Ganapathy [20]), and the system developed by Abolfazl et al. [23] in terms of serendipity. This is due to the fact that the use of weighted AOM, sentiment score, and fuzzy temporal rules incorporated into GRNN.

Figure 6 shows the nDCG value of the proposed system and the existing recommendation systems such as the Fuzzy recommendation system (Sankar et al. [32]), MDH Approach (Karthik and Ganapathy [21]), Fuzzy Recommendation System (Karthik and Ganapathy [20]), and the systems developed by Abolfazl et al. [23].

From Figure 6, it is demonstrated the superiority of the proposed PRS while coamparing with the available Fuzzy recommendation system (Sankar et al. [32]), MDH Approach (Karthik and Ganapathy [21]), Fuzzy Recommendation System (Karthik and Ganapathy [20]) and the system developed by Abolfazl et al. [23] in terms of nDCG value. The reason for obtaining better nDCG is the application of weighted AOM, sentiment score, and GTNN with fuzzy logic and temporal constrained rules.

Figure 5
Serendipity Value Analysis

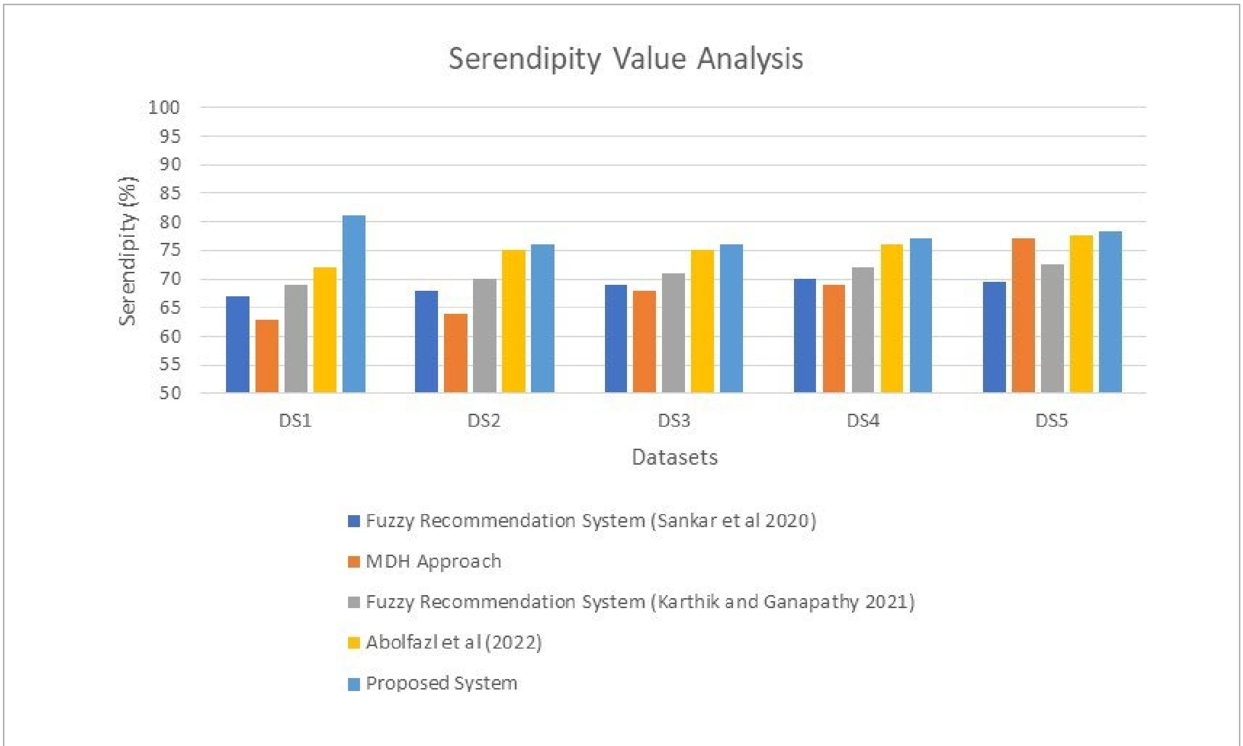


Figure 6
nDCG Value Analysis

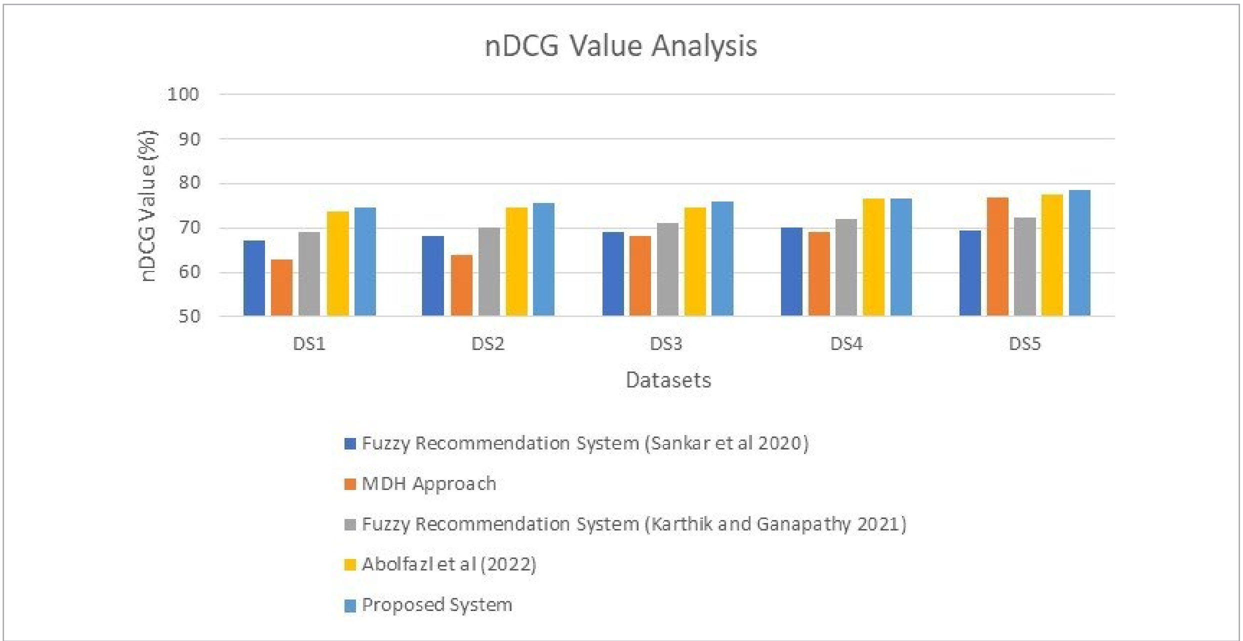


Figure 7
Prediction Accuracy Analysis

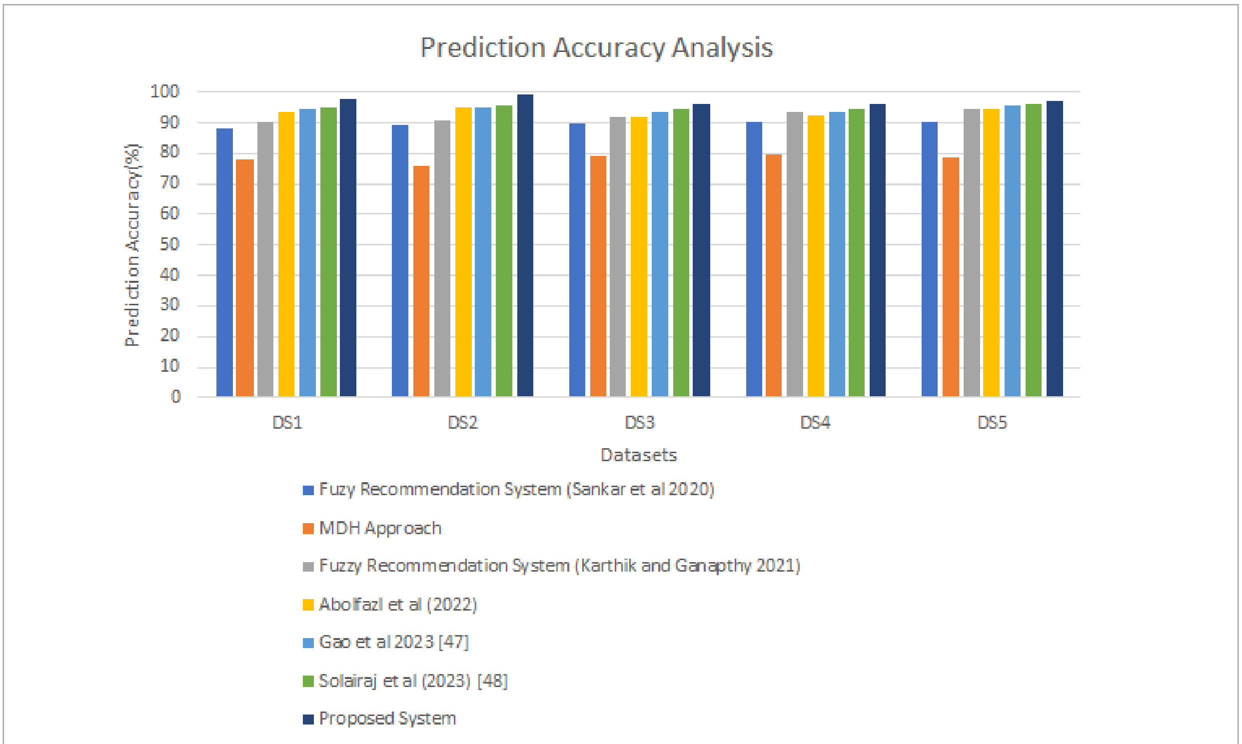


Table 2 demonstrates the comparative analysis by considering the newly developed PRS and the various RSs on top 10 product recommendation. The proposed product recommendation system takes evaluation metrics like precision, recall, serendipity, and nDCG into account. It implies that a new product is recommended based on the context and relevant to current user interest. This improves user satisfaction as well. Table 2 demonstrates the consolidated results with the conducted results. Both serendipity

Table 2

Comparative outcome analysis for Top10 recommendation

Dataset	Recommendation system	Precision	Recall	Serendipity	nDCG
Dataset 1	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
