Journal of Intelligent Systems and Internet of Things
Vol. 16, No. 02, PP. 174-186, 2025
DOI: https://doi.org/10.54216/JISIoT.160213

Blockchain with IoT Integrated Framework for Tourism Service Customization and Management

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Abstract
The Internet of Things (IoT) has extensively converted the industry of tourism, reforming travel design, supply, and experiences. The technology of Blockchain (BC) signifies a paradigm shift with the latent to transform many industries, more like spreadsheets altered office efficiency. BC technology provides frequent potential advantages to the tourism industry, with enhanced transparency, security, and efficacy in regions such as payments, bookings, and identity verification, which potentially mains to a more perfect and reliable travel experience. In the tourism region, BC with IoT is mainly attractive owing to the latent benefits it provides in terms of improving the experience of tourism, enhancing operational efficacy, and guaranteeing data security and transactions. Recently, numerous scholars globally have employed deep learning (DL) technology in the industry of tourism to combine physical and social influences for improved travel recommendation services. This study presents a Blockchain for Tourism Service Customization and Management using Whale-goshawk Optimization Algorithm (BCTSCM-WOA) technique. The main goal of the BCTSCM-WOA method relies on improving the effectual model for tourism service customization. Initially, blockchain technology is applied to provide secure, transparent, and decentralized solutions for handling traveler data, payments, and service personalization. Then, the data pre-processing employs min-max scaling to transform input data into a suitable format. Besides, the crayfish optimization algorithm (COA) to select the most relevant features from the data has executed the feature selection procedure. For the classification process, the proposed BCTSCM-WOA method projects multi-dimensional attention-spiking neural network (MASNN) technique. At last, the parameter tuning process is performed through the whale-goshawk optimization (WGO) algorithm for refining the classification performance of MASNN model. The experimental evaluation of the BCTSCM-WOA algorithm has been examined on a benchmark dataset. The extensive outcomes highlight the significant solution of the BCTSCM-WOA approach to the classification process when compared to existing techniques.

Received: December 12, 2024 Revised: February 16, 2025 Accepted: March 10, 2025

Keywords: Blockchain; Tourism Service Customization; IoT; Whale-goshawk Optimization Algorithm; Feature Selection

1. Introduction

The emergence of digital transformation comprising Artificial Intelligence (AI) involved in Internet of Things (IoT) and Blockchain (BC) has paved the method for the examination of upcoming technologies and the incorporation of novelties through several industries, employing technology as a device to generate value and attain a competitive benefit [1]. Particularly in recent times, the combination of BC technology with the IoT has developed a favorable solution to handle various challenges in multiple industries like agriculture, energy management, supply chain management, tourism, and medical care [2]. In the tourism area, this combination is captivating owing to the possible advantages, of enhancing operational efficacy and guaranteeing the security of transactions and data. The grouping of IoT and BC is generally related to the “blockchain of things” (BoT) [3]. The application of BoT is in the primary phase in tourism sector. It contains the utilization of BC to handle and secure the huge number of data created by IoT gadgets namely cameras, wearables, and sensors. This data might be employed to enhance tourism knowledge by offering personalized suggestions and improving the security and safety of tourists [4]. Furthermore, the association of tourism industry and BoT can also allow the formation of revenue streams and novel business methods.

Digitization and Technological growth in the tourism industry have paved the method for development of customer-based value suggestions [5]. These propositions are aimed at data transparency, flexible customization, and decentralized autonomous value chains. Consequently, there is a requirement for a model shift from conventional business methods to customer-centric techniques. In accordance with, the United Nations World Tourism Organization (UNWTO), the universal tourist arrival has grown yearly by 6 percent around the world [6]. Therefore, there is a requirement to keep trust between hospitality stakeholders, travelers, and tourism. It offers continuous services like payments and ticket bookings while guaranteeing a proper communication channel among several tourists [7]. Unfavorably, conventional centralized methods cannot cope with the above-mentioned stringent conditions. As a result, there is a necessity for decentralized mechanism that generates further possibilities in the hospitality sector and service-based tourism [8]. The application of BoT is probable to change the industry by increasing security, efficiency, and transparency [9]. DL technology projects a spatially aware hierarchical collaborative from the perception of heterogeneous aspects to layer spatially aware personal preferences that effectually extract the concern of data sparseness in travel service recommendations [10].

This study presents a Blockchain for Tourism Service Customization and Management using the Whale-goshawk Optimization Algorithm (BCTSCM-WOA) technique. Initially, BC technology is applied to provide secure, transparent, and decentralized solutions for handling traveler data, payments, and service personalization. Then, the data pre-processing employs min-max scaling. Besides, the crayfish optimization algorithm (COA) has executed the feature selection (FS) procedure. For the classification process, the proposed BCTSCM-WOA method projects a multi-dimensional attention spiking neural network (MASNN) technique. At last, the parameter tuning process is performed through whale-goshawk optimization (WGO) algorithm for refining the classification performance of MASNN model. The experimental evaluation of the BCTSCM-WOA algorithm can be tested on a benchmark dataset.

