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[*] **Corresponding author**.

bmanibala@gmail.com

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Sentiment and Fuzzy Aware Product Recommendation System Using HOA and FT-DBN in E- Commerce

B Manikandan[1,2*], P Rama[3], S Chakaravarthi[4]

1 Research Scholar, Department of Computer Science and Engineering, Bharath Institute of Higher Education and Research, Chennai, 600073, Tamilnadu, India
2 Department of Computer Science and Engineering, MNR College of Engineering and Technology, Sangareddy, Hyderabad, 502285, Telangana, India
3 Department of Computer Science and Engineering, Bharath Institute of Higher Education and Research, Chennai, 600073, Tamilnadu, India
4 Department of Artificial Intelligence and Data Science,Panimalar Engineering College, Chennai, 600123, Tamilnadu, India

Abstract

Objectives: To identify and select the customers' liked products by introducing a new product recommendation system. **Methods:** This work proposes a new product recommendation system that incorporates a new feature optimization method called Sentiment weighted Horse herd Optimization Algorithm (SHOA) to identify the most suitable words that help perform effective prediction. This work's prediction process is carried out by applying a newly proposed Deep Belief Network incorporating fuzzy temporal features. This work uses two different Amazon datasets. The first dataset contains 51, 00,000 review comments about various products, including books and movies. The second dataset is built with 82,00,000 review comments on Toys and Games. These data sets consider the product id and review rate important features and are used to compare with all other available works through experimental results. **Findings:**The experiments have been conducted using the Amazon dataset and proved better than other recommendation systems in terms of effectiveness and efficiency through Precision, Recall, Serendipity and nDCG value. **Novelty:** The introduction of a new DBN with Fuzzy Temporal rules and the newly developed SHOA is novel in this work to recommend suitable products to the customer.

Keywords: Feature Optimization; CNN; LSTM; Product Recommendation System; Fuzzy Logic; Fuzzy Rules

1 Introduction

The product recommendation systems playing a major role in this direction to recommend playing a major role in recommending suitable customer asked products to behaviour customers by analysing the customer's purchase behaviour and fuzzy-aware best movement products. This work introduced a new fuzzy-aware product recommendation system incorporating a new optimisation technique for finding the more suitable customer decision-making products. In this recommendation system, an optimisation algorithm plays a vital role in making decisions about the huge products by properly identifying the review comments. The recommendation systems generally incorporate methodologies and consider various factors to find the users' interests. The decision-making frequently changes according to the factors considered in work[1]. In the review analysis process, semantic and sentiment analysis plays a vital role and also be an important factor in making purchase decisions by knowing the customer's interests. Before that, the initial level preprocessing, such as tokenisation, stemming, Parts of Speech (PoS), PoS tagging and stop word removal, is to be done to enhance the performance of the feature extraction process. The more relevant features will be extracted from the detailed review and categorised as positive, negative and neutral comments. The categorisation is also to be done in the initial level of data preprocessing itself. The semantic and sentiment analysis is to be done to identify positive and negative terms. Then feature optimisation is done to finalise the features (terms) that help predict the user's interest and recommend suitable products to the customers.

Feature optimisation is an important task in data preprocessing used to identify the more relevant terms and enhance the recommendation system's performance with less time. The standard optimisation algorithms such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Whale Optimization Algorithm (WOA), Honey Bee Optimization (HOA), Spotted Hyena Optimization Algorithm (SHOA) and Simulated Annealing (SA) are used to optimise the feature in various fields include product recommendation system. The optimised features will be considered input for the classifier to predict the users' uninterested purchase patterns.

The various classification algorithms, including Random Forest, Logistic Regression, Decision Tree, C4.5, Support Vector Machine (SVM), Multiclass SVM, Neural Networks, Deep Belief Networks (DBN), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long-Short Term Memory (LSTM) and Bidirectional LSTM (Bi-LSTM)[2] are used in this field to categorise the user's interests according to their purchase behaviour and predicts the customers purchase behaviour. According to the classification result, the products are recommended to the customers. These algorithms are used in product recommendation systems to make final decisions about the products. Even though a system needs to perform more and requires recommendation accuracy in various fields, for this purpose, a new product recommendation system incorporating a new feature optimization method called SHOA is proposed to identify the most suitable words that help perform effective prediction. The prediction process is carried out in this work by applying a new ensemble deep learner named Fuzzy Temporal DBN.

