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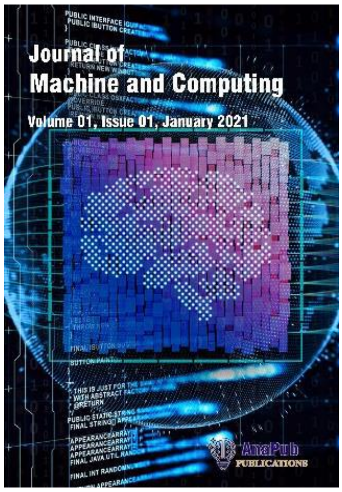

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Customer Behavior Classification Using Deep Stacked Autoencoder with Dragonfly Optimization

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Abstract

Customer Relationship Management (CRM) plays a major role in analyzing customer behavior and the opinions of an organization or enterprise. Data mining methods are widely uutilize to analyze customer data to increase business and revenue. Data mining refers to the extraction of essential and useful information from customer feedback and activities on websites through mining technologies. However, extracting essential information from customer behavior is quite challenging as it requires a detailed analysis of customer desires, requirements, buying patterns, etc., all the information in the e-commerce market is essential for an enterprise as it will support knowing the customer behavior. Deep learning algorithms based on customer behavior classification models are evolved in recent times. However, the performance can be improved if the network parameters are optimized through optimization algorithms. Based on this, a deep stacked autoencoder-based customer behavior classification model is presented in this research work along with the dragonfly optimization algorithm. The network parameters of the deep-stacked autoencoder are optimized using the dragonfly optimization algorithm to attain enhanced classification accuracy. Benchmark customer behavior dataset is used for experimentation and analyzed the performance in terms of recall, precision, F1-score, and accuracy. The proposed optimized deep learning model attains better performance compared to deep learning approaches like Long-Short Term Memory (LSTM), Convolutional Neural network (CNN), and Autoencoder models.

Keywords: Customer relationship management, customer behavior analysis, classification, deep learning, optimization, dragonfly optimization.

1. INTRODUCTION

Predicting human behavior is quite complex unless any communication or contact is made. The general way of human communication is face-to-face, phone calls, emails, or text messages. Human behavior changes frequently and it is difficult for anyone to stay in the same mood all the time. To balance the work tension or for pleasure, generally, shopping is preferred by people in recent times. Shopping gives pleasure and remedies to people who need mood changes. Due to the fast increase of e-commerce, online shopping is preferred in recent times. To attract customers, e-commerce websites organize different mega-sale offers and provide huge discounts. Even if the customer does not require a product the e-commerce advertisements make them buy by triggering the user. Rather than instantly buying customers, the person who spends hours and hours on e-commerce websites is mainly selected for customer behavior analysis. Customers with such shopping behaviors will take the shopping industry to the next level high profitable place. Thus, customer behavior analysis is widely adopted in all major and minor e-commerce sites.

Organizations spend a lot of money and implement different strategies to sell products to customers. Advertisers test the customer's shopping pattern and provide novel choices to sell the products. The marketing strategy in the e-commerce industry includes multiple terms like product cost, distribution, sale, and customer attraction. Identifying unique feature of products and presenting it to customers is considered one of the important marketing strategies. The less-sold goods combined with high-selling goods to earn the minimum profit is one of the marketing strategies followed in recent times. Based on the customer search behavior the additional offers are displayed on the websites to make the customer buy the product [1]. However, in the analysis of customer behavior, the factors that influence shopping habits are categorized based on financial condition, desire to buy, and customer needs. Mining useful data based on these factors can discover the relationship between the customer and shopping sites.

Datamining in customer behavior analysis extracts the essential data from customer search and buying patterns. The extracted patterns are analyzed periodically and they can be used to increase sales. All the information provided by the customer is stored and processed in data warehouses for future analysis [2]. Using data mining techniques, the stored data is analyzed to identify the possible points to increase sales. Earlier machine learning techniques like logistic regression, random forests and support vector machines etc., are widely employed in customer behavior analysis [3]. These machine learning algorithms perform classification based on feature vectors with fixed lengths. While classifying customer behavior, the data has to be converted into a fixed set of features. Usually, the domain experts handcraft the features. However, finding reliable features manually for the classification process is quite complex and it requires highly time-intensive human efforts. Moreover, it is difficult to explain the reason for classification output in terms of customer behavior. To get the better of this, deep learning approaches are adopted in data mining applications. conventional deep learning networks provide better performances than machine learning approaches. as a further enhancement in the classification accuracy, optimization models are incorporated with deep learning approaches. The latter objective of this investigation work is to improve the classification accuracy in the customer behavior analysis process. to attain this objective, an optimized deep learning model is given in this research work. The contributions made in this research work are presented as follows.

- An optimized deep learning model for customer behavior analysis is presented using a deep stacked autoencoder and dragonfly optimization algorithm.
- The network parameter like the learning rate of the deep stacked autoencoder is optimized using the dragonfly optimization algorithm.
- Simulation analysis of the present technique is performed using benchmark customer behavior data set and compared with previous techniques to demonstrate the superiority of the present model.

The remaining arrangements are presented in the following order: Section 2 presents a detailed literature analysis of existing customer behavior analysis models. Section 3 presents the present optimized deep learning method for customer behavior classification. Section 4 presents the simulation analysis and discussion. The conclusion is presented in the last section.

