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Optimized Isogeometric neural networks for Customer Behavior Path Analysis and Online Advertising Strategy

***Abstract:* -** In the dynamic landscape of online advertising, understanding and predicting customer behavior is essential for optimizing advertising strategies. Traditional methods often face challenges in effectively capturing the intricacies of customer journeys and subsequently tailoring advertising strategies. To address these challenges, this paper introduces a novel approach leveraging Optimized Isogeometric Neural Networks for Customer Behavior Path Analysis and Online Advertising Strategy (ISNN-CBPA-OAS). Initially, the data are obtained from Online Shoppers Purchasing Intention Dataset. Then, the data are provided to pre-processing phase. During the pre-processing phase, data cleaning is conducted using Learnable Edge Collaborative Filtering (LECF). Then, the pre-processing output is fed to feature extraction phase. The features are extracted using Dual-Tree Complex Discrete Wavelet Transform (DTCDWT) to extract demographic features, such as gender, age, postal code, education level, occupation. The selected features are given to Isogeometric neural networks (ISNN) for effectively identifying customer behavior such as Browsing, Shopping, Cart, and Marketing. Generally, ISNN doesn't show some optimization adaption techniques to determine optimum parameter to offer accurate prediction. Reptile search optimization algorithm (RSOA) is proposed to enhance ISNN classifies the customer behavior accurately. The proposed technique is executed and efficacy of ISNN-CBPA-OAS technique is assessed with support of numerous performances like accuracy, recall, precision, F1-scorce and computational time is analyzed. Then, performance of ISNN-CBPA-OAS technique is analyzed with existing techniques likethe impact of digital marketing strategies on customer's buying behavior in online shopping utilizing the rough set theory (PCC-CBPA-OAS), A Comparison along Interpretation of Machine Learning Algorithm for the Prediction of Online Purchase Conversion(CNN-CBPA-OAS), Predicting customers' purchase behavior using deep learning(ANN-CBPA-OAS)respectively.

Keywords: Dual-Tree Complex Discrete Wavelet Transform, Learnable Edge Collaborative Filtering, Reptile search optimization algorithm and Isogeometric neural networks.

I. INTRODUCTION

Modern Internet technology is changing the way that entertainment products like concerts, sports, and movies are marketed in the ticketing service sector. Authorised online ticket distributors are dominating the industry [1], giving consumers more options for ticketing services. Examples of these companies are Gewara, Damai, Ticketmaster, and StubbHub. In order to promote sales, the ticket service business also uses online platforms [2]. Customers may instantly access these promotional materials and use pricing and service comparisons across many internet platforms to help them make judgments about what to buy [3]. Marketers are worried about the overall purchase conversion rate in promotions because it is a significant factor in determining a company's revenue [4]. Predicting customer behaviour is seen as critically significant both conceptually and practically, as it becomes a necessity for marketing decision-making [5]. Online merchants can improve the efficacy of their retargeting advertisements, for example, by accurately identifying visitors who are most likely to make a purchase. While most research supports a macro-level increase in purchase conversion rate in the presence of promotions [8], certain potential customers may not complete the purchase for a variety of reasons, such as failing to notice the promotion material [6, 7]. Targeting potential consumers with a tailored marketing approach is expected to try to boost their buy conversion rate during sales [9]. Therefore, the ability to predict the micro-level buy intent of customers is a prerequisite for implementing personalized marketing strategies and is a critical factor in increasing the total purchase conversion rate. Customers' purchase intent prediction during promotions can be expressed as a binary classification job [10], in which customers are divided into two groups based on whether or not they have purchase intents. Online shoppers are constantly looking for new items that meet their budgets, new styles, and most importantly, prices that are reasonable [11]. The greatest method to save time and money at home or anyplace else is to use the internet to make affordable, time- and money-saving purchases [12]. There are no restrictions on online buying for customers. They also use the internet to browse social media, compare pricing for products and services, get news [13], and do information searches, among other things [14].

Numerous studies have attempted to investigate client buy intent in promotions, and they have shown that the intent of customers to make purchases is directly related to their profile, including past purchases and demographics [15, 16]. New research has repeatedly shown that browsing habits of consumers in an online setting can provide insight into the factors that precede their final purchasing decisions [17, 18]. Numerous machine learning methods have been utilized to make predictions depend on these attributes [19, 20], with positive prediction outcomes.

