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Retraction

Retracted: Consumption Behavior Prediction Based on Multiobjective Evolutionary Algorithm

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] J. Li, N. S. Jaharudin, and Y. Song, "Consumption Behavior Prediction Based on Multiobjective Evolutionary Algorithm," *Journal of Sensors*, vol. 2022, Article ID 2525740, 11 pages, 2022.

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Research Article

Consumption Behavior Prediction Based on Multiobjective Evolutionary Algorithm

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Consumption behavior prediction reveals customer attributes, personal preferences, and intrinsic laws. Organizations would benefit from knowing further about customer needs and business desires by monitoring client behavior to provide more precise recommendations and boost acquisition rates. The economics of the customer, buyer groupings, and product quality are only a few of the numerous variables that influence customer behavior. The key issue that has to be resolved at this time is how to filter out useful information from these vast amounts of data to forecast customer behavior. For customer consumption behavior prediction and analysis with an advanced quantitative research process, we proposed the multiobjective evolutionary algorithm, which significantly boosts the accuracy of consumption behavior predictions. The dataset is initially gathered based on consumer preferences and behaviors as the essential information for the entire prediction model. Min-max normalization is used as a component of the preprocessing of the data to get the elimination of redundant and superfluous data. The Word2vec model is utilized for feature extraction, and boosted ant colony optimization (BACO) is employed to choose the best features. Utilizing the suggested multiobjective evolutionary algorithm (MOEA), the predictions are made. The suggested system's performance is assessed, and the metrics are contrasted with more established methods. The findings demonstrate that the suggested MOEA technique performs well than the traditional ML, XGB, AI, and HNB algorithm methods in terms of accuracy (95 percent), quality of prediction (97 percent), precision (99 percent), recall (93 percent), $F1$-score (98 percent), and prediction time (50 seconds). Hence, the outcomes show that the regression model is sustainable. The suggested consumption behavior prediction system has demonstrated its efficiency in boosting profitability.

1. Introduction

Many business websites on the internet offer a wealth of data about occasions, connections, and attitudes. Understanding customer behavior may be useful in analyzing consumer traits, the interaction between products, and other topics. Therefore, building consumption structures based on data on distinct consumers' purchase behavior is a very useful study topic. To perform consumption behavior prediction, information extraction, and user influence analysis, a variety of technologies including text mining, statistical theory, association analysis, and visualization have to be employed. By evaluating the behavior data of e-commerce platforms, the behavior prediction extracts users' consuming preferences and habits and calculates the complete likelihood to anticipate future payment behavior. Applications for forecast findings include product suggestions, placement of advertisements, and other things (Guo et al. [1]). Prediction of consumption behavior shows consumer characteristics, individual choices, and underlying constraints. By observing consumer behavior, businesses may gain greater insight into customer demands and company desires, which will help them, make more accurate suggestions, and increase the terms of the market. Only a handful of the many factors that affect consumer behavior include product quality, buyer groups, and customer economics. Well, how to extract relevant data from these massive volumes of data to predict client behavior is the main problem that has to be solved at the moment. Consumption behavior prediction that successfully increases the prediction efficacy of consumer behavior is used for company growth prediction and analysis using sophisticated quantitative research methods. It is used to filter out useful information from this vast amount of data to anticipate (Tian et al. [2]).

In real-world applications, unbalanced data has made categorization issues much more difficult. Customers engage in online business by browsing and looking for similar items to carry out chores like purchasing or other connected activities in a computer-mediated environment. The unification and coherence of customer requirements, incentive, behavior, and recollection are the purchase choice. The probable links underlying several customer actions may be mined from the communication networks, and the prediction purpose can be achieved. The adoption of the consumer prediction strategy was rapid and efficient for identifying and segmenting consumer groups. It also made it easier to map the differences between these groups and to compare how customers behaved in other marketplaces (Li et al. [3]). Business has emerged as one of the primary means through which people are consuming in their daily lives, strictly monitoring the fast growth of computer Internet advances and the Internet service. Well, how value-extract from a big amount of user behavior consumption data, meanwhile, is a current issue (Mody and Bhoosreddy [4]). This is still a challenge for many businesses, especially when it comes to effectively analyzing and forecasting user behavior, creating customer information, classifying users based on similar actions, and providing individualized marketing and product recommendations.

Figure 1 depicts the application of consumption behavior prediction. In response to the aforementioned problems that e-commerce is experiencing, this performs a visual analysis of the many factors that influence customers' purchase decisions. Making tailored advice for pertinent firms and raising their operational profitability is important from a practical standpoint. It uses a logic model to forecast the user's buying behavior to fully understand the influence of the business (Xiao and Tong [5]). It is urgently necessary for individuals to adjust their consumption behavior to be more responsible to provide safe and wholesome living circumstances for both the coming generations due to the speeding up of biodiversity loss, economic reform, and related crises. Even though studies have demonstrated that individuals are buying goods and using service offerings that the surrounding habitat can renew, manage, or compost, most people still appear to think of the economy as largely being related to the creation and consumption of merchandise. To facilitate the transition to a circular economy, the present consuming culture must change with consumer prediction (Garg [6]).