2. RELATED WORKS

An elaborated literature review of previous research work in customer behavior analysis is presented in this section to discuss the methodology, feature merits, and demerits. Customer behavior analysis is not only used for e-commerce industries, it is widely used in other applications like energy consumption analysis in smart grids, logistic services, etc. The load forecasting based on customer behavior is predicted using sparse continuous conditional random fields in research work [4]. Initially, hierarchical clustering is performed to group the customer behaviors and by using sparse continuous conditional random fields the clusters are fine-tuned for load forecasting. The presented customer behavior analysis strategy identifies the energy consumption and improves the prediction accuracy. The fuzzy logic-based customer prediction method explained in [5] analyzes the consequences of real-time pricing in power grids. The analysis pattern includes real-time pricing methods and consumption factors to predict the demands. Unlike other prediction models, the presented approach analyses customer behavior for real-time pricing in terms of flexibility, awareness, and motivation to define future demands.

A log-based session profiling and the online behavior prediction model are presented in [6] to enhance the marketing strategies in e-commerce sites. The presented approach handles the historical information and clusters the clickstreams to predict customer requirements. neural network architecture is used for information classification so that better recommendations can be provided to customers online. A temporal annotated recurring sequence arrangement for customer behavior prediction is presented in [7] to understand customer requirements. The presented annotated prediction model adopts the supply chains and provides suggestions to the customers. Due to this, the shopping experience of customers has increased as well as speedups the shopping sessions.

A content-based sequential opinion influence method for customer behavior analysis is presented in [8] to track user opinions. The importance of social media in opinion exchange is considered in this behavior analysis model which includes historical communication for the analysis. Simulation analysis on three different Twitter datasets validates that the presented approach performs better than existing approaches. Customer behavior analysis is generally performed based on user feedback and search preferences in shopping. At the same time, it is essential to look into social media to analyze customer behavior as people share their opinion on social media in the digital era. A multi-document key phrase extraction model presented in [9] considers social media posts to predict customer requirements in the future. The presented approach initially performs document filtering. Followed by filtering, key phrases are ranked to define the promotion list to customers. the ground truths are extracted automatically from future specifications and based on that new product proposals can be made in a simple manner.

The importance of social influence, firm-initiated contacts, and informational inquiries made by customers are studied in detail in research work [10]. The investigation model includes the non-transactional behaviors, lifetime value, and profitability in the analysis to present the long-term and short-term benefits to customers to enhance sales in e-commerce. Similar social media opinions were analyzed to predict the customer behavior presented in [11] to improve the food quality in restaurants. The learning algorithm used in the presented approach categorizes the customer preferences using latent Dirichlet allocation and a self-organizing map clustering process. Further regression trees and classification techniques are used to predict customer preferences and classify satisfaction levels. Based on the results, the quality of service can be enhanced which directly improves sales.

An ensemble learning model is presented in [12] for customer booking prediction in transport services. The customer booking behavior is predicted using an ensemble learning model to meet the transport demand in suburban areas. Simulation analysis confirms that the presented approach attains better performance than existing logistic regression, random forest and support vector machine-based prediction methods. A machine learning-based customer behavior model is presented in [13] to predict customer purchases. The presented approach considers behavior data for the feature clustering in the initial phase and an imbalance prediction model is presented to handle the data imbalances. Finally, cost-sensitive ensemble learning is used to enhance the maximized marginal in the analysis.

Decision tree and Support vector machine algorithm, and multi-layer perceptron-based customer behavior investigation technique is presented in [14] to classify customer behavior patterns. The presented approach initially applies recency, frequency, monetary, and data modeling systems to detect customer behavior patterns. Further, it is classified using machine learning approaches to attain maximum classification accuracy compared to existing methods. The customer behavior analysis model presented in [15] incorporates familiar machine learning approaches like Naive Bayes, decision tree and random forest to classify customer behavior in online shopping experiences. The classification model considers the product quality, product availability in the local market, return policy, and delivery time in the classification process. Simulation analysis of presented approaches concludes that the Naive Bayes approach attains better performance than other machine learning approaches.

A fully connected long short-term network-based customer behavior analysis model is presented in [16] to predict the purchase interest of customers. The presented model analyzes the interactions between promotion channels and customers using a fully connected long-short-term network. In the analysis, customer behavior in browsing, sequence correlations, demographics, and purchase history are included to enhance the prediction performance. The deep learning-based customer behavior prediction model presented in [17] predicts online customer purchase behavior on large multidimensional data samples. Customer characteristics and platform engagement are considered in the prediction model and the performances are compared with machine learning models like the decision tree, random forest, support vector machine, and artificial neural networks. Recently the load forecasting model for power systems is analyzed using a convolution neural network with squeeze and excitation modules and micrometeorological data [18]. the presented approach analyzes the active and casual consumption behaviors using CNN. Initially, a sparse autoencoder is used to extract the features and classified using the CNN model. results validate that the presented approach attains better feasibility and improved accuracy than existing load forecasting techniques. from the analysis, it can be observed that the features of deep learning algorithms are less explored in customer behavior prediction and classification approaches. Though machine learning models like random forest, support vector machine and decision tree models are widely used their performances can be overcome through deep learning approaches. similarly, the importance of optimization algorithms is not incorporated into the customer behavior analysis. To as of now, this is the novel work of this time that incorporates deep learning and optimization algorithms for customer behavior classification. The following section provides the mathematical model proposed optimized deep learning model for customer behavior classification in detail.