	Abolfazl *et al.*, 2022	0.50	0.50	0.042	0.36
	Proposed system	0.52	0.52	0.045	0.38
Dataset 2	FBPRR	0.31	0.26	0.012	0.21
	Fuzzy rule	0.45	0.45	0.023	0.24
	MDH	0.63	0.38	0.03	0.2
	Fuzzy recommendation	0.43	0.43	0.039	0.35
	Abolfazl *et al.*, 2022	0.49	0.48	0.039	0.36
	Proposed system	0.56	0.53	0.040	0.37
Dataset 3	FBPRR	0.34	0.23	0.021	0.23
	Fuzzy rule	0.52	0.32	0.025	0.25
	MDH	0.45	0.45	0.035	0.21
	Fuzzy recommendation	0.45	0.45	0.042	0.34
	Abolfazl *et al.*, 2022	0.52	0.53	0.044	0.36
	Proposed system	0.58	0.56	0.048	0.38
Dataset 4	FBPRR	0.31	0.26	0.022	0.23
	Fuzzy rule	0.52	0.41	0.024	0.24
	MDH	0.45	0.45	0.025	0.26
	Fuzzy recommendation	0.49	0.45	0.042	0.38
	Abolfazl *et al.*, 2022	0.51	0.51	0.043	0.37
	Proposed system	0.52	0.56	0.045	0.36
Dataset 5	FBPRR	0.25	0.23	0.020	0.25
	Fuzzy rule	0.45	0.42	0.024	0.24
	MDH	0.46	0.45	0.025	0.39
	Fuzzy recommendation	0.45	0.49	0.038	0.38
	Abolfazl *et al.*, 2022	0.47	0.51	0.042	0.39
	Proposed system	0.52	0.52	0.045	0.41