The existing unprecedented growth structure will not be changed by the integrated resource action plan, which will remain purely theoretical instruments. Although ideas on sustainable consumption behavior have existed for some time, there is still a need for more study on the fundamental concepts because of the phenomenon's complexity and myriad justifications. For instance, there has been a request for a study that investigates the relationships between combinations of factors rather than just one component to assess how well corporate concerns can anticipate consumer behavior (Saari et al. [7]). Consumers behave in groups or organizations while selecting and obtaining services, commodities, experiences, or innovations to meet their needs and to have an influence on the buyer and society. Entrepreneurial competitiveness is ensured by knowledge of the conditions, variables, and behavioral reasons of customers (Ahmed et al. [8]). An in-depth examination of market segmentation and customer needs is necessary to assess consumer behavior for the company's creation of new goods, new beliefs, and society's psychology. Companies must afterward adopt a dependable, efficient, and adaptable marketing plan that ensures earnings and sales based on an analysis of client behavior. By using strategic planning and an objective market segment objective based on a computational model, it has succeeded. This consumption durability component focuses on assessing how consumers' behavior is affected by promises and addressing obstacles to the transition of values into actions (Zhao et al. [9]). As a result, we suggested a multiobjective evolutionary algorithm, which much improves forecasts of consumer behavior and to lessen the inadequacies of existing technologies.

1.1. Contribution of the Study

(i) This study offers a novel multiobjective evolutionary algorithm methodology for consumer forecasting to enhance business growth

(ii) Min-max normalization is used for preprocessing to execute a sequence of procedures to modify or remove redundant data

(iii) Using the Word2Vec model, the optimal data features may be extracted from unstructured data

(iv) The metrics of the proposed model are examined and contrasted with conventional prediction techniques

(v) This method corrects existing technology's inadequacies and significantly improves commercial forecasts of customer behavior

The remaining sections in the paper are structured as follows. The associated literature and the problem statement are presented in Section 2. The explanations of the proposed work are provided in Section 3. Section 4 has results and discussions. The proposed paper's conclusion is presented in Section 5.

2. Literature Survey

Shukla et al. [10] utilized supervised and unsupervised machine learning algorithms for investigation for correlation to the causality of consuming behavior prediction when integrating predictive ability with explanatory capacity and offer a more comprehensive understanding of proenvironmental business consuming behavior. It is unable to obtain

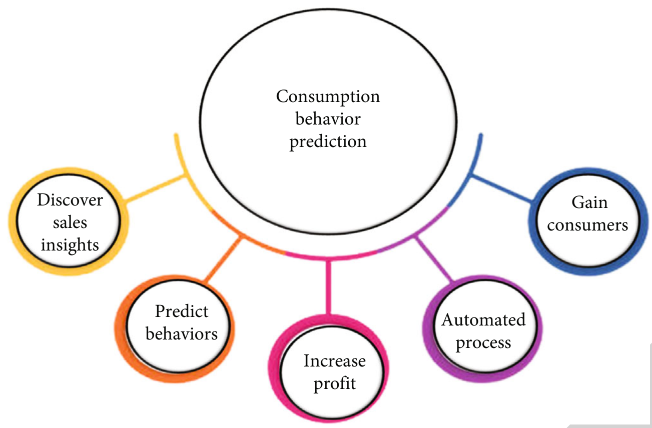

Figure 1: Application of consumption behavior prediction.

exact data filtering parameters. Chen et al. [11] employed the attitude-behavior-context (ABC) theory, which builds a methodological approach to discover whether a consumer's perception of a company's usefulness affects the acquisition of that product. It also looks at the partial mediator of an eco-friendly product's utilization mindset as well as the comment moderation impact of technology and communication implementations. Its incomplete consumer statistics data might affect the performance. Liu et al. [12] presented a bit-based latent spatiotemporal feature extraction approach for the optimum learning behavior. Organizations in a variety of industries continue to create new consumer consumption behavior value assessment algorithms owing to the advancement of big data and artificial intelligence to increase the likelihood of getting customer predictions. This modality performs poorly in terms of classification accuracy. Amasyali and El-Gohary [13] suggested the notion of big data technology based on machine learning to process data and analyze it to forecast customer behavior on social media. He stated that the social media is widely used in our community, currently. Social networking platforms are being used by people to consume a variety of goods. Data preprocessing in machine learning gives low enhancement of data and less accuracy in prediction.

VLN and Deeplakshmi [14] advocated the use of support vector machines based on machine learning to create effective systems for predicting consumer behavior. These systems may help businesses increase their revenue by attracting new clients, retaining existing ones, and improving customer loyalty. The targeted classifications might overlap occasionally (Shahabaz and Afzal [15]). Wang et al. [16] presented an adaptable deconstruction approach based on regression to break down the original measured values into a pattern sequence and a collection of variation posts and then create the matching prediction line regression model for the pattern sequence in consumption behavior prediction and to exhibit results in specific test situations in commercial users. If there are nonlinear correlations in the data, the linear regression model performs poorly. Revati et al. [17] suggested employing Gaussian process regression to anticipate consumer behavior to focus on a data-driven approach to load profile prediction with the emphasized benefit of a model-free environment and useful for setting up a specific demand response plan to receive incentives like money. This modal cannot locate the grouped data. Malik et al. [18] promoted the use of machine learning techniques and functional link neural networks to build efficient systems for predicting customer multiresource cloud data centre consumption. To solve the under- and overprovisioning problems, overprovisioning of services results in higher expenses and increased energy use. The prediction of multi-variety cloud resource use is a difficult problem due to the potential for quick and disproportionate variations in resource utilization. It has very low accuracy.