2. Literature Review

Chrysafiadi et al. [11] introduced an innovative fuzzy logic (FL)-based application method intended for improving personalization in smart tourism. The projected method combines real-world user data and provides customized services for every specific consumer. Specifically, the presented model integrates a suggestion mechanism that blends Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) with FL for evaluating standards and user choices and offers precise and all-around personalized travel destination suggestions. Long and Chen [12] intend to implement big data mining technology in the area of smart tourism. Initially, it concentrates on collaborative filtering technology and image summary selection involves big data mining. Souha et al. [13] advanced a Domain-Specific Language (DSL) structure, which modernizes, and speeds up RS progression for smart tourism applications over a Model-Driven Engineering (MDE) model. The structure of DSL modernizes the generation of code, which utilizes the services offered by the Apache Mahout structure for applying suggestion models, summarizing the essential intricacies, and allowing developers to emphasize higher-level method design instead of the technological aspects of model implementation. Moreover, this structure combines a modeling tool and code generator.

Semwal et al. [14] projected an advanced AI-IoT method, which focuses on enhancing tourism analytics by providing practical and instant perceptions of behavior of travellers. This method offers accuracy of excellent prediction and effective data processing by combining IoT sensors with ML models. This method integrates an extensible cloud framework with edge computing to do local data pre-processing, thus ensuring higher dependability and minimum delay. Singh et al. [15] employ augmented reality (AR) and virtual reality (VR) to progress environmentally friendly tourism virtually enveloping experiences are presented. Predictive analytics are also vital to dealing with visitor resorts and safeguarding tourists initiated for visitation in a way that will never distress the environmental integrity.

Virutamasen et al. [16] presented a novel automated application intended to offer users personalized attraction recommendations adapted to their interests and existing situations. Employing a contextual and sophisticated ML methodology, this method builds a comprehensive user profile by deliberating features such as demographic data, historical behaviour, and current context. By assimilating multi-dimensional user methods involved in context, the method improves the platform's adaptability and personalization eventually assisting in the intensification of Destination Branding and the cultivation of enriched Tourism. Panda and Khatua [17] advanced a historical analysis, discovering the permeation of e-commerce in the tourism industry and travel. This study emphasizes consistent customer experiences through different airlines, channels, and international together with domestic travel, mainly in developing economies with restricted internet availability.

3. Research Design and Materials

In this paper, we have presented a novel BCTSCM-WOA technique. The main goal of the BCTSCM-WOA method relies on improving the effectual model for tourism service customization. To perform that, the BCTSCM-WOA technique has BC technology in smart tourism, data preprocessing, dimensionality reduction, classification process, and parameter selection are demonstrated in Fig. 1.

A. BC Technology in Smart Tourism

Initially, BC technology is applied to provide secure, transparent, and decentralized solutions for handling traveler data, payments, and service personalization. The combination of BC technology offers a new development for smart tourism and reveals a unique location for the intelligent and digital expansion of the tourism field [18]. In our generation, smart tourism has not only provided online booking services. BC technology gives a high security level for smart travel over a decentralized framework and great encryption mechanism. The tourism sector manages sensitive information, including financial data and personal identity. By keeping this data in the BC, the information might not be distributed, and the thread of data leaked or being hacked inside is decreased.