3. PROPOSED WORK

The proposed customer behavior classification model using an optimized deep learning model incorporates a deep stacked autoencoder and dragonfly optimization algorithm. Compared to other deep learning approaches the deep stacked autoencoder has numerous pieces of information in an encoded form which empirically supports the systems to converge for the better optimal solution. Similarly, the reliability of the deep stacked autoencoder is much better than other deep learning techniques. Due to these reasons, a deep stacked autoencoder is selected for customer behavior classification in the present work. The optimal performance of the present autoencoder is further optimized using a nature-inspired dragonfly optimization algorithm which optimizes the learning rate to attain better classification accuracy compared to existing machine learning and deep learning methods.

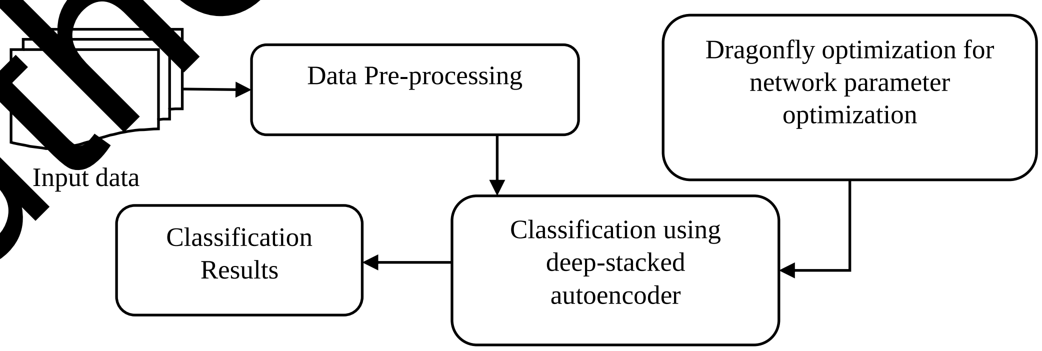


Fig 1 Overview of proposed optimized deep learning-based customer behavior classification

The process overview of the present customer behavior classification model is represented in figure 1. The process starts with pre-processing the customer data which removes the unnecessary features, and multiple and wrong entries. Further, the features are selected and classified using the stacked autoencoder. Dragonfly optimization algorithms optimize the network parameters to attain better performances in the customer behavior classification process. The proposed stacked autoencoder model is presented as a simple illustration in figure 2. The deep-stacked autoencoder is obtained by training multiple autoencoder networks. The hidden layers in the autoencoder networks are stacked together to obtain the stacked network structure. Consider if the stacked autoencoder has l layers, then in the pretraining of the autoencoder network, using the training set input, the first hidden layer will be obtained. Using the hidden layer obtained in the first layer is used as input to the second layer autoencoder network. In the second layer, a hidden layer will be obtained and it is provided as input to the third layer. Similarly, the process gets repeated till the last layer. In the last, all the hidden layers are stacked to obtain the stacked autoencoder network.

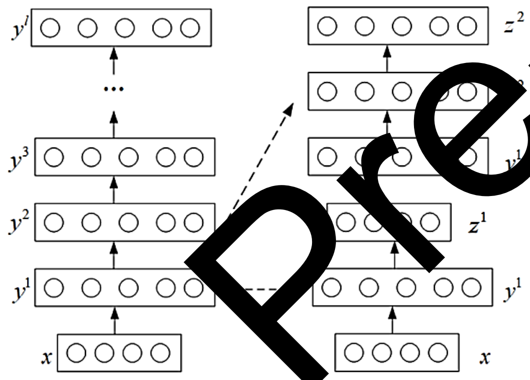


Fig 2 Stacked autoencoder by layer-wise training to obtain hidden layers

The proposed deep-stacked autoencoder network is an unsupervised deep-learning architecture that includes multiple autoencoders. A single autoencoder structure has an input layer, hidden layer, and output layer. The autoencoder has a feature that the output z is always equal to input x and the network can be reconstructed from y. so the input network can also be expressed using y. Mathematically the encode and decode function for an autoencoder network is formulated as

$$y(x) = f(w_1 x + b_1) \qquad (1)$$

where the encoding weight matrix is represented as w_1, the encoding bias vector is represented as b_1, and the function that encodes x as y is represented as $f(.)$ which is a sigmoid function represented as $\frac{1}{1+e^{-x}}$, Similarly, the decode function of the network is mathematically formulated as

$$z(x) = g(w_2 y(x) + b_2) \qquad (2)$$

where the decoding weight matrix is represented as w_2, the decoding bias vector is represented as b_2, and the function that encodes x as y is represented as $g(.)$ which is the sigmoid function represented as $\frac{1}{1+e^{-x}}$. For the given set of training data $\{x^{(1)}, x^{(2)}, x^{(3)}, \dots\}$, based on equation (1) the sample $x^{(i)}$ obtains hidden layer outputs as

$y(x^{(i)})$. further based on equation (2) the hidden layer output $y(x^{(i)})$ has been decoded into $z(x^{(i)})$. The deep-stacked autoencoder in the proposed customer behavior classification process extracts feature from the collected data and performs classification. A simple illustration of a single autoencoder network is depicted in figure 3 for a better understanding