Najman et al. [19] proposed using a GNG neural network to find and explore trends in customer purchasing behavior. This would help marketers fully appreciate customer behavior and create targeted tactics for international business. Predicting behavior requires more time. Chakladar et al. [20] employed robust long short-term memory-(LSTM-) based deep neural network model was constructed to categorize consumer preferences while visualizing advertising for consumers and seeks to provide a major contributor to the area of consumer behavior since it gives guidelines regarding the consumer preferences after viewing the internet commercials. LSTMs are susceptible to specific initializations of activation functions (Li [21]). Phyo et al. [22] suggested the utilization of machine learning algorithms with reduced error rates that are taught to create the planned voting regressor model, which is essential for energy producers in order to meet the needed quantity of energy between consumption and supply. The classification of data set is more complex by using this model.

Asiri et al. [23] employed multiclass random forest for predicting consumer behavior, which is a crucial sector in the industry for deciding how much to charge for each merchandise. The majority of a company's profit is directly related to the proportion of sales, which depends on a variety of client characteristics, including consumer behavior and market competition. The approach may be too sluggish and inefficient for authentic forecasts due to the enormous number of trees. Subroto and Christianis [24] suggested utilizing a multilayer perceptron to forecast consumer behavior in categorizing reviews as highly or poorly rated using relevant business criteria. Having a better understanding of customer reviewing behavior can result in the adoption of effective strategy by the parties involved in this study, such as a policy to manage customer reviews by maintaining high levels of customer satisfaction. Tuning of features affects multilayer perceptrons (Salihu and Iyya [25]). Jupalle et al. [26] proposed the usage of machine learning algorithms to gather reviews from the internet and sort them into five categories highly positive, favourable, balanced, awful, and severely negative in attempt to forecast how people will behave while making purchases. Massive data sets are needed for machine learning in order to train the data set.

Chaubey et al. [27] recommended using k-nearest neighbors (KNN) to predict consumer behavior since many sales and service-providing businesses need to highlight connected clients while introducing new goods, services, and improved versions of old goods. They must focus on their current clients while doing this. These consumers' actions provide businesses with data on how to market their goods. It is rather inefficient in terms of computing. Sheoran and Kumar [28] investigated how the theory of planned behavior (TPB) has been used to comprehend the multifaceted character of sustainability consumer behavior using descriptive and analytical methodologies and to perform consumption behavior prediction, information extraction, and user influence analysis. It takes a lot of time and effort. Zhang and Wang [29] developed an enhanced deep forest strategy for predicting consumer behavior, which is crucial for growing a firm. It is among the most crucial element of corporate intelligence. Consumer predicting and estimation provide information on how a business should handle its labor, working capital, and revenue assets Maddikunta et al. [30]. When splitting the trees, it employs the complete feature memory space. Table 1 shows the list of existing methodologies.

The existing approaches have limitations with their inability to perform in nonlinear data correlations, inaccurate classification, inadequate data filtering, poor feature tuning, and more time consumption. Therefore, the procedures mentioned above are no longer able to satisfy the actual requirement of customer behavior. Therefore, this motivates to address the shortcomings of existing technology and greatly enhance predictions of consumer behavior; we presented a multiobjective evolutionary algorithm.

2.1. Problem Statement. The prediction of consumption behavior reveals consumer traits, personal preferences, and fundamental constraints. Businesses may better understand customer needs and corporate goals by monitoring consumer behavior. This will enable them to provide more informed suggestions and expand their market share. The development of several prediction models has several shortcomings in the categorization and prediction of consumer behavior. We thus introduced a multiobjective evolutionary algorithm to solve the limitations in existing technology and considerably improve predictions of customer behavior.

3. Proposed Methodology

Successful consumption behavior prediction improves the predictive value of consumer behavior and increases business profitability. Thus, we suggested a multiobjective evolutionary algorithm and for feature extraction, the Word2vec model is used, and boosted ant colony optimization (BACO) is used to choose the best features which improve the prediction of consumption behavior. Figure 2 depicts the flow of the proposed work, and this section gives a thorough description of it.

3.1. Data Collection. The data was gathered online utilizing QQ, e-mail, and WeChat from Chinese consumers who have participated in at most one online shopping carnival (OSC) in the preceding three years. As a result, a comfort survey method was used to gather information from consumers living in Changchun and Jilin City (N-E China), tier 2 and 3 cities in terms of social marketplace utilization (online networking) (DATA500). However, because the investigation was limited to four cities from the tier 1 bunch of social marketplace utilization, it was recommended that they also cover other geographic areas when examining OSC behavior. Initial data collection involved 357 questionnaires, however, after eliminating the invalid ones, 300 valid surveys (84.03 percent) were kept (Liu et al. [31]).

3.2. Data Preprocessing Using Min-Max Normalization. Data preprocessing is done as the first stage and is crucial to investigation since it assesses the data integrity for each prediction model's effectiveness in making predictions. Low information quality is the consequence, making it impossible to find quality findings and necessitating data changes for data analysis prediction. One of the most popular techniques for normalizing data is min-max normalization. Every feature's lowest and maximum values are each converted to a 0 and a 1, respectively, while all other values are converted to a decimal between 0 and 1. Each element in the complete data set y is represented by a value between 0 and 1.

It establishes a data range by designating the denominator as the difference between the greatest and lowest number. It is feasible to display each component as a value among 0 and 1 for the numerator by deducting the minimum value of each y component from each y component. It is feasible to establish a big value near to "1" and a lesser number close to "2" in respect of the numerator by deducting the maximum value of every y component from each y component, as shown in equation (2) shifting and inverted min-max normalization. It involves converting measured values from one scale to another, and it can get even more complicated to match the posterior distribution of the modified values. Min-max normalization splits the data values by the range, or the distance between the maximum and minimum, and deducts the data points with the minimum value.

$$Y^* = \frac{[Y - \min(Y)]}{\text{range}(Y)}, \tag{1}$$

where $\min(Y)$ represents the minimum, $\max(Y)$

Table 1: List of existing methodologies.

