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RESEARCH ARTICLE

Enhancing Online Food Service User Experience Through Advanced Analytics and Hybrid Deep Learning for Comprehensive Evaluation

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ABSTRACT User experience (UX) analysis of Online Food Delivery Services (OFDS) involves features like order placement efficacy, delivery tracking reliability, ease of navigation, menu visibility, and payment process simplicity. By examining these factors, OFDS offers can optimize its platforms to improve user satisfaction, streamline ordering procedures, minimize friction points, and improve customer retention. We can gain valued visions into customer opinions and preferences by connecting sentiment analysis, recommendation systems, feature extractors, and XAI platforms. Then, this information can be employed to develop the superiority of service, personalize UX, and finally develop customer fulfilment and platform victory. This paper presents a Reptile Search Algorithm with a Hybrid DL-based UX Detection (RSAHDL-UXD) approach on OFDSs. The RSAHDL-UXD approach utilizes data preprocessing and a word2vec-based word embedding process. For UX recognition, sliced multi-head self-attention slice recurrent neural network (SMH-SASRNN) methodology is employed. Finally, the hyperparameter tuning procedure was executed using RSA. To validate the upgraded performance of the RSAHDL-UXD methodology, a wide array of models was executed on manifold online food services datasets. The experimental outcomes stated that the RSAHDL-UXD model highlighted the superior accuracy of 98.57% and 93.33% on the Swiggy and Zomato datasets, respectively.

INDEX TERMS Online food delivery services, deep learning, artificial intelligence, reptile search algorithm, hyperparameter tuning.

I. INTRODUCTION

Customer satisfaction is most important in evaluating how a company's service or product meets customer prospects. It is a vital tool for organizations because it provides chief perceptions of their business, thus aiding them in enhancing their incomes or reducing marketing expenditures [1]. Generally, customer opinion or response may help study aspects not thought of beforehand, like secure packing, politeness, shipping, obtainable customer service specialists, and an accessible platform [2]. Nothing can make clients feel more essential than enquiring about their perspectives and respecting their feedback. Clients feel respected and related to the business When requested for their view about the product or service experiences [3]. In the food business, customers typically view restaurant reviews or feedback before

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placing their orders. In the present scenario, hotels or OFDS have a combined review method in their media platform [4]. However, only some act on client thoughts owing to the vast amount of analysis data on numerous websites and the absence of customer service experts who will review these remarks and perform on them. Currently, businesses only want to rely on experts to study some of the feedback as they can trust and use artificial intelligence (AI) to resolve their issues and save expenses [5].

Due to the high growth of OFDS platforms after COVID-19, OFDSs have changed the accessibility and diversity of hotels to luxury and handiness [6]. The growth in migration from dissimilar states has also increased the number of novel foods being presented. Customers are offered a wide variety of food choices and the ability to order and get food from popular restaurants or hotels in urban areas, such as their homes or workplaces, without any hassle [7]. With apps becoming a regular smartphone service and global positioning systems (GPS) made accessible to all, food supply to a customer's precise place is not a problem. Other features like performance expectations, navigational structure, and product usability can also affect customer happiness and satisfaction. For example, many research studies have inspected what impacts users' ability to download and utilize OFDS apps for the initial time [8].

The users can obtain the food delivery applications and improve their ease level so that they do not have any technical problems when utilizing them. Considering the decreasing occurrence of official issues more is needed to concentrate entirely on technical tolerability. Recognizing why customers desire to buy or purchase online is vital for food production. Several studies have proven a sturdy link between mindset and the need to assume novel technologies [9]. It is well recognized that customers are very excited to pay additional for amenities that save them energy, effort, and time while purchasing online. Present studies have offered that the values and preferences customers hunt from their purchases may also be important purchasing reasons [10]. Besides, both hedonistic and pragmatic thoughts support the decision to buy food online.

This work presents a reptile search algorithm with a hybrid DL-based UX detection (RSAHDL-UXD) technique on OFDSs. The primary objective of the RSAHDL-UXD system is to identify and classify UX. To accomplish this, the RSAHDL-UXD technique undergoes data pre-processing to convert input data into a beneficial layout, and the word2vec method is applied to the word embedding process. For UX detection, the sliced multi-head self-attention slice recurrent neural network (SMH-SASRNN) model. The hyperparameter tuning process was executed using RSA to enhance the detection results of the SMH-SASRNN system. To validate the amended performance of the RSAHDL-UXD methodology, many simulations have been executed on two online food services datasets. The critical contribution of the study is listed as follows.

