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A blockchain-based evaluation approach to analyse customer satisfaction using AI techniques

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A R T I C L E I N F O

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Regression analysis

A B S T R A C T

Due to technological advancements and consumer demands, online shopping creates new features and adapts to new standards. A robust customer satisfaction prediction model concerning trust and privacy platforms can encourage an organization to make better decisions about its service and quality. This study presented an approach to predict consumer satisfaction using the blockchain-based framework combining the Multi-Dimensional Naive Bayes-K Nearest Neighbor (MDNB-KNN) and the Multi-Objective Logistic Particle Swarm Optimization Algorithm (MOL-PSOA). A regression model is employed to quantify the impact of various production factors on customer satisfaction. The proposed method yields better levels of measurement for customer satisfaction (98%), accuracy (95%), necessary time (60%), precision (95%), and recall (95%) compared to existing studies. Measuring consumer satisfaction with a trustworthy platform facilitates to development of the conceptual and practical distinctions influencing customers' purchasing decisions.

1. Introduction

Technology has transformed customers' purchase habits faster, securely, and conveniently. The perception of the customer affects how reasonably they are willing to buy from a particular online retailer based on previous customer reviews and ratings [1]. An essential benefit of analyzing online reviews is attracting new prospective customers by furnishing relevant information to support purchasing decisions [2]. Comprehensive data review can make sentiment analysis efficient and functional [3]. Customer satisfaction is developed after purchasing, using, and utilizing a product or service. The customer's perspective, evaluation, and expressive response contribute to satisfaction [4]. Customer reviews can be analyzed, evaluated, and categorized using natural language processing, text analysis, and statistics [5]. The e-commerce platform drives online shopping more convenient and beneficial for sellers and customers. Fig. 1 depicts the factors making customer satisfaction [6].

Artificial Intelligence (AI) is a technology that accomplishes complicated assignments and needs human brains [7]. AI is considerably employed to measure customer satisfaction and blockchain. Privacy has evolved into a crucial consideration due to leaks and

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misuse of private data. Further raising considerations with AI possess trustworthiness as the technique does not interact or communicate with human users and, therefore, cannot be ensured or entrusted [8].

Blockchain has attained growing concentration as a technology with a broad scope of applications in different areas in a secure and trusted manner. It is cost-effective and ensures as it eradicates the necessity for centralized control to confirm transactions [9]. A blockchain application model combines encryption, peer-to-peer transmission, data storage, and a consensus protocol. Preserving point-to-point distributed transactions in an immutable format with a timestamp boosts system performance and reduces costs since nodes may establish a trust foundation. With cryptographic privacy, blockchain emphasizes data privacy [10]. Any data transmission that follows a precise method creates the initial building block of the chain. This paper uses blockchain to furnish a trustworthy platform for various stakeholders to share and receive data on customer satisfaction ratings.

Blockchain can offer privacy, and trust to AI-based applications, whereas AI can enhance scalability and security while resolving the personalization and governance issues for blockchain-based technologies. The convergence of AI and blockchain has brought many new opportunities [11]. AI and blockchain have been used to measure customer satisfaction and financial services, enabling trustworthy data sharing and facilitating automated transactions [12]. Several studies have measured customer satisfaction using machine learning [13] and other AI techniques [14]. This work extends the existing studies by utilizing the blockchain-based framework to provide a trustworthy platform and using AI techniques to measure customer satisfaction [15]. The MDNB-KNN algorithm [16] is used for customer satisfaction, and the MOL-PSOA optimization [17] technique is utilized to measure the model's performance. The significant contribution of the paper follows as under.

1. The blockchain-based framework is utilized for data validation, storage, and Proof Of Work (POW) consequences algorithm to ensure the authenticity of the data can assist organizations in making better decisions.
2. The MDNB-KNN is utilized to evaluate customer satisfaction, and the MOL-PSOA is employed to evaluate the performance analysis.
3. The proposed method is compared with the existing study, and the time consumption of blockchain enactment is assessed to confirm the feasibility.

The remaining paper is formulated as follows. The related works are discussed in Section 2. In Section 3, the proposed work, along with the blockchain framework, is illustrated. The performance analysis is presented in Section 4. The discussion is presented in Section 5. Finally, the paper is concluded in Section 6.

2. Literature review

Kitsios et al. [18] performed a multicriteria analysis to determine customer satisfaction in an online appointment system. While the gratification association is accurate and statistically significant ($r = .101$), more valuable insights can be gained from the explanation of modifying and mediating variables [19]. Zouari et al. [20] presented a study on the significant correlation between consumer service quality and satisfaction analysis findings to enhance customer service and environmental and socioeconomic durability. Eklof et al. [21] presented a study on customer commitment and satisfaction to the profitability of profit margin, operational profits, and market indicators. Davras et al. [22] proposed a symmetrical and asymmetrical hotel service effectiveness method and a big-data customer satisfaction rating methodology.

Blockchain technology can provide accurate quantitative data while highlighting limits in creating subjective counterfeits, such as rating fraud. Each rating fraud case assesses blockchain-based reputation systems' trustworthiness [23]. Lim et al. [24] presented how blockchain technology can influence a business's advertising campaigns. Pandey et al. [25] explored five use cases to explain blockchain technology and its various applications. The framework enables businesses to disclose names, addresses, or phone numbers. Wang et al. [26] presented a study on the existing body of knowledge by demonstrating through empirical analysis that adopting blockchain technology can boost businesses' marketing performance. The outcomes show that the popularity of blockchain technology affects customers. Wang et al. [27] proposed a Logit-Support Vector Machine (SVM) method that uses distance to quantify overall customer satisfaction performance. Sherman et al. [28] presented a blockchain method to develop e-commerce, especially Customer to Customer (C2C). The proposed approach benefits e-commerce enterprises using blockchain technology to verify product information.

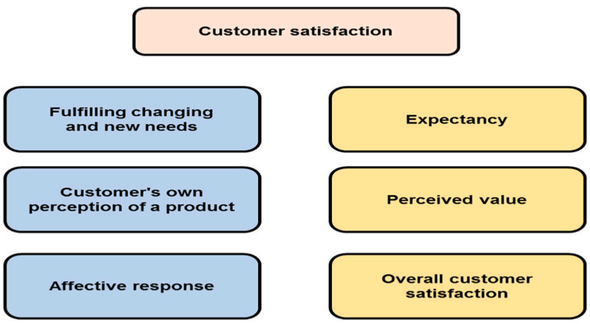

Fig. 1. Factors making customer satisfaction.

