Efficient Collaborative Filtering based Recommendation System for Business Promotions Using Deep Neural Network

R.P. Jaia Priyankka, S. Arivalagan, P. Sudhakar

Abstract--- ***In the last decade, recommendation system (RS) has become popular due to its capability to foresee whether the specific customer would have preference for the item or not depending over the customer profile. Collaborative filtering methods in RS constructs the model after the consideration of the history of the user such as ratings given by the user to particular products, previously bought, wish list, etc. In addition, it also considers the identical decisions made by various users and then employs the model to determine the product or rating in which the user may be interested in. As the user's rating plays a major part in collaborative filtering, it is needed to develop a classification model to classify the product reviews. In this paper, we introduce a collaborative filtering method using deep neural network (DNN) to classify the online produce reviews. Based on the classification of the reviews, the products will be properly recommended to the user. The proposed DNN model is validated using a set of four dataset collected from online product reviews from Amazon namely Canon dataset, iPod dataset, DVD and Nokia dataset. The experimental values proves that the DNN model is effective than the compared methods.***

Keywords--- ***Classification, Collaborative Filtering, Deep Neural Network, Recommendation System.***

I. INTRODUCTION

Exponential increase in the sum of digital data available and count of surfs over internet has formed a major challenge of data overload that suppresses the accessing speed over the internet which is items of interest. DevilFinder, Altavista and Google are the information retrieval systems that solved this issue partially; however, personalization and prioritization of the data were in absence. This has enhanced the need for recommender system (RS) more than before years. In order to the customer interest, preference otherwise behavior over the item[1], RS deal with a loads of data [2] through filtering significant data with the above constraints. It has capability to foresee whether the specific customer would have preference for the item or not depending over the customer profile. For together the customer and service providers, it is found to be beneficial [3]. Within the online shopping site, it decreases the transaction costs of selecting and finding items [4]. RS also enhances quality and decision making procedure [5]. In e-commerce environment, RS improves revenue; they are effective in selling some more products. RS aid customer through enabling them to surf beyond searching catalog in scientific libraries. Hence, the requirement to employ accurate and efficient RS in a system which it gives dependable and relevant recommendations for customers cannot be overemphasized. Beneath complex data setup[6], RS is described as a decision making scheme for customer. From the view of e-commerce, RS was defined as a tool that aids in customer search by records of knowledge that is relevant to customers' preference or interest [7]. RS was described in terms of augmenting and assisting the social procedure of employing suggestions of other to create options while there is no enough experience or personal knowledge of those alternatives [8]. By giving the customer exclusive content, service recommendations and personalized contents, RS manages the issue of data overload which customer usually going through. Nowadays, different methods for constructing RS have been developed, that can use content-based filtering, collaborative filtering and hybrid filtering [9–11].

Collaborative filtering method is the most common and mature model that has been implemented. By assuming same decision created through various customers and past behavior of the customer, Collaborative filtering is used to estimate the rating or item that the customer may interested in. By assuming the customer comprise same interest, user-based Collaborative filtering approaches creates recommendations. It relates the product and as per the user. In the Fig. 1, 1st user is recognized with the 3rd user comparatively to second, since the rating set by the third customer is very similar to the 1st one. This is why the item 3 is recommended to the user. Collaborative filtering suggests items through recognizing other user with same taste; it employs their choice to suggest items to the active user. In various application domains, Collaborative RS have been implemented. Out of gigantic news database, GroupLens is a news-based structure that used collaborative schemes in guiding the customer to position articles [12]. To construct user profile depending on the ratings over music albums [10], Ringo is an online social data filtering system which employs collaborative filtering. To enhance the suggestion, Amazon employs topic diversification method [13]. To avoid scalability problem, this system employs collaborative filtering scheme through producing a similar items table which is offline by the use of item-to-item matrix. Based on the customers' purchase history, the machine then suggests other products.

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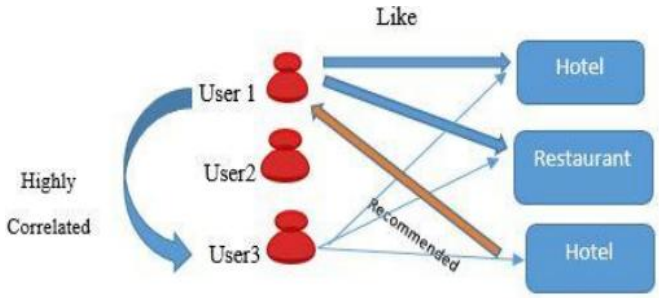