S. no	References	Techniques	Drawbacks
1.	Shukla et al. [10]	Supervised and unsupervised machine learning algorithms	It is unable to obtain exact data filtering parameters.
2.	Chen et al. [11]	Attitude-behavior-context (ABC) theory	Its incomplete consumer statistics data might affect the performance.
3.	Liu et al. [12]	Bit-based latent spatiotemporal approach	This modality performs poorly in terms of classification accuracy
4.	VLN and Deeplakshmi [14]	Support vector machines (SVM) based on machine learning	The targeted classifications might overlap occasionally
5.	Wang et al. [16]	Adaptable deconstruction approach	If there are nonlinear correlations in the data, the linear regression model performs poorly
6.	Revati et al. [17]	Gaussian process regression	This modal cannot locate the grouped data.
7.	Najman et al. [19]	Growing neural gas	Predicting behavior requires more time.
8.	Chakladar et al. [20]	Long short-term memory-(LSTM-) based deep neural network model	LSTMs are susceptible to specific initializations of activation functions
9.	Asiri et al. [23]	Multiclass random forest	It is sluggish and inefficient for prediction
10.	Subroto and Christianis [24]	Multilayer perceptron	Tuning of features affects multilayer perceptrons
11.	Chaubey et al. [27]	K-nearest neighbors (KNN)	Inefficient in terms of computing
12.	Sheoran and Kumar [28]	Theory of planned behavior (TPB)	It takes a lot of time and effort
13.	Zhang and Wang [29]	Enhanced deep forest strategy	When splitting the trees, it employs the complete feature memory space.
14.	Amasyali and El-Gohary [13]	Big data technology based on machine learning	Data preprocessing in machine learning gives low enhancement of data and less accuracy in prediction
15.	Malik et al. [18]	Machine learning techniques and functional link neural networks	Disproportionate precision variations in resource utilization
16.	Phyo et al. [22]	Machine learning algorithm and voting regressor model	The classification of data set is more complex by using this model
17.	Jupalle et al. [26]	Machine learning algorithm	Massive data sets are needed for machine learning in order to train the data set.

represents the maximum, and range (Y) represents the difference between maximum and minimum

$$Y^* = \frac{[Y - \min(Y)]}{[\max(Y) - \min(Y)]^a}, \quad (2)$$

where a is the constant of the denominator power.

3.3. Feature Extraction Using the Word2Vec Model. Feature extraction is the process of transforming unstructured data into numerical characteristics when the original data collection has the necessary information. In contrast to applying artificial intelligence to the raw data, computerized feature extraction uses specialized algorithms or neural networks to automatically extract features from data without requiring human input. This approach may be quite useful when trying to make a quick transition from creating raw data to artificial intelligence systems. To extract data features, we employed the Word2Vec model. The Word2Vec model is created after the initial procedures.

Using this approach, Word2Vec is a two different layer, shallower neural network that has been trained to recreate data contexts in linguistic terms. A consumption data corpus serves as the input and a set of extracted vectors serves as the output of Word2vec. It features a huge corpus of texts as input and outputs a vector space, usually with several hundred dimensions, where each distinct word in the corpus is given a matching vector. The Word2vec approach maximizes the probability of guessing the word context or neighboring words by calculating each word's vector value and measuring the semantic distance between words. It uses a value of zero to identify characteristics in the data. The value will be changed to terms having semantically equivalent relationships.

Word2Vec determines the separations between the data in each text and the spam and ham keywords. Two more

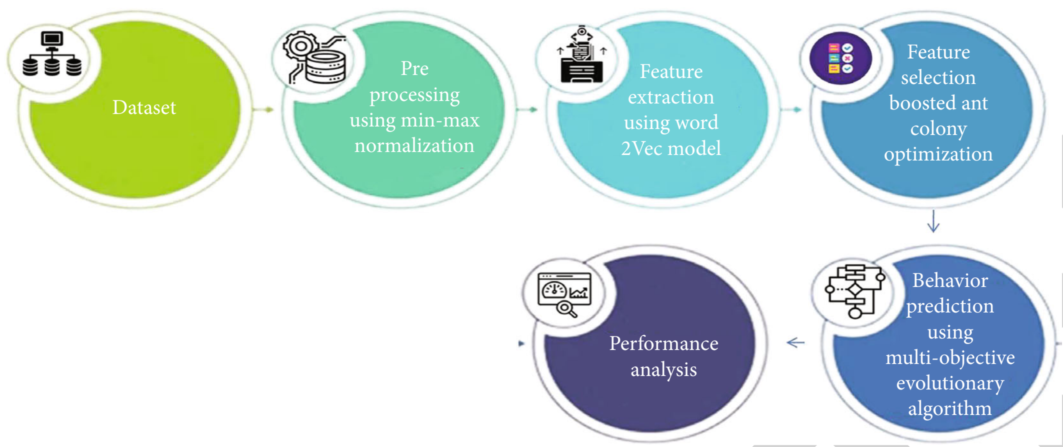

FIGURE 2: Flow of proposed work.

characteristics are created when the classes individually add these values. Organizational data is represented using the Word2vec-calculated distributed vector which is shown in equation (3). The fundamental benefit of distributed representations is the spatial proximity of related consumer data, which makes it easier to generalize observed patterns and produces a more accurate model estimate. Creating word vector representations that are exceptionally effective at predicting their context within the same material is the goal of Word2Vec training.