The researchers developed many product recommendation systems to predict the user's interests and recommend suitable products according to their expectations that are expressed indirectly in social media as feedback. The existing product recommendation systems applied semantic analysis, sentiment analysis, feature selection and classification to predict the customer's exact products. Among them, Khanvilkar and Vora[3] conducted a comparative analysis of various ML algorithms such as Logistic Regression, NB, DT, Random Forest and SVM. These algorithms use sentiment scores on reviews of a product to make decisions. Among them, the Random Forest performed better than other ML algorithms regarding product recommendation accuracy. Dau and Salim[4] developed a new neuro-sentiment deep recommender to capture the aspects and sentiments for predicting suitable products. Specifically, a new semi-supervised topic model is developed for extracting the products' aspects associated with sentiment lexicons incorporated into the LSTM encoder through a neural network-based mechanism to perform better learning. In addition, they also have introduced a fine-grained user-item interaction model to enhance prediction accuracy. The experiments conducted by them achieved better performance than other systems.

Saurabh et al.[5] extensively reviewed the context-aware recommendation system. They have concentrated on the various methodologies and datasets used in their domain, future research and the challenges the available systems face. End of their survey, they suggested some ideas to overcome the challenges and ways to enhance the performance of the existing systems. Sankar et al.[6] developed a new recommendation system that applies fuzzy logic to recommend products by considering the product rating and similarity score. They have tested their system and proved better than the existing systems regarding recommendation accuracy.

Lei et al.[7] proposed a new travel recommendation system that satisfied the various tasks parallelly by considering the important keywords. They have integrated the system's long-term and short-term user preferences and generated the keywords according to the products. They tested their system using the large tourism e-commerce website and demonstrated that their model is better than others. Dheeraj et al.[8] constructed a new ranking method according to the relevancy score. Their method understands and analyse customer personalisation through a metasearch software tool. They have satisfied all the customers according to scalability, failure support and extensibility. Finally, they have proved that their method is more efficient and effective than other ranking methods.

Karthik and Sannasi[9] developed a new product recommendation system incorporating fuzzy rules to decide on various suitable customer products. They have developed a new algorithm for identifying the sentiment score of each product available in the market. The newly generated fuzzy rules and ontological table are used to make decisions accurately according to the sentiment score of the products. The experimental results demonstrate the effectiveness of the recommendation system. David and Hamid[1] examined the association between the different kinds of products and their ratings. Moreover, they have investigated the different types of products and the associated customers. Finally, according to the sentiment analysis result, they have suggested the products and the related customers.

Abolfazl et al.[10] designed a new model that works automatically to analyse the products by conducting sentiment analysis on reviews online. They have performed data normalisation to increase the understandability of input data. Moreover, they have extracted the relevant features by applying the term frequency, latent semantic analysis and speedup the robust features. Ultimately, they used DBN and Whale Optimization methods to perform the feature optimisation and sentiment classification. They also achieved better performance than other methods in accuracy and efficiency. Irem and Sule[11] developed a new recommendation system that works hierarchically to enhance the performance of the e-commerce website in terms of recommendation. Their system has two levels: an encoder representing the item as text and an attention-aware model to recommend the items in sequence order. Finally, their system outperformed other recommendation systems.

Rosewelt and Renjith[12] compared the various ML algorithms, such as Logistic Regression, NB, DT, Random Forest and SVM. These algorithms use sentiment scores on reviews of a product to make decisions. Among them, the Random Forest performed better than other ML algorithms regarding product recommendation accuracy. Idris et al.[13] designed a new LSTM-based Sentiment Scoring Model that considers the rating and review as input for the prediction. Moreover, they also developed a new adaptive LSTM model to enhance prediction accuracy. They used an Amazon dataset with the review comments on Cell Phones, Accessories and fine food. Finally, they have proven their model better than the existing models available in this direction regarding accuracy.

Chen et al.[14] developed a new domain transfer network for selecting the relevant items in various domains according to the user's preferences. Moreover, they have developed a new learning model based on dual-domain contrastive adversarial for performing the pre-training process using the features. They have conducted various experiments and proved superior to other models. Gao et al.[15] address the issues of cross-platform recommendations for users who purchase products online via e-commerce websites. They have collected various purchase behaviour from the user's purchase history on e-commerce websites. Finally, they have designed a framework for recommending suitable products to the customers and proved that their framework is better than other models. Ma et al.[16] developed a new neural classifier built and works based on a social graph that incorporates multiple-hop social relationships. Here, the social relationships are extracted through social media with the help of a graph. Finally, they conducted experiments and performed better on various record sets.