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The major contributions of this work are abbreviated below:

- This research Optimized Isogeometric Neural Networks for Customer Behavior Path Analysis and Online Advertising Strategy (ISNN-CBPA-OAS) is developed a with feature combination that uses fully connected Isogeometric Neural Networks.
- Initially data are gathered from Online Shoppers Purchasing Intention Dataset.
- This article extracts features in DTCDWT model to analyze client browsing behaviour across many channels.
- ISNN models customer interactions with promotion channels, including nonlinear sequence correlations along cumulative impacts on browsing behaviour.
- To increase prediction performance, the system combines other consumer profile information like purchase history and demographics, combining them to an end-end framework.

Remaining sections are organized as: part 2 defines literature survey, part 3 describes proposed method, part 4 illustrates the outcomes, part 5 presents the conclusion.

II. LITERATURE REVIEW

Numerous studies were already suggested in literature connected to Customer Behavior Path Analysis and Online Advertising Strategy from that few works are revised here:

Forghani., et.al, [21] have suggested rough set theory to demonstrate the way digital marketing tactics affect consumers' online purchasing decisions. The aim of the suggested paper was to examine how these tactics affect consumers' purchasing decisions when they shop online in Tehran. To ensure that the linguistic information collected from clients was preserved, a 2-tuple fuzzy linguistic representation technique was employed during the data gathering process. The Rosetta software's results indicate that the most significant aspects influencing online shoppers' purchasing decisions are five rules that regulate customer behaviour. It provides high recall and low accuracy

Lee., et.al, [22] have presented an analysis and comparison of machine learning algorithms for predicting the conversion rate of online purchases. In this paper, 374,749 online consumer behaviour data from Google Merchandise Store, an online retail mall, were examined to suggest research questions. The empirical research indicates that oversampling is the most effective way to reduce data imbalance bias, and that the ensemble model eXtreme Gradient Boosting model performs best at predicting online consumers' buy conversion. It offers high precision and low computational time

Chaudhuri., et.al, [23] have presented Predicting customers' purchase behavior using deep learning. In this work suggested Retail customers' online purchases are primarily predicted by two different sets of variables: customer characteristics and platform engagement, compared the predictive ability of our deep learning approach to those of other well-liked machine learning techniques like support vector machines, random forests, artificial neural networks and decision trees. These analyses advances the academic understanding of online ecommerce platform purchase prediction while assisting platform builders in making plans for increased platform interactions. It provides high specificity and low recall.

Wibowo., et.al, [24] have presented the connection between customer experience and social media marketing. In order to assess the quality of the customer-provider relationship, which influences consumer behavioral outcomes like purchase intention, loyalty intention, and participation intention, the presented article analyzes social media marketing activity and customer experience (CX). 413 online questionnaire surveys were measured and analyzed using Smartly 3. The results show that SMMA and CX have a positive influence on customer relationship quality, which in turn has a positive effect on consumer behavioral outcomes. It provides high F1-scorce and low accuracy.

Chou., et.al, [25] have presented the identification of the crucial elements influencing consumer behaviour: an integrated viewpoint on marketing strategy and attitude components. The presented study's suggested research technique clarifies the reason consumers in Taiwan were motivated to practice environmental responsibility. Structural equation modelling (SEM) using data from 977 internet users served as the foundation for the model. The results showed that intentions to consume green products were strongly and indirectly impacted by attitudes regarding green products. It provides high F1-scorce and low accuracy.

Mathew., et.al, [26] have presented the digital content marketing influences travellers' decisions extension of the concept for technology acceptance. The presented study suggests to assess and contrast the impact of DCM on travel and tourist consumer behaviour in two distinct Middle East and North Africa countries, an extended technology acceptance model was empirically investigated. Additionally, it has been found that consumers' attitudes, which affect their intention and action while using DCM to purchase or select a certain tourism good or service, are antecedents of felt enjoyment and perceived convenience.. It provides high precision and low recall.

Cheung., et.al, [27] have presented the moderating influence of ethical convictions in the relationship between consumer perceptions of retailers' ethics and word-of-mouth and purchasing behaviour. Customers' perceptions of retailer ethics were presented in the suggested paper. Create a multidimensional conceptual model of consumer perceptions of retailer ethics (CPER) based on a review of the literature on marketing and consumer research. It was suggested that strong ethical beliefs have a greater influence on consumers' purchase behaviour and word-of-mouth communication than weak ones. Using a random sample of 399 respondents from a collectivist culture, the model was verified. It provides high specificity and low accuracy. Show that the fig1, Proposed ISNN-CBPA-OAS method.

