Predicting Vehicle Driver Preference from the Analysis of In-Vehicle Coupon Recommendation Data

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Abstract

A coupon is a ticket or document used in marketing that may be redeemed for a monetary discount or refund when purchasing a product. The problem, in this case, is to know if a customer will accept a coupon for a particular venue. The answers that the user will drive there 'right away' or 'later before the coupon expires' are labeled as 'Y = 1', and the answers 'no, I do not want the coupon' is labeled as 'Y = 0'. This paper proposes integrating three machine learning techniques to create an ensemble boosting classification (EBC) model for a vehicle coupon recommendation. The algorithms used are k-nearest Neighbor (KNN), Support Vector Machine (SVM), and Decision Tree (DT). The results show that the EBC model surpasses the three machine learning models and achieves the highest performance of accuracy 97.37%, precision 94.14%, recall 96.41%, and F1-score 95.28%.

1. Introduction

A coupon is a ticket or document used in marketing that may be redeemed for a monetary discount or refund when purchasing a product. Coupon values include discounts, free delivery, buy one and get one free, trade-in for redemption, first-time customer coupons, free trial deals, launch offers, festival savings, and free giveaways [1], [2]. Coupons may also be used to encourage people to buy something, cut the price, give them a free sample, or assist marketers learn more about their customers' demographics. Coupons can also be used to investigate different client groups' price sensitivity. Prices are affected by time, location, and size [3].

Data mining approaches established in their capacity to simulate and model numerous physical phenomena in assessing coupon recommendations can be used to classify a vehicle coupon recommendation. Data mining is a technique for extracting useful information from large amounts of data. Data mining is a single application that may be used in various domains, such as research [4]. The researcher can utilize data mining as a strategy to help forecast data accurately as an application of data mining. In this case, the issue is determining whether a consumer would take a coupon for a specific location. Replies of 'right now' or 'later before the coupon expires' are labeled with a 'Y = 1', while answers of 'no, I don't want the coupon' are labeled with a 'Y = 0'. This project uses a data mining method to create a classification model for a vehicle coupon recommendation based on Amazon Mechanical Turk.

Classification is an approach that may categorize dataset pieces based on their attributes and, in most situations, includes substantial modelling interactions. Lawes et al. [3] propose an interpretable classification model for categorization, the learning of Boolean rules in either disjunctive normal form (DNF, ORof-ANDs, akin to decision rule sets) or conjunctive normal form (CNF, AND-of-ORs). Experiments on traditional fair machine learning datasets showed that our approach is comparable with the best in the field, outperforming popular fair classifiers on two of three datasets and remaining unbeaten in strict fairness regimes. Overall, their CG algorithm is helpful for practitioners who require a simple, interpretable, and potentially fair machine learning model in socially sensitive situations.

Based on Patil et al. [4] research, this paper proposes a method to predict users' coupon usage behavior. They use gradient boosting for the best classifier use to help minimize the parameters and coefficients in a regression equation. The programming languages used are Python and R. From the study, 2.5% of users mostly buy the code once they have viewed the coupon, and the probability of users buying the code rises to 32% after viewing it three or more times. 38% chance of customers to purchase the same coupon for the next order. So, the probability of purchasing a coupon code rises from less than 0.1% to more than 0.6% if the coupon code is purchased with determined requirements.

In their research, Wang et al. [5] propose a Bayesian technique for learning rule set (DNF) classifiers in two priors: Beta-Binomial Prior and Poisson Prior. The dataset is collected from the Amazon Mechanical Turk. It outlines several driving scenarios, such as the destination, current time, weather, the passenger, and so on, before asking the user if he will take the voucher if he is the driver. It has a sample size of 12684 persons and is connected with classification tasks. According to the findings of this study, basic guidelines based on a user's context can be immediately effective in anticipating the user's response. Wang et al. developed a machine learning strategy for creating classifiers with the fewest disjunctions of conjunctions (or's of and's). This is an example of a type of classifier: If X matches the requirements (x1 = 'blue' AND x3 ='middle') OR (x1 = 'blue' AND x2 = '15') OR (x1 = 'yellow'), we expect Y=1. Otherwise, they expect Y=0. A literal is a pair of attributes and values, while a pattern is a collection of literals. Because they create a collection of criteria that characterize a given class, these models benefit from being interpretable by human specialists. The Bayesian Or's of And's (BOA) model is used in context-aware tailored recommender systems in vehicles to predict user behavior. Wang et al. [6] conducted a previous study in which they applied Rule Set models to ten UCI data sets and compared their performance to that of other interpretable and uninterpretable models. They demonstrated how to develop Rule Set models using Bayesian priors, allowing users to alter the model's form. Then, they established theoretical scenarios in which using pre-mined rules does not provably change the MAP optimum solutions. They obtained a rules space that expanded from 1 to 9 and 13 because of the trials. The rule space is decreased to 9.0% of its original size at a minimum support of 9; with a minimum support of 13, it is reduced by 4.7%.