Research Gaps: All the available works are working well even though they need to fulfil the current requirement regarding effectiveness and efficiency.

The proposed model fulfils the gaps in efficiency and effectiveness by achieving better prediction accuracy quickly. For this purpose, a new product recommendation system is proposed in this work for recommending suitable products on time to the customers according to their interests by using the new optimisation techniques, fuzzy logic incorporated deep classifier. Here, the optimisation technique optimises the features that help perform effective classification. The fuzzy rule incorporated deep classifier can perform effective training and testing processes. Finally, the proposed deep classifier recommends suitable products to customers according to their interests.

2 Methodology

This section describes the workflow of the proposed system graphically by providing the overall system architecture. Moreover, the algorithms and equations explain the feature selection, optimisation, and classification in detail.

2.1 Proposed work

A new product recommendation system is proposed to recommend suitable products to the customers according to their interests in this work and explained in detail in this section. The initial level data preprocessing activities such as tokenisation, stemming, stop word removal and PoS tagging are done to extract the core terms that help perform prediction. Moreover, a new feature optimisation method named Sentiment and weight aware Horse herd Optimization Algorithm (SHOA) is proposed for optimising the identified features in the reviews. Using these optimised features, the review comments will be analysed by applying newly developed DBN with fuzzy temporal features to predict the suitable products according to the positive and negative comments about the specific product. First, the feature extraction process is explained.

The overall architecture of the proposed product recommendation system is shown in Figure 1, that consists of four important components such as Amazon Dataset, User Interaction Module, Decision Manager and Product Recommendation System that has three phases such as Sentiment Analyzer, Data Preprocessing and Sentiment Classification Module.

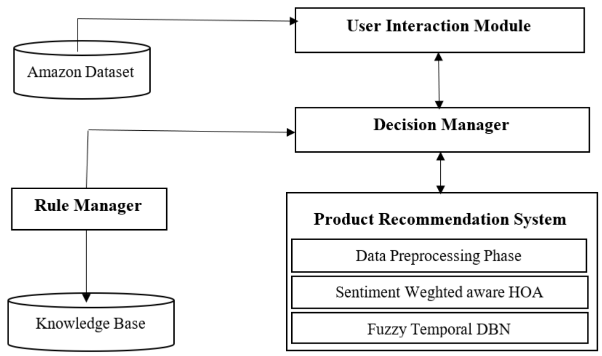

Fig 1. System Architecture

The necessary data is extracted from the Amazon dataset using the user interaction module and transferred to the decision manager. The decision manager forwards them into the product recommendation system. The product recommendation system consists of three important phases: data preprocessing, sentiment-weighted aware HOA, and Fuzzy Temporal DBN. The data preprocessing module performs the data preprocessing tasks, including stemming, stop word removal, tokenisation and syntax analysis. Finally, the preprocessed data is to be moved to the sentiment analyser capable of analysing the data as per sentiments. The proposed sentiment-weighted aware HOA is used to perform the feature optimisation process effectively, and the optimised features or terms are to be used for performing effective classification using Fuzzy Temporal DBN and making final decisions. The sentiment analyser 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 using 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 helps manage the rules available in the knowledge base according to the suggestions of the decision manager. The Amazon dataset contains the customers' purchase history and feedback as review comments.

2.2 Dataset

The standard Amazon dataset evaluates the newly developed product recommendation system. The Amazon dataset also considered various items such as Kindle store items, books, magazines, CDs, Toys, Greeting Cards, Crafts and Video games, groceries, office products, pantries, and home and gourmet food. All these items are categorised into different datasets according to the type of products. The full data set is used to conduct various experiments and also finalise the performance of the proposed product recommendation system.

2.3 Feature Extraction

This section explains in detail the initial data preprocessing and feature extraction level useful for performing effective product recommendations.

2.3.1 Initial Level Data Preprocessing Tasks

This subsection explains the tokenisation, POS Tagging and Parsing in detail. These preprocessing tasks help perform effective classification.

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

POS Tagging: It provides the data on how the terms are applied in a sentence and also identifies the "Nouns", "Pronouns", "Adjectives", and "Verbs" that are tagged on tokens. Moreover, it labels the terms over the POS tagging. Every token is identified and tagged with POS to identify the relevant terms to predict the user's interest.

Parsing: It 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 word's relevancy in terms of subject or object.