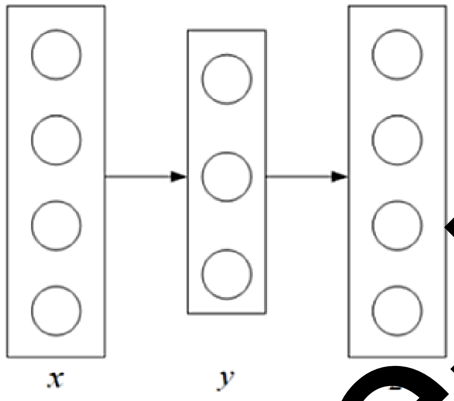


Fig 3 Autoencoder

Further, the training process of the stacked autoencoder is splitted into two phases. In the initial phase, greedy layer-wise unsupervised learning is performed to pretrain the hidden layer. in the second phase, a backpropagation algorithm is utilized to fine-tune the entire network. It is essential to minimize the reconstruction error for a single-layer autoencoder through the network parameters like w_1, w_2, b_1, and b_2. In the training process, if any one of the parameters is included then the remaining parameters will be kept as same without any changes. Once the pretraining is performed for hidden layers, the backpropagation algorithm is incorporated for fine-tuning the entire network. all the parameters are expressed as θ and mathematically the network parameters are formulated as

$$\theta^* = argmin_\theta L(x, z) \quad (3)$$

$$\theta^* = argmin_\theta \frac{1}{2}\sum_{i=1}^{N}\left\|x^{(i)} - z(x^{(i)})\right\|^2 \quad (4)$$

The parameters after applying back propagation are formulated as

$$\theta = \theta - \alpha \frac{\partial L(x,z)}{\partial \theta} \quad (5)$$

Where the number of the training set is represented as N and the gradient descent step is represented as α. The features are extracted in the initial stage and classified in the last stage to classify the customer behavior. The features $\{y^{(1)}, y^{(2)}, y^{(3)}, \ldots\}$ which are obtained through training were fed into a stacked autoencoder network as $\{x^{(1)}, x^{(2)}, x^{(3)}, \ldots\}$. Finally, the features are classified using SoftMax function which is mathematically expressed as

$$\sigma\left(x^{(i)}\right) = \frac{e^{x^{(i)}}}{\sum_k e^{x^{(k)}}} \tag{6}$$

Further, the network parameters are optimized using the dragonfly optimization algorithm to improve the classification accuracy in the customer behavior analysis process. compared to other optimization algorithms, dragonfly requires minimum parameters and provides a better solution to real-time problems. The optimal solution can be obtained with minimum iterations thus it reduces the computation time and complexity compared to other nature-inspired optimization algorithms. In the proposed work, the optimization model is incorporated to decrease the mean square error and increase the classification accuracy by optimizing the learning rate of the deep-stacked autoencoder network.

Dragonfly algorithm is formulated based on the swarming behavior of dragonflies for searching food and escaping from enemies. The swarming characteristics of dragonflies are generally categorized into static and dynamic which used for better exploration and exploitation. For the exploration phase, static swarming characteristics are considered and for exploitation dynamic swarming characteristics are considered. Static warming has the major features like local movement and adapts for abrupt changes in flying path. Similarly dynamic swarming has the ability to cover wide area and able to migrate in one direction for long distances. The major characteristics of dragonfly algorithm is termed as separation, alignment, cohesion. In addition to the fly characteristic for food and enemy is considered for mathematical model. The separation behavior defines the static collision avoidance of individuals whereas alignment behavior defines the velocity matching of individuals with others. The cohesion behavior the tendency of individual to move towards the center of mass. The food and enemy define the motion of flies towards the food and away from the enemy.

Survival is the major objective of swarm so attraction towards the food and distracted from enemies should be performed. The separation behavior of dragonflies are mathematically formulated as

$$s_i = \sum_{j=1}^{m} l - l_j \tag{7}$$

where current individual position is denoted as l and the position of neighbor is represented as l_j. The total value of neighbors is described as m. Similarly, the alignment behavior is mathematically formulated as

$$A_i = \frac{\sum_{j=1}^{m} v_j}{m} \tag{8}$$

where the velocity of neighbor is described as v_j. The cohesion behavior of dragonflies are formulated as

$$C_i = \frac{\sum_{j=1}^{m} l_j}{m} - l \tag{9}$$

where the position of individual is represented as l and position of neighbor is represented as l_j. The behaviors of attraction towards the food and distraction from enemy is mathematically formulated as

$$f_i = l^f - l \tag{10}$$

$$e_i = l^e + l \tag{11}$$

where the position of individual is represented as l and position of food source is represented as l^f. Similarly, the position of enemy is represented as l^e. Combining these five behaviors the characteristics of dragonflies can be obtained. In order to formulate the real characteristics in simulation environment two vectors are required for defining the step and position. The vector function for step is considered as Δl and l is considered for position. These step vectors define the direction of dragonfly's movement. Mathematical formulation for combined characteristics is given as

$$\Delta l_{t+1} = (b s_i + d A_i + g C_i + h f_i + \mathcal{K} e_i) + w\Delta l_t \quad (12)$$

where s_i represents the i^{th} individual separation, alignment, cohesion, food and enemy behaviors. Similarly, the b, d, g, h, $\mathcal{K}$ and w represents the weight factor for separation, alignment, cohesion, food, enemy and inertia weight. t represents the iteration counter. Based on the step vector, the position vector is calculated as follows.

$$l_{t+1} = l_t + \Delta l_{t+1} \quad (13)$$

where t represents the iteration counter. Using these weight factors of dragonflies different exploitative and explorative behaviors can be accomplish in the optimization steps. In order to obtain better exploration characteristics dragonflies with high alignment and low cohesion is generally preferred. This can be obtained from the static swarming behavior. Similarly for better exploitation characteristics dragonflies with low alignment and high cohesion are preferred which can be obtained from dynamic swarming behavior. Based on the number of iterations, the neighbor radius is increased to attain better transition between exploration and exploitation. In other way, the swarming behavior weight factors can be fine-tuned to obtain better exploration and exploitation in the optimization process. compared to other swarm optimization algorithms, the convergence and divergence of dragonfly algorithm because of its best and worst solution selection process. Figure 5 represents the process flow of the present optimized deep learning method for customer behavior analysis.