Fig. 1: Collaborative filtering

To the customer characteristics, content-based technique matches content resources on the other hand. Unlike collaborative techniques [14, 15], the techniques in Content-based filtering usually depend on their predictions over customers' data and it avoids contributing with the other customers. By employing naive Bayesian classifier, Pazzani et al. [16] modeled an agent that predicts pages in internet that the customer is interested in. This agent enables a customer to give training samples through rating various pages as either cold or hot. In Usenet news setup, Jennings and Higuchi [17] demonstrates a NN which models the user interests. For processing, the ANNs containa set of interconnected computational model and artificial neurons. Over different kinds of ANNs, Kohonen Self Organizing Maps (SOMs), Feedforward networks, Back Propagation NN (BPNN), Hopfield networks are some techniques. The ANNs comprise the capability to model non-linear dependencies [18], to learn, memorise, and to give relationship between the input data. The RS depended over ANNs are represented below. For TV program suggestions, context-aware RS is projected in [19]. Within adjacent vector space, the TV programs available are noted and continuously a common transform is given to reduce its dimension. A Feedforward NN is applied to predict whether a particular TV program is of main interest to the customer or not. Through learning the habits of viewing TV of the viewer, in this approach, the cold start issue is avoided. The temporal context together with the programming information is loaded into a Feedforward NN with single hidden layer. By commencing extra input nodes, the contextual data is gained out of the machine clock and is additionally given to the NN. With one hidden layer, testing this method over four past customer interactions shows accuracy of 92%. But, over small scale machine, this was tested. Enhancing the count of nodes at the entire layer needs weight adjustment which is not preferable over large-scale. To give personalized suggestion, depending over the notion which the customer with same navigation features that comprises same interest, Chou *et al.* [20] projected a technique.With the same navigation characteristics, a BPNN training model is employed to improve the suggestion accuracy through dividing the customers into classes. By the approach of unsupervised Web mining, the customer navigation characteristics are analyzed further through deriving the patterns of navigation. The researches had chosen a website which is successful in selling skin and soap products to examine the projected method validity. In hidden layer, with eight nodes, the accuracy seems to be the best in classification. But, the system might go through the scalability issues hence it is not sure how to decide the count of intermittent nodes. However, the machine was unable to give suggestions accurately, for the items and customers with some occurrences. A content recommendation tool for Web personalization depending on the ANNs and Kano's scheme [21] is projected in [22]. By the pattern and demographic information for internet, the behaviors in online shopping of the customer belonging to various groups were analyzed. In spite of traditional clustering methods like *k*-means, this method avoids the issue of cold start through giving the ANN to the customer grouping. But, this method seems to be poor when to deal with the issue of sparsity since it needs initially massive dataset and enough count of customer ratings. A movie RS is developed by Biancalana *et al.* [23], which depends on the consideration that the things happening in circumstance might impact over recommendations. Using the time intervals predefined like one month, one week or one day, the customer information were pre-processed through clustering the count of movie ratings through the given customer. To conclude the ratings of the customer, the authors employed NN afterwards. Using input parameter, the NN was trained: (a)distribution of count of customers rating for a movie per week and per day, (b)rating submission date, and (c)the total number of ratings given to a movie. The classification accuracy of 71.9% was attained when testing the neural network over training sets and testing sets of more or less identical sizes. A method to ease the problem of cold start and sparsity in RS is projected in [24]. Depending on the rating matrix, Probabilistic NN (PNNs) is used for the estimation of trust over the customers. By employing the estimated trust values, the presented method is efficient in sparse rating matrix smoothing. By employing PNN, the trust values and trusted clusters for customer in those groups are recognized. With the enhancement in level of sparsity, the projected system performs better for sparsity issue. But, Pearson worked well at 50% level of sparsity. While testing with the issue of cold start, the projected method majorly performs well than the and Pearson with an error of 0.2 compared to the average error of 0.4 of the other systems and cosine. When compared to the other methods, the projected method performance by means of MAE shows enhanced results.

As the user's rating plays a major part in collaborative filtering, it is needed to develop a classification model to classify the product reviews. In this paper, we introduce a collaborative filtering method using deep neural network (DNN) to classify the online produce reviews. Based on the classification of the reviews, the products will be properly recommended to the user. The proposed DNN model is validated using a set of four dataset collected from online product reviews from Amazon namely Canon dataset, iPod dataset, DVD and Nokia dataset. Different classification measures are employed for validating the characteristics of DNN model.

The upcoming section of the paper is mentioned as follows: the proposed DNN model is explained in Section 2 and the results are discussed in Section 3. In section 4, the paper is concluded.

II. PROPOSED MODEL

This section explains the process involved in the collaborative filtering of RS which classifies the online product reviews and recommends the best reviewed product to the user. The overall procedure of the proposed method consists of 3 steps namely preprocessing, extracting features and classifying data.

2.1. Preprocessing

In the preprocessing stage, the original user reviews about the product is gathered from the Amazon website. Several noises such as buzzy words, URLs, stop words, hash tag, and etc might be present in the collected reviews. These noises should be eliminated before proceeding to the feature extraction step. Hence, we employ two levels of preprocessing in prior to extracting features.

Level 1

In the 1st level, the unwanted words are discarded from the product reviews using the following conditions:

- URLs are discarded using regular expression matching.
- @Username will be filled with "user" via regular expression matching
- Since the hash tag hold essential data, the hash tag will be elimination and the remaining text will be retained. For example, replace #news by news
- Symbols (, [, }, /, \ and _ are discarded from the user reviews as well as many white spaces are filled with a single white space.

Level 2

In the second level, stop words are acronyms are employed for improving the precision of the data generated from the previous level. To perform this, a set of operations which are listed below will be performed.