Letham et al. [7] aim to construct prediction models that are reliable and interpretable by human analysts. Their models are decision lists consisting of a sequence of statements (for example, if blood pressure is high, then stroke) that discretize a multivariate feature space into a collection of simple, clearly interpretable decision statements. Experiments indicate that the Bayesian Rule List has predictive accuracy comparable to the greatest machine learning algorithms for prediction available today.

With the focus on extending the usage of ensemble models to compensate for the drawbacks of using single algorithms to analyze vehicle coupon recommendation, the research fills a theoretical and methodological void regarding the ability to address diverse and developing forms of the spam pattern. Prior approaches may fail to be very accurate and have high recall rates due to their lack of robustness for use on dynamic data sets. This project proposes to evaluate three classification algorithms, k-Nearest Neighbor (KNN), Decision Tree (DT), and Support Vector Machines (SVM), for predicting vehicle driver preference by analyzing in-vehicle coupon recommendation data. Evaluating the algorithms ensures that they provide the most accurate and efficient results to recommend automobile coupons. Later, these algorithms are combined in one ensemble boosting classification (EBC) model. The EBC model intends to maximize the performance of recommending automobile coupons by fusing the prediction results of the three machine learning algorithms. Hence, the main contribution of this work is proposing the EBC model and validating its ability to surpass the traditional machine learning models. This work proposes the new ensemble EBC model with an accuracy of 97.37%. Moreover, it points out the limitations of the standalone classifiers and comes up with a well-formatted approach for a much better analysis of the vehicle coupon recommendation.

The rest of this paper is laid out as follows: Section 2 reviews all the methods used on automobile coupon suggestions using the CRISP-DM methodology. It includes the dataset, assessment measures, and the technique to complete the recommended automobile coupon method. Section 3 discusses the findings from the obtained results, and Section 4 ends the paper with a simple summary of the research and recommendations for further research.

2. Methodology

This study uses the Cross-Industry Process for Data Mining (CRISP-DM) approach to predict the automobile coupon by applying k-Nearest Neighbor (k-NN), Decision Tree (DT), and Support Vector Machines (SVM) to the suggestion dataset. The CRISP-DM approach is a six-phase process model that properly captures the data science life cycle. It is a set of standards that may be used to plan, organize, and implement data science (or machine learning) initiatives [8]. Figure 1 depicts the CRISP-DM approach of this work.
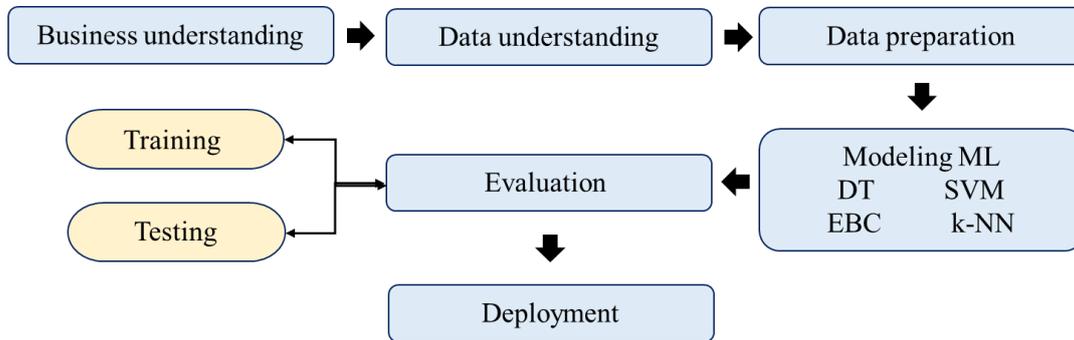
Fig. 1 *The CRISP-DM methodology of this work*

All steps of the CRISP-DM approach are planned, structured, and well-defined to guarantee that all involved parties understand the overall project planning and are easily altered.