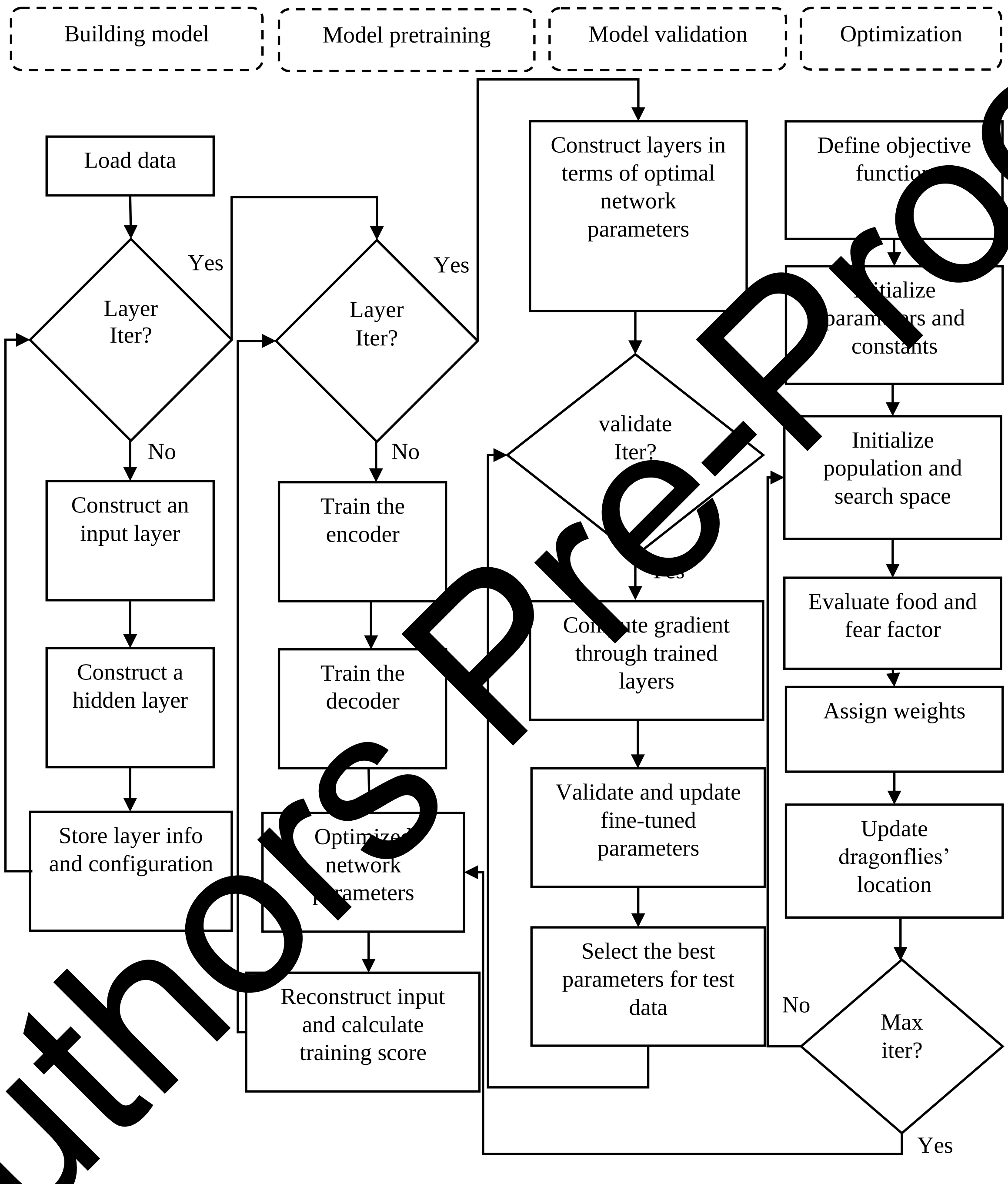


Fig 5 Process flow of proposed optimized deep learning model

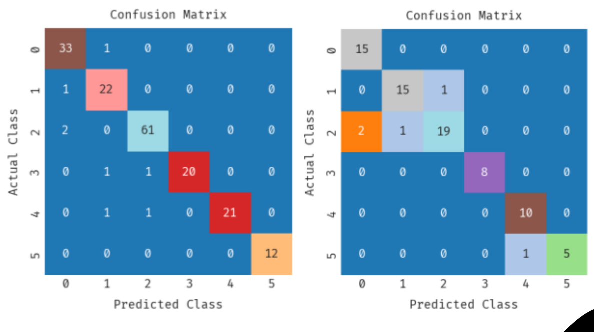
4. RESULT AND DISCUSSION

The execution analysis of the present optimized deep learning model for customer behavior classification is performed in the python platform. The essential packages required to simulate the proposed model in python are tensor flow-GPU 2.2.0, pandas, pretty table, pyqt5, matplotlib, seaborn, scikit-learn, and NumPy. The Benchmark dataset of customer behavior in e-commerce is obtained from Kaggle [19] and experimented with the proposed model and a few other deep learning approaches like long-short term memory (LSTM), convolutional neural network (CNN), and conventional autoencoder models. The dataset is basically defining the customer behavior on e-commerce sites where a survey is performed with 254 participants. The questionaries include the basic information about the personal details which is provided as optional for participants. The remaining questions are marked as compulsory and specific reasons are provided as multiple choices to select. The data collected for the duration of 8 days and the dataset is publicly available in Kaggle website. The simulation parameters used in the proposed analysis is depicted in table 1.