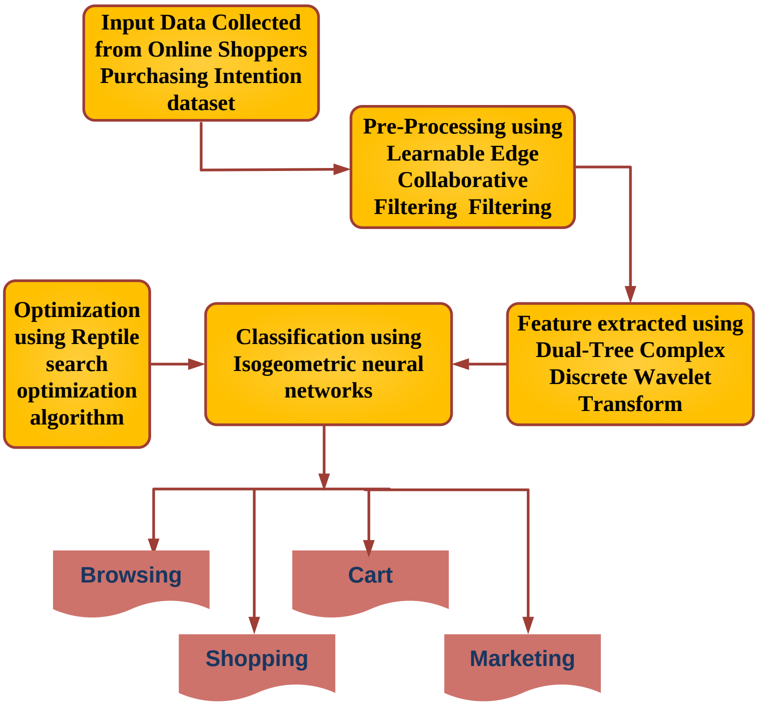

Figure 1: Proposed ISNN-CBPA-OAS method

III. METHODOLOGY

A. Data acquisition

The data is gathered from Online Shoppers Purchasing Intention Dataset [28].The dataset consists of feature vectors from 12,330 different sessions. The dataset was designed to ensure that each session would belong to a distinct user over the course of a year in order to prevent any tendency to a specific campaign, special day, user profile, or timeframe.

B. Pre-processing using Learnable Edge Collaborative Filtering (LECF)

In this step,Learnable Edge Collaborative FilteringLECF[29] is used for data cleaning. The historical relationships among users and things are represented as bipartite graph in LECF.Data preprocessing is a theoretical and practical method of converting data vectors from real-world situations into new vectors that remove one or more so-called data problems. One type of data problem could be the inability to conduct data analysis on a certain dataset, such as when there is insufficient or inaccurate data. Then the LECF, presented with quality assessment of the data and it is denoted in equation (1)

$$v_t(h, j) = p(v_{p,j}) \tag{1}$$

Where $p(v_{p,j})$denotes words removal, transition probability for next product v_t the point where the query data intersects with its nearest neighbours to limit overall count of data. Learnable models indicate test functionthe Customer product between finite element analysis.Typically, the learnable models represent similarity as the Customer product of two temporal sequence predictions it is expressed in eqn (2)

$$L(t_{q+1} \mid t_q) = \left\{ \frac{1-\beta}{|M(vq)|} \right. \tag{2}$$

Where, L implies observed products, t_{q+1} represents the online timing, β gives us a special dataset to watch how customers behave. $M(vq)$ is carrying out data analysis on a specific dataset. It can also be thought of as a normalization word that prevents the scores' scale from growing when additional are spotted. Offer discounts of the product is shown in equation (3)

$$\hat{p}_c = \sum_{b' \in \mathrm{O}} g_c^t (c^t)(z_c^{\mathrm{K}} z_{c'}) \tag{3}$$

Here, $\hat{p}_c$ signifies set of sales promotions, g_c^t denotes number of online productin c^t. The binary function's objective is to use z_c^{K} and $z_{c'}$ to create data embedding $\sum_{b' \in \mathrm{O}}$ .Applying dynamic processes to remove data useless words and linear regression model can be urbanized in equation (4),

$$B = \sum_{(v,j,i) \notin C} -1h\partial(z_t) - y_t(F,i) + \gamma \tag{4}$$

Where $y_t(F,i)$ signifies training set, F denotes set of online purchasing data, each detected interactions, in sigmoid function, $h\partial$ signifies method parameters, γ signifies parameter to control quality. Then clean the data is given in equation (5)

$$\hat{p}_{ai} = z_a^{\mathrm{K}} z_i \tag{5}$$

It is possible to think of these user-item relationship-based models as a specific instance of LECF that does away with the edge-edge similarity component. In this case, $\hat{p}_{ai}$ entries of the cleaneddata are all equal to one. LECF cleaned the unwanted data and the preprocessing data is given to feature extraction.