- Words in the user product review are changed to lowercase
- Stop words will be discarded
- Sequence of identical characters in the word will be filled by a single character, e.g., "helllooo" is changed to "hello".
- Words which does not start with the alphabets are discarded
- By the use of acronym dictionary, the shorter forms of words are changed to whole sentences.

2.2. Feature extraction

After the online product reviews are pre-processed, they are converted to feature vectors through the computation of 10 features from the employed dataset. The features extracted from the given data are listed below and some samples of the various features are given in Table 1:

- Total number of characters: It represents the number of words present in the user reviewindicates the word count in the online product review
- Positive Emojis: It denotes the symbols which expresses the state of happiness.
- Negative Emoji: It denotes the symbols which expresses the state of sorrow.
- Neutral Emoji: It denotes the symbols which does not expresses any state of feeling
- Positive Exclamation: It denotes the exclamatory words which conveys a position opinion about a particular topic
- Negative Exclamation: It denotes the exclamatory words which conveys a negative opinion about a particular topic
- Negation: It denotes the words which indicate the negative expression and this feature counts the number of negation words in the user reviews.
- Positive Words: it denotes the word which indicates the positive feelings. In addition, the two continuous negative words indicate a positive word.
- Negative Words: It gives a total count of the number of negative words present in the user reviews
- Neutral Words: It gives a total count of the number of neutral words present in the user reviews

Table 1: Samples of various features

S. No	Feature name	Descriptions
1	**Stopwords**	Ah, can't, etc, isn't
2	**Positive Emoji**	:-),:-],:-3,:),:],:3,:>,8),:},:->,8-)
3	**Negative Emoji**	:-(,:(,:-c,:c,:-<,:<,:-[,:[,:-||,>:[,:{
4	**Neutral Emoji**	:-/,:/,:-.,>:\,>:/,:\,=/,=\,:L,=L,:S
5	**Positive Exclamation**	Ah,Oh, Oof, Phew, Whew, Aha, Boo-yah, Ho-ho
6	**Negative Exclamation**	Ack, Bah, Ew, Gak, Ick, Ugh, Yuck, yech
7	**Negation**	No, Not, None, No one, Nobody, Nothing, Neither
8	**Positive words**	Accomplished, accurately, adaptable, beautiful
9	**Negative words**	Abnormal, abort, abuse, anxious, ashamed
10	**Neutral words**	okay, fine, adequate, family, rarely

2.3. DNN based classification algorithm

A collaborative filtering method using deep neural network (DNN) is used to classify the online produce reviews. Based on the classification of the reviews, the products will be properly recommended to the user. As mentioned before, the collaborative filtering methods constructs the model after the consideration of the history of the user such as ratings given by the user to particular products, previously bought, wish list, etc. In addition, it also considers the identical decisions made by various users and then employ the model to determine the product or rating in which the user may be interested in. As the user's rating plays a major part in collaborative filtering, it is needed to develop a classification model to classify the

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product reviews. For classification, DNN is highly preferred and is presently employed in different fields and ensured that it is an effective tool for solving complex problem.

Using DNN, the computer model can learn the classification task directly from the images, documents, etc. It is an improved model of NN with the use of multiple hidden layer in the network between the input and output layers for defining the complex and non-linear relationship. This concept gained attention among various research people to identify optimal solutions. Although DNN is devised in the 1980s, it became famous in the last decade due to the following uniqueness:

- DNN requires more amount of labeled data like the designing of driverless cars undergo training with billions of images and several weeks of videos
- It requires high computation power

From the various DNN models, the CNN is commonly used for operating difficult functions using convolution filters. Though CNN model has the advantageous of the no need of extracting features before the classification task, the time needed to train CNN will be high. It also needs more labeled dataset for constructing and training the model before it is given to the classifier. The DNN is a default feed forward NN where the input comes from the input layer to the output layer using different hidden layers, usually more than two layers. The structure of the DNN is provided in the Fig. 2. The three unique methods to construct the DNN classification model are given here.

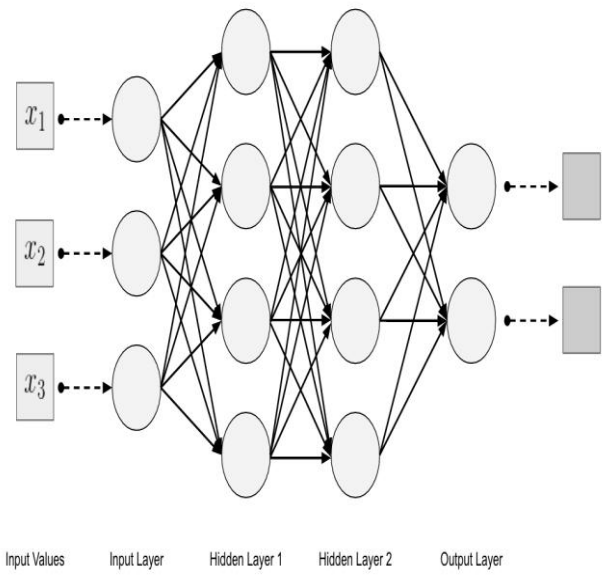

Fig. 2: Architecture of DNN

Training DNN

To train the DNN from the beginning, it is essential to gather large quantity of labeled data and construct a network model for learning the available features. It will be helpful for the new applications or the ones with more output classes. It is an infrequently employed approach because of the large amount of available data and the time consuming training process which may lasts for weeks to months.