- Presenting a novel RSAHDL-UXD system designed for OFDS platforms that proficiently navigates over massive food possibilities and preferences, improving the user's browsing experience by rapidly presenting appropriate selections.
- Execution of advanced pre-processing approaches to clean and establish data, ensuring the quality and reliability of input data for the following analysis stages.
- Improvement of a sophisticated SMH-SASRNN structure tailored for OFDS applications, leveraging self-attention mechanisms and RNNs to efficiently capture intricate user preferences and behaviours.
- The RSA is employed for parameter tuning, optimizing the efficacy of DL approaches in UX recognition on OFDS platforms. This ensures that the DL-based systems adjust to the specific requirements and features of the food delivery service domain.

The rest of the paper is organized as follows: Section II provides the related works, section III offers the proposed model, section IV gives the result analysis, and section V concludes the paper.

II. RELATED WORKS

Yahya et al. [11] projected a hybrid DL system to identify and categorize NFRs affording to the performance, trustworthiness, usability, and supportability of mobile applications utilizing natural language process techniques. It begins with a dataset production removed from the customer's textual feedback. The hybrid method integrates three DL frameworks: recurrent neural network (RNN) and dual long short-term memory (LSTM) techniques. Tao and Zhou [12] proposed a method to predict business conclusions. The presented model included numerous new artefacts, such as incorporating DL and time sequence analysis methods, removing data inserted in online feedback by executing a hybrid classification approach, and integrating a new multiple-word embedded technique for text representation. In [13], a new rating forecast model has been developed to afford the gated recurrent unit (GRU) DL technique with semantic features, including a dual-stage model. A BiGRU neural network was accepted in the primary stage, affording word attention. In the second stage, the method divides the customer's feedback into words and makes attention to semantic vectors depending on Latent Dirichlet Allocation and selected words. Then, the XGBoost model has been implemented to forecast customer preference ratings.

In [14], the research aims to cultivate a robust end-to-end architecture utilizing AI/Machine learning (ML) models. This technique reviews the ML and DL approaches with an explainable AI (XAI) model to forecast customer emotion in the FDS area. Moreover, it projects the execution of the XAI method using DL techniques to test the outcomes. Lastly, negative and positive views are gathered by employing a categorized model. Trivedi and Singh [15] developed a method that utilized Twitter as the data collection website where users' tweets associated with all three businesses have been raised by employing Lexicon-based and R-Studio sentiment analysis techniques used on the tweets made to the companies. An analytical process has been employed to calculate the total of dissimilar views. A negative and positive feeling word list is formed to equal the words on the tweets and depend upon the comments. In [16], a structure is recommended for uniting the convolutional neural networks (CNNs) and Bidirectional LSTM (BiLSTM) techniques. ConvBiLSTM is applied, a word-embedded method that utilizes mathematical values to denote tweets. The CNN takes the inputs feature implant and the lowest feature as an output. In this case, an elephant herd optimizer has been utilized to perfect the BiLSTM weights.

Khan et al. [17] projected a hybrid technique depending upon the RNNs method. This method utilized LSTM and GRU as forecast techniques, and GA optimizer was used equally to elevate the hybrid method. The technique picks the optimum training parameters by GA and flows LSTM with GRU. The method estimated the developed method's solution for a dissimilar number of customers. Rostami et al. [18] offered an Explainable Food Recommendation method that utilizes the visual food content in the recommendation system. Specifically, a novel resemblance score depends upon a trend that measures the level to which the customer community desires a particular food type and is presented and combined in the method.

While DL approaches have exposed potential in examining UX on OFDS, a vital research gap exists concerning the need for parameter tuning to optimize model performance. Present studies frequently deploy DL approaches for UX analysis on OFDS platforms that need to sufficiently address the task of adjusting model hyperparameters to suit the particular features of the food delivery domain. Hyperparameters like rate of learning, batch sizes, and network structures significantly affect the efficiency and robustness of DL-based UX analysis systems. Nevertheless, the optimum hyperparameter structure may vary depending on regional culinary preferences, user preferences, and restaurant diversity. Accordingly, there is a pressing requirement for research that systematically examines the effect of hyperparameter tuning on the performance and generalized abilities of DL approaches for UX analysis on OFDS environments. Addressing this gap can bring more reliable and productive UX analysis systems, eventually enhancing user satisfaction and arrangement in the online food delivery experience.