- Business Understanding: This phase identifies the project's objectives and requirements related to vehicle coupon recommendations. After extracting the dataset of car coupon suggestions with proper classes, the project aimed to determine whether a consumer would take a coupon for a specific venue.
- Data Understanding: This phase begins with the acquisition of the dataset and continues with its examination.
- Data Preparation: Raw data will be used to create the final dataset throughout this step. The variables or features in the dataset must be identified and prepared to create the models utilized in the following phase. This classification model was constructed for a dataset including a car coupon class.
- Modeling: In this phase, three classification models, DT, SVM, and k-NN, were chosen and applied to predict the vehicle coupon state from the driver's perspective. An EBC model is also proposed as a better solution that combines the prediction ability of the three machine learning algorithms.
- Evaluation: This phase must evaluate the performance of classification models generated during the modeling step. In addition to examining the models' performance, evaluation is essential to determine whether the data models have solved the challenges highlighted during the business knowledge phase. This study evaluated the accuracy, precision, recall, and f1-score of the developed categorization models.
- Development: This step might be as basic as implementing the proposed solution as a web application for the interest of an automobile organization.

Four experiments were carried out using the RStudio tool. The first three experiments use a 5-fold validation method for training and testing.

2.1 Dataset

This project focuses on classifying vehicle coupon recommendations based on data collected from Amazon Mechanical Turk via a survey. The dataset was taken from UCI Machine Learning Respiratory [9] and published in the Machine Learning Repository in 2020. It comprises 12684 instances with 26 features, one class label (Y), and missing values. The dataset is shown in Table 1.

Table 1 *In-vehicle-coupon-recommendation features*

Feature Name	Data Type	Description
destination	object	No Urgent Place, Home, and Work are referred to driving destinations
passenger	object	Alone or with a Friend(s) or Kid(s)or Partner referred to who are the passengers in the car

weather	object	Sunny, Rainy, and Snowy
temperature	int64	55,80, and 30 in Fahrenheit
time	object	2PM, 10AM, 6PM, 7AM, and 10PM
coupon	object	Restaurant (<$20), Coffee House, Carry Out & Take Away, Bar, Restaurant ($20-$50)
expiration	object	The coupon timer runs out after 1 day or 2 hours.
gender	object	Female or Male
age	object	Below 21, 21 to 25, 26 to 30, etc
maritalstatus	object	Unmarried Partner, Single, Married Partner, Divorced, and Widowed
has_children	int64	The number of children among the passengers is 1, 0, or more than 1.
education	object	Colleges with no degree, Some High School, High School Graduate, Associate degree, Bachelor degree, or Graduate degree (Master or Doctorate)
occupation	object	Retired; Protective Service; Life Physical Social Science; Community & Social Services; Arts Design Entertainment Sports & Media; Sales & Related; Office & Administrative Support; Installation Maintenance & Repair; Transportation & Material Moving; Building & Grounds Cleaning & Maintenance; Healthcare Practitioners & Technical; Personal Care & Service; Architecture & Engineering; Farming Fishing & Forestry; Management; Food Preparation & Serving Related; Student; Construction & Extraction; Healthcare Support; Education & Training & Library; Legal; Production Occupations; Business & Financial; Computer & Mathematical
income	object	The annual income is $37500-$49999, $62500-$74999, $12500-$24999, $75000-$87499, $50000-$62499, $25000-$37499, $100000 or More, $87500-$99999, Less than $12500.
car	object	These are missing values; there are only 108 non-null values. So, in this sample of data, we didn't include the feature
Bar	object	This indicates how many times the passengers visit a bar each month: never, less than 1, 13, 48, gt8 (greater than 8)
CoffeeHouse	object	This indicates how many times the passengers visit a coffee shop each month: never, less than 1, 13, 48, gt8 (greater than 8)
CarryAway	object	This displays how many times every month the passengers order take-away meals; never, less than 1, 13, 48, gt8 (greater than 8)
RestaurantLessThan20	object	This indicates how often times each month the passengers went to a restaurant with an average cost per person of less than $20; never, less than 1, 13, 48, gt8 (greater than 8)
Restaurant20To50	object	This demonstrates how frequently the passengers visit a restaurant with an average cost per person of $20-$50 per month; never, less than 1, 13, 48, gt8 (greater than 8)
toCoupon_GEQ5min	int64	0 and 1 (0 if the driving distance to the restaurant or bar for using the coupon > 5 minutes)
toCoupon_GEQ15min	int64	0 and 1 (0 if the driving distance to the restaurant or bar for using the coupon > 15 minutes)
toCoupon_GEQ25min	int64	0 and 1 (0 if the driving distance to the restaurant or bar for using the coupon > 25 minutes)