Transfer Learning

Various DNN applications employ transfer learning technique which fine tunes the earlier trained model. For example, present network such as AlexNet or GoogLeNet, and news feed data comprises of previously unknown states. When few tweets are made in the network, a new process will be carried out like classifying the animals like dogs or cats instead of 1000 different objects. It is beneficial due to the requirement of less training and less computation time reduced from weeks to minutes or hours.

Feature Extraction

An additional use of DNN is the process of extracting features. Since the layers undergo processing using specific features from the pictures, the feature extraction from the network at any instance can be carried out while training the networks. These features can be provided as the input to the ML approach which performs the classification task.

III. EXPERIMENTAL RESULTS AND DISCUSSION

The proposed DNN model is validated using a set of four dataset collected from online product reviews from Amazon namely Canon dataset, iPod dataset, DVD and Nokia dataset.

The details of the dataset are given in Table 2. The number of instances in the dataset varies from a minimum of 585 to a maximum of 1811 instances.

Table 2: Dataset description

S.No	Dataset	No.of instance	No. of classes	Positive	Negative
1	**Canon**	636	2	500	136
2	**iPod**	1811	2	380	1431
3	**DVD**	839	2	684	155
4	**Nokia**	585	2	135	450

A detailed comparative analysis is also made with proposed method on various classifiers namely ACO, ACO-K, PSO, CSK, SVM and NN methods. The parameter settings for these methods are tabulated in Table 3. The existing methods are also implemented using the same set of four datasets.

To highlight the efficiency of DNN over other methods, several performance metrics are used for comparison purposes.

The performance metrics are False Positive Rate (FPR), False Negative Rate (FNR), sensitivity, specificity, accuracy, F-score, Youden index (Y), discriminant power (DP), G-measure, Mathew correlation coefficient (MCC), Positive likelihood (P^+), Negative likelihood (P^-), False Discovery Rate (FDR), False Omission Rate (FOR) and kappa coefficient value (K).

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Table 3: Parameter settings

S.No	Parameter	DNN	ACO	ACO-K	PSO	CSK	SVM	NN
1	Probability (P_a)	-	-	-	-	0.25	-	-
2	Step Scaling Factor (∞)	-	-	-	-	0.01	-	-
3	No of Iterations	600	600	600	600	600	600	600
4	Cognitive Constant(C_1)	-	-	-	2	-	-	-
5	Social Constant(C_2)	-	-	-	2	-	-	-
6	Inertia Weight (W)	-	-	-	0.8	-	-	-
7	Zeta (Diversification)	-	1	-	-	-	-	-
8	Intensification Factor (Q)	-	0.5	-	-	-	-	-
9	Seed	2001	-	-	-	-	1	-
10	Degree	-	-	-	-	-	3	-
11	Learning Rate	0.0001,0.1	-	-	-	-	-	0.3
12	Momentum	0.68,0.99	-	-	-	-	-	0.2
13	Neurons	200	-	-	-	-	-	-
14	Hidden Layer	3	-	-	-	-	-	-

The details of the extracted features from the four applied dataset are given in Table 4.

The values in the table show the mean and standard deviation (SD) of the 10 features discussed in the previous section.

As the total characters indicates the character count exist in the dataset, the mean and SD values are found to be comparatively high.

Fig. 3 shows the distribution of the positive and negative words present in the four dataset.

It indicates the random distribution of the positive and negative words in the dataset where the number of positive and negative words is competitive to each other which help to verify the consistent performance of the DNN model. Next, the confusion matrix (with positive 'P' and negative 'N' elements) and the classification results of the four dataset are discussed in the next subsection.

Table 4: Extracted features from various dataset

S.No	Feature name	Canon dataset		iPod		DVD		Nokia	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD
1	Total characters	72.013	47.352	68.049	43.894	58.098	37.408	65.272	42.018
2	Positive Emoji	0	0	0	0	0	0	0	0
3	Negative Emoji	0	0	0	0	0	0	0	0
4	Neutral Emoji	0	0	0	0	0	0	0	0
5	Positive Exclamation	0.009	0.097	0.015	0.123	0.023	0.149	0.012	0.109
6	Negative Exclamation	0	0	0	0	0	0	0	0
7	Negation	0	0	0	0	0	0	0	0
8	Positive words	1.459	1.648	1.273	1.623	0.886	1.278	1.246	1.402
9	Negative words	0.998	1.441	1.350	1.654	1.031	1.338	0.957	1.362
10	Neutral words	0.011	0.104	0.007	0.081	0.027	0.163	0.009	0.109