III. THE PROPOSED METHOD

In this work, we focus on designing and developing the RSAHDL-UXD model on OFDSs. The primary objective of the RSAHDL-UXD system is to identify and classify UX. The RSAHDL-UXD technique undergoes data preprocessing, classification model, and hyperparameter tuning process to accomplish this. Fig. 1 illustrates the complete procedure of the presented RSAHDL-UXD algorithm.

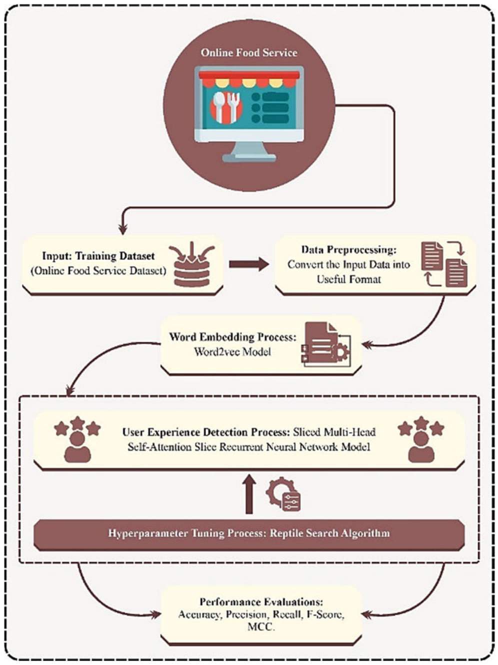

FIGURE 1. The overall process of the RSAHDL-UXD technique.

A. DATA PREPROCESSING

The RSAHDL-UXD technique endures data pre-processing to convert input data into a beneficial layout, and the word2vec system is applied to the word embedding process.

B. TWEET PRE-PROCESSING

Tweets regularly contain partial phrases, many noises, and poorly organized sentences because of abbreviations, non-dictionary terms, abnormal words, and incorrect grammar [19]. For these reasons, it is vital to create the rare text that is organized for removal. Almost all tweets have redundant content like hashtags, punctuation, emoticons, and symbols they consume to be clarified. The organized dataset was attained using numerous pre-process methods. The basic procedure used to clean the noise data is to eliminate redundant words that have no value in the sentiment analysis. With the aid of this technique, many symbols like links start with "http" in the texts, punctuation marks, numeric expressions, emojis, and user names (beginning with @ sign) in the manuscripts that belong to Twitter were detached. After, all the text content is changed to lowercase letters, and the spaces at the start and end of the texts have been detached.

C. WORD EMBEDDING

Effective text representation begins with a space of vector method for demonstrating text, mainly used to represent documents and later prolonged to a term or word representation. We utilized word embeddings to construct neural language techniques depending on word vectors with the help of the Word2Vec tool. Word embeddings are replications that are projected to maintain syntactic and semantic similarity.

TABLE 1. Summary of existing studies on online food service user experience.

Reference Number	Objective	Method	Dataset	Measures
Yahya et al. [11]	To propose a hybrid deep learning model to detect and classify NFRs of mobile apps using natural language processing methods	Deep Learning Recurrent Neural Network Long Short-Term Memory Machine Learning Classifiers	Two datasets	WODA, WDA, F1
Tao and Zhou [12]	This research investigates the prediction of business closure from online consumer reviews and validates the predictive models in the restaurant industry, which is subject to a relatively high attrition rate	Deep Learning Time-Series Analysis Techniques Hybrid Classification Method Triple Word Embedding Model	review data collected from TripAdvisors.com	Yelp online reviews
Lai et al. [13]	This paper introduces a novel rating prediction method using an attention-based GRU deep learning model with semantic aspects and XGBoost	Gated Recurrent Unit Deep Learning	Benchmark dataset	https://www.yelp.com/dataset
Adak [14]	This study aims to develop an end-to-end model utilizing AI/ML to anticipate customer sentiment accurately, employ XAI methods on DL models, and classify sentiments for process improvement and staff rewards.	Long Short-Term Memory Bidirectional Long Short-Term Memory Hybrid Embedded Bidirectional GRU LSTM CNN	Menulog, Deliveroo, Uber Eats and Youfoodz across Australia	Precision, Recall, F1_Score, OA
Trivedi and Singh [15]	A descriptive-analytical technique computes sentiment scores by matching words in tweets to positive and negative word lists, determining positive, negative, and neutral scores accordingly.	R-Studio and Lexicon-based sentiment analysis method	Benchmark dataset	Accuracy, Precision, etc.,