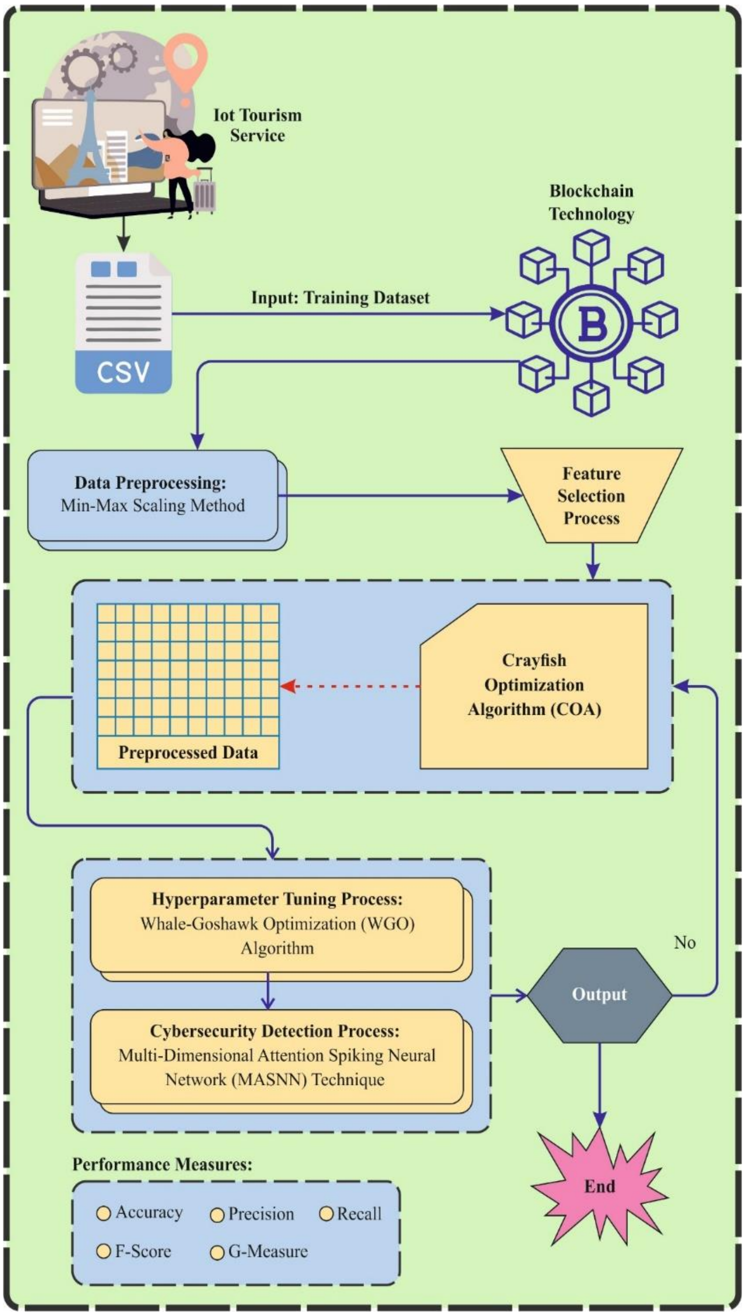

Figure 1. Overall process of BCTSCM-WOA technique

Simultaneously, users' controls over personal information have even been reinforced, which encounters the higher request for the protection of privacy in the current world. This implies that consumers, suppliers, and other applicants can clearly realize the price, quality, source, and other information of tourism services and products. Simultaneously, the non-tampering of BC technology guarantees data discoverability and assistance to resolve disputes and challenges. A BC-based travel platform utilizes smart contracts for encoding the cancellation of flight tickets and altering rules onto the BC. If the user is required to cancel and modify the ticket, the smart contract will spontaneously apply the related rules, guaranteeing the fairness and transparency of the method, decreasing human interference, and promising disputes. However BC itself assistances in enhancing data security, after processing and storing a larger number of personal data in the traveling platform, it is essential to guarantee that the information on the BC is anonymous, encrypted, and available only to authorized people. As a result, it is more significant to choose a proper consensus model and support network security.

B. Data Preprocessing

Then, the data pre-processing employs min-max scaling to transform input data into a suitable format. Min-max scaling is a normalization system employed in tourism service customization and management to rescale data in a fixed range, normally [0, 1] or [-1,1]. It aids in normalizing varied datasets like booking trends, customer preferences, and spending patterns, which makes them similar and refining data-driven decision-making [19]. By maintaining relationships amongst values, min-max scaling improves the accuracy of AI and ML techniques employed for modified travel recommendations. It averts supremacy of superior numerical values, certifying balanced service customization. In BC-based tourism management, regularized data enhances secure transactions and seamless interoperability. This method eventually improves customer fulfillment by allowing exact and personalized travel experiences.

C. Dimensionality Reduction Process

Besides, the COA to select the most relevant features from the data has executed the FS procedure. The crayfish's behavioural features inspire COA, a very adjustable freshwater crayfish [20]. They grow up in alluvial deposits, using them for hiding and feeding, and show temperature-dependent behaviors: they search for housing in caves throughout higher temperatures and hunt actively inside their better range of $20-30^{O}C.$ According to these adaptive behaviors, 3 algorithmic phases are outlined: foraging, summer resort, and competition, integrating them into the exploitation and exploration stages in the model, as presented below.

1) Exploration stage: If crayfish look for caves, fights take place randomly. During COA, this is demonstrated with$rand < 0.5$, and the crayfish location is upgraded utilizing Eq. (1).

$$X_{i,j}^{t+1} = X_{i,j}^{t} + C_2 \times rand \times \left(X_{shade} - X_{i,j}^{t}\right) \tag{1}$$

Now, $X_{i,j}^{t+1}$ signifies crayfish location at iteration $t+1$; X_{shade} refers to cave position measured from the present and global best solutions, $X_{i,j}^{t}$ represents location at iteration t; and C_2 denote adaptive parameter calculated by Eq. (2).

$$C_2 = 2 - \left(\frac{t}{T}\right) \tag{2}$$

Whereas t stands for present iteration number and T symbolizes maximal iteration counts.

2) Exploitation stage:

Competition case phase

If $temp > 30$ and $rand \geq 0.5$, crayfish arrive in the contest for the cave phase, and they will achieve delves by clutching, as presented in Eq. (3).

$$X_{i,j}^{t+1} = X_{i,j}^{t} - X_{z,j}^{t} + X_{shade} \tag{3}$$

Now, z denotes randomly chosen crayfish, computed by Eq. (4).

$$z = round\left(rand \times (N-1)\right) + 1 \tag{4}$$

Foraging phase

If $temp \leq 30$, it is appropriate for crayfish to forage. They will transfer near the nutrition, and upon discovering, evaluate its size. The location of the food is described in Eq. (5).

$$X_{food} = X_G \tag{5}$$

The size of the food is outlined in Eq. (6).

$$Q = C_3 \times rand \times \left(\frac{fitness_i}{fitness_{food}}\right) \tag{6}$$

Whereas C_3 symbolize food feature that characterizes the larger food, set the value to 3; $fitness_i$ signifies the fitness value of the ith crayfish; and $fitness_{food}$ characterizes the fitness value of the food.