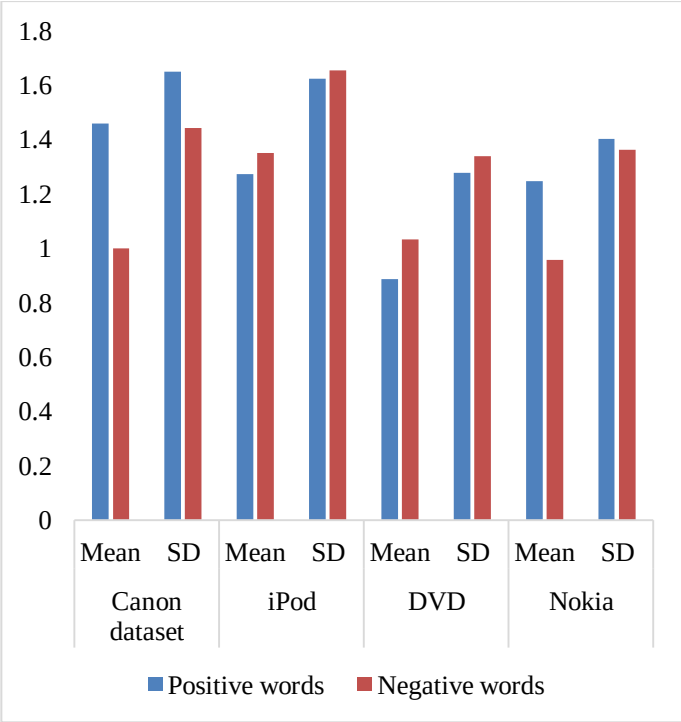

Fig. 3: Distribution of Positive vs Negative words

3.1. Result analysis on Canon dataset

Table 5 and Table 6 shows the obtained confusion matrix and the classification results of the proposed and compared methods on the applied Canon dataset. From the table 1, it is shown that the proposed DNN model attains maximum classification performance with the FPR of 2.96, FNR of 0.99, sensitivity of 99.00, specificity of 97.03, accuracy of 99.10, Y of 96.03, ρ^+ of 33.41, ρ^- of 97.23, DP of 5.06, GM

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of 99.10, MCC of 0.96, FDR of 0.80, FOR of 3.68 and kappa value of 95.77. Measuring the classifier results using FPR and FNR, the DNN shows better results whereas the CSK shows worse results with the higher values of 48.46 and 15.81 respectively.

Table 5: Confusion Matrix of Canon Dataset

Experts	DNN		ACO-K		ACO		PSO		CSK		SVM	
	P	N	P	N	P	N	P	N	P	N	P	N
P	496	4	491	9	486	14	450	42	426	63	455	47
N	5	131	7	129	9	127	69	75	80	67	78	56

The table shows that minimum values are obtained by the DNN whereas the maximum values of FPR and FNR are obtained by CSK, SVM, NN and PSO. At the same time, the ACO and ACO-K algorithms manages to show better performance than all the other methods except the DNN model. In the same way, the maximum sensitivity and specificity value of 99 and 97.03 is attained by the DNN indicating the positive results whereas the minimum values of 84.18 and 51.53 is attained for CSK. The better classification accuracy of 98.58 is attained by the DNN model. At the same time, the ACO and ACO-K algorithms shows competitive results than the compared ones except DNN. As a whole, the proposed DNN model is superior to the compared classifiers interms of different measures implying that it is the appropriate classifier model for the Canon dataset. In addition, Fig. 4 shows the comparative analysis of various classifiers interms of Accuracy, F-score and kappa on the Canon dataset. From the figure, it is apparent that the DNN is superior to other methods.

Table 6: Comparative results of different classifiers on Canon dataset

Classifier	FPR	FNR	Sens.	Spec.	Accu	F-score	Y	ρ^+	ρ^-	DP	GM	MCC	FDR	FOR	Kappa
DNN	2.96	0.99	99.00	97.03	98.58	99.10	96.03	33.41	97.23	5.06	99.10	0.96	0.80	3.68	95.77
ACO-K	6.52	1.40	98.59	93.47	97.48	98.39	92.07	15.11	66.50	4.65	98.39	0.92	1.8	5.14	92.55
ACO	9.92	1.81	98.18	90.07	96.38	97.68	88.25	9.88	49.53	4.34	97.68	0.89	2.80	6.61	89.38
PSO	35.89	13.29	86.70	64.10	82.54	89.02	50.80	2.41	4.82	1.90	89.05	0.47	8.53	47.91	46.63
CSK	48.46	15.81	84.18	51.53	77.51	85.62	35.72	1.73	3.25	1.57	85.64	0.34	12.88	54.42	34.07
SVM	45.63	14.63	85.36	54.36	80.34	87.92	39.73	1.87	3.71	1.69	87.96	0.35	9.36	58.22	35.43
NN	41.28	13.28	86.71	58.71	81.91	88.82	45.43	2.10	4.42	1.85	88.85	0.41	8.96	52.23	41.64