$$\frac{1}{S}\sum_{s=1}^{S} Q \sum_{i=-k}^{i=k} \log q(x_{s=i} \mid x_s). \tag{3}$$

3.4. Feature Selection Using Boosted Ant Colony Optimization (BACO). An algorithm inspired by nature called boosted ant colony optimization (BACO) imitates how ants look for feedstuffs. Since BACO offers parallelization while minimizing process dependence and provides feedback on the actions of ants in the search space, it is more rational than other algorithms. To make statistical judgments, BACO considers the pheromone trail and heuristic data. As they go along a path, the BACO updates the pheromone level at any feature. The more consumer data that pass over a feature, the more pheromones are deposited there, increasing the likelihood that the feature will be found along the short way.

$$Sq_i^j(G) = \begin{cases} \dfrac{[\tau_i(G)]^{\alpha}[\eta_i]^{\beta}}{\sum_{c\epsilon c_i^j}[\tau_c(g)]^{\alpha}[\eta_c]^{\beta}}, & \text{if } c \,\epsilon\, c_i^j, \\ 0, & \text{otherwise.} \end{cases} \tag{4}$$

The largest number of data points and the short way will both follow the way with the greatest pheromone value. Data are widely dispersed throughout a set of features with a predetermined largest amount of generations S, and the pheromone value $c = 1$ is initialized at each of the N features. The alternatives exist $Sq_i^j(G)$ of jth data at ith feature is displayed below for each generation G which is shown in equation (4).

$$\tau_i(G+1) = (1-q)\tau_i(G) + \sum_{j=1}^{N} \Delta\tau_i^j(G), \tag{5}$$

where τ_i^j is a list of potential neighbors of the ith features that the jth data does not reach. Nonnegative variables, accordingly, provide the relevance of pheromone level i and heuristic information (c) for the motions of the data which shown in 5. A fitness function (FF) is used to evaluate the new set of selected features when the next feature in the data route has been picked. If the fitness value does not increase following the addition of any new feature, the jth ant's movement is stopped. The quantity of pheromone level at the following generation $(G+1)$ at the ith feature is updated in followed equation (6) if the halting requirements are not met.

$$\Delta\tau_i^k(g) = \begin{cases} \mathrm{FF}\dfrac{(S^j(G))}{|S^j(G)|}, & \text{if } i \,\epsilon\, S^k(g), \\ 0, & \text{otherwise,} \end{cases} \tag{6}$$

where N is the number of data, $S^j(G)$ displays the number of features that were chosen, and ji indicates the pheromone that was deposited by jth ant if ith feature is on the shortest path of the data; otherwise, it is 0. As soon as G hits the predetermined maximum S, the halting requirements are satisfied. A group of characteristics will be chosen as a selected feature if it has the greatest pheromone level and lowest fitness value which is shown in equation (6). Figure 3 depicts the BACO's entire procedure.

3.5. Consumption Behavior Prediction Using Multiobjective Evolutionary Algorithm. Multiobjective evolutionary algorithm (MOEA) is the best method for predicting the consumption behavior of consumers, and it leads to an increase in sales and profitability of businesses. The two main categories of prediction algorithms are traditional gradient-based methods and gradient-free direct approaches. One of the traditional prediction techniques,

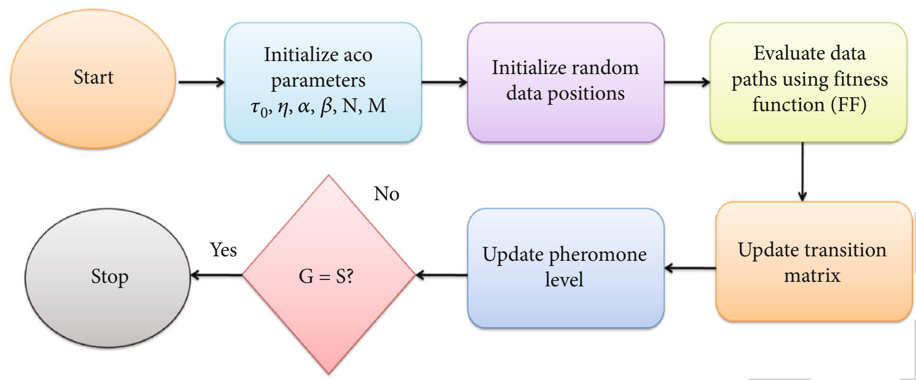

Figure 3: Flow of BACO.