If $Q > \frac{C_3+1}{2}$, it indicates that the food is relatively great, then the crayfish will split the food, and the mathematical modelling of tearing is presented in Eq. (7).

$$X_{food} = exp\left(-\frac{1}{Q}\right) \times X_{food} \tag{7}$$

After the food is split, the crayfish nourishes as an alternative to the grabbed food, and the mathematical representation of feeding is demonstrated in Eq. (8).

$$X_{i,j}^{t+1} = X_{i,j}^{t} + X_{food} \cdot p \cdot \left(\cos\left(2\pi \cdot\ rand\right)\right) \tag{8}$$

$$-X_{food} \cdot p \cdot \left(\sin(2\pi \cdot rand)\right)$$

If $Q \leq \frac{C_3+1}{2}$, the crayfish only ought to travel near the food and directly contribute, and its mathematical formulation is presented in Eq. (9).

$$X_{i,j}^{t+1} = \left(X_{i.j}^{t} - X_{food}\right) \times p + p \times rand \times X_{i,j}^{t} \tag{9}$$

During this foraging stage, crayfish utilize various feeding techniques based on the food size Q. If the food is larger, it is first split into bits and then fed; after the food is smaller, it is directly moved toward it to feed; over the foraging stage, the COA estimates the best solution to discover the globally best solution.

In the COA approach, the fitness function (FF) employed is intended to have a balance among the amount of chosen features in each solution (least) and the accuracy of classifier (highest) accomplished by retaining these selected features, Eq. (10) indicates the FF to appraise solutions.

$$Fitness = \alpha\gamma_R(D) + \beta\frac{|R|}{|C|} \tag{10}$$

Here, $\gamma_R(D)$ embodies the classifier rate of error of a chosen method. $|R|$ denotes the cardinality of the selected sub-set and $|C|$ means the total amount of features, α and β denote binary parameters which correspond to the prominence of classifier excellence and sub-set length. ∈ [1,0] and $\beta = 1 - \alpha$.

D. Classification Strategy with MASNN Model

For the classification process, the proposed BCTSCM-WOA method projects the MASNN technique. MASNN incorporates attention mechanisms (AM) with SNNs to enhance the precision of the prediction of time series [21]. Normal SNNs contest with processing symmetrical and multi-dimensional dependencies in time-series data. In comparison with conventional deep learning methods such as LSTMs and RNNs, MASNNs are naturally tailored for sequential data processing utilizing event-driven calculation. It initiates with the extraction of the feature from historic data, such as network traffic and CPU utilization, handling time-series and statistic models of analysis. A Temporal-wise Attention (TA) layer, to concentrate on related time windows. The basic structure is a MASNN that utilizes naturally inspired neuron models such as Conductance-Based (CA) dynamics. The last output of the MASNN is decoded to forecast upcoming workload and resource use.

SNNs: These are the most standard neuron methods in SNNs such as Leaky Integrate-and-Fire (LIF). This technique uses spiking neurons that imitate real neurons by transferring information over distinct spikes instead of constant activations.

$$E^{t,0} = p(S_t) = \sum_{t'=x*n}^{x*(t+1)-1} E_{t'} \tag{11}$$

$E^{t,0}$ denotes the actual valued edges, p indicates the data value of parameter, S_t specifies the millisecond-level temporal resolution, x denotes computation of successive spike designs, $E_{t'}$ signifies the data valued at tth time, and t refers to time-step.

Multi-Dimensional AMs: MASNN combines a multi-dimensional AM that allows the model to focus on relevant features of input data while ignoring unrelated details. MASNN was possible for scalable and efficiency through different applications mimicking the larger-scale SNN layer is provided in Eq. (12).

$$\eta \frac{\partial v(t)}{\partial t} = -v(t) + A(t) \tag{12}$$

η denotes the constant time, $-v(t)$ refers to membrane, and $A(t)$ signifies the input collected over presynaptic neurons. The new input over convolutional process was computed in Eq. (13).

$$D^{n.t} = avgpool\left(bn\left(conv(M^t * E^{n,t-1})\right)\right) \tag{13}$$

$D^{n.t}$ signifies the unique amount of input data prediction, $avgpool$ means average pooling, bn represents the batch normalization, $conv()$ refers to convolution process, M^t stands for weighted matrix, and $E^{n,t-1}$ specifies the spiking tensor time computation. Spike-timing-dependent plasticity (STDP) is a naturally stimulated learning method whereas synaptic weight upgrades rely on the neuron spike timing.

Temporal-wise Attention: Its multidimensional nature specifies that the AM works through different sizes of the input data, thus enhancing its ability to seize complex relationships and the temporal resolution level. Then, mathematically computed utilizing Eq. (14).

$$D_{NX}^t = rn(D^n) \otimes D^n \tag{14}$$

D_{NX}^t signifies the temporal-wise advanced blocks of feature, rn stands for workload prediction, D^n refers to prediction of amount of data, and $\otimes$represents multiplication operator. By connecting its SNN structure and AM, MASNN precisely forecasts upcoming values of workload and resource metrics utilizing historical information.

$$u_{ed}^{n,t} = r_e(V^{n,t}) \otimes V^{n,t} \tag{15}$$

$u_{ed}^{n,t}$ symbolizes the prediction of resource time series, r_e represents the unique data output, and $V^{n,t}$ indicates the variation in the amount of data.