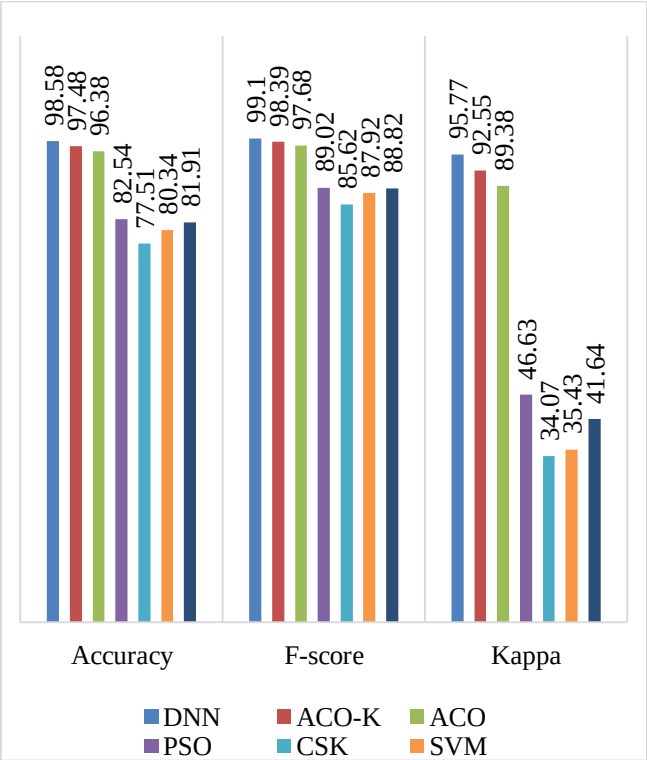

Fig. 4: Performance analysis of various methods on Canon Dataset

3.2. Result analysis on ipod dataset

Table 7 and Table 8 shows the obtained confusion matrix and the classification results of the proposed and compared methods on the applied ipod dataset. For this dataset, SVM and NN exhibit worse performance than its competitors. At the same time, it is noted that PSO and CSK as well as ACO and ACO-K achieves almost closer performance in some of the criteria such as FPR, FNR, accuracy and F-score. Similarly, the ACO-K exhibit maximum classification performance than the compared methods except the DNN model.

Table 7: Confusion Matrix of ipod Dataset

Experts	DNN		ACO-K		ACO		PSO		CSK		SVM	
	P	N	P	N	P	N	P	N	P	N	P	N
P	375	5	373	7	371	9	271	90	249	112	255	220
N	13	1418	20	1411	36	1395	65	1385	54	1396	56	1289

Here, the presented DNN model attains maximum classifier results and shows better classification performance with the FPR of 0.35, FNR of 3.35, sensitivity of 96.64, specificity of 99.64, accuracy of 99.00, F-score of 97.65, Y of 96.29, ρ^+ of 27.5, ρ^- of 29.74, DP of 3.72, GM of 97.66, MCC of 0.97, FDR of 1.31, FOR of 0.9 and kappa value of 97.02.

The values present in the table indicated that the DNN model provides significantly better predictive results in all criterions.

In addition, Fig. 5 shows the comparative analysis of various classifiers interms of Accuracy, F-score and kappa on the Canon dataset. From the figure, it is clearly shown that the DNN is the effective classifier than the compared ones.

Table 8: Comparative results of different classifiers on ipod dataset

Classifier	FPR	FNR	Sens.	Spec.	Accu	F-score	Y	ρ^+	ρ^-	DP	GM	MCC	FDR	FOR	Kappa
DNN	0.35	3.35	96.64	99.64	99.00	97.65	96.29	275.0	29.74	3.72	97.66	0.97	1.31	0.90	97.02
ACO-K	0.49	5.08	94.91	99.50	98.50	96.50	94.41	192.2	19.55	3.25	96.52	0.95	1.84	1.39	95.55
ACO	0.64	8.84	91.15	99.35	97.51	94.28	90.51	142.2	11.23	2.61	94.33	0.92	2.36	2.51	92.69
PSO	6.10	19.34	80.65	93.89	91.44	77.76	74.55	13.21	4.85	1.65	77.81	0.72	24.93	4.48	72.47
CSK	7.42	17.82	82.17	92.57	90.83	75	74.75	11.06	5.19	1.75	75.28	0.69	31.02	3.72	69.44
SVM	14.57	18.00	81.99	85.42	84.83	64.88	67.41	5.62	4.74	1.69	66.34	0.57	46.31	4.16	55.74
NN	14.31	16.72	83.27	85.68	85.27	65.90	68.96	5.81	5.12	1.78	67.38	0.59	45.47	3.86	57.02