2.3.2 Sentiment Analysis through Subjective Score

This research considers the review comments as input for performing sentiment analysis. In the sentiment analysis process, the terms are categorised into "Positive Terms" and "Negative Terms" that are used to find the user's interest in products. Generally, the sent WordNet is used for handling the review comments based on the parts of speech and objective. Here, the positive and negative scores are to be calculated according to the subjective and objective review comments given as input[17]. The positive and negative sores will be calculated according to the number of times the terms appeared. The terms "Glad", "Low Quality", "Bad", "Worst", "Best", "Good", "Not Bad", and "Not Good". Based on the appearance of these words in review comments, the subjective score will be calculated using the equation (1).

$$\mathrm{Subscore}(\mathrm{Re}\,v) = \frac{\sum_{i=1}^{n} (\mathrm{Pos}\,T_i + NegT_i)}{n} \tag{1}$$

Where the variable n indicates the total number of terms in review comments, the variable Rev represents the comments. Here, Rev contains entire comments that are a combination of positive and negative terms. For example, consider the below review comments:

Review 1: The product cost is low.

Review 2: But the product quality could be better.

In the above example, Review 2 has more sentiment than Review 1 regarding product quality. At the same time, Review 1 is a positive comment, and Review 2 is a negative comment. Here, the outcome of Review 1 is stronger than Review 2 in terms of subjective manner. The subjective score is considered and reflects the sentiment score of the comments.

2.3.3 Feature Extraction

After performing the initial level of data preprocessing, the LSA and TF-IDF methods are applied to extract the relevant features from the extracted comments. The TF-IDF method extracts useful features based on sentiment and semantical results. The term frequencies are determined, and how the term arises in the reviews and the TF and IDF are expressed in the equation (2) and (3).

$$TF = \frac{\text{Number of times the word arises in a reviewer comment}}{\text{total number of words in a reviewer comment}} \tag{2}$$

$$IDF = \log \frac{\text{total number of reviewer comments}}{\text{number of reviewer comments with word}} \tag{3}$$

In addition, the LSA is used to extract the relevant terms with context. Generally, the LSA is an unsupervised method used to analyse and identify patterns. Here, the mutual constraints are considered and assigned to all the terms to determine the similarity between the terms. Finally, the more relevant features (terms) are to be extracted according to the similarity between the terms.

2.4 Feature Optimization

This section described the newly developed Sentiment and weighted aware HOA (SHOA) that works in two different aspects for optimising the features. The proposed Sentiment and weighted aware Horse herd Optimization Algorithm (SHOA) is developed based on the standard Horse herd Optimization Algorithm (HOA) that is developed by MiarNaeimi et al.[18].

2.4.1 Sentiment and weighted aware Horse herd Optimization

The HOA inspires the horse herding and social characteristics such as defense, hierarchy, grazing, imitation, sociability and roaming mechanism of horses of various ages. The horses have a defense character to avoid the attackers and to fit with the attackers. In hierarchy characters, the horses live in herds, few horses act as leaders, and others act as followers. In grazing, the horses are preferred to stay in the pasture where the plants, water, pasture, etc., are available. In imitation characters, horses imitate each other in a good or bad manner. In sociability, the horses are liked to stay in groups in which some horses may fight with other horses and also able to stay with other animals such as dogs, sheep and cattle. Finally, in their roaming characteristic, it finds the available pasture. The steps of the Sentiment Weighted aware Horse herd Optimization Algorithm (SHOA) are as follows:

Input: Review Comments

Output: Optimized features

Step 1: Initialize the parameters such as population size $(N)$and the maximum number of iterations (MAX_ITER) .

Step 2: Generate the positions according to the customers location (search space) and stored as two-dimensional matrix by considering the different skills of horses such as defense, hierarchy, grazing, imitation, sociability and roaming.

Step 3: Find the fitness value by using the objective function $f(X_m), \forall m = 1, 2, \ldots, N$ subjective score and weights.

Step 4: Determine the age of the customers range between 1-10, 11-18, 18-24, 25-40, 40-55, 55-70 and above 70.

Step 5: Update the velocity according to the customers age group like the features of horse including grazing, Sociability, hierarchy and defense.

Step 6: The location is updated according to the customers positions and their age.

Step 7: The identified customers comments are to be selected as optimized terms.

Step 8: Store the optimized features into the separate space.

Step 9: The steps 3 to 8 need to be repeated until reach the maximum number of iterations (MAX_ITER) . After reaching the MAX_ITER this process can be stopped.

The proposed SHOA optimises the terms that help categorise the customers' liked and not liked products according to their interests based on their review comments analysis results. The number of iterations is fixed according to the available review comments. Moreover, given the various products available in the market, different age groups customer review comments are considered.