E. Hybrid WGO-based Parameter Tuning

At last, the parameter tuning process is performed through the WGO for refining the classification performance of the MASNN model. In WOA, locations are arbitrarily upgraded according to the locations of another whale instead of the present best whale, improving global searching capability in the initial phases but leading to inadequate local searching ability later on [22]. NGO that mimics the searching behaviour of northern goshawks comprises dual phases: prey attack and identification, accompanied by search and escape. However, NGO additionally upgrades locations according to another prey instead of the best goshawk, its global search is less efficient than WOA. Nevertheless, the second phase of NGO enhances local search, permitting it to discover optimal solutions than WOA inside the possible time.

1) Phase 1: Prey Identification

In the initial phase of searching, the northern goshawk randomly chooses prey and quickly attacks. WGO enhances this by separating the prey location X into dual portions: the WOA model produces one part, and the other is a randomly chosen prey location to avoid WGO from being stuck in a local optimal. The guiding feature assists in rapidly finding higher-quality searching regions, whereas the random feature guarantees the model prevents local best.

$$P_i \sim X_i, i = 1,2, \dots, N, j = 1,2, \dots, Z \tag{16}$$

$$P_i^{new,t} = \begin{cases} WOA(P_i^{t-1}), & \gamma > rand, \\ Rand\ (P_i^{t-1}), & \gamma \le rand, \end{cases} \tag{17}$$

$$\gamma = 0.3\left(1 - \frac{t}{T}\right) \tag{18}$$

$$p_{i,j}^t = \begin{cases} p_{i,j}^{new,t}, & F_{i,j}^{new,t} > F_{i,j}^{t-1}, \\ p_{i,j}^{t-1}, & F_{i,j}^{new,t} \le F_{i,j}^{t-1}, \end{cases} \tag{19}$$

$$x_{i,j}^{new,P1} = \begin{cases} Rd(x_{i,j} + r(p_{i,j} - Ix_{i,j})), & F_{P_i} > F_i, \\ Rd(x_{i,j} + r(x_{i,j} - p_{i,j})), & F_{P_i} \le F_i, \end{cases} \tag{20}$$

$$X_i = \begin{cases} X_i^{new,P1}, & F_i^{new,P1} > F_i, \\ X_i, & F_i^{new,P1} \le F_i. \end{cases} \tag{21}$$

Whereas P_i denote prey location of the ith northern goshawk, and F_{P_i} and F_i represents value of the objective function. X_i refers to location of the northern goshawk, and $P_i^{new,t}$ stands for creating a new suggested location at time t, and P_i^{t-1} epitomizes the prey's location at time $t-1$. In Eq. (18), t denotes iteration counter and T denotes maximal iteration counts. Eq. (19) states the upgraded procedure of the prey location, $p_{i,j}^{t}$ signifies the jth dimension location variable of the prey at tth time, and $F_{i,j}^{t-1}$ refers to location variable t of this dimension the objective function value at time $t-1$. $p_{i,j}^{new,t}$ stands for jth dimension location variable of $P_i^{new,t}$, and $F_{i,j}^{new,t}$ represents value of the objective function. In Eq. (20), $x_{i,j}^{new,P1}$ is the jth dimension location variable of $X_i^{new,P1}$, $Rd()$ signifies rounding function, and r mean interval $[0,1]$, and I symbolizes random number with a value of 1 or 2. During Eq. (21), $X_i^{new,P1}$ refers to new service combination in the initial step, and $F_i^{new,P1}$ means value of the objective function.

2) Stage II: Chase and Escape Operation

Once the northern desert goshawk attacks, the prey tries to escape, prompting the goshawk to continue its search. Mimicking this behavior improves the model's capability to implement effective local searches inside the searching region. In WGO, the next phase of searching is separated into dual cases: the initial is when $SS_i = \emptyset$, the local search is even perform; the next is when $SS_i \neq \emptyset$, the local search is performed in the related service set SS_i.

Case 1 ($SS_i = \emptyset$) :

$$x_{i,j}^{new,P2} = Rd\big(x_{i,j} + R_1(2r-1)x_{i,j}\big) \tag{22}$$

$$R_1 = 0.02\left(1-\frac{t}{T}\right) \tag{23}$$

$$X_i = \begin{cases} X_i^{new,P2}, & F_i^{new,P2} > F_i, \\ X_i, & F_i^{new,P2} \leq F_i, \end{cases} \tag{24}$$

Case 2 ($SS_i \neq \emptyset$) :

$$X_i \Rightarrow SX_i, \tag{25}$$

$$sx_{i,j}^{new,P2} = Rd\big(sx_{i,j} + R_2(2r-1)sx_{i,j}\big) \tag{26}$$

$$R_2 = \mu\left(1-\frac{t}{T}\right) \tag{27}$$

$$SX_i = \begin{cases} SX_i^{new,P2}, & SF_i^{new,P2} > F_i, \\ SX_i, & SF_i^{new,P2} \leq F_i. \end{cases} \tag{28}$$

Here, $\mu = 0.2 * size(SS_i)$ refers to scale parameter of SS_i. $X_i^{new,P2}$ and $SX_i^{new,P2}$ represents novel solutions for Cases 1 and 2, individually. $F_i^{new,P2}$ and $F_i^{new,P2}$ signifies objective function values. $x_{i,j}^{new,P2}$ symbolize jth dimensional location variable of $X_i^{new,P2}$, $sx_{i,j}^{new,P2}$ stands for jth of $SX_i^{new,P2}$ dimensional location variable.