It has dual structures to signify words in multiple dimensions, such as a continuous bag of words (CBOW) and skip-gram (SG) systems. The CBOW method aims to learn embeddings by forecasting the leading term in a text and

TABLE 1. *(Continued.)* **Summary of existing studies on online food service user experience.**

Vatambeti et al. [16]	This study presents a framework joining CNN and Bi-LSTM methods, implementing ConvBiLSTM with word embedding and fine-tuning Bi-LSTM weights using elephant herd optimization.	Convolutional Neural Network Bi-directional Long Short-Term Memory	Standard dataset	Accuracy, Precision, etc.,
Khan, Byun, and Park [17]	A hybrid RNN technique is presented integrating LSTM and GRU, optimized implementing GA for hyperparameter tuning.	Recurrent Neural Networks Long Short-Term Memory Gated Recurrent Units Genetic Algorithm	Open-source dataset	Under diverse seasonal effects
Rostami et al. [18]	This study proposes an explainable food recommendation system that implements visual food content, a novel similarity score, and rule-based explainability for transparency.	Food Recommendation System	Crawled dataset (Standard dataset)	Precision, Recall, F1, and Normalized Discounted Cumulative Gain (NDCG)

screening the other words without esteeming their direction. The SG method employs the opposing technique of CBOW to specify the surrounding context words set the crucial word. In the Word2Vec technique, the SG method removes concept classification by vectorizing words. All prepared training data has been employed to form word embedding, and the vector size is 50.

D. UX DETECTION USING THE SMH-SASRNN MODEL

For UX detection, the SMH-SASRNN model can be applied in the classification model. RNN is commonly utilized in NLP challenges due to its capability to arrest the time-based features of the series but has the drawback of slow training speed [20]. Yu et al. developed the SRNN framework to create equivalent training probability to resolve the defects of RNN. Similarly, SRNN can take all the data from the series. SRNN cuts the unique sequences into many minimal sub-sequences of a similar extent. The characteristic data removed from every layer is conveyed to the system.

Set an input sequence, X of length T has been stated as:

$$X = [x_1, x_2, \ldots, x_T] \tag{1}$$

On the other hand, x denotes an input at every step.

Then, X is split into n equivalent length sub-sequences, and N is employed to signify the single sub-sequence length, which is:

$$N = \frac{T}{n}(2) \tag{2}$$

where n symbolizes the slice counts; therefore, the order X is conveyed as:

$$X = [N_1, N_2, \ldots, N_n] \tag{3}$$

Next, each sub-sequence N is separated into n equal-length sub-sequences again. The slicing process is repeated k times till it is cut into the essential minimal sub-sequence. The length of the minimal sub-sequence can be set as follows:

$$l_0 = \frac{T}{n^k} \tag{4}$$

s_0 represents the number of minimal sub-sequences, which is:

$$s_0 = n^k \tag{5}$$

The abovementioned is a summary of the SRNN principle. The input order length T is 8, and the slice numbers in every layer n is 2. Next, a new input series is cut into four minimal sub-sequences; every sub-sequence length is 2.

The attention module is a weighted average of elements with weight calculated according to the element's key and input query [21]. Query (Q) is the series for which attention is paid. Key (K) is the vector that identifies an element that requires further attention based on Q. The attention weight is averaged to attain the value vector (V). A score function determines the aspect that needs additional attention. The score function takes Q and K as input and outputs the attention weight of the query key pair.

$$SelfAttention\,(Q, K, V) = Softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{6}$$

The scaled dot product enables the DL network to attend over the sequence. However, the sequence has various features, and the single weighted average vector could not take it. Thus, the multi-head attention (MHA) exploits query-key-value triplets (heads) on similar features. Luong et al. first introduced self-attention, an attention module relating dissimilar positions of a single sequence to compute the representation of a similar sequence. Meanwhile, self-attention is u used, a similar sequence initializes K and V, and the respective matrices are renovated into n sub-values, sub-queries, and sub-keys and later passed over the scaled dot product. Then, the attention output from every head is fused, and the last weight matrix (W^O) is computed.