C. Feature extraction using Dual-Tree Complex Discrete Wavelet Transform

In this section, the preprocessed data are given to Dual Tree Complex Wavelet Transform (DTCDWT) for feature extraction [30]. It extracts the features such as gender, age, postal code, education level, and occupation. This model suggests methods to extract information from customer and promotion channel interactions and customer's reaction for promotion.As demonstrated in DTCDWT, the elements of a data offer hints about the products themselves in addition to the name of the online channel. But the majority of internet retailers offer a. In the DWT, data $k(t)$ is expressed as a linear basic function combination and it is expressed in equation (6),

$$k(t) = \sum_{p,q} x_{p,q} c_{p,q}(t) \tag{6}$$

Where p denotes product information of online channels, $x_{p,q}$ signifies candidate URL, q implies search filter out all relevant URLs from weblogs and $c_{p,q}(t)$ are a set of basic functions that are obtained by the matching of a candidate function λ and a mother wavelet function γ. When the map behavior data is given in equation (7)

$$I(t) = \sum_{n=-\infty}^{\infty} s_n \lambda(t-n) + \sum_{n==\infty}^{\infty} \sum_{m=0}^{\infty} p_{m,n} \gamma(2^m t - n) \tag{7}$$

Where, s_n and $p_{m,n}$ are the browsing frequency and dice coefficients, respectively. The dual tree Complex Discrete Wavelet transform of customer's multi-channel browsing data a is computed by passing it to a time series detector. First, the samples are passed using impulse response h resulting in a convolution of a, h, and expressed in equation (8),

$$b[j] = (a * h)[j] = \sum_{n=-\infty}^{\infty} s[n] h[j-n] \tag{8}$$

The outputs give the dice coefficients and Jaccard coefficients.The over pageview, or anterior auxiliary line, features concavity and convexity in female anatomy, which was used to trace the lateral and upper bounds variables within the vector that display differences across channels and dates. Predicting customer purchases with the use of multiple channel browsing in equations (9)

$$d_{fiirst}[j] = \sum_{n=-\infty}^{\infty} s[n] h[2j-n] \tag{9}$$

Here $d_{fiirst}[j]$ indicates Predicting customer purchases. The objective of the $s[n]$ is the temporal sequence classification issue, forecast the future purchase result based on the preceding T data. The customer's purchase intention prediction can be expressed as formula using the previously defined explanatory variables is expressed in equation (10)

$$b_{last}[j] = \sum_{n=-\infty}^{\infty} a[n] k[2j-n] \tag{10}$$

Where, One significant feature category that disregards client preferences and future purchase intentions is the purchase history. Purchase history includes previous frequency of transactions, previous spending amounts and quantities, and previous duration between purchases.The extracted features are given in equation (11)

$$f^{m}[j]=\sum_{n=0}^{p-1}k[n]*c^{m-1}[2j-n],\ g^{m}[j]=\sum_{n=0}^{p-1}h[n]*c^{m-1}[2j-n] \tag{11}$$

Where $h[n]*$ signifies feature category of past purchases, the level of decomposition, and c^{m-1} illustrates the particular quality. Finally, the purchase frequencies are presented towards the feature extraction phase.Customer demographics, which include details like gender, age, and postal code, have also been extensively employed to forecast purchase intention. Lastly DTCDWT extracted the features likegender, age, postal code, education level, occupation. Afterwards the data is given to classification section.