3) Repeating Process and Flow of the WGO Algorithm

After upgrading each population member based on the initial and second stages of the presented WGO model, the iteration procedure starts. This stage establishes the novel values for the objective function, the population members, and the best service structure attained thus far.

The WGO model derives an FF to obtain enhanced performance of the classifier. It regulates an optimistic numeral to epitomize the better outcome of the candidate solution. Here, the classifier rate of error minimization is measured as FF, as set in Eq. (29).

$$fitness(x_i) = ClassifierErrorRate(x_i) = \frac{no.of\ misclassified\ samples}{Total\ no.of\ samples} * 100 \tag{29}$$

4. Results Evaluation and Discussion

The performance analysis of the BCTSCM-WOA technique is inspected under the tourism management dataset [23]. This dataset holds 1000 records under nine class labels as represented in Table 1. It has 13 no. of features in total but only 8 features are selected.

Table 1: Details of dataset

Class Labels	Record
Satisfaction Level-1	114
Satisfaction Level-2	87
Satisfaction Level-3	118
Satisfaction Level-4	108
Satisfaction Level-5	120
Satisfaction Level-6	113
Satisfaction Level-7	123
Satisfaction Level-8	121
Satisfaction Level-9	96
Total Record	1000

Table 2 shows the classifier performance of BCTSCM-WOA methodology under 80%TRAPHA and 20%TESPHA. The values in the table suggest that the BCTSCM-WOA methodology has attained an enhanced solution. With 80%TRAPHA, the BCTSCM-WOA model delivers an average $accu_y$, $prec_n$, $reca_l$, F_{score}, and $G_{Measure}$ of 97.64%, 89.39%, 89.42%, 89.35%, and 89.38%, respectively. Also, depending on 20%TESPHA, the BCTSCM-WOA approach provides average $accu_y$, $prec_n$, $reca_l$, F_{score}, and $G_{Measure}$ of 98.56%, 93.70%, 93.58%, 93.44%, and 93.54%, respectively.

Table 2: Classifier outcome of BCTSCM-WOA method under 80%TRAPHA and 20%TESPHA

Class Labels	$\boldsymbol{Accu_y}$	$\boldsymbol{Prec_n}$	$\boldsymbol{Reca_l}$	$\boldsymbol{F_{score}}$	$\boldsymbol{G_{Measure}}$
TRAPHA (80%)					
Satisfaction Level-1	96.88	90.70	82.11	86.19	86.29
Satisfaction Level-2	98.12	89.71	88.41	89.05	89.05
Satisfaction Level-3	97.12	89.01	86.17	87.57	87.58
Satisfaction Level-4	97.38	86.17	91.01	88.52	88.56
Satisfaction Level-5	97.50	88.79	92.23	90.48	90.49
Satisfaction Level-6	97.88	91.01	90.00	90.50	90.50
Satisfaction Level-7	98.00	89.13	93.18	91.11	91.13
Satisfaction Level-8	98.00	93.41	89.47	91.40	91.42
Satisfaction Level-9	97.88	86.59	92.21	89.31	89.35
Average	97.64	89.39	89.42	89.35	89.38

TESPHA (20%)					
Satisfaction Level-1	98.00	94.12	84.21	88.89	89.03
Satisfaction Level-2	99.50	100.00	94.44	97.14	97.18
Satisfaction Level-3	99.50	100.00	95.83	97.87	97.89
Satisfaction Level-4	100.00	100.00	100.00	100.00	100.00
Satisfaction Level-5	99.00	94.12	94.12	94.12	94.12
Satisfaction Level-6	97.50	87.50	91.30	89.36	89.38
Satisfaction Level-7	98.50	100.00	91.43	95.52	95.62
Satisfaction Level-8	98.50	92.59	96.15	94.34	94.36
Satisfaction Level-9	96.50	75.00	94.74	83.72	84.29
Average	98.56	93.70	93.58	93.44	93.54

Table 3 illustrates the average solution of the BCTSCM-WOA method under 70%TRAPHA and 30%TESPHA. Based on 70%TRAPHA, the BCTSCM-WOA methodology delivers average $accu_y$, $prec_n$, $reca_l, F_{score}$, and $G_{Measure}$ of 97.84%, 90.76%, 90.04%, 90.27%, and 90.33%, respectively. Furthermore, based on 30%TESPHA, the BCTSCM-WOA model provides an average $accu_y, prec_n$, $reca_l, F_{score}$, and $G_{Measure}$ of 97.04%, 86.20%, 85.62%, 85.59%, and 85.75%, correspondingly.