Then, the BiGRU layer pipelines the output from the MHA layer. Later, the production from the Bi-GRU layer is passed over the FC and Softmax layers to generate the prediction. Therefore, the output prediction O_{MHGRU} from these components is attained.

$$\begin{aligned} MultiHead(Q, K, V) &= Concat(head_1, \ldots, head_n)W^O \\ head_i &= SelfAttention\left(QW_i^Q, KW_i^K, VW_i^V\right), \end{aligned} \tag{7}$$

where W^Q, W^K, and W^V are the weight matrixes of K and V correspondingly/

The output prediction from the component is concatenated and passed over the FC layer to obtain the last prediction.

$$F : \Delta\left(O_{CNNT} \oplus O_{MHGRU}\right) \rightarrow Y \tag{8}$$

Initially, assumed that the new series X passes over the embedding layer. Every word X needs to be changed into the BERT representation, and this sequence has been used as input data for the Bi-SGRU system. Next, the SGRU method is divided into sub-sequences of equivalent length. The sequence length T is 8, and the most petite sub-sequence length is 2. Then, x_i refers to the i^{th} text, and x_{ij} denotes the word vector. Over the slicing model, the training speed is enhanced. The hidden layer (HL) of the sub-sequences on lth layer of the Bi-SGRU system is:

$$\overrightarrow{h_{ij}^1} = \overrightarrow{GRU}\left(x_{ij}, \overrightarrow{h_{i(j-1)}^1}\right) \tag{9}$$

$$\overleftarrow{h_{ij}^1} = \overrightarrow{GRU}\left(x_{ij}, \overrightarrow{h_{i(j-1)}^1}\right) \tag{10}$$

The output state attained via the MSA layer is as follows:

$$S = MultiHead\,(H, H, H) \tag{11}$$

where H denotes the HL state of every smallest sub-sequence of the Bi-SGRU system.

The MSA layer attains the resultant sequence S. The mathematical formulation is as follows:

$$\overrightarrow{h_t^2} = \overrightarrow{GRU}\left(s_{t\times\frac{m_0}{m_1}-l_0+1} \sim s_{t\times\frac{m_0}{m_1}}\right) \tag{12}$$

$$\overleftarrow{h_t^2} = \overrightarrow{GRU}\left(s_{t\times\frac{m_0}{m_1}-l_0+1} \sim s_{t\times\frac{m_0}{m_1}}\right) \tag{13}$$

where h_t^2 signifies the state of HL of the t-th sub-sequence of the SGRU system, m_0 denotes the number of minimal sub-sequences, m_1 represents the number of sub-sequences in the next layer, and l_0 refers to the length of the minimal sub-sequence.

The other states of HL in the SGRU system are as follows:

$$\overrightarrow{h_t^n} = \overrightarrow{GRU}\left(\vec{h}_{t\times\frac{m_{n-1}}{m_n}-l_n+1} \sim \vec{h}_{t\times\frac{m_{n-1}}{m_n}}\right) \tag{14}$$

$$\overleftarrow{h_t^n} = \overrightarrow{GRU}\left(\overleftarrow{h}_{t\times\frac{m_{n-1}}{m_n}-l_n+1} \sim \overleftarrow{h}_{t\times\frac{m_{n-1}}{m_n}}\right) \tag{15}$$

Eqs have attained the last output of the technique. (14) and (15). The forward system output is related to the backward system, and a softmax layer is included to categorize the labels. The mathematical formulation is as follows:

$$Y = concat\left(\vec{Y}, \overleftarrow{Y}\right) \tag{16}$$

$$P = softmax\,(W_Y Y + b_Y) \tag{17}$$

Meanwhile, W_Y and b_Y denote the training parameters.

E. RSA-BASED HYPERPARAMETER TUNING

Finally, the hyperparameter tuning process has been executed using RSA. The RSA attracts motivation from the behaviours of encircling and hunting crocodiles [22]. These behaviours include crocodiles functioning together to attack and arrest their target.