2.5 Classification

The classification process is explained in this section in detail by explaining the newly developed deep classifier called Deep Neural Network with the incorporation of Fuzzy Temporal features (FT-DBN) that is developed according to work proposed by Abolfazl et al.[10]. The proposed FT-DBN assigned the necessary parameters by performing the pre-training and adopts back propagation method to fine-tune weights of the network connection. Here, the k subset $(DC_1, DC_2, \ldots, DC_k)$ is applied from the training process for performing the training process with the k sub DBN classification method where the subset $DC_i = 1, 2, \ldots, K$is assigned to train the corresponding $DBN_i = 1, 2, \ldots, K$. Moreover, each DBN contains three important layers: one input layer, three processing layers and an output layer. Here, the processing layers are used to learn the optimised features automatically from each subset. In addition, the group is obtained from the collection, which is classified into k number of disjoint subsets $DC_1, DC_2, \ldots, DC_k$ where these groups are used to compute the fuzzy membership matrix with temporal constraints $U = [\mu i, j] < t1, t2 >, i = 1, 2, \ldots, K; j = 1, 2, \ldots, N$

The nearest neighbor sample c_i of the i^{th} group is applied for each test sample $x_j$to compute the fuzzy membership degree $\mu i, j$. Then, the sub-DBNs are used to train the test data for each trained classification algorithm $DBN_i = 1, 2, \ldots, K$ to classify the reviews according to the user's emotions or sentiments over the online products in Amazon web applications. Since the prediction results of each sub DBN, the classification algorithms are grouped according to the fuzzy membership function degree $(\mu i, j)$ used in this work. The test output $\vec{x}_j$ in each sub DBN_i that is described as $DBN_i(x_j)$,

and the fuzzy aggregation process is performed to get the aggregated output of each sample presented in the equation (4).

$$\text{Output } = \sum_{i=1}^{k} \mu_i, j < t1, t2 > \times DBN_i(\vec{x}_j) \tag{4}$$

The parameter settings of FT-DBN are provided in this section with the 100-batch size, 200 epochs, and activation functions such as ReLU and Sigmoid with a learning rate of 0.01. The network size is [2,6,8,10] used in this FT-DBN for evaluating the model using the Amazon dataset. This work uses two activation functions and a different number of approaches to train and test the model by considering the Amazon dataset. Finally, the best result is considered the classifier's final output.

3 Results and Discussion

This section describes the standard dataset, performance metrics and experimental results that are conducted to evaluate the proposed product recommendation system and the relevant discussion. First, it explains the standard Amazon datasets[19,20] used in this work. Generally, 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 categorised into different datasets according to the type of products. The dataset is taken online and categorises the customers' feedback according to the products they purchased in various periods. Here, we have considered 100 product reviews as samples and conducted experiments. In this work, we have considered the 70% training and 30% testing datasets for conducting experiments.

3.1 Performance metrics

The proposed product recommendation system is evaluated using standard parameters such as Precision and Recall metrics shown in equations (5) and (6).

$$\text{Precision} = \frac{\text{Relevant Recomended Products}}{\text{Total Recomended Products}} \tag{5}$$

$$\text{Recall} = \frac{\text{Relevant Recomended Products}}{\text{Total no.of relevanted products to be Recomended}} \tag{6}$$

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

Serendipity: This metric is very useful for recommending the suitable product to the user. Serendipity value is calculated by using the formula given in equation (7).

$$P_x = \frac{no\,. - \text{rank}_x}{no\,. - 1} \tag{7}$$

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 equation (8).

$$nDCG(L,k) = \frac{1}{|L|}\sum_{x=1}^{|L|} Z_{kx} \sum_{m=1}^{k} \frac{2^{R(x,m)} - 1}{\log_2(1+m)'} \tag{8}$$

The performance as mentioned above metrics are applied to measure the actual performance of the newly developed product recommendation system.

3.2 Experimental results

Various experiments have been done to evaluate the performance of the proposed product recommendation system. This work evaluates by considering the evaluation parameters such as precision, recall, serendipity and nDCG. Among them, the proposed system considers the precision value. Figure 2 shows the precision value analysis between the proposed product recommendation system and the existing recommendation systems such as Fuzzy recommendation system[6], Recommendation system[21], Fuzzy Recommendation System[9], Irem and Sule[11] and Abolfazl et al.[10]. Here, the five different sets of reviews such as 1000, 2000, 3000, 4000 and 5000 have been considered in the experiments E1, E2, E3, E4 and E5.