Table 1 simulation parameters

S.No	Parameters	Value
1.	Encoder and decoder dimensions	128×128
2.	Number of layers in the autoencoder	2
3.	Learning rate	0.01
4.	Number of iterations	128
5.	Number of dragonflies	25
6.	Number of wavelengths	100
7.	Tuning type	Adaptive
8.	Number of epochs	100

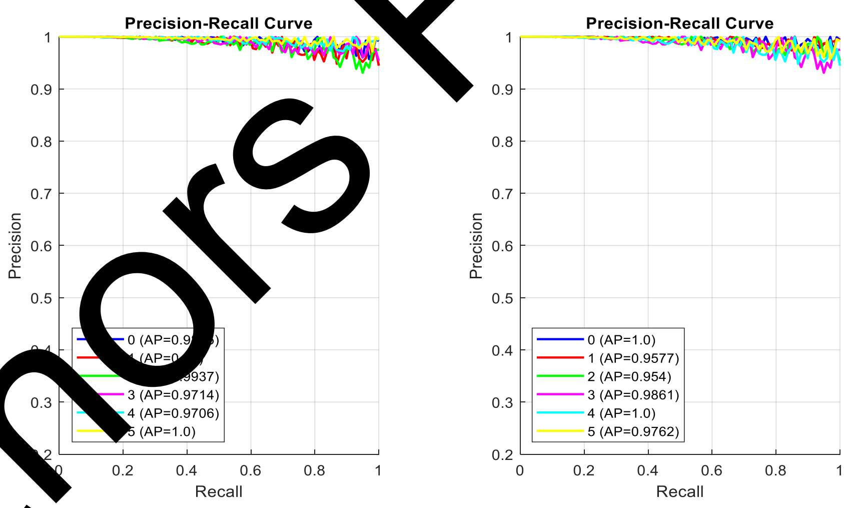
The proposed customer behavior classification model includes initial-level data preprocessing, feature extraction, and classification. Meanwhile, the optimization model is incorporated to optimize the learning rate of the classification network. The benchmark dataset used for simulation analysis has columns like time stamps and city details which are not included in the analysis. so, the unwanted columns in the dataset have been removed. Next to the removal of unwanted columns, mixed data columns are processed. For example, in the age column if one of the customers entered in numbers and another customer entered in wordings then in the preprocessing all the data in that age column are converted into numerical values. Next to the mixed data column, spelling mistakes while entering product details are processed. Multiple subproducts are converted into a single product in the last step of data preprocessing so that all the data can be converted into standard numerical values which can be further processed using a deep learning technique. The deep-stacked autoencoder selects the features and classifies the customer behavior. The dragonfly optimization model optimizes the learning rate of a deep stacked autoencoder and reduces the mean square error thus an enhanced performance is attained in the proposed model. The confusion matrix obtained for the training and test process is depicted in figure 6 (a) and (b) respectively. Based on the confusion matrix values, the performance metrics like recall, precision, f1-score, and accuracy are evaluated for the proposed optimized deep stack autoencoder model.



(a) (b)

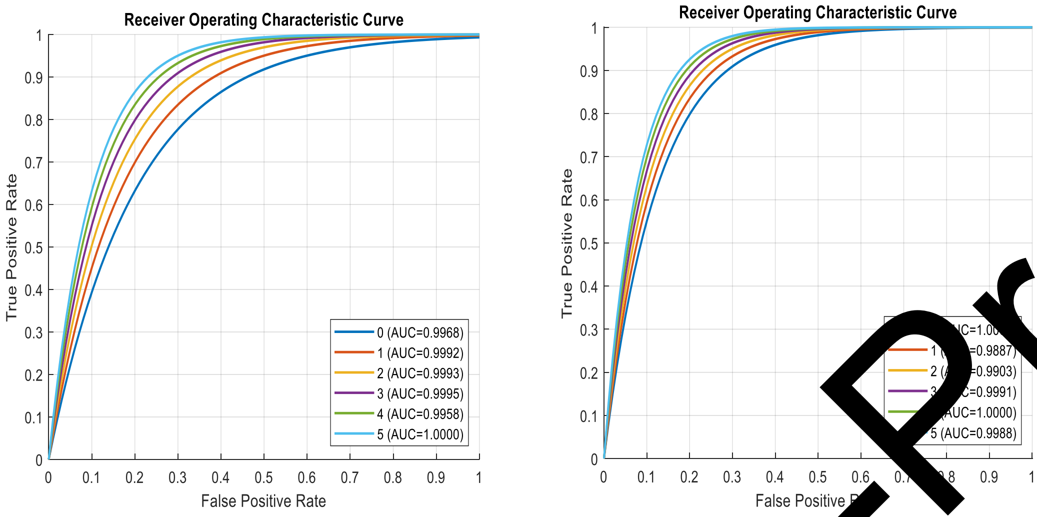
Fig 6 Confusion matrix (a) Train (b) Test

Figure 7 (a) and (b) depict the relation between precision and recall for the training and testing process for different threshold values. The precision-recall curve demonstrates the better tradeoff between recall and precision. High precision show that the outcomes have low false positive values and high recall show that the outcomes have low false negative values. Where the high precision and recall indicate that the classification performance is more accurate and provides the majority of the positive results. This is can be confirmed by figures 7(a) and (b). The proposed model has high precision values and provides correct results. Similarly, the receiver operating characteristic curve (ROC) curve of the present technique for training and testing is depicted in figure 8(a) and (b) respectively. It can be determined that the present technique provides maximum true positive values in both the training and testing process which indicates better performance in the behavior classification process.