Scott et al. [29] proposed a model to build social and solidarity-based funding; cryptocurrencies and blockchain technology is becoming more critical. George et al. [30] presented a model to improve food products' traceability using a blockchain framework and assistance in rating food quality for human consumption.

Several studies have been conducted to measure customer satisfaction based on customer reviews using machine learning [31,32], and deep learning [33,34]. Khasby et al. [35] presented a model for customer satisfaction analysis from the customer reviews collected from the google play store using the KNN and the Naive Bayes technique. Adamu et al. [36] proposed a model using the particle swarm optimization technique for feature selection and evaluated the model's performance. Budh et al. [37] proposed a model using multi-Level PSO (ML-PSO) to optimize the parameters of ensemble models for customer sentiment analysis—the proposed model improved prediction accuracy. Zare et al. [38] proposed a model using the extracting knowledge for customer data using an improved k-means algorithm. The proposed model extends the speed and accuracy. Munusamy et al. [39] proposed a modified dynamic fuzzy c-means algorithm utilizing a retail supermarket dataset with new data updates for dynamic customer segmentation. Eswaraet al. [40] presented a modem using long short-term memory (LSTM) to measure user happiness and induce degradation of the user experience rate. Using robotics process automation, Goyal et al. [41] demonstrated the relevance of automated customer support request desks in the tourism and travel sector. Goyal [42] presented a study to automate the customer service request desk in the hotel industry. Dave et al. [43] proposed a distributed edge-fog node-based video surveillance device for intelligent home settings to protect people's privacy. The proposed system employs motion detection to identify incursions and filters out extraneous data inside the monitoring system, making it event-driven programming and resource-efficient. Table 1 summarizes the existing studies.

The motivation of this study is to use a blockchain-based trustworthy platform for data validation, storage, and POW consequences algorithm. Based on the secure platform, the proposed MDNB-KNN measures customer satisfaction, and the MOL-PSOA is utilized to evaluate the performance analysis.

3. Methodology and proposed work

This section demonstrates the proposed method to measure online customer satisfaction demonstrated in Fig. 2.

3.1. Collections and processing of data

The data source is collected from the Suning.com (https://www.suning.com/) website. The database has 117,585 customer evaluations; each has its ID number, star rating (1–5), 5 being the highest star and 1 being the lowest, and reviewer comments. We considered 105,263 reviews after deleting duplicates and blanks. There is a record of all product's features and benefits in the product dataset. Combining the product and review datasets, we collected 71,909 data points from the reviews presented in Table 2.

The decentralized nature of the method depends on peer-to-peer networks. Data from each participant in a blockchain network is added to a shared record. Each peer in the network uses a unique block. All members of a team or system now have instant access to data thanks to blockchain technology. Attribute selection and dimensionality reduction are employed. After the data has been cleaned and prepared, it is divided into groups for training and testing. The training data sets are transferred from the blockchain framework, where they have been trained using the proposed approach.

3.2. Regression analysis

Regression analysis estimates the connection between a dependent variable and one or more independent variables [44]. The most common models are simple linear and multiple linear models. Multiple fields are intricately connected to regression analysis in forecasting and prediction, computed using equation (1).

$$Y_j = f\left(X_j, \alpha\right) + E_j \tag{1}$$

Where the reliant parameter is Y_j, the separate parameter is X_j, the consistent value α, and the incorrect sentence value is E_j.

Table 1
Summaries of related work.

Work	Technique	Data set	Description
Davras et al. [22]	Asymmetric and symmetric consumer satisfaction effects.	Survey and hotel reviews.	Implementation of goods or services is vital to consumer satisfaction.
Lim et al. [24]	Blockchain technology's use for client loyalty.	Text distance review sets	The research is focused on the advantages and difficulties of blockchain characteristics in e-commerce platforms.
Wang et al. [26]	Examine how blockchain technology affects customer behaviour.	Food product	Customer behavior is estimated based on multiple case studies.
Zare et al. [38]	Identifying customer satisfaction using the K means technique.	Customer review data.	Customer satisfaction measurement.
Munusamy et al. [39]	Dynamic customer segmentation.	RFM attributes	Methods for dividing customers into groups on the market.
Eswara et al. [40]	User quality of experience.	Netflix Database	The continuous QoE prediction helps furnish insights for understanding the user's overall experience.

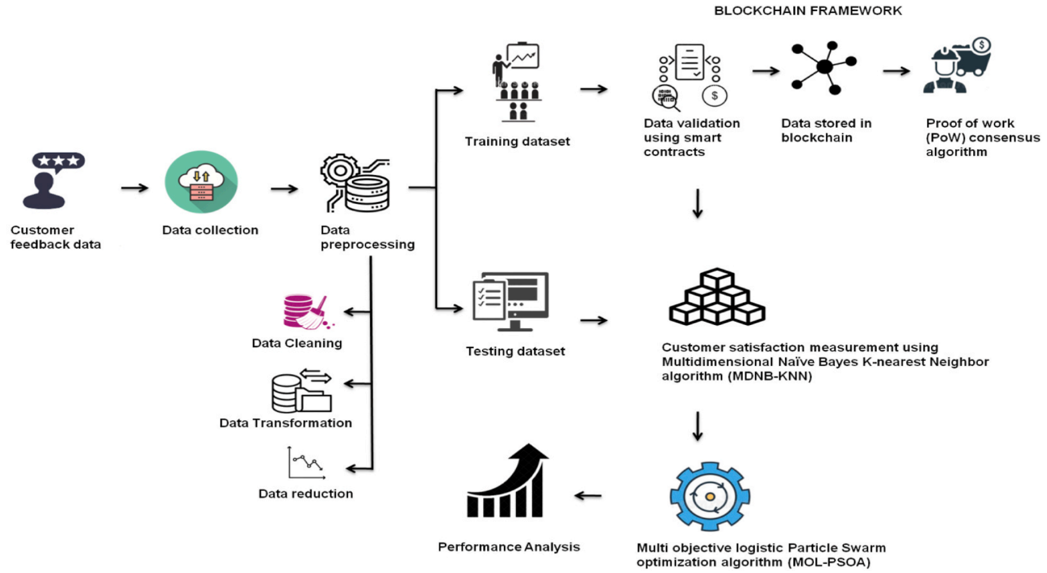

Fig. 2. Proposed approach for online purchasing consumer satisfaction.