Figure 2 demonstrates that the performance of the proposed product recommendation system is proved as better than the existing systems such as the Fuzzy recommendation system[6], Recommendation system[21], Fuzzy Recommendation System[9], Irem and Sule[11] and Abolfazl et al.[10]. The reason for the performance is the use of weighted semantic optimiser, and fuzzy temporal rules incorporated deep classifier.

Figure 3 shows the recall value analysis between the proposed product recommendation system and the existing recommendation systems such as Fuzzy recommendation system[6], Recommendation system[21], Fuzzy Recommendation System[9], Irem and Sule[11] and Abolfazl et al.[10]. Here, the five different sets of reviews such as 1000, 2000, 3000, 4000 and 5000 have been considered in the experiments E1, E2, E3, E4 and E5.

Figure 3 demonstrates that the performance of the proposed product recommendation system is proved as better in terms of recall value than the existing systems such as the Fuzzy recommendation system[6], Recommendation system[21], Fuzzy Recommendation System[9], Irem and Sule[11] and Abolfazl et al.[10]. The reason for the performance is the use of weighted semantic optimiser, and fuzzy temporal rules incorporated deep classifier.

Figure 4 shows the Serendipity value analysis between the proposed product recommendation system and the existing recommendation systems such as Fuzzy recommendation system[6], Recommendation system[21], Fuzzy Recommendation System[9], Irem and Sule[11] and Abolfazl et al.[10]. Here, the five different sets of reviews such as 1000, 2000, 3000, 4000 and 5000 have been considered in the experiments E1, E2, E3, E4 and E5.

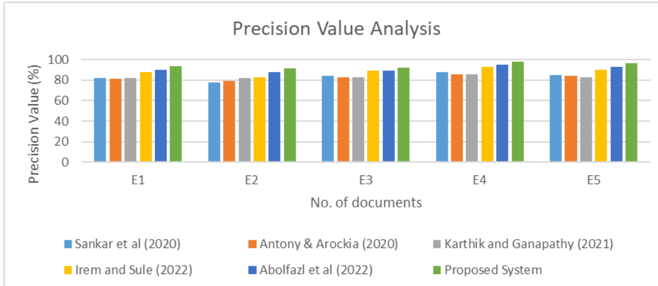

Fig 2. Precision Value Analysis

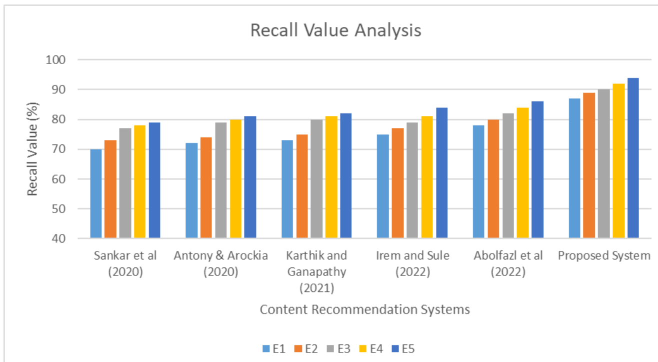

Fig 3. Recall Value Analysis

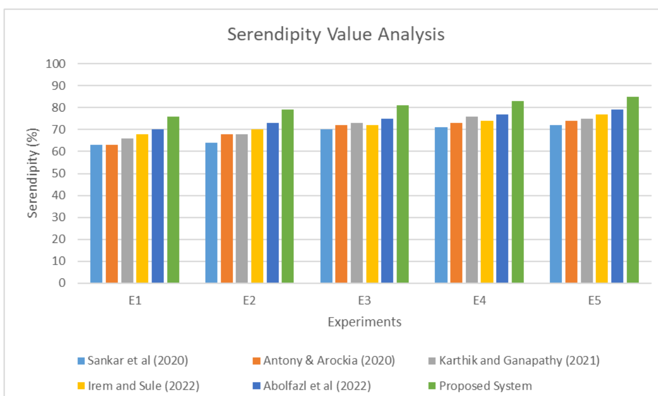

Fig 4. Serendity Value Analysis

Figure 4 demonstrates that the performance of the proposed product recommendation system is proved as better in terms of serendipity value than the existing systems such as the Fuzzy recommendation system[(6)], Recommendation system[(21)], Fuzzy Recommendation System[(9)], Irem and Sule[(11)] and Abolfazl et al.[(10)]. The reason for the performance is the use of weighted semantic optimiser, and fuzzy temporal rules incorporated deep classifier.