RSA utilizes an arithmetical model to mimic these actions and generate a population-based and gradient-free optimizer procedure. This means it can grab optimizer tasks of various difficulties, with or without exact restraints.

Phase of Initialization; RSA starts the optimizer by making possible solutions, signified as X in Eq. (18), over a stochastic method. Then, the process finds the optimum performance gained and reflects as an estimation of the optimum result in every iteration.

$$X = \begin{bmatrix} x_{1,1} & \cdots & x_{1,j} & x_{1,n-1} & x_{1,n} \\ x_{2,1} & \cdots & x_{2,j} & \cdots & x_{2,n} \\ \cdots & \cdots & x_{i,j} & \cdots & \cdots \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{N-1,1} & \cdots & x_{N-1,j} & \cdots & x_{N-1,n} \\ x_{N,1} & \cdots & x_{N,j} & x_{N,n-1} & x_{N,n} \end{bmatrix}. \tag{18}$$

The candidate solutions, X utilized in the RSA, are produced randomly through Eq. (19), $x_{i,j}$ denotes the solution value at the jth location in the ith candidate solution. N is the number of candidate solutions, whereas n refers to the problem size.

$$x_{ij} = rand \times (UB - LB) + LB, j = 1, 2, \ldots, n. \tag{19}$$

1) PHASE OF EXPLORATION

Dual exploration search techniques have been applied in the RSA. Each module has been assumed as a scaling factor to obtain various results and inspect dissimilar places. The location-updated equations applied in the exploration stage are intended to reproduce the nearby performance of crocodiles. They are provided in Eq. (20). Significantly, the procedure uses the most straightforward regulation to simplify this behaviour.

$$x_{(i,j)}(t+1) = \begin{cases} Best_j(t) \times -\eta_{(i,j)}(t)\, t \leq \dfrac{T}{4} \\ \times \beta - R_{(i,j)}(t) \\ \times rand, \\ Best(t) \times x_{(r_1,J)} t \leq 2\dfrac{T}{4} andt > \dfrac{T}{4}. \\ \times ES(t) \times rannd, \end{cases} \tag{20}$$

The values utilized in this equation contain $est_j(t)$, which signifies the location of the jth element. The integer $rand$ is formed randomly and sorts from 0 to 1. T denotes the upper bound, and t represents the current iteration count. Eq. (21) is employed to estimate the hunt operation, signified as for the jth position. Iterations are directed with a secure sensitive parameter, β, fixed to 0.1, to normalize the exploration accurateness at the time of the encircling stage. $R_{(i,j)}$ denotes a reduction function used to find the search region. Its calculation is defined by Eq. (22). r_1 represents the random amount produced among $[1N]$ and is employed to signify a stochastic position in i^{th} solution, denoted by $x_{(r_1,J)}$. The value of N indicates the amount of candidate results. The Evolutionary Sense ES (t) possibility ratio differs randomly between 2 and -2 at every iteration based on Eq. (23).

$$\eta_{(i,j)} = Best_j(t) \times P_{(i,j)}, \tag{21}$$

$$R_{(i,j)} = \frac{Best_j(t) - x_{(r_2 j)}}{Best_j(t) + \in}, \tag{22}$$

$$ES(t) = 2 \times r_3 \times \left(1 - \frac{1}{T}\right). \tag{23}$$

This equation defines a few variables employed in RSA and contains r_2, a random amount among $[1N]$, and $\in$, a small value. It also includes the usage r_3, which signifies an arbitrary value between -1 and 1. $P_{(ij)}$ is an additional variable that denotes the proportional variance. This calculation is executed utilizing Eq. (24).

$$P_{(i,j)} = \alpha + \frac{x_{(i,j)} - M(x_i)}{Best_j(t) \times \left(UB_{(j)} - LB_{(j)}\right) + \in}. \tag{24}$$

This excerpt clarifies the variables utilized in hunt cooperation. The average location of the present solution is represented by (x_i) and intended to utilize Eq. (24). $LB_{(j)}$ and $UB_{(j)}$ signify the lowest and upper limits of the jth location individually. The parameter α is set as 0.1 in this paper.