Table 3
Statistical analysis by applying Chi-Square-test

Positive / Negative Comments and Product recommended	Weighted Mean of Amazon dataset (Observed Value)	Weighted Mean according to the survey (Expected Value)	$\frac{(Observed\ value - Expected\ value)^2}{Expected\ value}$	$X^2 = \sum \frac{(OV - EV)}{EV}$	P-Value
Awareness about positive Comments and the products	7.59	4.56	0.64	4.21	0.67
Awareness about the Negative comments and the products	6.29	3.66	0.79		
Positive comments availability	7.89	4.78	0.59		
Online sales assistance	7.28	3.62	1.00		
Recommendation period	7.49	4.65	0.56		
Scenario	6.42	4.27	0.50		

and nDCG, recommendation-specific metrics, are improved without affecting or jeopardizing precision and recall values.

Table 2 proves the effectiveness of the newly developed PRS, which is better in terms of all the evaluation metrics than the available Fuzzy recommendation systems (Sankar et al. [32]), the MDH Approach (Karthik and Ganapathy [21]), the Fuzzy Recommendation System (Karthik and Ganapathy [20]), and the system developed by Abolfazl et al. [23] by considering the top 10 products in all datasets DS1, DS1, DS2, DS3, DS4, and DS5. The reasons for the improved performance are the use of weighted AOM, sentiment score, and fuzzy temporal rules incorporated into GRNN.

Figure 7 demonstrates the prediction accuracy analysis between the newly developed PRS and the available PRSs like the Fuzzy recommendation system (Sankar et al. [32]), MDH Approach (Karthik and Ganapathy [21]), Fuzzy Recommendation System (Karthik and Ganapathy [20]), and the systems developed by Abolfazl et al. [22] and the works done by Gao et al [13], Solairaj et al [34]. Here, five different experiments were conducted by considering the five different sizes of datasets as input.

Figure 7 demonstrates that the prediction accuracy of the proposed product recommendation system that is proved as superior than the available PRSs like Fuzzy recommendation system (Sankar et al. [32]), MDH Approach (Karthik and Ganapathy [21]), Fuzzy Recommendation System (Karthik and Ganapathy [20]) and the system developed by Abolfazl et al. [23] and the works done by Gao et al [13], Solairaj et al [34] in terms of prediction accuracy. The reason for the enhanced performance is the use of weighted AOM, sentiment score, and fuzzy temporal rules incorporated into GRNN.

5.4. Statistical Analysis

A statistical analysis is done in this work by applying Chi-Square-test based on the different inputs of the contents.

Hypothesis 1: There is a significant influence between positive comments and the number of products recommended.

Hypothesis 2: There is no relationship between the negative comments and the total number of products recommended.

To test: There is a significant influence between negative comments and the number of products recommended.

This statistical analysis considers the p value is not less than 0.01. So that, the NULL hypothesis / Error Rate is acceptable at the level of 1% in total. Therefore, the positive comments and the negative comments are not influencing the product recommendation.