Table 2
Dataset explanation.

Data source	Actual data	After eliminating duplicates and filling up the blanks
Check data.	117,585	105,263
Product data	105,265	71,909

3.3. *Verification of data via blockchain contracts*

The validation method is created to check data files. While the validation procedures remain consistent across data types, the data and identification can be tweaked to suit a given application better. Once the information has been validated, it is added to the blockchain. The smart contract is carried out on a distributed ledger called a blockchain, and its protocol is stored in several places throughout the platform [45].

The contract's terms and the supporting data are stored on a distributed blockchain ledger. The stipulation is included in a smart contract. The smart contract's triggering condition is recorded on the blockchain when a reservation is canceled. Smart contracts in a blockchain are portrayed in Fig. 3.

3.4. *Consensus algorithm based on proof of work*

After a smart contract has been validated, the resultant data is recorded in the blockchain. The specific data IDs are converted to their corresponding data and a collection of all identifiers. Aside from mapping, the smart contract also allows for adding new information. This procedure is invoked with a validator and identification. The pair of identifiers and validation are then added to the map. The identifier is saved in an array [46]. The process of providing proof of work is demonstrated in Fig. 4.

3.5. *The MDNB-KNN for measuring customer satisfaction*

The feature sets of similar individuals can be predicted by applying Bayesian classification to a data item. Correlation in the

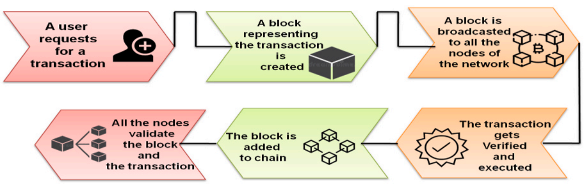

Fig. 3. Blockchain-based intelligent connections.

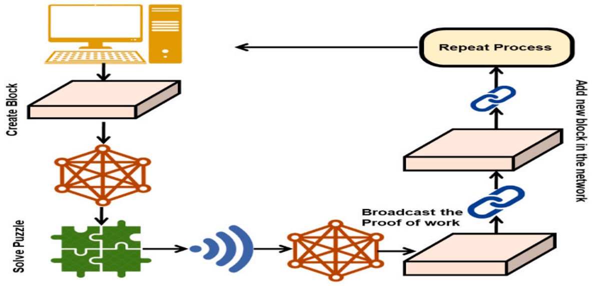

Fig. 4. Work-proof flowchart.

characteristics' levels is used to categorize data subsets that have already been identified. Bayes' theorem makes inferential inferences about unknown groups when some feature values are known [47]. A probabilistic classifier is used to categorize the new input pieces generated by the learning process in this scenario. We get: x is a class variable; b1 and b2 are dependant characteristic vectors using equations (2)–(5).

$$Q\left(a / b_{1,}b_{2}, \ldots..b_{m}\right) = \frac{Q(a)Q\left(b_{1,}\ldots..b_{m}/a\right)}{Q\left(b_{1,}\ldots..b_{m}\right)} \tag{2}$$

$$Q\left(a / b_{1,}b_{2}, \ldots..b_{m}\right) = \frac{Q(a)\pi_{i=1}^{m}Q\left(b_{j}/a\right)}{Q\left(b_{1,}\ldots..b_{m}\right)} \tag{3}$$

$$Q\left(a / b_{1,}b_{2}, \ldots..b_{m}\right)b\ Q(a)\prod\nolimits_{i=1}^{m}Q(b_{i} / a) \tag{4}$$

$$\widehat{a} = arg\max_{a}Q(a)\prod\nolimits_{i=1}^{m}Q(b_{i} / a) \tag{5}$$

The probability value of every attribute data is determined and then integrated using the MDNB-KNN method. Then, the KNN method is used for the data with the highest likelihood. K-Nearest Neighbor analysis determines G (b, a) for all data collected. We rank the minimal values of G (b, a) based on the final computation. Input is taken from training data through a KNN method prediction. The KNN technique is sped up by combining these two methods since it no longer has to calculate the complete data set but instead uses the existing probabilities. The proposed technique is illustrated in Algorithm 1, and the proposed flowchart is presented in Fig. 5.

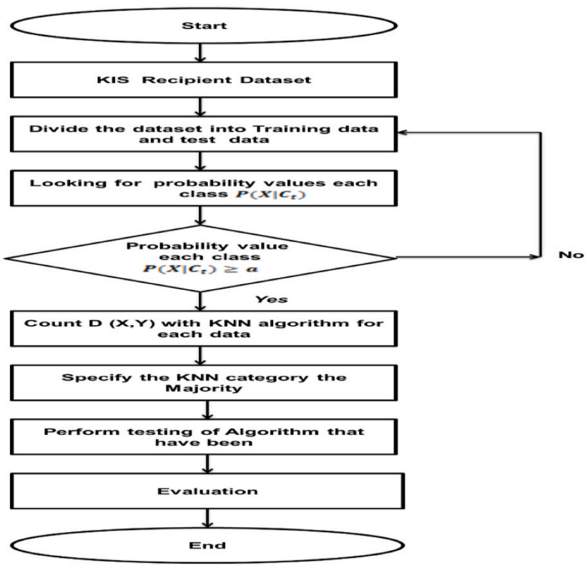

Fig. 5. The MDNB-KNN flowchart.

Algorithm 1. MDNB-KNN.