D. Classification using Isogeometric neural networks

The proposed ISNN [31] feature-combined deep learning framework, integrates heterogeneous and multi-source data into an end-end neural network structure. Initially ISNN is used to model the customer-promotion channel interactions, nonlinear sequence correlations, and cumulative impacts between the customers' browsing behaviour.The extraction of time-delayed data from the consumer browsing data is expressed in equation (12)

$$\hat{v}_{ISNN}(C(\xi,\eta)=\sum_{i=0}^{a}\sum_{j=0}^{b}H_{i,s}(\xi)H_{i,s}(\eta)\hat{v}_{ISNN,i,j} \tag{12}$$

Where $\hat{v}_{ISNN}$ coefficients of the ISSN outputs elements from the transaction history that pertain to the frequency $C(\xi,\eta)$ is always has precisely the same number of outputs as control points in the URLs, the indexing method is correct. Since the URLsproduced by the ISSN immediately correspond to control points inthe control channelsof the URLs data and it is given in equation (13)

$$\nabla.(h\nabla s)+c=0,\quad Y\in\Omega \tag{13}$$

Where trial ∇ and $h\nabla s$ test function browsing behavioris chosen. As is done in a typical ISSN method to c, $Y\in\Omega$ this statement is recast to a finite-dimensional form by selecting to represent the test and trial functions.These qualities do not significantly influence customer behaviour and modified to solve prediction using equation(14)

$$\tilde{v}_{ISNN}^{k}(Y(\xi,\eta)=\sum_{i=o}^{a}\sum_{j=0}^{b}(\xi)H_{i,s}(\eta)\hat{v}_{ISNN,i,j} \tag{14}$$

$H_{i,s}$ represents the prediction task, $\tilde{v}_{ISNN}^{k}$ signifies coefficients of the ISSN η is the multiplied by zero in order to enforce the multi-source data fusion a and b the coefficient values that most closely approximate the least-squares sense boundary condition are added. The Customer demographics are commonly used to predict purchase intention and it is shown in equation (15)

$$E_{i,j}(\mathrm{Z})\hat{v}_{j}(\mathrm{Z})=P_{i}(\mathrm{Z}) \tag{15}$$

Here, $E_{i,j}$ loss formulation is obtained in relation to the use of ISNN to resolve a data behavior, browsing frequency and time intervals, the IGN technique can be used with a larger class of product recommendationand identifying the customer behavior using equation(16)

$$\underset{\theta}{Min}=\frac{1}{G_h}\sum_{G_h}^{G_h}\left\|P_i(\mathrm{Z}_h)-E_{i,j}\right\| \tag{16}$$

Here, $\underset{\theta}{Min}$ Customer profile data includes buying history and demographics. G_h Denotes the endless number of stiffness product would need to be assembled and stored. Z_h lowers the computational cost and storage needs for ISNN training, P_i the feature category of purchase history. Finally ISNN identify the customer behavior such as Browsing, Shopping, Cart, and Marketing. Utilizing Reptile Search Optimization Algorithm employed to enhance ISNN optimum parameters L *and* z. The RPO used to adjust the ISNN weight and bias parameter.

E. Stepwise procedure for Reptile Search Optimization Algorithm

Here, stepwise procedure described to identify the customer behavior of ISNN using **Reptile Search Optimization Algorithm** (RSOA)[32]. Being semi-aquatic reptiles, crocodiles have distinct morphological traits such a streamlined body form, the capacity to walk with their legs raised to the side, belly walk, ability to swim. These qualities enable to develop into effective hunters in wild.Subject to certain restrictions, the population-based, gradient-free RSOA algorithm can resolve both basic and complicated optimization issues. ISNN doesn't show whichever modification of optimization methods identifying best parameters that assure exact predicting crop. Then, method of comprehensive step following,

***Step 1*:** Initialization

During this stage, chaotic maps are used to produce the initial candidate solutions.Also, specified the objective function and the search space. Prior to computation, all parameter values are also set and it is given in equation (17)

$$E=\begin{bmatrix} e_{1,1} & .... & e_{1,y} & e_{1,m-1} & e_{1,m} \\ e_{2,1} & .... & e_{2,y} & e_{2,m-1} & e_{2,m} \\ .... & .... & e_{x,y} & e_{x.m-1} & e_{x,m} \\ .... & .... & .... & .... & \\ e_{M-1,1} & .... & e_{M-1,y} & .... & e_{M-1,m} \\ e_{M,1} & .... & e_{M,y} & e_{M-1,m} & e_{M,m} \end{bmatrix} \tag{17}$$

Where E represent the candidate solutions; $a_{x,y}$ indicates the search agent of positions of x^{th} solution; M represent the potential solutions numbers; m indicates the problem size.

Step 2: Random generation

Randomly initialize the ISNN parameters or use a predefined set. Input weight parameter $\{\hat{v}, g\}$ developed randomness via RSOA method.