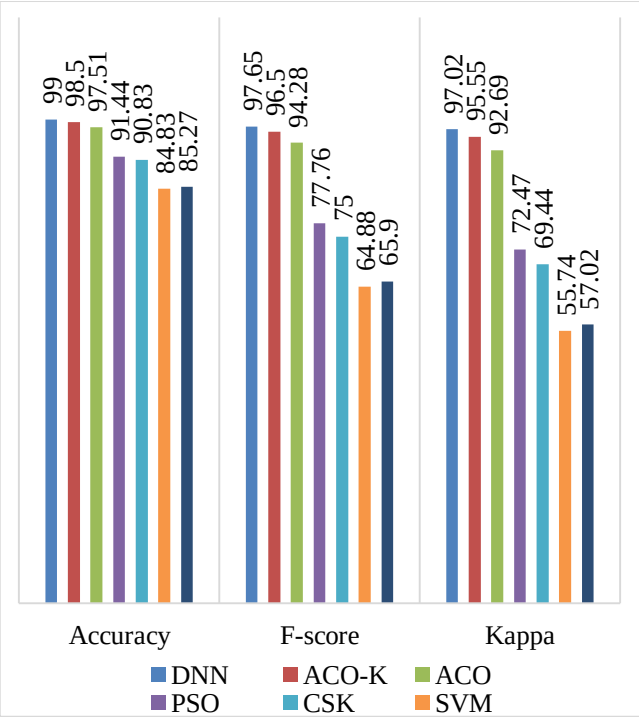

Fig. 5: Performance analysis of various methods on iPod Dataset

3.3. Result analysis on DVD dataset

Table 9 and Table 10 shows the obtained confusion matrix and the classification results of the proposed and compared methods on the applied DVD dataset. From the table 1, it is shown that the proposed DNN model attains maximum classification performance with the FPR of 8.21, FNR of 1.17, sensitivity of 98.82, specificity of 91.87, accuracy of 97.49, Y of 90.69, ρ^+ of 12.16, ρ^- of 77.97, DP of 4.84, GM of 98.45, MCC of 0.91, FDR of 1.90, FOR of 5.16 and kappa value of 91.79. Measuring the classifier results using FPR and FNR, the DNN shows better results whereas the NN shows worse results with the higher values of 28.38 and 6.06 respectively.

The table shows that minimum values are obtained by the DNN whereas the maximum values of FPR and FNR are obtained by CSK, SVM, NN and PSO. At the same time, the ACO and ACO-K algorithms manages to show better performance than all the other methods except the DNN model.

In the same way, the maximum sensitivity and specificity value of 98.82 and 91.87 is attained by the DNN indicating the positive results whereas the minimum values of 93.93 and 71.61 is attained for NN.

The better classification accuracy of 97.49 is attained by the DNN model. At the same time, the ACO and ACO-K algorithms shows competitive results than the compared ones except DNN.

Table 9: Confusion Matrix of DVD Dataset

Experts	DNN		ACO-K		ACO		PSO		CSK		SVM	
	P	N	P	N	P	N	P	N	P	N	P	N
P	671	13	668	16	662	22	620	40	595	60	601	55
N	8	147	12	143	14	141	22	157	23	161	19	164

Table 10: Comparative results of different classifiers on DVD dataset

Classifier	FPR	FNR	Sens.	Spec.	Accu	F-score	Y	ρ^+	ρ^-	DP	GM	MCC	FDR	FOR	Kappa
DNN	8.12	1.17	98.82	91.87	97.49	98.45	90.69	12.16	77.97	4.84	98.45	0.91	1.90	5.16	91.79
ACO-K	10.06	1.76	98.23	89.93	96.66	97.94	88.17	9.76	50.96	4.38	97.94	0.89	2.33	7.74	89.03
ACO	13.49	2.07	97.92	86.50	95.70	97.35	84.43	7.25	41.76	4.18	97.35	0.86	3.21	9.03	86.03
PSO	20.30	3.42	96.57	79.69	92.61	95.23	76.26	4.75	23.25	3.57	95.24	0.78	6.06	12.29	78.76
CSK	27.14	3.72	96.27	72.85	90.10	93.48	69.12	3.54	19.57	3.43	93.51	0.73	9.16	12.5	73.05
SVM	25.11	3.06	96.93	74.88	91.18	94.20	71.82	3.85	24.43	3.66	94.23	0.76	8.38	10.38	75.85
NN	28.38	6.06	93.93	71.61	87.84	91.82	65.55	3.30	11.80	2.87	91.85	0.68	10.18	18.40	68.15

As a whole, the proposed FCP model is superior to the compared classifiers in terms of different measures implying that it is the appropriate classifier model for the DVD dataset. In addition, Fig. 6 shows the comparative analysis of various classifiers in terms of Accuracy, F-score and kappa on the Canon dataset. From the figure, it is apparent that the DNN is superior to other methods.

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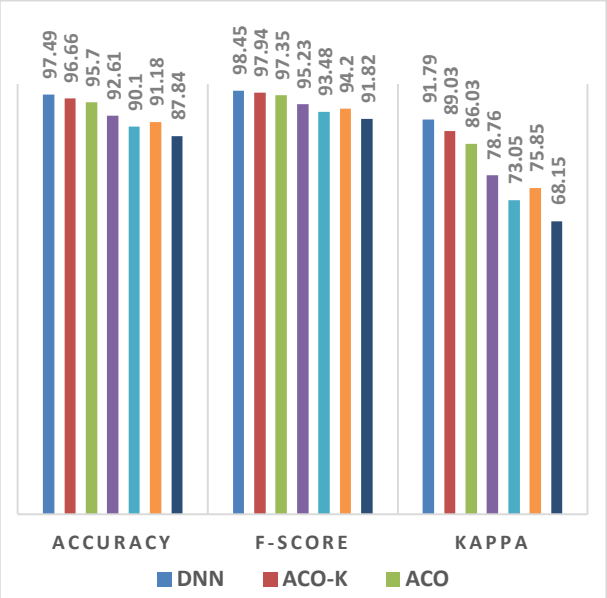