Pseudocode for MDNB-KNN method
Input:
x: a matrix of training data, where each row is a feature vector
b: a vector of class labels for the training data
k: the number of neighbors to consider in KNN
num_classes: the number of unique class labels in *b*
Train a Naive Bayes model for each class label
for *i* in range (*num_classes*):
Get the indices of training examples that belong to this class
indices = [*j* for *j* in range (*len*(*b*)) if *b*[*j*] = = *i*]
Extract the subset of training data and compute the mean and variance for each feature
class_data = *x* [indices, :]
class_mean = *class_data*.mean(*axis* = 0)
class_var = *class_data*.*var*(*axis* = 0)
Store the mean and variance for this class
class_params[*i*] = {'*mean*' : *class_mean*, '*var*' : *class_var*}
Predict the class label
for *x_test* in *X_test*:
Compute the prior probability for each class label
class_probs = []
for *i* in range (*num_classes*):
prior = *len*([*j for j in range*(*len*(*y*)) *if y*[*j*] = = *i*]) / *len*(*y*)
Compute the likelihood of the test example given the mean and variance for this class
likelihood = 1
for *j* in range (*len*(*x_test*)):
likelihood * = gaussian(*x_test*[*j*], *class_params*[*i*]['*mean*'][*j*], *class_params*[*i*]['*var*'][*j*])
Compute the posterior probability for this class
posterior = *prior* * *likelihood*
class_probs.append(*posterior*)
Use KNN to choose the most likely class label from the k nearest neighbors
k_nearest = k_nearest_neighbors(x_test, X, k)
*k_nearest*_labels = [*y*[*idx*] *for idx in k_nearest*]
mode_label = *mode*(*k_nearest_labels*)
Combine the Naive Bayes and KNN predictions by multiplying the Naive Bayes posterior by the KNN vote
final_prob = *class_probs*[*mode_label*] * *len*([*label for label in k_nearest_labels if label* = = *mode_label*]) / *k*
predictions.*append*(*final_prob*)
Output:
Predictions: a vector of predicted class probabilities.

3.6. The MOL-PSOA method

The MOL-PSOA relies on collective intelligence. MOL-population PSOA's dynamics mimic bio-inspired behaviors, in which all members exchange knowledge and let the material profit from the innovations and experiences of all the other materials [48]. The ideal parameters for the RST controllers employed. The first controller settings vector is chosen at random. The length of this vector is M2. The number of iterations in the prediction horizon is MX, and my, the degree of X (k1) and Y (k1).

The swarm's particle velocities are recalculated at each iteration (n) by drawing on the one optimal place, present, and visitor employing equations (6) and (7).

$$z_i = (v+1) = y_t z_i(v) + c_1 t_1 \left(X_{pbest}(v) - x_i(v)\right) + c_2 t_2 \left(x_{gbest}(v) - x_i(v)\right) \tag{6}$$

$$x_i(v+1) = x_i + z_i(v+1) \tag{7}$$

Each particle represents a potential explanation and is located at the x_i coordinate, where t_1 and t_2 are random variables in the range [0; 1], and c_1 and c_2 are the social and cognitive scaling factors, respectively (u). Controlling how much past velocity affects present velocity is the inertia weight, xr. Global search performance was good with a large inertial weight, whereas a smaller one facilitates the local search. The maximum and minimum velocities wj(u) are [xmax + xmax]. If the speed exceeds the range, it is reset to its previous settings using equation (8).

$$x_s = (x_{max} - x_{min}) \frac{u_{max} - u}{u_{max}} + x_{min} \tag{8}$$

The highest and lowest values of x_s are denoted by x_{max} and x_{min}, respectively, and most iterations are denoted by u_{max}.

The mean cost function is used as a reliable evaluative metric since minimizing the discrepancy between the current model's output and the reference model's using equation (9).

$$MCF = \frac{1}{ST} \sum_{l=1}^{ST} k(l) \tag{9}$$

ST denotes the time spent in the simulated plant, I is for the cost-predictive function, and l is for the number of iterations. Since the objective is to decrease the value of the cost function, the fitness function can be defined using equation (10).

$$Gg_i = \max(MCF) - MCF_j, j = 1, \ldots, NP \tag{10}$$

Algorithm 2 illustrates the pseudo-code for the proposed MOL-PSOA technique.

Algorithm 2. MOL-PSOA

Pseudocode for MOL-PSOA
Step 1: Initialization
Initialize the swarm with random positions and velocities
Initialize the personal and global best positions
Evaluate the fitness of each particle
Set the current iteration $t = 0$
Step 2: Optimization loop
While $(t < max\_iter)$ and (not converged):
For each particle i in the swarm:
Step 3: Update velocity and position
Calculate the new velocity
Update the particle's position
Apply bounds to the new position
Evaluate the fitness of the new position
Step 4: Update personal and global best positions
If the new position is better than the particle's personal best:
Update the personal best position
If the new position is better than the global best:
Update the global best position
Step 5: Update the inertia weight
Calculate the new inertia weight
Step 6: Determine the non-dominated solutions
Rank the particles using a non-dominated sorting algorithm
Assign each particle a crowding distance
Select the best solutions from the non-dominated fronts using a crowding distance comparison
Step 7: Update the swarm size
If the size of the non-dominated set is larger than the swarm size:
Remove the worst solutions using a crowding distance comparison
Step 8: Update the convergence criteria
If the change in the global best fitness is less than the threshold value:
Set converged = True
Step 9: Update the iteration count
Incrementt
Step 10: Return the non-dominated set
Return the set of non-dominated solutions
End

Fig. 6 portrays the proposed MOL-PSOA flowchart.

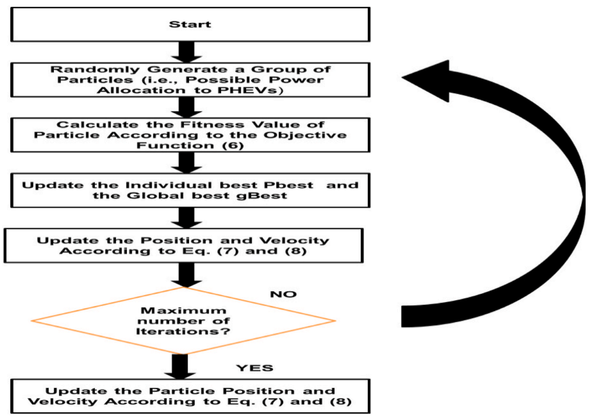

Fig. 6. Flowchart of MOL-PSOA.

4. Performance evaluation

This section discusses the performance of the proposed model.

Regression Analysis: Table 3 presents the outcomes of the regression analysis, which shows that the coefficients for the regression coefficient (3 pulsators) are 1.012. The correlation for the regression coefficient 3 drums is 0.130. Comparing a pulsator washer to a combination washer-dryer, they demonstrate a 175.1% improvement in satisfaction with the former and a 13.9% increase with the latter. Reducing satisfaction occurs when the color is changed from silvery to white or grey. The coefficient value of the golden color (four golden) is 0.095 ($p = 0.008$), indicating buyers are ten percent happier with golden washing machines than with silver ones. This kind of screen is not just an essential but important consideration. We identified seven aspects that ensured satisfied customers per the coefficient standard errors; the washing machine and the loading method have a much more significant impact. The more traits did have impacts, although these effects were weaker. Organizations may consider the seven variables affecting customer satisfaction when developing a new product.