6. Conclusion with Future Direction

In this paper, a new sentiment and fuzzy aware PRS has been developed to predict the most favorite and suitable product for the users based on their purchase behaviors and patterns. The newly developed PRS incorporates the standard data preprocessing tasks such as Stop Word Removal, Tokenization, POS tagging and parsing; a new sentiment and semantic score calculation procedure; and a new feature optimization technique called the Weighted Aquila Optimization Method (WAOM). Moreover, the sentiment and semantic classification processes are performed by applying a GRNN with sentiment score, fuzzy temporal features, and obtained better classification results. The experiments have been done in this work and also proved that the proposed PRS is superior than the available PRSs. The limitation of this work is to provide more prediction accuracy in short span of time crisply. For this purpose, this work can be enhanced further with the use of fuzzy roughest aware temporal constraints during the sentiment analysis and to perform fuzzy classification using reinforcement learning classifier.

References

1. Abualigah, L., Yousri, D., Elaziz, M. A., Ewees, A. A., Al-qaness, M. A., Gandomi, A. H. Aquila Optimizer: A Novel Meta-Heuristic Optimization Algorithm. Computers & Industrial Engineering, 2021, 157, 1-37.https://doi.org/10.1016/j.cie.2021.107250
2. Alshuwaier, F., Areshey, A., Poon, J. Applications and Enhancement of Document-Based Sentiment Analysis in Deep Learning Methods: Systematic Literature Review. Intelligent Systems with Applications, 2022, 15, 1-46. https://doi.org/10.1016/j.iswa.2022.200090
3. Agarwal, B., Sharma, V. K., Mittal N. Sentiment Classification of Review Documents Using Phrase Patterns, In: 2013 International Conference on Advances in Computing, Communications and Informatics (ICACCI), Mysore, India, 2013, 1577-1580.https://doi.org/10.1109/ICACCI.2013.6637415
4. Alantari, J. H., Imran, S. C., Yiting, D., Sameer, S. An Empirical Comparison of Machine Learning Methods for Text-Based Sentiment Analysis of Online Consumer Reviews. International Journal of Research in Marketing, 2022, 39(1), 1-19. https://doi.org/10.1016/j.ijresmar.2021.10.011
5. Aminu, D., Salim, N. Sentiment-Aware Deep Recommender System with Neural Attention Networks. IEEE Access, 2019, 7, 45472-45484. https://doi.org/10.1109/ACCESS.2019.2907729
6. Antony Rosewelt, L., Arokia Renjit, J. A Content Recommendation System for Effective E-learning Using Embedded Feature Selection and Fuzzy DT Based CNN. Journal of Intelligent & Fuzzy Systems, 2020, 39(1), 795-808. https://doi.org/10.3233/JIFS-191721
7. Aravindan, S., Ekbal, A. Feature Extraction and Opinion Mining in Online Product Reviews. In: 2014 International Conference on Information Technology, Bhubaneswar, India, 2014, 94-99. https://doi.org/10.1109/ICIT.2014.72
8. Boumhidi, A., Benlahbib, A., Nfaoui, E. H. Cross-Platform Reputation Generation System Based on Aspect-Based Sentiment Analysis. IEEE Access, 2022, 10, 2515-2531. https://doi.org/10.1109/ACCESS.2021.3139956
9. Cagatay, C., Mehmet, N. A Sentiment Classification Model Based on Multiple Classifiers. Applied Soft Computing, 2017, 50, 135-141. https://doi.org/10.1016/j.asoc.2016.11.022
10. Dai, Y., Shou, L., Gong, M., Xia, X., Kang, Z., Xu, Z., Daxin Jiang, D. Graph Fusion Network for Text Classification, Knowledge-Based Systems, 2022, 236, 107659. https://doi.org/10.1016/j.knosys.2021.107659
11. Efstratios, K., Christos, B., Theologos, D., Nick, B. Ontology-based Sentiment Analysis of Twitter Posts. Expert Systems with Applications, 2013, 40(1), 4065-4074. https://doi.org/10.1016/j.eswa.2013.01.001
12. Feng, T., Fan, W., Kuo-Ming, C., Qinghua, Z., Nazaraf, S., Tian, L., Jia. A Topic Sentence-Based Instance Transfer Method for Imbalanced Sentiment Classification of Chinese Product Reviews. Electronic Commerce Research and Applications, 2016, 16, 66-76. https://doi.org/10.1016/j.elerap.2015.10.003
13. Gao, C., Lin, T. H., Li, N., Jin, D., Li, Y., Cross-Platform Item Recommendation for Online Social E-Commerce. IEEE Transactions on Knowledge and Data Engineering, 2023, 35(2), 1351-1364. https://doi.org/10.1109/TKDE.2021.3098702
14. Ge, L., Xian, Y., Yan, J., Wang, B., Wang, Z. (2020). A Hybrid Model for Short-Term PV Output Forecasting Based on PCA-GWO-GRNN. Journal of Modern Po-