Figure 5 shows the nDCG value analysis between the proposed product recommendation system and the existing recommendation systems such as Fuzzy recommendation system[(6)], Recommendation system[(21)], Fuzzy Recommendation System[(9)], Irem and Sule[(11)] and Abolfazl et al.[(10)]. Here, the five different sets of reviews such as 1000, 2000, 3000, 4000 and 5000 have been considered in the experiments E1, E2, E3, E4 and E5.

Figure 5 demonstrates that the performance of the proposed product recommendation system is proved as better in terms of nDCG value than the existing systems such as the Fuzzy recommendation system[(6)], Recommendation system[(21)], Fuzzy Recommendation System[(9)], Irem and Sule[(11)] and Abolfazl et al.[(10)]. The reason for the performance is the use of weighted

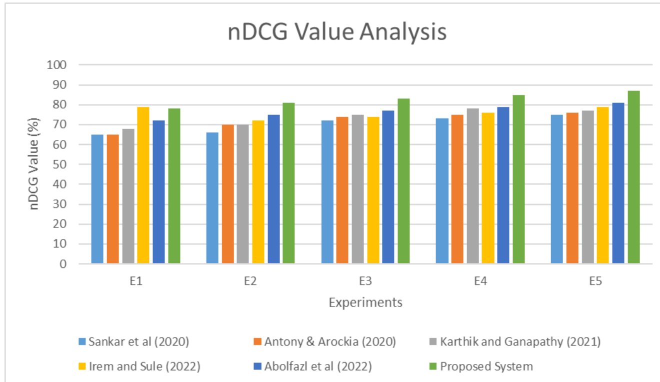

Fig 5. nDCG Value Analysis

Table 1. Comparative analysis

Experiments	Sankar et al (2020)	Antony & Arockia (2020)	Karthik and Ganapathy (2021)	Irem and Sule (2022)	Abolfazl et al (2022)	Proposed Recommen-dation System
E1	78.46	81.13	84.57	88.78	91.24	94.5
E2	78.94	81.24	84.75	88.88	89.23	94.8
E3	85.61	84.66	86.26	91.32	90.45	95.6
E4	89.76	85.32	87.48	92.67	93.56	97.8
E5	86.21	85.78	87.92	92.76	94.25	97.9

semantic optimiser, and fuzzy temporal rules incorporated deep classifier.

Table 1 shows the comparative analysis by considering the prediction or recommendation accuracy between the proposed product recommendation system and the existing systems such as Fuzzy recommendation system [6], Recommendation system [21], Fuzzy Recommendation System [9], Irem and Sule [11] and Abolfazl et al. [10]. Here, the five different sets of reviews such as 1000, 2000, 3000, 4000 and 5000 have been considered in the experiments E1, E2, E3, E4 and E5.

Table 1 demonstrates that the performance of the proposed product recommendation system is proved as better in terms of prediction or recommendation accuracy than the existing systems such as the Fuzzy recommendation system [6], Recommendation system [21], Fuzzy Recommendation System [9], Irem and Sule [11] and Abolfazl et al. [10]. The reason for the performance is the use of weighted semantic optimiser, and fuzzy temporal rules incorporated deep classifier.

4 Conclusion

A new product recommendation system has been proposed and implemented to identify suitable customer products. Here, a newly developed feature optimization method called Sentiment Weighted aware HOA is used to identify the most suitable words that help perform effective prediction. This work predicts by applying a new ensemble deep learner that combines the existing deep learning algorithm DBN with fuzzy temporal features. This work uses the proposed SWHOA to select and optimise useful features for enhancing classification accuracy. Moreover, the proposed fuzzy temporal rules incorporated DBN are used to categorise the more relevant products and recommend suitable products to the customer. The experiments have been conducted using the Amazon dataset and proved better than other recommendation systems in terms of prediction accuracy and time. The proposed system obtained 96.12% prediction accuracy, more than 4% better than the existing works. Incorporating new feature optimisation achieves this to enhance the efficiency and fuzzy rules incorporated deep classifier for improving the effectiveness. Future work that can be done in this direction is introducing a new sentiment-aware feature selection method and effective deep learning algorithm.