The parameters considered for evaluation are customer satisfaction, measurement accuracy, time consumption, precision, recall, and F1 score. The parameters are compared with the existing methods, namely (i) Improved K-means Algorithm (IKA), (ii) Fuzzy c-means Clustering Algorithm (FCM), and (iii) Long Short Term Memory (LSTM). The K-means is one of customer relationship management's most important data mining techniques [49]. It qualifies for accurately predicting customer behavior by identifying patterns and allowing the organization to align efforts with customers' preferences better. Clustering has attracted significant study since it is an unsupervised machine-learning technique. FCM is the standard method, alongside deterministic and probabilistic approaches [50]. FCM is performed by minimizing an objective function by effectively assessing the decision variables, precisely the values of the membership function and the cluster representatives, within a limited context. LSTM networks are a type of Recurrent Neural Network that can gain knowledge order dependence [51]. In RNN, the outcome of the last phase is used as the input for the next step.

Customer Satisfaction: It determines if a consumer is satisfied or dissatisfied with a product based on how well it meets their needs using equation (11).

$$\% \text{ of satisfied customers} = \frac{The\ total\ number\ of\ 4\ and\ 5\ reaction}{number\ of\ total\ reaction} \times 100 \tag{11}$$

Fig. 7 and Table 4 portray a comparison of customers' levels of satisfaction. The proposed method achieves 75% of customer satisfaction, IKA achieves 68%, FCM achieves 58%, and LSTM achieves 62%.

Accuracy: The ratio of precisely expected comments is calculated and divided by the total number of comments in the dataset using equation (12).

$$\text{Accuracy (A)} = \frac{\text{True Positive} + \text{True Negative}}{\text{True Positive} + \text{True Negative} + \text{False Positive} + \text{False Negative}} \tag{12}$$

Fig. 8 and Table 5 depict the accuracy of the proposed model compared to the existing methods. The proposed method achieves 82% accuracy, whereas IKA reaches 78%, FCM reaches 62%, and LSTM reaches 70%.

Time consumption: The proposed system consumes less time, 38%, while IKA consumes 68%, FCM consumes 55%, and LSTM consumes 62%, illustrated in Fig. 9 and Table 5.

Precision: It is the correlation of a series of identical measurements obtained under identical conditions and evaluated using equation (13). The proposed method achieves 90%, IKA of 78%, FCM of 62%, and LSTM of 70%, as presented in Fig. 10 and Table 6. The proposed method has a high degree of performance.

$$Precision = \frac{true\ positive}{true\ positive + false\ positive} \tag{13}$$

Recall: It is determined using equation (14) and indicates how many precise measurements are made among all potential positive measures. The proposed techniques perform at 92%, IKA at 82%, FCM at 78%, and LSTM at 70%, as presented in Fig. 11 and Table 7. The proposed method has the most significant degree of recall compared to existing methods.

Table 3
Satisfaction of customers as related to production attributes.

Variable	p-value
"$\beta4_{\_golden}$	0.008
$\beta7_{\_LCD}$	0.013
$\beta3_{\_pulsator}$	<0.001
$\beta4_{\_white}$	<0.001
$\beta4_{\_grey}$	<0.001
$\beta9_{\_up}$	0.002
$\beta10_{\_top}$	0.002
$\beta3_{\_drum}$	0.066″

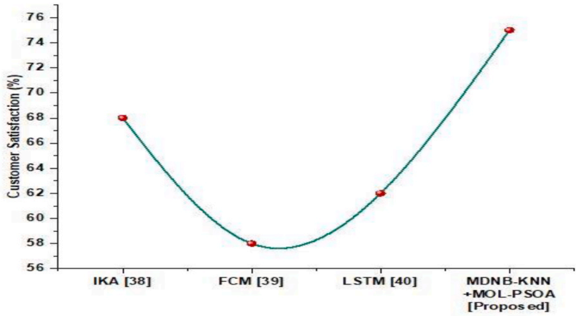

Fig. 7. Comparison of customer satisfaction.

Table 4
Comparison of customer satisfaction.

Method	Customer Satisfaction (%)
IKA [38]	68
FCM [39]	58
LSTM [40]	62
MDNB-KNN + MOL-PSOA	75

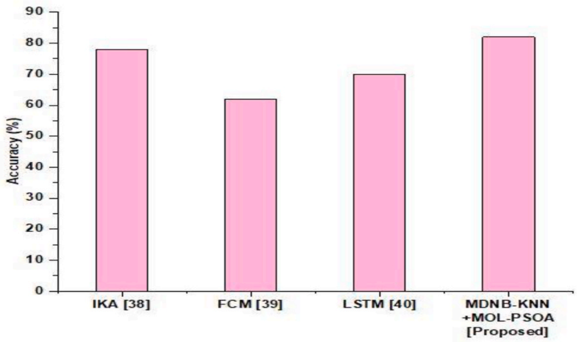

Fig. 8. Comparison of accuracy.

Table 5
Comparison of accuracy.

Method	Accuracy (%)
IKA [38]	78
FCM [39]	62
LSTM [40]	70
MDNB-KNN + MOL-PSOA	82

$$Recall = \frac{TP}{TP + FN} \tag{14}$$

F1 Score: It is calculated as the mean of the precision and recall scores using equation (12). The existing methods, such as IKA, FCM, and LSTM, had the F1 score of 68%, 77%, and 85%, respectively. The proposed method's F1 score of 96% is presented in Fig. 12 and Table 8.

A confusion matrix [52] is a table that displays the various outcomes of a classification task's predictions and actual results. Fig. 13 depicts the confusion matrix. The class label 0 denotes positive, and 1 represents negative for customer satisfaction using the proposed model.

Table 9 and Fig. 14 summarize the outcomes of customer satisfaction, the accuracy of measurement, time consumption, precision, recall, and F1 score compared to the existing studies.