Table 3: Classifier outcome of BCTSCM-WOA method under 70%TRAPHA and 30%TESPHA

Class Labels	$\boldsymbol{Accu_y}$	$\boldsymbol{Prec_n}$	$\boldsymbol{Reca_l}$	$\boldsymbol{F_{score}}$	$\boldsymbol{G_{Measure}}$
TRAPHA (70%)					
Satisfaction Level-1	97.86	92.31	88.89	90.57	90.58
Satisfaction Level-2	98.00	96.00	80.00	87.27	87.64
Satisfaction Level-3	97.29	91.03	85.54	88.20	88.24
Satisfaction Level-4	97.71	90.59	90.59	90.59	90.59
Satisfaction Level-5	98.14	89.16	94.87	91.93	91.97
Satisfaction Level-6	98.00	88.61	93.33	90.91	90.94
Satisfaction Level-7	97.14	86.36	90.48	88.37	88.40
Satisfaction Level-8	97.57	87.63	94.44	90.91	90.97
Satisfaction Level-9	98.86	95.16	92.19	93.65	93.66
Average	97.84	90.76	90.04	90.27	90.33
TESPHA (30%)					

Satisfaction Level-1	96.67	84.85	84.85	84.85	84.85
Satisfaction Level-2	97.33	82.76	88.89	85.71	85.77
Satisfaction Level-3	96.00	92.59	71.43	80.65	81.33
Satisfaction Level-4	96.00	78.95	65.22	71.43	71.75
Satisfaction Level-5	98.00	90.91	95.24	93.02	93.05
Satisfaction Level-6	96.33	82.93	89.47	86.08	86.14
Satisfaction Level-7	98.33	90.48	97.44	93.83	93.89
Satisfaction Level-8	98.00	85.71	96.77	90.91	91.08
Satisfaction Level-9	96.67	86.67	81.25	83.87	83.91
Average	97.04	86.20	85.62	85.59	85.75

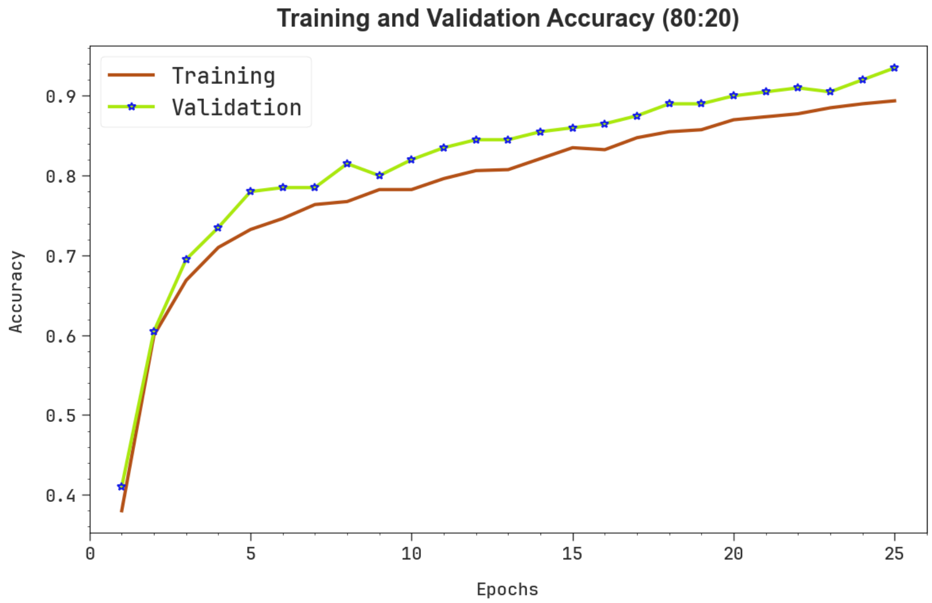

Figure 2. $Accu_y$ Curve of the BCTSCM-WOA model under 80:20

In Fig. 2, the training (TRAN) $accu_y$ and validation (VALN) $accu_y$ performance of the BCTSCM-WOA method under 80:20 is illustrated. The outcome emphasized that either $accu_y$ value shows an increasing trend that reported the capability of the BCTSCM-WOA technique with enhanced outcomes over multiple iteration counts. Additionally, the either $accu_y$endures closer over the epoch counts that specify minimum over-fitting and show superior outcomes of the BCTSCM-WOA methodology, ensuring consistent prediction on unseen instances.

In Fig. 3, the TRAN loss (TRANLOS) and VALN loss (VALNLOS) outcome of the BCTSCM-WOA approach under 80:20 is demonstrated. It is depicted that either value shows a reducing trend, reporting the ability of the BCTSCM-WOA to balance a trade-off between generalization as well as data fitting. The recurrent decrease in loss values moreover ensures the improved outcome of the BCTSCM-WOA method and adjusts the prediction outcomes over time.