Fig. 6: Performance analysis of various methods on DVD Dataset

3.4. Result analysis on Nokia dataset

Table 11 and Table 12 shows the obtained confusion matrix and the classification results of the proposed and compared methods on the applied Nokia dataset. For this dataset, ACO and NN exhibit worse performance than its competitors. At the same time, it is noted that PSO and CSK as well as SVM and ACO-K achieves almost closer performance in some of the criteria such as FPR, FNR, accuracy and F-score. Similarly, the ACO-K exhibit maximum classification performance than the compared methods except the DNN model.

Table 11: Confusion Matrix of Nokia Dataset

Experts	DNN		ACO-K		ACO		PSO		CSK		SVM	
	P	N	P	N	P	N	P	N	P	N	P	N
P	131	4	127	8	124	11	110	20	112	18	116	21
N	9	441	13	437	18	432	23	432	14	441	18	430

Table 12: Comparative results of different classifiers on DVD dataset

Classifier	FPR	FNR	Sens.	Spec.	Accu	F-score	Y	ρ^+	ρ^-	DP	GM	MCC	FDR	FOR	Kappa
DNN	0.89	6.42	93.57	99.10	97.77	95.27	92.67	15.41	2.98	104.09	95.28	0.93	2.96	2.00	93.82
ACO-K	1.79	9.28	90.71	98.20	96.41	92.36	88.91	50.45	10.57	2.55	92.37	0.90	5.92	2.88	90.01
ACO	20.37	12.67	87.32	79.62	85.20	89.53	66.95	4.28	6.28	2.07	89.55	0.64	8.14	29.50	64.36
PSO	4.42	17.29	82.70	95.57	92.64	83.65	78.28	18.69	5.52	1.80	83.65	0.78	15.38	5.05	78.91
CSK	3.92	11.11	88.88	96.07	94.52	87.5	84.96	22.66	8.64	2.33	87.51	0.84	13.84	3.07	83.99
SVM	4.65	13.43	86.56	95.34	93.33	85.60	81.91	18.59	7.09	2.10	85.61	0.81	15.32	4.01	81.27
NN	5.41	21.83	78.16	94.58	90.59	80.14	72.75	14.42	4.33	1.51	80.17	0.74	17.77	6.88	73.99

Here, the presented DNN model attains maximum classifier results with classification performance of FPR of 0.89, FNR of 6.42, sensitivity of 93.57, specificity of 99.10, accuracy of 97.77, F-score of 95.27, Y of 92.67, ρ^+ of 15.41, ρ^- of 2.98, DP of 104.09, GM of 95.28, MCC of 0.90, FDR of 5.92, FOR of 2.00 and kappa value of 93.82.The values present in the table indicated that the DNN model provides significantly better predictive results in all criterions. In addition, Fig. 7 shows the comparative analysis of various classifiers in terms of Accuracy, F-score and kappa on the Nokia dataset. From the figure, it is clearly shown that the DNN is the effective classifier than the compared ones.

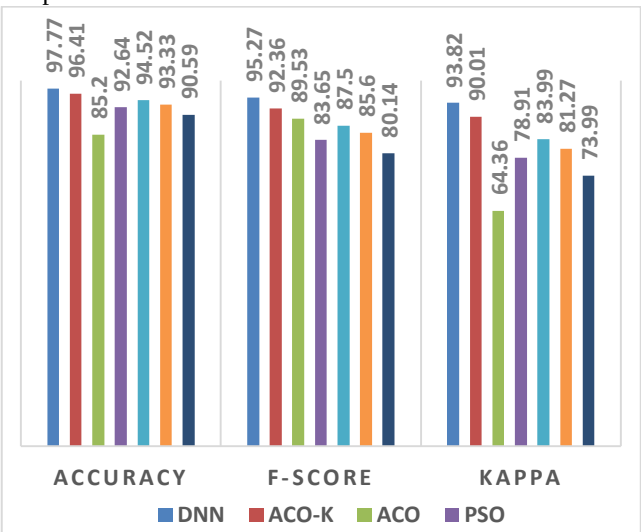

Fig. 7: Performance analysis of various methods on Nokia Dataset

IV. CONCLUSION

In this paper, we devise a new DNN model to assist the RS by classifying the online product reviews. Based on the classification of the reviews, the products will be properly recommended to the user. The proposed DNN model is validated using a set of four dataset collected from online product reviews from Amazon namely Canon dataset, iPod dataset, DVD and Nokia dataset. Different classification measures are employed for validating the characteristics of DNN model. A detailed comparative analysis is also made with various classifiers namely ACO, ACO-K, PSO, CSK, SVM and NN methods. The obtained results indicated the supremacy of the DNN model over compared ones on all the applied dataset.

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