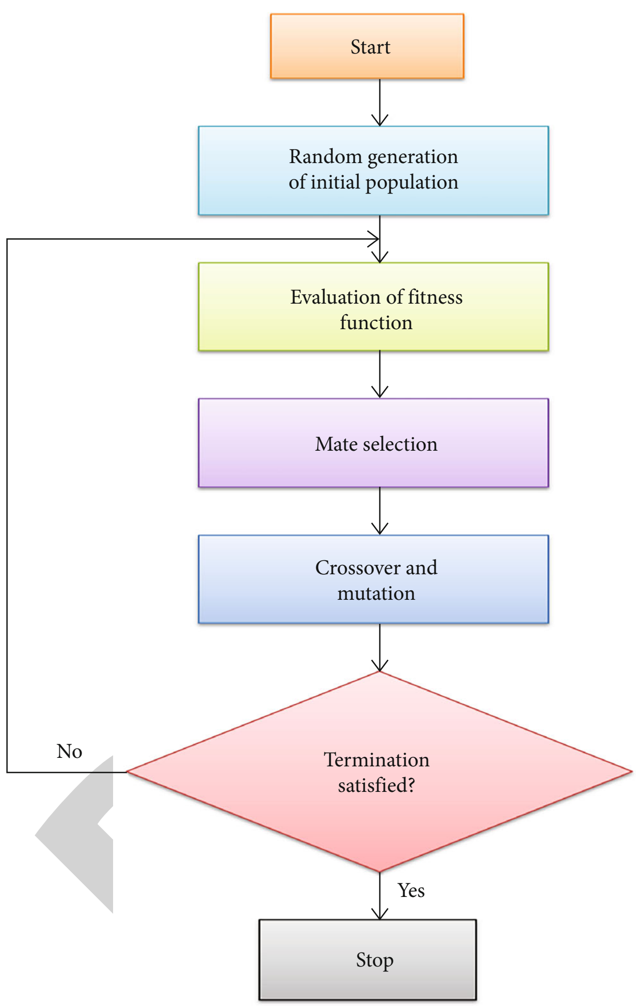

Figure 4: Steps of MOEA.

the multiobjective evolutionary algorithm predicts the best course of action by using variations of the nonlinear objective variable. The starting values are given greatly influence how well this algorithm performs. If the goal and constraint functions are differentiable, it converges to the best forecast.

Discontinuous or nondifferentiable variables can be predicted efficiently by the multiobjective evolutionary algorithm. This technique is appropriate for consumption prediction in the company since the link between the consumption characteristics and one another is nonlinear and produces a continuous function. This may be applied to resolve corporate concerns with consumption forecasting. To obtain the prediction answer, the MOEA algorithm is inspired by the evolutionary processes of replication and evolutionary theory. The replication, selection, crossover, and mutation processes in this algorithm are crucial ones. Figure 4 depicts the basic steps of the MOEA algorithm used for consumption prediction.

Algorithm 1 shows the working flow of the MOEA. To generate several viable solutions to the issue, population growth is the first step. The next step is to assess the prediction fitness function, which stands for the optimal prediction that has to be optimized. The most effective strategies are chosen to create the following population in this assessment. After a fitness assessment, mate selection is necessary so that the chosen prediction can go through a cross-over. Additionally, a new population is created to replace the existing one. Until the consumption prediction termination requirements are satisfied, this procedure continues constantly. The existing techniques exploit a collected data to construct an appropriate explanatory or predicting model. Multiobjective evolutionary algorithms improve their hyperparameters, frequently under competing performance objectives, and identify the optimal solution for a specific task. It correctly determines the inputs to the objective function in order to arrive at the best possible solution for the specified function and satisfy all necessary constraints. By avoiding the populations of data from evolving insanely identical to one another and so delaying or even blocking convergence to the global optimum, mutation operations are employed to try to avoid local minima. By switching some or all of the dataset's data, the crossover of two original datasets generates new solutions. It has higher probability.

4. Result

In this research, a multiobjective evolutionary algorithm is used to examine consumer consumption prediction (MOEA). Chinese consumer preferences data who have participated in at least one online shopping carnival (OSC) are used in this paper. The effectiveness of the consumer's

```
Start
Input the consumer data
If (initialize the variable generation population)
    Calculate the fitness function of consumer data
    Selection of appropriate prediction of consumer data
    Crosscheck the prediction value by crossover and mutation
    Consumer prediction termination satisfied
Else
    Again initialize the population
End
```

ALGORITHM 1: Multiobjective Evolutionary Algorithm.

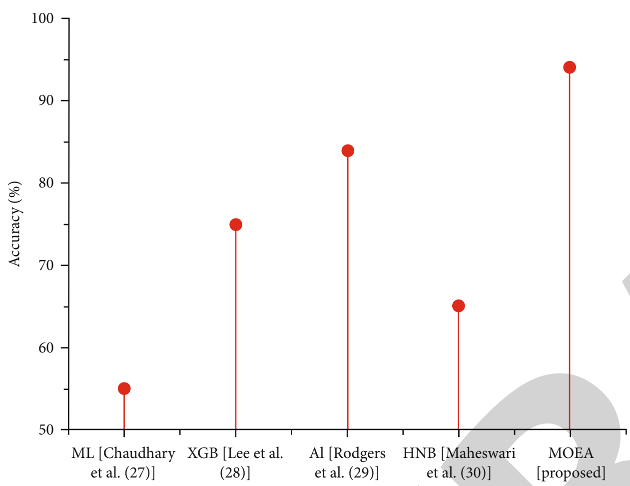

FIGURE 5: Comparison of accuracy.

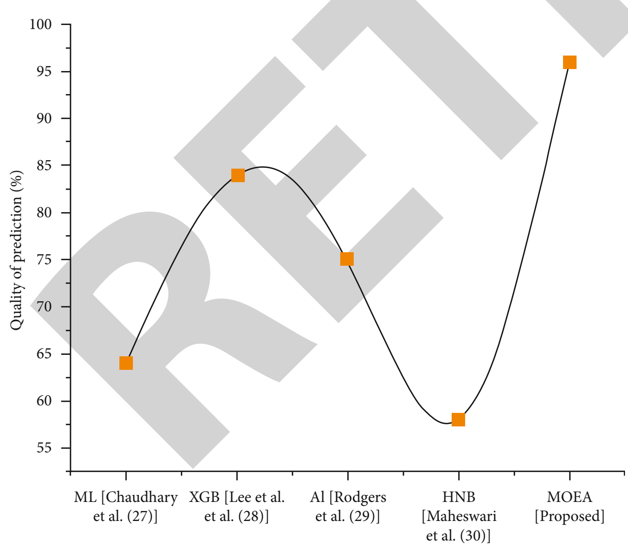

FIGURE 6: Comparison of quality of prediction.

consumption prediction is examined in this section. Accuracy, recall, precision, $f1$-score, quality of prediction, and prediction time are the key parameters. These metrics are used to assess the efficacy of the proposed approach (MOEA). The results were contrasted with that of traditionally used techniques including machine learning (ML), eXtreme Gradient Boosting (XGB), artificial learning (AL), and hybrid naive Bayes (HNB).