wer Systems and Clean Energy, 2020, 8(6), 1268-1275. https://doi.org/10.35833/MPCE.2020.000004

15. Guanhua, M., Junhua, M., Hao, L., Yiming, W., Zhaohua, W., Bin, Z. Customer Behavior in Purchasing Energy-Saving Products: Big Data Analytics from Online Reviews of E-Commerce. Energy Policy, 2022, 165, 112960. https://doi.org/10.1016/j.enpol.2022.112960
16. Hadi, E., Rachita, M., Sukant, K. B., Rawaa, A., Rojalina, P. A Hybrid E-Learning Recommendation Integrating Adaptive Profiling and Sentiment Analysis. Journal of Web Semantics, 2022, 72, 100700. https://doi.org/10.1016/j.websem.2021.100700
17. Hu, Z., Hu, J., Ding, W., Zheng, X. Review Sentiment Analysis Based on Deep Learning. In: 2015 IEEE 12th International Conference on e-Business Engineering, Beijing, China, 2015, 87-94. https://doi.org/10.1109/ICEBE.2015.24
18. Ji, P., Zhang, H., Wang, J. A Fuzzy Decision Support Model with Sentiment Analysis for Items Comparison in E-Commerce: The Case Study of http://PConline.com. IEEE Transactions on Systems, Man, and Cybernetics: Systems, 2019, 49(10), 1993-2004. https://doi.org/10.1109/TSMC.2018.2875163
19. Karthik, R. V., Ganapathy, S., Kannan, A. A Recommendation System for Online Purchase Using Feature and Product Ranking. In: 2018 Eleventh International Conference on Contemporary Computing (IC3), Noida, India, 2018, 1-6. https://doi.org/10.1109/IC3.2018.8530573
20. Karthik, R. V., Ganapathy, S. A Fuzzy Recommendation System for Predicting the Customers Interests Using Sentiment Analysis and Ontology in E-Commerce. Applied Soft Computing, 2021, 108, 107396. https://doi.org/10.1016/j.asoc.2021.107396
21. Karthik, R, V., Ganapathy, S. Online Product Recommendation System Using Multi-Scenario Demographic Hybrid (MDH) Approach. In: Chandrabose, A., Furbach, U., Ghosh, A., Kumar M., A. (eds) Computational Intelligence in Data Science. ICCIDS 2020, IFIP Advances in Information and Communication Technology, 2020, 578, Springer, Cham. https://doi.org/10.1007/978-3-030-63467-4_20
22. Kumar, S., De, K., Roy, P. P. Movie Recommendation System Using Sentiment Analysis from Microblogging Data. IEEE Transactions on Computational Social Systems, 2020, 7(4), 915-923. https://doi.org/10.1109/TCSS.2020.2993585