***Step 3*:** Fitness Function

Evaluate the fitness of each parameter by applying an objective function to the corresponding solution it represents and it is given in equation (18)

$$fitness\ \ function\ = Optimizing\ \left[\hat{v}\, and\ \ g\right] \tag{18}$$

***Step4*:** Exploration Phase

The exploration behaviour of RSOA is discussed. The exploratory search yields a large search space; it may take multiple searches to locate the promising area. The main search strategies used by RSOA exploration mechanisms belly and high walking to explore the search space as well asidentifyaimprovedresponseare focus of this work.Reptile individuals explore the parameter space, and the adaptation is performed based on the gradient of the model's performance on a few training samples (meta-training).

Presented is the position updating during the exploring phase is expressed in equation (19)

$$Q_{(i,j)} = \alpha + \frac{z_{(i,j)} - N(z_i)}{Best_j(r) \times \left(SA_{(j)} - LA_{(j)}\right) + \in} \tag{19}$$

Where, $N(z_i)$ represents average i^{th} solution position, $SA_{(j)}, LA_{(j)}$ denotes j^{th} position boundary, α indicates critical parameter, $Q_{(i,j)}$ denotes difference among j^{th} position of best-obtained solution and j^{th} position current solution.

Step5: Exploitation phase

Exploitation is the final stage. These tactics mimic the exploitation search and the location updating formula for exploitation is included in original RSOA. It is expressed in equation (20)

$$z_{(i,j)}(r+1) = \begin{Bmatrix} best_j(r) \times Q_{(i,j)}(r) \times Rand, & r \le 3\dfrac{P}{4}\, and \quad r > 2\dfrac{P}{4} \\ best_j(r) - \eta_{(i,j)}(r) \times \in & \\ -E_{(i,j)}(r) \times Rand, & r \le R\, and \quad r > 3\dfrac{P}{4} \end{Bmatrix} \tag{20}$$

Here, $best_j(r)$ represents the ideal-found solution j^{th} position , $\eta_{(i,j)}$ denotes j^{th} position hunting parameter in i^{th} solution, $Q_{(i,j)}$ represents difference among j^{th} position of best-obtained solution along j^{th} position of present solution, $E_{(i,j)}(r)$ represents amount used to decrease the search region in present iteration.This phase emphasizes leveraging the knowledge gained during exploration to fine-tune the ISNN for better adaptation to the CVD prediction task.