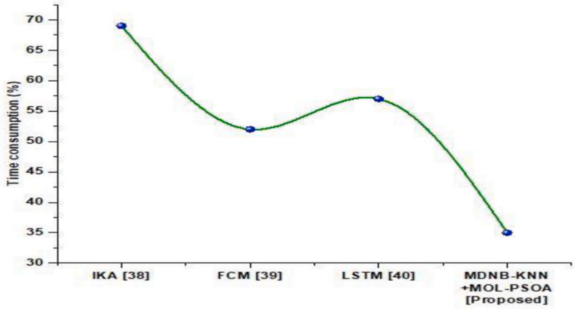

Fig. 9. Time consumption.

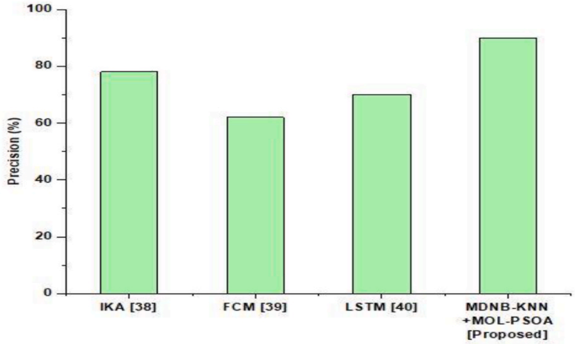

Fig. 10. Comparison of precision.

Table 6
Comparison of precision.

Method	Precision (%)
IKA [38]	78
FCM [39]	62
LSTM [40]	70
MDNB-KNN + MOL-PSOA	90

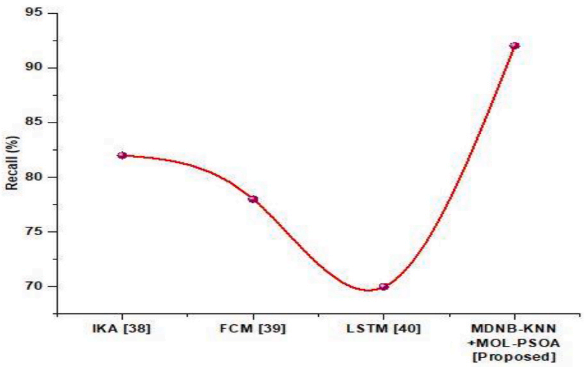

Fig. 11. Comparison of recall.

5. Discussion

The proposed model is compared with the existing IKA, FCM, and LSTM work. Different factors are evaluated, such as customer satisfaction, measurement accuracy, time consumption, precision, and recall. Limitations arise for the Improved K-means algorithm

Table 7
Comparison of recall.

Method	Recall (%)
IKA [38]	82
FCM [39]	78
LSTM [40]	70
MDNB-KNN + MOL-PSOA	92

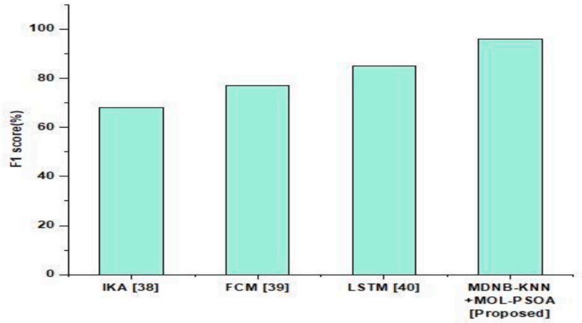

Fig. 12. Comparison of F1 score.

Table 8
Comparison of F1 score.

Method	F1 score (%)
IKA [38]	68
FCM [39]	77
LSTM [40]	85
MDNB-KNN + MOL-PSOA	96

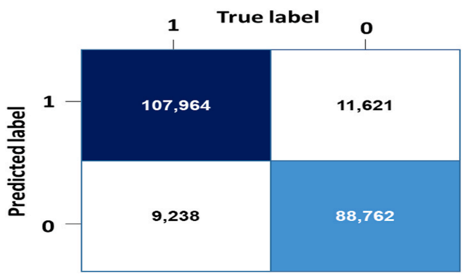

Fig. 13. Representation of the confusion matrix of the proposed model.

Table 9
Overall comparison results.

	IKA [38]	FCM [39]	LSTM [40]	MDNB-KNN + PSOA
Precision (%)	78	62	70	90
Recall (%)	82	78	70	92
Customer satisfaction (%)	68	58	62	75
Time consumption (%)	68	55	62	38
F1 score	68	77	85	96
Accuracy of measurement (%)	78	62	70	82

[38] when clusters are of varying sizes and densities and have non-spherical shapes. When the dataset has noise or outliers, the algorithm can stumble. The solution is conditional on which preliminary clusters are chosen. Without a well-established method, pinpointing cluster centers remains a formidable challenge. The approach cannot be adjusted if no data points are found to be part of a cluster in a given algorithm iteration. The fuzzy c-mean algorithm [39] tends to offer high membership numbers for outlier data. Due to

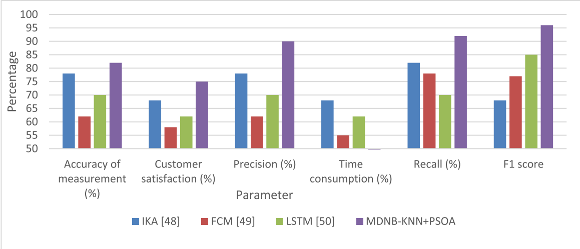

Fig. 14. Comparative analysis with existing studies.

its starting state sensitivity, the algorithm is often stuck in a local optimum. The primary shortcoming of LSTM networks [40] is that they need to assess the proposed model's viability in real-time video streaming over a wireless network. Blockchain technology can improve online shopping. Blockchain provides more efficient money transfers, decentralized control, anti-fraud mechanisms, and lower transaction costs. In this study, the proposed approach overcomes the existing issues. It exceeds in measuring customer satisfaction by 98%, precision of 95%, recall of 95%, and accuracy of 95%, which requires 60% less time than others. Customer satisfaction related to production attributes is calculated using regression analysis and exhibited in Table 3. The confusion matrix of the proposed model is demonstrated in Fig. 13. The comparative analysis with existing studies is illustrated in Fig. 14.

The quality of the data stored in such data collection should be good. The proposed architecture and customer satisfaction process introduce blockchain to sustainability. Governments and financial institutions can be equipped to evaluate logistics companies and make decisions that lead to more sustainability with this data in hand [53].