Direction_same	int64	0 and 1 (0 if the restaurant or bar is not in the same direction as the passengers' current destination, 1 if it's in the same direction)
Direction_opp	int64	1 and 0 (1 if the restaurant or bar is in a different direction as the passenger's current direction, 0 if it's in the same direction)
Y	int64	1 and 0 (1 if the coupon is accepted, 0 if it's not accepted)

2.2 Algorithms

k-Nearest Neighbors (KNN), Decision Tree (DT), and Support Vector Machine (SVM) are the prediction algorithms employed in this research (SVM) [10]-[14]. As indicated in Figure 1, these algorithms are used during the modeling step of the CRISP-DM technique.

- k-Nearest Neighbors (KNN): One of the simplest and the most natural classification methods is the k-NN classification in cases where no much is known about the distribution of data. It should be one of the initial choices to be made while performing a classification study. If the probability densities of the population are not known or are difficult to estimate using parametric methods, discriminant analysis is the next requirement, which results in the need to develop a k-NN algorithm [12]. The formula of the k-NN for calculating Euclidean distances is shown in Eq. 1.

$$(a + b)^2 = a^2 + 2ab + b^2 \tag{1}$$

- Decision Tree (DT): The DT is an ordinary data mining approach used to construct classifiers from numerous features or model a target parameter. The population is divided into branch-like groups, so there is a structure in the form of an inverted tree with the root, interior, and leave nodes. Because it is non-parametric in nature, the method is capable of processing extensive large volumes of data, which may be transformed and modified in real-life big data complications without a complex parametric structure. Seemingly, if the sample size is large enough, the data can be split into training and validation datasets. Develop a decision tree model from the training data and determine the right size of the tree from the validating data in order to have the best final model [13].

- Support Vector Machines (SVM): The SVM is a supervised machine learning technique for training data in order to enable prediction on demanding classes. However, as was mentioned before, classification is the only best solution to such a problem. The SVM method seeks to determine a hyperplane in an N-dimensional space that separates the points with maximum margin. The size of the hyperplane depends upon the number of features that are taken into consideration. It will just be a line in case the number of characteristics used as input reduces to two. If the number of input characteristics is close to three, then the hyperplane becomes a two-dimensional plane. As the number of qualities increases, it becomes impossible to imagine even three characteristics. The hyperplane of a positive class with positive x values is given in Equation 2. On the other hand, the negative class hyperplane with negative x values is defined below w = {w1, w2, w3...wk, wK}; x = {x1, x2, x3...xN}; and b = {b1, b2, b3...bN;} as shown in Equation 3 [14].

$$w.x_i + b = 1 \tag{2}$$

$$w.x_i + b = -1 \tag{3}$$

Equation 4 shows the equation for maximizing the margin between two hyperplanes or classes, representing the minimum magnitude of vector w.

$$min|w| = y_i(w.x_i + b \geq 1; \quad i = 1; \dots, N \tag{4}$$

2.3 Ensemble Boosting Classification Model

Ensemble Boosting Classification (EBC) is a machine learning model that uses a set of classifiers, K-NN, DT, and SVM, to form a strong classifier. The vital concept is that classifiers must be trained successively so that the failure of one classifier is rectified by the next.

Let: $D = \{(x_i, y_i)\}_{i=1}^N$ represent the dataset where $x i \times j$ is the feature vector, and y_i is the label. $h_t()$ is a machine learning classifier iterating based on t in which T is the total number of boosting rounds. $f(x)$ be the final strong classifier that is formulated as:

$$f(x) = \sum_{t=1}^{T} \alpha_t h_t(x) \tag{5}$$

where α_t is the weight assigned to weak classifier $h_t(x)$, determined by its performance.

The boosting process starts with per-sample weights being set equally and evenly across the dataset so that every sample will contribute equally in forming the first weak classifier. Later, these weights are changed iteratively, and the steepest slope of the cost function is found for misclassified samples targeting the model to attend harder samples. In each of them, a weak classifier is constructed using current weights, and the weak classifier is assessed based on the weighted error rate. Thanks to this error, it is possible to define how important the classifier is in the whole model by using the calculated weight. The poorly performing classifiers are given a low weight, while the better performing ones are given more weight.