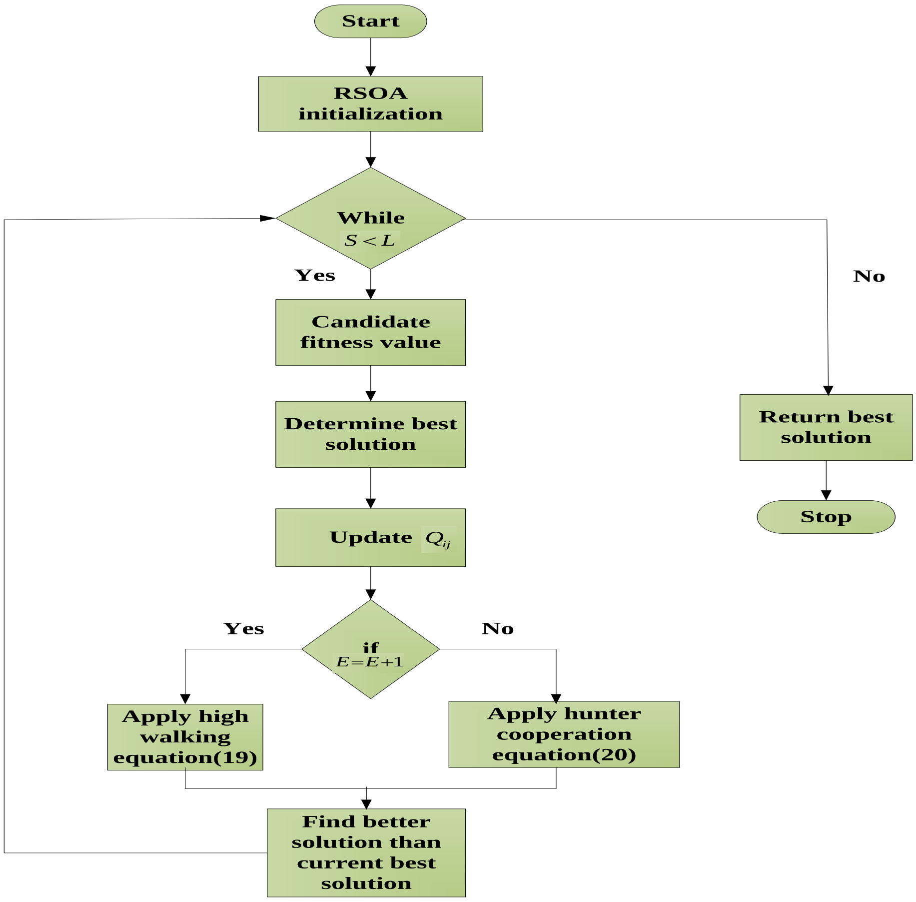

Figure 2: Flow Chart for RSOA for optimizing ISNNparameter

Step 6: Termination

The parameter $\hat{v}\, and \;\; g$ from Double Integral Enhanced Zeroing Neural Network optimized with RSOA, will continue till the position information is obtained $E = E + 1$ is met. The flow chart for RSOA is given in figure2. Then finally, ISNN-CBPA-OASidentify the customer behavior with low computational time.

IV. RESULT AND DISCUSSION

Experimental results of proposed system covered. The proposed ISNN-CBPA-OAS approach is implemented in Python. Proposed technique analyzed with existing techniques PCC-CBPA-OAS, CNN-CBPA-OAS, ANN-CBPA-OAS respectively.

A. Performance Measures

It utilized to validate performance of proposed method. Performance metrics likes accuracy, recall, precision, F1-score and computational time are evaluated.

1)Accuracy

It is the correct prediction ratio to total events in dataset.It is measured using eqn (21),

$$Accuracy = \frac{T_P + T_N}{T_P + T_N + F_P + F_N} \tag{21}$$

2) Recall

It is a performance metric that assesses the system's capacity to provide accurate positive predictions and it is shown in equation (22)

$$\mathrm{Re}call = \left(\frac{T_P}{T_P + F_N} \right) \times 100 \tag{22}$$

3) F1-score

It is computed by equation (23),

$$F1-score=\frac{2T_p}{2(T_p+F_p+F_n)} \tag{23}$$

4) Precision

The classifiers ability to calculate normal review without restrictions. This is shown in equation (24),

$$\Pr ecision = T_P \big/ (T_P+F_P) \tag{24}$$

B.Performance Analysis

Figure 3 to 6 shows the simulation results ofOptimized ISNN-CBPA-OAS. The performance measuresincluding accuracy, recall, precision, F1-scorce and computational time examined. The proposedISNN-CBPA-OASanalyzedto PCC-CB PCC-CBPA-OAS, CNN-CBPA-OAS, ANN-CBPA-OAS PA-OAS, CNN-CBPA-OAS, ANN-CBPA-OAS methods.

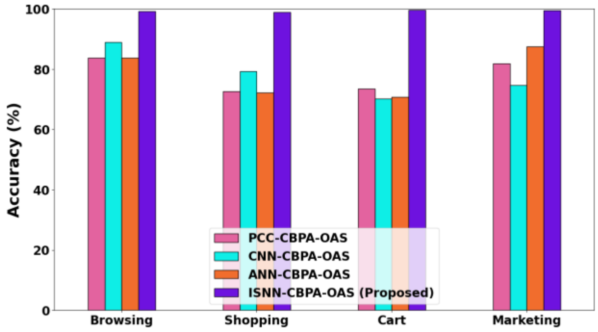

Figure 3: Accuracy analysis

Fig 3 represents accuracy analysis. The proposed ISNN-CBPA-OASprovides 25.42%, 32.24% and 27.30%higher accuracy for excellent; 30.42%, 28.28% and 19.25%higher accuracy for Browsing; 24.37%, 26.48% and 33.39%higher accuracy for Shopping; 25.42%, 26.65% and 33.42%higher accuracy forCart; 23.52%, 35.23% and 28.30% higher accuracy inMarketingclassification analyzed to the analyzed withpresent PCC-CBPA-OAS, CNN-CBPA-OAS, ANN-CBPA-OAS methods.