6. Conclusion

This study employs the blockchain-based framework as a trustworthy platform, and AI techniques are utilized to evaluate consumer satisfaction. The data utilized is transparent and immutable, ensuring its integrity. The proposed MDNB-KNN approach evaluates customer satisfaction, and the MOL-PSOA method enhances the data quality and performance. The factors impacting customer satisfaction are analyzed using a regression model. The proposed method achieves an accuracy of 95%, customer satisfaction of 98%, increased precision of 95%, reduced time of 60%, and recall of 95% compared with existing studies.

The proposed approach does have certain limitations. Only one set of datasets is employed to test and evaluate the proposed method. The different factors preventing businesses from using blockchain tracing systems can include the regulatory environment, business practices, and supply chain connections are not considered. The blockchain platform's technical features and customer service assistance are not considered. Future studies are invited to utilize the blockchain-based secure framework and AI-based customer sentiment analysis techniques in customer sentiment analysis. We intend to use the model on different domains of customer review datasets with different features.

Author contribution statement

Kousik Barik; Sanjay Misra; Ajoy Kumar Ray; Ankur Shukla: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Data availability statement

Data included in article/referenced in article.

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Declaration of competing 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.

References

[1] P. Oghazi, S. Karlsson, D. Hellström, K. Hjort, Online purchase return policy leniency and purchase decision: mediating role of consumer trust, J. Retailing Consum. Serv. 41 (2018) 190–200.
[2] S. Pais, J. Cordeiro, M.L. Jamil, NLP-based platform as a service: a brief review, Journal of Big Data 9 (1) (2022) 1–26.

[3] F. Tang, L. Fu, B. Yao, W. Xu, Aspect-based fine-grained sentiment analysis for online reviews, Inf. Sci. 488 (2019) 190–204.

[4] A.P. Darko, D. Liang, Modeling customer satisfaction through online reviews: a FlowSort group decision model under probabilistic linguistic settings, Expert Syst. Appl. 195 (2022), 116649.

[5] D.T. Cuong, The relationship between product quality, brand image, purchase decision, and repurchase intention, in: Proceedings of International Conference on Emerging Technologies and Intelligent Systems: ICETIS 2021, vol. 1, Springer International Publishing, 2022, pp. 533–545.

[6] J. Bucko, L. Kakalejcjk, M. Ferencova, Online shopping: factors that affect consumer purchasing behaviour, Cogent Business & Management 5 (1) (2018), 1535751.

[7] Z. Shao, R. Zhao, S. Yuan, M. Ding, Y. Wang, Tracing the evolution of AI in the past decade and forecasting the emerging trends, Expert Syst. Appl. (2022), 118221.

[8] R. Tian, L. Kong, X. Min, Y. Qu, Blockchain for ai: a disruptive integration, in: 2022 IEEE 25th International Conference on Computer Supported Cooperative Work in Design (CSCWD), IEEE, 2022, pp. 938–943.

[9] A. Rashid, A. Masood, A.U.R. Khan, Zone of trust: blockchain assisted IoT authentication to support cross-communication between bubbles of trusted IoTs, Cluster Comput. (2022) 1–18.

[10] S.S. Jeris, A.N.U.R. Chowdhury, M.T. Akter, S. Frances, M.H. Roy, Cryptocurrency and Stock Market: Bibliometric and Content Analysis, Heliyon, 2022, e10514.

[11] E.E. Makarius, D. Mukherjee, J.D. Fox, A.K. Fox, Rising with the machines: a sociotechnical framework for bringing artificial intelligence into the organization, J. Bus. Res. 120 (2020) 262–273.

[12] D. Gong, S. Liu, J. Liu, L. Ren, Who benefits from online financing? A sharing economy E-tailing platform perspective, Int. J. Prod. Econ. 222 (2020), 107490.

[13] Z. Latinovic, S.C. Chatterjee, Achieving the promise of AI and ML in delivering economic and relational customer value in B2B, J. Bus. Res. 144 (2022) 966–974.

[14] Á. Aldunate, S. Maldonado, C. Vairetti, G. Armelini, Understanding customer satisfaction via deep learning and natural language processing, Expert Syst. Appl. 209 (2022), 118309.

[15] S. Pal, B. Biswas, R. Gupta, A. Kumar, S. Gupta, Exploring the factors that affect user experience in mobile-health applications: a text-mining and machine-learning approach, J. Bus. Res. 156 (2023), 113484.

[16] C. Zhou, G. Yang, D. Liang, J. Hu, H. Yang, J. Yue, L. Xu, Recognizing black point in wheat kernels and determining its extent using multidimensional feature extraction and a naive Bayes classifier, Comput. Electron. Agric. 180 (2021), 105919.

[17] G. Yildirim, A novel grid-based many-objective swarm intelligence approach for sentiment analysis in social media, Neurocomputing 503 (2022) 173–188.

[18] F. Kitsios, S. Stefanakakis, M. Kamariotou, L. Dermentzoglou, E-service Evaluation: user satisfaction measurement and implications in the health sector, Comput. Stand. Interfac. 63 (2019) 16–26.

[19] Deepnshu Singh, Jyotinder Kaur Chaddah, A study on application of blockchain technology to control counterfeit drugs, enhance data privacy and improve distribution in online pharmacy, Asia Pacific Journal of Health Management 16 (3) (2021) 59–66.

[20] G. Zouari, M. Abdelhedi, Customer satisfaction in the digital era: evidence from Islamic banking, Journal of Innovation and Entrepreneurship 10 (1) (2021) 1–18.

[21] J. Eklof, O. Podkorytova, A. Malova, Linking customer satisfaction with financial performance: an empirical study of Scandinavian banks, Total Qual. Manag. Bus. Excel. 31 (15–16) (2020) 1684–1702.

[22] O. Davras, M. Caber, Analysis of hotel services by their symmetric and asymmetric effects on overall customer satisfaction: a comparison of market segments, Int. J. Hospit. Manag. 81 (2019) 83–93.

[23] Y. Cai, D. Zhu, Fraud detections for online businesses: a perspective from blockchain technology, Financial Innovation 2 (1) (2016) 1–10.

[24] Y.H. Lim, H. Hashim, N. Poo, D.C.C. Poo, H.D. Nguyen, Blockchain technologies in E-commerce: social shopping and loyalty program applications, in: International Conference on Human-Computer Interaction, Springer, Cham, 2019, July, pp. 403–416.

[25] P. Pandey, R. Litoriya, Promoting trustless computation through blockchain technology, Natl. Acad. Sci. Lett. 44 (3) (2021) 225–231.