The model then adjusts the sample weights, placing a big emphasis on misclassified samples and cutting emphasis on well-classified ones. This compensation makes the next classifiers pay more attention to complicated instances. These weights are standardized for the sake of validity to avoid augmented fluctuations during training. At the end of each round, the Residual feature space is selected, and the final strong classifier is formulated by summing up all the weak classifiers with their corresponding coefficients. This weighted combination thus leads to a strong classifier that is capable of combining all the elements of the constituent parts. Figure 2 shows the diagram illustrating the processing steps of the EBC model.
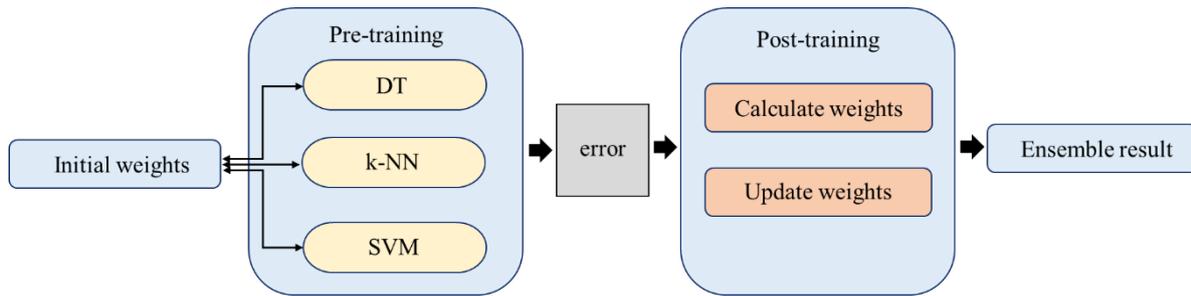
Fig. 2 *The processing steps of the EBC model*

The key features of the EBC model will be described together with several crucial features. The boosting mechanism is fundamentally at its heart, where the difficult samples are iteratively highlighted in order to offer optimum and accurate classification [11]. With this approach, the weights of the samples are updated so that the model spends the most time on the difficult to classify areas of the feature space. This weighted aggregation process integrates weak classifiers, which are weak decision boundaries, and those with higher performance are given more weights, making the decision boundary strong. It also generalizes on any weak learning algorithm whose input can handle weights as the weights apply to the data. This makes it ideal to be applied for various analyses since it is used for both classification and regression studies [15], [16]. The work boosts iteratively and may add upon the incrimination, resulting in a strong classifier that may combine the high precision and recall value [17].

2.4 Evaluation Metrics

Accuracy, Precision, and Recall were the evaluation criteria employed in the tests. They are used to compare and evaluate the performance of KNN, DT, SVM, and EBC [18]-[20].

- Accuracy. The number of successfully categorized data instances divides the total number of data instances. Equation 6 shows the formula for calculating accuracy.

$$\text{Accuracy} = \frac{(TP+TN)}{(TP+TN+FP+FN)} \tag{6}$$

Where TP is True Positive, TN is True Negative, FP is False Positive and FN is False Negative.

- Precision. The total number of samples is divided by the number of samples reliably labeled positively. Equation 7 shows the accuracy calculation formula.

$$Specificity = \frac{TP}{(TP+FN)} \tag{7}$$

Where TP is True Positive and FP is False Positive.

- Recall. The number of positive samples in the testing set is divided by the total number of positive samples in the testing set. Equation 8 shows the formula for calculating recall.

$$Sensitivity = \frac{TP}{(TP + FN)} \qquad (8)$$

Where TP is True Positive.

- F1-Score. Precision and Recall are weighted and averaged. As a result, this score considers both true positives and erroneous negatives. Equation 9 shows the formula for calculating recall.

$$F1 - Score = \frac{2 * (Recall * Precision)}{(Recall + Precision)} \qquad (9)$$

Accuracy, precision, recall, and F1-Score are going to be employed to compare the performance of the classification approaches.

3. Results and Discussion

The study aims to compare the performance of three algorithms for in-vehicle coupon recommendation: KNN, SVM, and DT. The four evaluation metrics that are used to classify the coupon data are accuracy, precision, recall, and f1-Score. Table 2 displays the testing results of the KNN, SVM, and DT for five folds of data split.