References

1) David RS, Hamid K. Recommendation systems and convergence of online reviews: The type of product network matters!. 2021. Available from: https://doi.org/10.1016/j.dss.2020.113475.
2) Rosewelt AL, Raju ND, Ganapathy S. An Effective Spam Message Detection Model using Feature Engineering and Bi-LSTM. In: 2022 International Conference on Advances in Computing, Communication and Applied Informatics (ACCAI). IEEE. 2022. Available from: https://doi.org/10.1109/ACCAI53970.2022.9752652.
3) Khanvilkar G, Vora D. Smart Recommendation System Based on Product Reviews Using Random Forest. In: 2019 International Conference on Nascent Technologies in Engineering (ICNTE). IEEE. 2019. Available from: https://doi.org/10.1109/ICNTE44896.2019.8945855.
4) A D, Salim N. Sentiment-Aware Deep Recommender System With Neural Attention Networks. *IEEE Access*. 2019;7:45472–45484. Available from: https://doi.org/10.1109/ACCESS.2019.2907729.
5) Saurabh K, Sunil FR. Context Aware Recommendation Systems: A review of the state of the art techniques. *Computer Science Review*. 2020;37:1–11. Available from: https://doi.org/10.1016/j.cosrev.2020.100255.
6) Sankar PP, 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. Available from: https://dx.doi.org/10.1504/IJBIDM.2019.10011148.
7) Lei C, Jie C, Guixiang Z, Youquan W, Weichao L. A multi-task learning approach for improving travel recommendation with keywords generation. 2021. Available from: https://doi.org/10.1016/j.knosys.2021.107521.
8) Dheeraj M, Omprakash R. An intelligent approach to design of E-Commerce metasearch and ranking system using next-generation big data analytics. *Journal of King Saud University - Computer and Information Sciences*. 2021;33(2):183–194. Available from: https://doi.org/10.1016/j.jksuci.2018.02.015.
9) Karthik RV, 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. Available from: https://doi.org/10.1016/j.asoc.2021.107396.
10) Abolfazl M, Varaprasad RM, Leo GD, Gerard J, Preethi V. Online product sentiment analysis using random evolutionary whale optimization algorithm and deep belief network. *Pattern Recognition Letters*. 2022;159:1–8. Available from: https://doi.org/10.1016/j.patrec.2022.04.024.
11) Irem I, Sule GO. A hierarchical recommendation system for E-commerce using online user reviews. 2022. Available from: https://doi.org/10.1016/j.elerap.2022.101131.
12) L AR, J AR. 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). IEEE. 2019. Available from: https://doi.org/10.1109/ICONSTEM.2019.8918796.
13) Idris R, Naomie S, Aminu D, Maged N. Modeling sentimental bias and temporal dynamics for adaptive deep recommendation system. *Expert Systems with Applications*. 2022;191:116262. Available from: https://doi.org/10.1016/j.eswa.2021.116262.
14) Chen X, Lei C, Liu D, Wang G, Tang H, Zha ZJ, et al. E-Commerce Storytelling Recommendation Using Attentional Domain-Transfer Network and Adversarial Pre-Training. *IEEE Transactions on Multimedia*. 2022;24:506–518. Available from: https://doi.org/10.1109/TMM.2021.3054525.
15) Gao C, Lin THH, Li N, Jin D, Li Y. Cross-platform Item Recommendation for Online Social E-Commerce. *IEEE Transactions on Knowledge and Data Engineering*. 2021;35(2):1–1. Available from: https://doi.org/10.1109/TKDE.2021.3098702.
16) Ma D, Wang Y, Ma J, Jin Q. SGNR: A Social Graph Neural Network Based Interactive Recommendation Scheme for E-Commerce. *Tsinghua Science and Technology*. 2023;28(4):786–798. Available from: https://doi.org/10.26599/TST.2022.9010050.
17) Ameen B, Zohair A, Ali D, Rabeeh AA, Hussain D. Aspect based Sentiment Analysis Polarity Estimation of. *Customer Reviews on Twitter Computers, Materials & Continua*. 2021;67(2):2203–2225. Available from: https://www.techscience.com/cmc/v67n2/41318/html.
18) Miarnaeimi F, Azizyan G, Rashki M. Horse herd optimization algorithm: A nature-inspired algorithm for high-dimensional optimization problems. *Knowledge-Based Systems*. 2021;213:106711. Available from: https://doi.org/10.1016/j.knosys.2020.106711.
19) Amazon Dataset. . Available from: https://app.datastock.shop/?site_name=Amazon_USA_Product_Details.
20) Amazon dataset. . Available from: https://www.kaggle.com/datasets/lokeshparab/amazon-products-dataset.
21) Antony RL, Arokia RJ. 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. Available from: https://doi.org/10.3233/JIFS-191721.