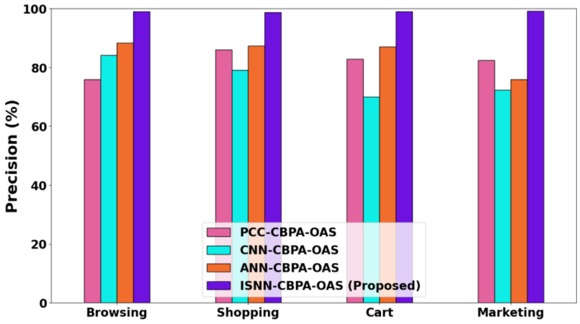

Figure 4: Precision analysis

Fig 4 represents precision analysis. The proposed ISNN-CBPA-OAS provides 23.60%, 27.24% and 25.09 %higher precisionfor excellent; 28.47%, 22.38% and 31.25% higher precisionfor Browsing; 30.26%, 30.48% and 24.39% higher precisionfor Shopping; 25.52%, 23.61% and 30.52% higher precisionforCart; 21.42%, 23.43% and 34.30% higher precisionin Marketing classification analyzed to the analyzed with present PCC-CBPA-OAS, CNN-CBPA-OAS, ANN-CBPA-OAS methods.

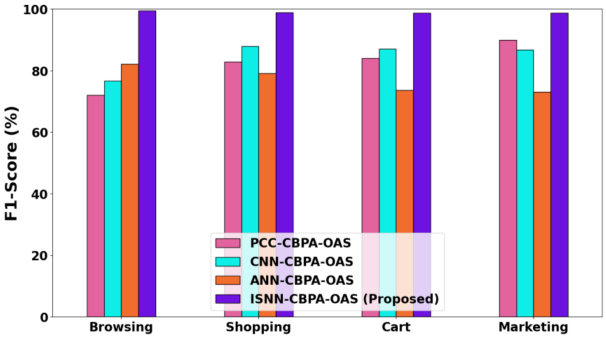

Figure 5: Recall analysis

Fig 5 represents recall analysis. The proposed ISNN-CBPA-OAS provides 25.42%, 32.24% and 26.30%higher recall for excellent; 30.55%, 21.28% and 25.44% higher recall for Browsing; 31.17%, 33.43% and 23.39% higher recall for Shopping; 29.50%, 23.65% and 34.22% higher recall forCart; 21.20%, 34.27% and 27.30% higher recall in Marketing classification analyzed to the analyzed with present PCC-CBPA-OAS, CNN-CBPA-OAS, ANN-CBPA-OAS methods.

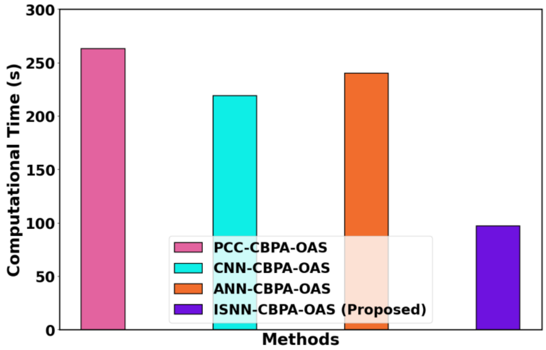

Figure 6: Computational time Analysis

Fig6 demonstrates the computation time analysis. The ISNN-CBPA-OAStechniqueachieves2.17%, 19.20% and 11.34% low computation time compared with PCC-CBPA-OAS, CNN-CBPA-OAS, and ANN-CBPA-OAS models.

C. Discussion

The proposed ISNN-CBPA-OAS work offers several avenues for further investigation because of the limitations. Sequence correlation was used in the suggested analysis of customer browsing behaviour, yet it's possible that other relationships in the prediction task were missed. Therefore, other correlations can be included in subsequent research. Future studies should address a few additional techniques that can handle multiple source data fusion, particularly for heterogeneous data. One further constraint is that the goods of other industries need to be covered in our future research, as our current study only concentrates on entertainment services like movies, sports, and concerts.Furthermore, the results of ISNN-CBPA-OAS have significant ramifications for businesses in terms of their comprehension of consumer behaviour and their ability to develop more individualized marketing plans.

V. CONCLUSION

In this paper, ISNN-CBPA-OASis successfully implemented. The proposed ISNN-CBPA-OASapproach is implemented in Python utilization of from Online Shoppers Purchasing Intention Dataset. The performance of proposed ISNN-CBPA-OASapproach attains 20.16%, 30.29% and 32.15% higher accuracy; 26.12%, 33.17% and 29.17% high recall; 31.23%, 28.41% and 21.32% higher precision analyzed to the existing PCC-CBPA-OAS, CNN-CBPA-OAS and ANN-CBPA-OASmethods respectively.

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