[26] Honglu Wang, Min Zhang, Hao Ying, Xiande Zhao, The impact of blockchain technology on consumer behavior: a multimethod study, Journal of Management Analytics 8 (sss) (2021) 371–390.

[27] Binni Wang, Pong Wang, Yiliu Tu, Customer satisfaction service match and service quality-based blockchain cloud manufacturing, International Journal of Production Economics240 (2021), 108220.

[28] S.M. Shorman, M. Allaymounq, O. Hamid, Developing the E-commerce model a consumer to consumer using blockchain network technique, Int. J. Manag. Inf. Technol. 11 (2019).

[29] B. Scott, J. Loonam, V. Kumar, Exploring the rise of blockchain technology: towards distributed collaborative organizations, Strat. Change 26 (5) (2017) 423–428.

[30] R.V. George, H.O. Harsh, P. Ray, A.K. Babu, Food quality traceability prototype for restaurants using blockchain and food quality data index, J. Clean. Prod. 240 (2019), 118021.

[31] P.K. Jain, R. Pamula, G. Srivastava, A systematic literature review on machine learning applications for consumer sentiment analysis using online reviews, Computer science review 41 (2021), 100413.

[32] A.P. Darko, D. Liang, Modeling customer satisfaction through online reviews: a FlowSort group decision model under probabilistic linguistic settings, Expert Syst. Appl. 195 (2022), 116649.

[33] S. Oh, H. Ji, J. Kim, E. Park, A.P. del Pobil, Deep learning model based on expectation-confirmation theory to predict customer satisfaction in hospitality service, Inf. Technol. Tourism 24 (1) (2022) 109–126.

[34] P.K. Jain, V. Saravanan, R. Pamula, A hybrid CNN-LSTM: a deep learning approach for consumer sentiment analysis using qualitative user-generated contents, Transactions on Asian and Low-Resource Language Information Processing 20 (5) (2021) 1–15.

[35] E.H. Khasby, G.I. Dzikrillah, Comparison of K-N earest neighbor (K-NN) and naïve Bayes algorithm for sentiment analysis on google play store textual reviews, in: 2021 8th International Conference on Information Technology, Computer and Electrical Engineering (ICITACEE), IEEE, 2021, pp. 180–184.

[36] A. Adamu, M. Abdullahi, S.B. Junaidu, I.H. Hassan, An hybrid particle swarm optimization with crow search algorithm for feature selection, Machine Learning with Applications 6 (2021), 100108.

[37] G.S. Budhi, R. Chiong, S. Dhakal, Multi-level particle swarm optimisation and its parallel version for parameter optimisation of ensemble models: a case of sentiment polarity prediction, Cluster Comput. 23 (2020) 3371–3386.

[38] H. Zare, S. Emadi, Determination of customer satisfaction using improved K-means algorithm, Soft Comput. 24 (22) (2020) 16947–16965.

[39] S. Munusamy, P. Murugesan, Modified dynamic fuzzy c-means clustering algorithm–Application in dynamic customer segmentation, Appl. Intell. 50 (6) (2020) 1922–1942.

[40] N. Eswara, S. Ashique, A. Panchbhai, S. Chakraborty, H.P. Sethuram, K. Kuchi, S.S. Channappayya, Streaming video QoE modeling and prediction: a long short-term memory approach, IEEE Trans. Circ. Syst. Video Technol. 30 (3) (2019) 661–673.

[41] N. Goyal, H. Singh, A design of customer service request desk to improve the efficiency using robotics process automation, in: 2021 6th International Conference on Signal Processing, Computing and Control (ISPCC), IEEE, 2021, pp. 21–24.

[42] N. Goyal, H. Singh, Workflow automation for implementing customer service request desk in hotel industry, in: 2021 6th International Conference on Signal Processing, Computing and Control (ISPCC), IEEE, 2021, pp. 25–28.

[43] M. Dave, V. Rastogi, M. Miglani, P. Saharan, N. Goyal, Smart fog-based video surveillance with privacy preservation based on blockchain, Wireless Pers. Commun. (2022) 1–18.

[44] S. Yi, X. Liu, Machine learning based customer sentiment analysis for recommending shoppers, shops based on customers' review, Complex & Intelligent Systems 6 (3) (2020) 621–634.

[45] B. Yong, J. Shen, X. Liu, F. Li, H. Chen, Q. Zhou, An intelligent blockchain-based system for safe vaccine supply and supervision, Int. J. Inf. Manag. 52 (2020), 102024.

[46] B. Sriman, S. Ganesh Kumar, P. Shamili, Blockchain technology: consensus protocol proof of work and proof of stake, in: Intelligent Computing and Applications: Proceedings of ICICA 2019, Springer Singapore, 2021, pp. 395–406.
[47] S. Joshi, R. Dubey, A. Tiwari, P. Jindal, Sentiment analysis algorithms: classifiers and their comparison, Intelligent Computing and Communication Systems (2021) 201–210.
[48] F.T. Chan, Z.X. Wang, A. Goswami, A. Singhania, M.K. Tiwari, Multi-objective particle swarm optimisation based integrated production inventory routing planning for efficient perishable food logistics operations, Int. J. Prod. Res. 58 (17) (2020) 5155–5174.
[49] H. Ren, H. Lu, Compositional coding capsule network with k-means routing for text classification, Pattern Recogn. Lett. 160 (2022) 1–8.
[50] Y. Pang, M. Shi, L. Zhang, X. Song, W. Sun, PR-FCM: a polynomial regression-based fuzzy C-means algorithm for attribute-associated data, Inf. Sci. 585 (2022) 209–231.
[51] K.L. Tan, C.P. Lee, K.S.M. Anbananthen, K.M. Lim, RoBERTa-LSTM: a hybrid model for sentiment analysis with transformer and recurrent neural network, IEEE Access 10 (2022) 21517–21525.
[52] A. Theissler, M. Thomas, M. Burch, F. Gerschner, ConfusionVis: comparative evaluation and selection of multi-class classifiers based on confusion matrices, Knowl. Base Syst. 247 (2022), 108651.
[53] Y. Xu, X. Li, X. Zeng, J. Cao, W. Jiang, Application of blockchain technology in food safety control: current trends and future prospects, Crit. Rev. Food Sci. Nutr. 62 (10) (2022) 2800–2819.