23. Mehbodniya, A., Varaprasad, R. M., David, L. G., Nigel, K. G. J., Vennam, P. Online Product Sentiment Analysis Using Random Evolutionary Whale Optimization Algorithm and Deep Belief Network. Pattern Recognition Letters, 2022, 159, 1-8. https://doi.org/10.1016/j.patrec.2022.04.024
24. Milagros, F., Tamara, Á., Jonathan, J., Enrique, C., Francisco, J, G. Unsupervised Method for Sentiment Analysis in Online Texts, Expert Systems with Applications, 2016, 58, 57-75. https://doi.org/10.1016/j.eswa.2016.03.031
25. Ni, J., Li, J., McAuley, J. Justifying Recommendations Using Distantly-Labeled Reviews and Fine-Grained Aspects. In: Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), Association for Computational Linguistics, Hong Kong, China, 2019, 188-197. https://doi.org/10.18653/v1/D19-1018
26. Ravi, K., Ravi, V. A Survey on Opinion Mining and Sentiment Analysis: Tasks, Approaches and Applications. Knowledge-Based Systems, 2015, 89, 14-46. https://doi.org/10.1016/j.knosys.2015.06.015
27. Rong L., Weibai Z., Debo, H. Sentiment Analysis of Ecommerce Product Review Data Based on Deep Learning. In: 2021 IEEE 4th Advanced Information Management, Communicates, Electronic and Automation Control Conference (IMCEC), Chongqing, China, 2021, 65-68. https://doi.org/10.1109/IMCEC51613.2021.9482223
28. Rosewelt, A., A. Renjit, A. Semantic Analysis-Based Relevant Data Retrieval Model Using Feature Selection, Summarization, and CNN, Soft Computing, 2020, 24(22), 16983-17000. https://doi.org/10.1007/s00500-020-04990-w
29. Rosewelt, A., Arokia Renjit, A. Sentiment Analysis Methods and Approaches: A Survey. International Journal of Advances in Computer and Electronics Engineering, 2018, 3(2), 1-8.
30. Rosewelt, A., L., Renjit, A., J. An Intelligent Subtype Fuzzy Cluster Based Relevant User Data Retrieval Model for Effective Classification. In: 2019 Fifth International Conference on Science Technology Engineering and Mathematics (ICONSTEM), Chennai, India, 2019, 49-54. https://doi.org/10.1109/ICONSTEM.2019.8918796
31. Sangheon, Lee., Wooju, K. Sentiment Labeling for Extending Initial Labeled Data to Improve Semi-Supervised Sentiment Classification. Electronic Commerce Research and Applications, 2017, 26, 35-49. https://doi.org/10.1016/j.elerap.2017.09.006
32. Sankar, P, P., Ganapathy, S., Kannan, A. REFERS: Refined and Effective Fuzzy E-Commerce Recommendation System. International Journal of Business Intelli-