4.1. Accuracy. The accuracy of the model is the extent to which evaluations of a quantity are closer to that number's true value. Through using proposed methodology, it forecasts the essential information based on customer preferences from consumer data from several sources, identifies patterns, and envisions trends and future consequences. When compared to the existing method, the suggested method's consumer consumption predictions are shown to be more accurate. Figure 5 shows consumption prediction of accuracy in existing systems, and the proposed system is denoted. ML has attained 50%, XGB has acquired 75%, AI has reached 85%, and HNB attains 65% whereas the proposed system attains 95% of accuracy.

4.2. Quality of Prediction. In an effort to predict how individuals would respond whenever purchasing goods, the suggested technique effectively and accurately identifies customer preferences for their incredibly positive, overwhelmingly favourable, reasonable thoughts, dreadful, and significantly unfavorable items. The prediction quality metric will demonstrate the efficiency of the system when evaluated on historical data to estimate the performance of the measurements. The quality of prediction is interpreted in Figure 6. The quality of prediction of ML acquires 67%, XGB acquires 82%, AI has reached 75%, and HNB attains 58% whereas the proposed system attains 97%. Hence, the proposed system has higher efficiency.

4.3. Precision. The probability of pertaining recovery of consumer preference prediction on average is known as precision. When applying the recommended approach, precision characterizes how consumer data could be predicted with a high degree of authenticity for consumption preferences across a variety of purchases.

The proportion of appropriate concepts among the recovered occurrences is known as precision, also known as positive predictive value. It can define that precision is the measure of quality. Figure 7 represents the comparison of precision in existing and proposed methodologies. The precision of the proposed work is much greater than the existing methodologies. The consumption prediction of

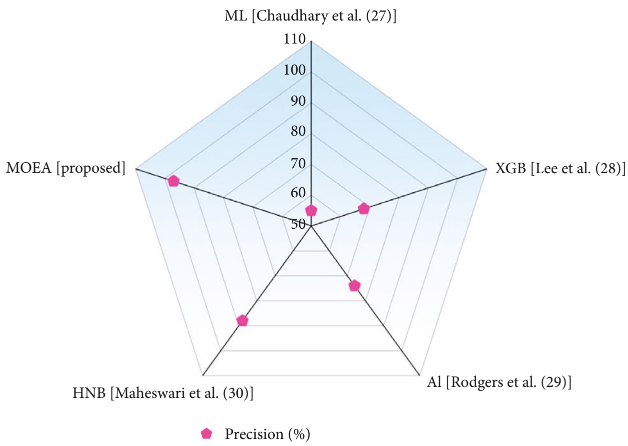

FIGURE 7: Comparison of precision.

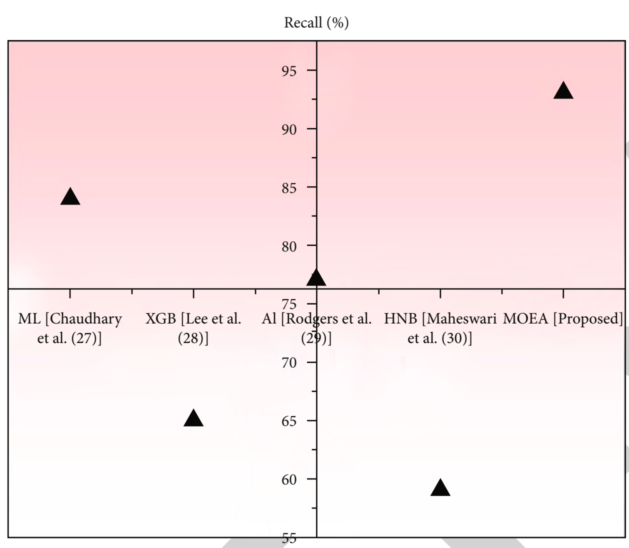

FIGURE 8: Comparison of recall.

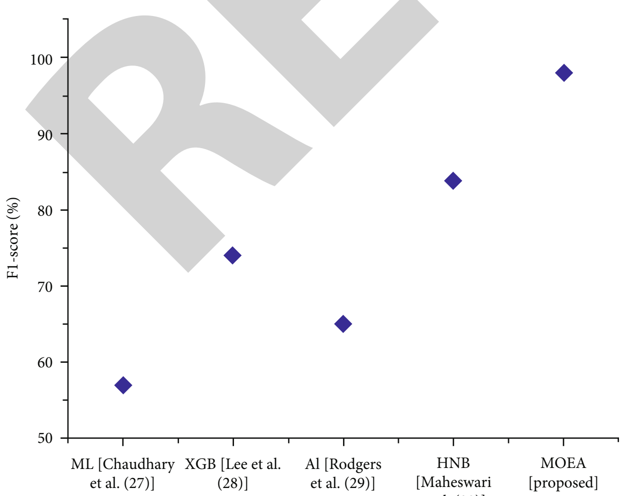

FIGURE 9: Comparison of $F1$-score.