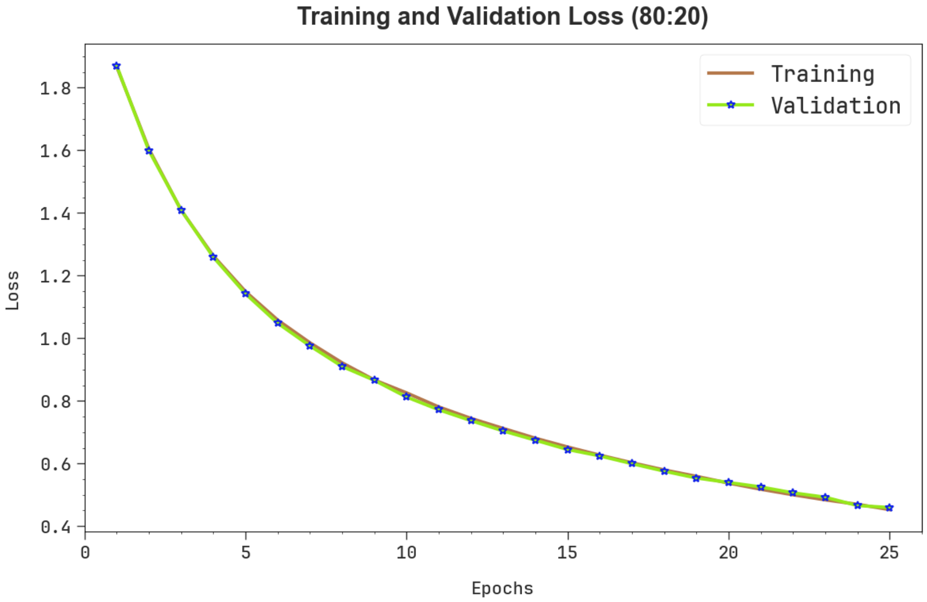

Figure 3. Loss curve of BCTSCM-WOA model under 80:20

The comparison results of BCTSCM-WOA approach with current approaches are illustrated in Table 4 [24-26]. The values in the table specify that the projected BCTSCM-WOA method outperformed enhanced solutions. Based on $accu_y$, the BCTSCM-WOA model has got greater $accu_y$ of 98.56% whereas the BiLSTM, TextCNN, Lightweight BERT, CatBoost, RoBERTa, AM-3D CNN, and RNN techniques attained lesser $accu_y$ of 90.44%, 92.20%, 89.47%, 94.81%, 91.53%, 91.98%, and 96.53%, correspondingly. Moreover, based on $prec_n$, the BCTSCM-WOA method has got superior $prec_n$ of 93.70% whereas the BiLSTM, TextCNN, Lightweight BERT, CatBoost, RoBERTa, AM-3D CNN, and RNN methods attained lesser $prec_n$ of 90.27%, 91.19%, 92.34%, 91.77%, 89.62%, 91.56%, and 90.27%, correspondingly. Furthermore, based on $reca_l$, the BCTSCM-WOA method has got greater $reca_l$ of 93.58% whereas the BiLSTM, TextCNN, Lightweight BERT, CatBoost, RoBERTa, AM-3D CNN, and RNN methods acquired smaller $reca_l$ of 92.93%, 91.48%, 92.18%, 91.85%, 90.07%, 91.46%, and 92.88%, correspondingly. Likewise, based on F_{score}, In addition, based on F_{score}, the BCTSCM-WOA method has got greater F_{score} of 93.44% although the BiLSTM, TextCNN, Lightweight BERT, CatBoost, RoBERTa, AM-3D CNN, and RNN techniques have gained lesser F_{score} of 90.17%, 89.38%, 90.52%, 89.50%, 93.02%, 91.65%, and 92.94%, correspondingly.

Table 4: Comparative outcome of the BCTSCM-WOA with existing models

Methodology	$\boldsymbol{Accu_y}$	$\boldsymbol{Prec_n}$	$\boldsymbol{Reca_l}$	$\boldsymbol{F_{score}}$
BiLSTM	90.44	90.27	92.93	90.17
TextCNN	92.20	91.19	91.48	89.38
Lightweight BERT	89.47	92.34	92.18	90.52
CatBoost	94.81	91.77	91.85	89.50
RoBERTa	91.53	89.62	90.07	93.02
AM-3D CNN	91.98	91.56	91.46	91.65
RNN	96.53	90.27	92.88	92.94
BCTSCM-WOA	98.56	93.70	93.58	93.44

5. Conclusion

In this study, we have presented a novel BCTSCM-WOA technique. The main goal of the BCTSCM-WOA method relies on improving the effectual model for tourism service customization. Initially, BC technology is applied to provide secure, transparent, and decentralized solutions for handling traveler data, payments, and service personalization. Then, the data pre-processing employs min-max scaling to transform input data into a suitable format. Besides, the COA to select the most relevant features from the data has executed the FS procedure. For the classification process, the proposed BCTSCM-WOA method projects the MASNN technique. At last, the parameter tuning process is performed through the WGO algorithm for refining the classification performance of the MASNN model. The experimental evaluation of the BCTSCM-WOA algorithm can be tested on a benchmark dataset. The extensive outcomes highlight the significant solution of the BCTSCM-WOA approach to the classification process when compared to existing techniques.

Funding: “The author gratefully acknowledges technical support provided by Department of Travel and Tourism Management, Faculty of Tourism, at King Abdulaziz University, Jeddah, Saudi Arabia”

Conflicts of Interest: “The authors declare no conflict of interest.”

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