(a) (b)

Fig 7 Precision-Recall curve (a) Train (b) Test



(a) (b)

Fig 8 ROC analysis (a) Train (b) Test

Figure 9 represents the training and validation loss attained by the proposed method for the different epochs. It can be determined that initially the loss is maximum and it reduces gradually due to fine-tuning of the network and optimization of network parameters. The epochs are observed till 100 as after this value it continues the same for further values. The validation curve closely follows the training curve indicates that the proposed model attains better training and testing performance.

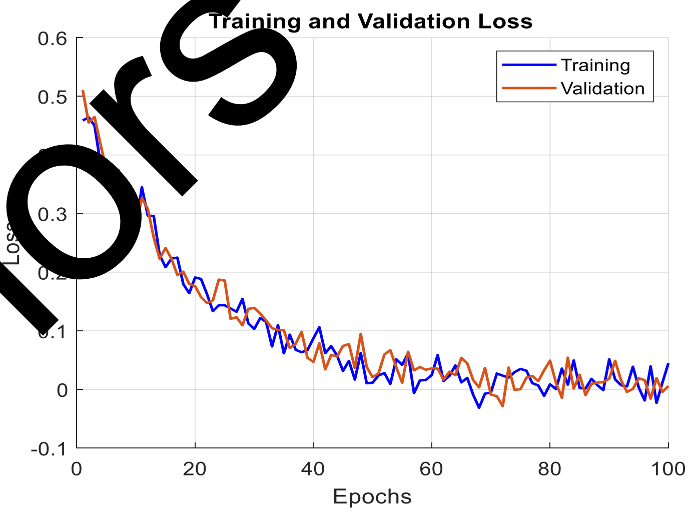


Fig 9 Analysis of training and validation Loss

Further to validate the execution of the present model, a few other deep learning techniques like LSTM, CNN, and autoencoder models are employed for customer behavior analysis. all the models are implemented separately and the results are comparatively presented in terms of recall, precision, f1-score, and accuracy to compared to other deep validate the improved representation of the present technique. Figure 10 show the comparative investigation of the present technique and other deep learning methods for recall, precision and f1-score. It can be determined from the results that the present technique attains best performance for all the metrics learning techniques. The incorporated optimization model enhances the precision and recall performance of the present technique which directly improves the f1-score over other deep learning techniques.

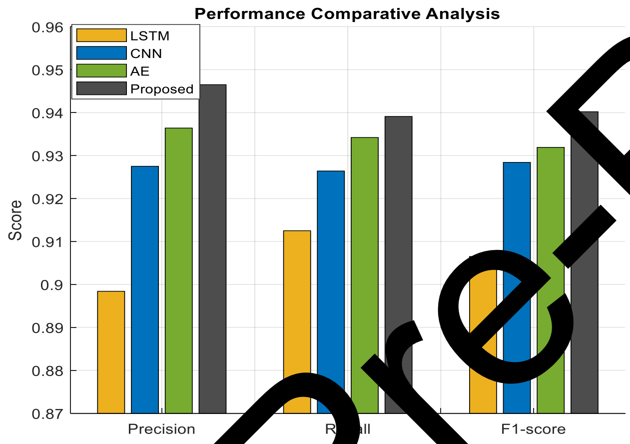


Fig 10 performance comparative analysis

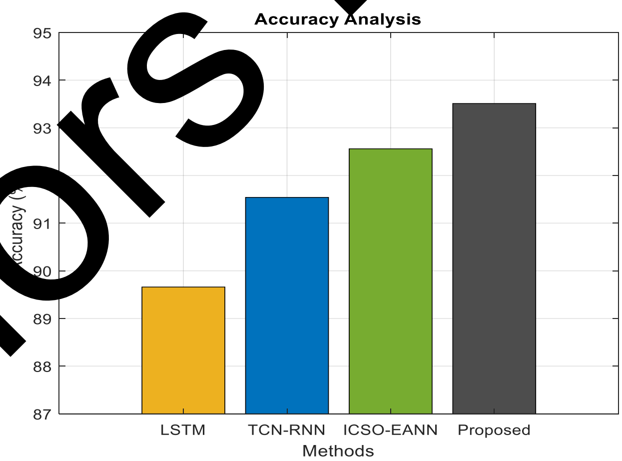


Fig 11 Accuracy analysis

Figure 11 Shows the accuracy analysis of the planned technique and other deep learning techniques results show the maximum accuracy of the present model over other techniques which is achieved due to optimized network parameters. The accuracy earned by the present method is 94% whereas LSTM lesser than the proposed optimized deep stacked encoder model.

ttains 89%, CNN attains 92% and traditional autoencoder attains 92.5% which is maximum

Table 2 performance comparative analysis

Methods	Precision	Recall	F1-score	Accuracy
Long-Short Term Memory (LSTM)	0.8984	0.9125	0.9065	0.[illegible]966
Convolutional Neural Network (CNN)	0.9275	0.9264	0.9284	0.9154
Autoencoder	0.9364	0.9342	0.[illegible]319	0.[illegible]256
Proposed Optimized deep stacked autoencoder (ODSAE)	0.9465	0.9391	0.940[illegible]	0.9351

The overall performance of comparison analysis of the present technique and other deep learning methods are presented in table 2 for different performance metrics. It can be observed that the present method attains better performance than other models and attains maximum classification accuracy in the customer behavior classification process.