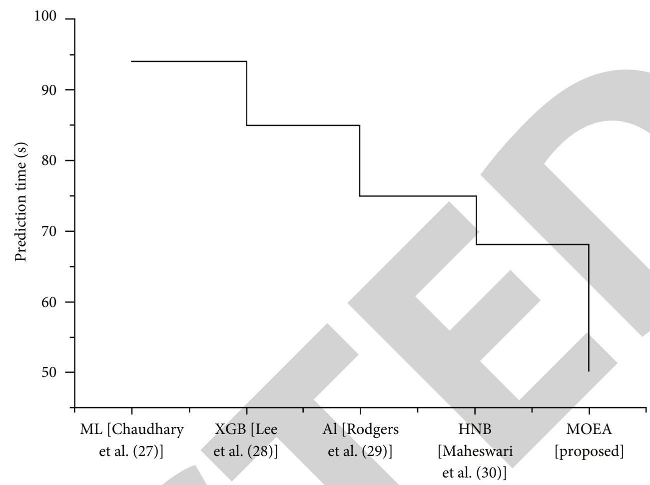

FIGURE 10: Comparison of prediction time.

precision in existing systems has the following level, therefore, ML has attained 55%, XGB has acquires 70%, AI has reached 75%, and HNB attains 90% whereas the proposed system attains 99% of precision. Hence, the proposed system has the greatest performance level.

4.4. Recall. Recall of proposed and existing methods is depicted in Figure 8. The percentage of pertinent occurrences that were recovered is known as a recall. The true positive rate or sensitivity is also referred to as the recall. Compared to the existing approaches, the proposed method has the highest level of recall. The behavior prediction of recall in existing systems has the following level of recall, therefore, ML has attained 84%, XGB has acquires 65%, AI has reached 76%, and HNB attains 58% whereas the proposed system attains 93% of recall. This denotes the efficiency of the proposed work is well-suited.

4.5. F1-Score. Figure 9 depicts the $F1$-score of existing and proposed techniques. A system's clarity and recollection are combined into a single statistic known as the $F1$-score by determining their harmonic means. It mainly serves to contrast the effectiveness of the two systems. A higher $F1$-score is considered a better system performance. From Figure 8, ML acquires 68%, XGB acquires 75%, AI has reached 65%, and HNB attains 85% whereas the proposed system attains 98% of the $F1$-score. It denotes that the proposed system has higher performance.

4.6. Prediction Time. Figure 10 depicts the prediction time of existing and proposed approaches. When a system is anticipated to forecast something about what it is predicting is known as the prediction time. From Figure 10, the prediction time of ML acquires 93 (s), XGB acquires 85 (s), AI has reached 75 (s), and HNB attains 65 (s) whereas the proposed system attains 50 (s).

It is known that the proposed system has a low prediction time compared to the existing approaches. Hence, it indicates that the proposed system has well effective for

Table 2: Comparative analysis of various parameters for existing and proposed methods.

	ML	XGB	AI	HNB	MOEA (proposed)
Accuracy (%)	50	75	85	65	95
Quality of prediction (%)	67	82	75	58	97
Precision (%)	55	70	75	90	99
Recall (%)	84	65	76	58	93
$F1$-score (%)	68	75	65	85	98
Time (s)	93	85	75	65	50

implementation. The comparative analysis for existing and proposed methods is shown in Table 2.

5. Discussion

Chaudhary et al. [32] suggested using machine learning (ML) to analyze customer activity on social networking sites based on a few metrics, requirements, and user attitudes. Massive data sets are needed for machine learning to be trained on, and they should result in lower-level prediction. Lee et al. [33] developed the eXtreme Gradient Boosting (XGB) model to develop powerful tools for forecasting customer behavior and to assist companies in generating revenue and sales. On sparse and unstructured data, it does not execute well. Rodgers et al. [34] advocated the employment of artificial intelligence (AI), which develops a methodical technique to determine predicting customer behavior perception of a business and the usefulness effects the acquisition of that product. For prediction, a longer time is needed. Maheswari et al. [35] stated hybrid naive Bayes (HNB) was developed to classify consumer trends when they are making purchases of items and aims to be a significant addition to the study of consumer behavior. Assuming that each feature is isolated, naive Bayes is unable to learn how to anticipate patterns. Therefore, the proposed model MOEA overcomes these shortcomings in the prediction of consumption behavior.

6. Conclusion

In an era where consumer prediction is one of the innovative technical features, the integration of consumption prediction with business will result in substantial changes in growth and profit for business management. Due to the concept of predicting consumer behavior, all business categories may now be characterized as quantitative, which enhances the efficiency, accuracy, and competence of the business organization. For the betterment of business, this chapter advocated employing a multiobjective evolutionary algorithm (MOEA) to precisely estimate client consumption forecast. The results show that, in terms of accuracy (95%), quality of prediction (97%), precision (99%), recall (93%), $F1$ -score (98%), and prediction time (50s), the proposed MOEA approach performs well than the conventional ML, XGB, AI, and HNB algorithm methods. For some ideas of the process in the suggested method, it might be challenging to comprehend and interpret. Future research on the topic might focus on improving the ability to predict consumer behavior for successful business development. In the future, we may think about using evolutionary algorithm techniques to improve performance metrics and the application of consumption prediction in business economic domains.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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