Table 2 *The classification performance of machine learning algorithms*

Data split (%)	Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
70-30	k-NN	73.19	81.92	67.19	73.83
	SVM	77.95	96.46	74.43	84.03
	DT	87.48	86.91	85.24	86.07
60-40	KNN	74.69	89.67	63.04	74.03
	SVM	77.85	93.71	57.17	71.02
	DT	85.72	84.28	82.65	83.46
50-50	KNN	75.95	88.07	65.24	74.96
	SVM	78.07	92.86	58.83	72.03
	DT	86.33	86.11	83.93	85.01
40-46	KNN	75.7	86.21	67.97	76.01
	SVM	80.73	85.55	69.24	76.54
	DT	75.77	86.24	62.99	72.80
30-70	KNN	78.73	91.13	68.64	78.30
	SVM	81.17	90.34	64	74.92
	DT	78.6	91.09	73.24	81.20

Experiments with k-NN, SVM, and DT distinguishable performance differences when evaluated on different data splits of the same set of fingerprints. In general, DT achieves accuracy and recall values higher than the other algorithms, and those values are the highest in our experiment: 87.48% accuracy and 85.24% recall for a 70-30 split. The precision of SVM is high, which can go up to 96.46 %, but its recall rate is low; a cause of a trade-off between precision and recall is observed. The performance of k-NN is moderate, but generally, the values are low compared to DT and SVM. However, in recall, the lowest value is recorded consistently. The given performance trends indicate that DT outperforms other splits in terms of Recall, which is the most stable algorithm for this model, and SVM focuses on precision.

Table 3 *The comparison between the classification performance of machine learning algorithms and EBC*

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
k-NN	73.19	81.92	67.19	73.83
SVM	77.95	96.46	74.43	84.03
DT	87.48	86.91	85.24	86.07
EBC	97.37	94.14	96.41	95.28

DT arrives at an average accuracy of 82.78% and the precision, recall values, as well as the F1 score are 86.93%, 77.61%, and 81.71% correspondingly. SVM follows with 79.15% accuracy, 91.78% precision, 64.73% recall, and an F1 score of 75.71%. k-NN finally comes with 75.65% accuracy and 87.40% precision of 66.42% recall and 75.43% F1 score. On the other hand, the EBC model, if calculated from the mean of the three models, appear to have better performance than all the single models. The proposed ensemble yields a projected accuracy of 97.37% and a precision of 94.14%, a recall of 96.41% and the F1 score of 95.28%. This shows that the ensemble is capable of harnessing the combined power of single models to perform better as well as evenly. This work provides this by combining DT, K-NN, and SVM; which provides a complementary approach that enhances the chances of prediction, making it the most efficient model for recognizing spam email based on content.

4. Conclusion

One real-life use case of vehicle coupon recommendation that encompasses supervised machine learning would be the recommendation of coupons to customers on the basis of their choices as well as the context, which could include geographical location or time, among others. In this paper, k-Nearest Neighbors (k-NN), Support Vector Machine (SVM), and Decision Tree (DT) are three algorithms chosen to assess and categorize the coupon recommendation data set based on different data splits. From the results, we observed that DT provided the highest accuracy and recall rate but low time complexity, while SVM and k-NN provided moderate accuracy and recall but less time complexity than DT. However, it was possible to detect that an Ensemble Boosting Classification Model would show considerably better results, with accuracy at 97.37% and precision, recall, and F1 scores of 94.14%, 96.41%, and 95.28%, respectively, due to the potential of the bonus feature of adding the strongest classifiers. Ensemble Boosting models provide stability, flexibility, and accommodation of different databases. Thus, they are used to enhance recommendation systems. It would be interesting to learn the issue of combining deep learning methods, such as reinforcement learning or neural collaborative filtering, with ensemble techniques to improve the accuracy of recommendations and responses to the immediate environment in future work.

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Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: **study conception and design:** *Dr Murtada Dohan , Rasha Bashar Mohammed;* **data collection** *Wisam Hazim Gwad , Mohammed Khalaf, Karam* M.Z. Othman; **analysis and interpretation of results:** *Ismail Dr Murtada Dohan , Rasha Bashar Mohammed, Mohammed Khalaf;* **draft manuscript preparation** *Dr Murtada Dohan, Mohammed Khalaf. All authors reviewed the results and approved the final version of the manuscript.*

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