5. CONCLUSION

An optimized deep-stacked autoencoder model for customer behavior classification method is presented in this work. To explore the Feature benefits of deep learning methods in customer relationship and behavior analysis a deep stacked autoencoder is incorporated in this research work. To enhance the classification performance of the proposed methods, a nature-inspired dragonfly optimization model is incorporated to fine-tune the network model parameters. The optimized network parameters increase the classification accuracy and reduce the computation complexity. Simulation results of the proposed model and other deep learning techniques are comparatively analyzed and validated the superior performance of the proposed model. the maximum classification accuracy earned by the present method is 94% which is much higher than the other deep learning techniques. in the future, this research work can be improved by adopting hybrid deep learning techniques for better prediction and classification performances.

REFERENCES

1. Thomas Reutterer, Michael Platzer, Nadine Schröder (2021), “Leveraging purchase regularity for predicting customer behavior the easy way”, International Journal of Research in Marketing, vol.38, no.[illegible] pp.194-[illegible]5.
2. Yuwei Yan, Chuanchao Huang, Bin Hu (2020), “Data mining of customer choice behavior in internet of things within relationship network”, International Journal of Information Management, vol.50, pp.566-574.
3. Andrés Martínez, Claudia Schmuck, Markus Haltmeier (2020), “A machine learning framework for customer purchase prediction in the non-contractual setting”, European Journal of Operational Research, vol.281, no.3, pp.588-[illegible]6.
4. Xishun Wang, Minjie Zhang, Fenghui Ren (2019), “Learning Customer Behaviors for Effective Load Forecasting”, IEEE Transactions on Knowledge and Data Engineering, vol. 31, no. 5, pp. 938-951.
5. Amjed Al-Mousa, Ayman Faza (2019), “A fuzzy-based customer response prediction model for a day-ahead dynamic pricing system”, Sustainable Cities and Society, vol.44, pp.265-274.
6. Javier Fabra, Pedro Álvarez, Joaquín Ezpeleta (2020), “Log-Based Session Profiling and Online Behavioral Prediction in E–Commerce Websites”, IEEE Access, vol. 8, pp. 171834-171850.

7. Riccardo Guidotti, Giulio Rossetti, Luca Pappalardo, Fosca Giannotti, Dino Pedreschi (2019), “Personalized Market Basket Prediction with Temporal Annotated Recurring Sequences”, IEEE Transactions on Knowledge and Data Engineering, vol. 31, no. 11, pp. 2151-2163.
8. Chengyao Chen, Zhitao Wang, Wenjie Li (2020), “Tracking Dynamics of Opinion Behaviors with a Content-Based Sequential Opinion Influence Model”, IEEE Transactions on Affective Computing, vol. 11, no. 4, pp. 627-639.
9. David Kilroy, Graham Healy, Simon Caton (2022), “Using Machine Learning to Improve Lead Times in the Identification of Emerging Customer Needs”, IEEE Access, vol. 10, pp. 37774-37795.
10. Jesús Cambra-Fierro, Lily (Xuehui) Gao, Iguácel Melero-Polo (2021), “The power of social influence and customer–firm interactions in predicting non-transactional behaviors, immediate customer profitability, and long-term customer value”, Journal of Business Research, vol.125, pp.103-119.
11. Mehrbakhsh Nilashi, Hossein Ahmadi, Ala Abdulsalam Alarood (2021), “Big social data and customer decision making in vegetarian restaurants: A combined machine learning method”, Journal of Retailing and Consumer Services, vol.62, pp.1-18.
12. Le-Minh Kieu, Yuming Ou, Chen Cai (2020), “A class-specific soft voting framework for customer booking prediction in on-demand transport”, Transportation Research Part C: Emerging Technologies, vol.114, pp.377-390.
13. Shui-xia Chen, Xiao-kang Wang, Hong-yu Zhang, Jian-qiang Wang (2021), “Customer purchase prediction from the perspective of imbalanced data: A machine learning framework based on factorization machine”, Expert Systems with Applications, vol.173, pp.1-12.
14. Mussadiq Abdul Rahim, Muhammad Mushafiq, Zulfiqar Ali Arain (2021), “RFM-based repurchase behavior for customer classification and segmentation”, Journal of Retailing and Consumer Services, vol.61, pp.1-9.
15. Nazmun Nessa Moon, Iftakhar Mohammad Talha, Imran Salehin (2021), “An advanced intelligence system in customer online shopping behavior and satisfaction analysis”, Current Research in Behavioral Sciences, vol.2, pp.1-7.
16. Chen Ling, Tao Zhang, Yuan Chen (2019), “Customer Purchase Intent Prediction Under Online Multi-Channel Promotion: A Feature-Combined Deep Learning Framework”, IEEE Access, vol. 7, pp. 112963-112976.
17. Neha Chaudhuri, Gaurav Gupta, Indranil Bose (2021), “On the platform but will they buy? Predicting customers' purchase behavior using deep learning”, Decision Support Systems, vol.149, pp.1-10.
18. Lilin Cheng, Haixiang Zang, Yan Xu, Zhinong Wei, Guoqiang Sun (2021), “Probabilistic Residential Load Forecasting Based on Micrometeorological Data and Customer Consumption Pattern”, IEEE Transactions on Power Systems, vol. 36, no. 4, pp. 3762-3775.
19. https://www.kaggle.com/datasets/mittaltandon/customer-behaviour/data