gence and Data Mining, 2020, 17(1), 117-137. https://doi.org/10.1504/IJBIDM.2019.10011148

33. Shariaty, S., Moghaddam, S. Fine-Grained Opinion Mining Using Conditional Random Fields. In: 2011 IEEE 11th International Conference on Data Mining Workshops, Vancouver, BC, Canada, 2011, 109-114. https://doi.org/10.1109/ICDMW.2011.85
34. Solairaj, A., Sugitha, G., Kavitha, G., Enhanced Elman Spike Neural Network Based Sentiment Analysis of Online Product Recommendation. Applied Soft Computing, 2023, 132, 1-12. https://doi.org/10.1016/j.asoc.2022.109789
35. Song, H., Chu, J., Hu, Y., Liu, X. Semantic Analysis and Implicit Target Extraction of Comments from E-Commerce Websites. In: 2013 Fourth World Congress on Software Engineering, Hong Kong, China, 2013, 331-335. https://doi.org/10.1109/WCSE.2013.62
36. Steenhof, K., Kochert, M. N., McDonald, T. L. Interactive Effects of Prey and Weather on Golden Eagle Reproduction. Journal of Animal Ecology 1997, 66(3), 350-362. https://doi.org/10.2307/5981
37. Susana, Z., Ivan, V., Moens, M F. Latent Dirichlet Allocation for Linking User-Generated Content and E-Commerce Data. Information Sciences, 2016, 367-368, 573-599. https://doi.org/10.1016/j.ins.2016.05.047
38. Vanaja, S., Belwal, M. Aspect-Level Sentiment Analysis on E-Commerce Data. In: 2018 International Conference on Inventive Research in Computing Applications (ICIRCA), Coimbatore, India, 2018, 1275-1279. https://doi.org/10.1109/ICIRCA.2018.8597286
39. Vinodhini, G., Chandrasekaran, R., M. A Sampling Based Sentiment Mining Approach for E-Commerce Applications. Information Processing & Management, 2017, 53(1), 223-236. https://doi.org/10.1016/j.ipm.2016.08.003
40. Yong, L., Xiaojun, Y., Yi, L., Ruijun, L., Qingyu, J. A New Emotion Analysis Fusion and Complementary Model Based on Online Food Reviews. Computers & Electrical Engineering, 2022, 98, 107679. https://doi.org/10.1016/j.compeleceng.2022.107679
41. Yongzheng, Z., Rajyashree, M., Benny, S. Concept Extraction and E-Commerce Applications, Electronic Commerce Research and Applications, 2013, 12(4), 289-296. https://doi.org/10.1016/j.elerap.2013.03.008
42. Sankar, P, P., Ganapathy, S., Kannan, A. REFERS: Refined and Effective Fuzzy E-Commerce Recommendation System. International Journal of Business Intelligence and Data Mining, 2020, 17(1), 117-137. https://doi.org/10.1504/IJBIDM.2019.10011148
43. Shariaty, S., Moghaddam, S. Fine-Grained Opinion Mining Using Conditional Random Fields. In: 2011 IEEE 11th International Conference on Data Mining Workshops, Vancouver, BC, Canada, 2011, 109-114. https://doi.org/10.1109/ICDMW.2011.85
44. Solairaj, A., Sugitha, G., Kavitha, G., Enhanced Elman Spike Neural Network Based Sentiment Analysis of Online Product Recommendation. Applied Soft Computing, 2023, 132, 1-12. https://doi.org/10.1016/j.asoc.2022.109789
45. Song, H., Chu, J., Hu, Y., Liu, X. Semantic Analysis and Implicit Target Extraction of Comments from E-Commerce Websites. In: 2013 Fourth World Congress on Software Engineering, Hong Kong, China, 2013, 331-335. https://doi.org/10.1109/WCSE.2013.62
46. Steenhof, K., Kochert, M. N., McDonald, T. L. Interactive Effects of Prey and Weather on Golden Eagle Reproduction. Journal of Animal Ecology, 1997, 66(3), 350-362. https://doi.org/10.2307/5981
47. Susana, Z., Ivan, V., Moens, M F. Latent Dirichlet Allocation for Linking User-Generated Content and E-Commerce Data. Information Sciences, 2016, 367-368, 573-599. https://doi.org/10.1016/j.ins.2016.05.047
48. Vanaja, S., Belwal, M. Aspect-Level Sentiment Analysis on E-Commerce Data. In: 2018 International Conference on Inventive Research in Computing Applications (ICIRCA), Coimbatore, India, 2018, 1275-1279. https://doi.org/10.1109/ICIRCA.2018.8597286
49. Vinodhini, G., Chandrasekaran, R., M. A Sampling Based Sentiment Mining Approach for E-Commerce Applications. Information Processing & Management, 2017, 53(1), 223-236. https://doi.org/10.1016/j.ipm.2016.08.003
50. Yong, L., Xiaojun, Y., Yi, L., Ruijun, L., Qingyu, J. A New Emotion Analysis Fusion and Complementary Model Based on Online Food Reviews. Computers & Electrical Engineering, 2022, 98, 107679. https://doi.org/10.1016/j.compeleceng.2022.107679
51. Yongzheng, Z., Rajyashree, M., Benny, S. Concept Extraction and E-Commerce Applications. Electronic Commerce Research and Applications, 2013, 12(4), 289-296. https://doi.org/10.1016/j.elerap.2013.03.008