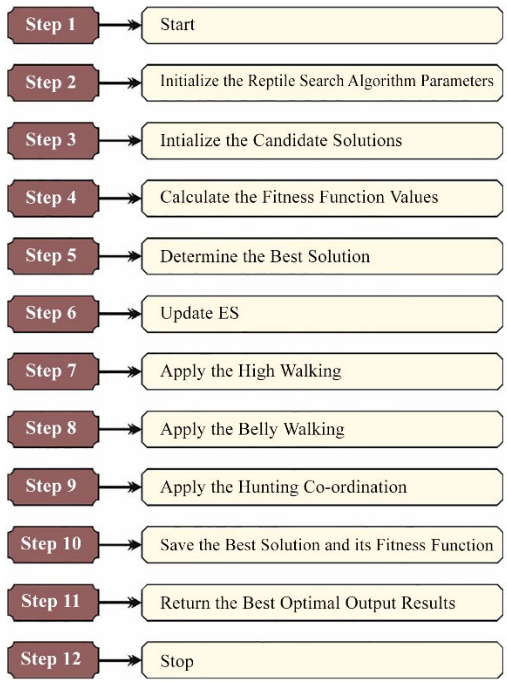

FIGURE 2. **Steps involved in RSA.**

Fig. 2 demonstrates the steps involved in RSA.

$$M(x_i) = \frac{1}{n}\sum_{j=1}^{n} x_{(i,j)}. \tag{25}$$

2) EXPLOITATION PHASE

The RSA method employs dual foremost search tactics, hunt cooperation and coordination, to inspect the search space and discover a perfect result. These tactics are displayed in Eq. (26) and are employed as exploitation devices.

$$x_{(i,j)}(t+1) = \begin{cases} Best_j(t) \times P_{(i,j)}(t)\, t \leq 3\dfrac{T}{4} andt > 2\dfrac{T}{4} \\ \times rand, \\ Best_j(t) - \eta_{(i,j)}(t)\, t \leq Tandt > \dfrac{3T}{4}, \\ \times \in -R_{(i,j)}(t) \\ \times rand \end{cases} \tag{26}$$

The jth position in the optimum solution attained till now is denoted by $Best_j(t)$. The hunting operator used to *the jth* position from the ith solution, represented as $\eta_{(i,j)}$, is considered utilizing Eq. (21). The difference ratio of the jth element in the present solution equated with the jth element is indicated by $P_{(i,j)}$, and calculated utilizing Eq. (24). $R_{(i,j)}$ represents the parameter applied to analyze the search space, whereas its value is defined using Eq. (22).

The RSA method develops a fitness function (FF) to attain a higher classification solution. It defines an optimistic integer to signify the superior candidate results. During this case, the classifier error values of minimization are measured as FF, as set in Eq. (27).

$$fitness\,(x_i) = ClassifierErrorRate\,(x_i) = \frac{NO.\ of\ misclassified\ instances}{Total\ no.\ of\ instances} \times 100 \quad (27)$$

IV. RESULT ANALYSIS AND DISCUSSION

In this part, the experimentation validation of the RSAHDL-UXD methodology has been tested employing two datasets [23]: the Swiggy and the Zomato datasets. The Swiggy dataset includes 100 instances with 2 class labels, as Table 2 defines. Next, the Zomato dataset contains 100 cases with 2 class labels, as represented in Table 3.

TABLE 2. Details on the Swiggy dataset.

Swiggy Dataset	
Classes	No. of Samples
Positive	50
Negative	50
Total Samples	100

TABLE 3. Details of the Zomato dataset.

Zomato Dataset	
Class Labels	No. of Instances
Positive	50
Negative	50
Total Instances	100

A set of measures used to examine the classification results are accuracy ($accu_{racy}$), precision (p□er cent), recall ($reca_{ll}$), and F-score (F_{score}).

Precision measures the proportion of correctly predicted positive instances out of all those predicted as positive.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (28)$$

Recallmeasures the proportion of positive samples correctly classified.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (29)$$

Accuracy measures the proportion of correctly classified samples (positives and negatives) against the total samples (number of samples that have been classified).

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \quad (30)$$

F-score is a measure combining the harmonic mean of precision and recall.

$$\text{F} - \text{score} = \frac{2\text{TP}}{2\text{TP} + \text{FP} + \text{FN}} \quad (31)$$

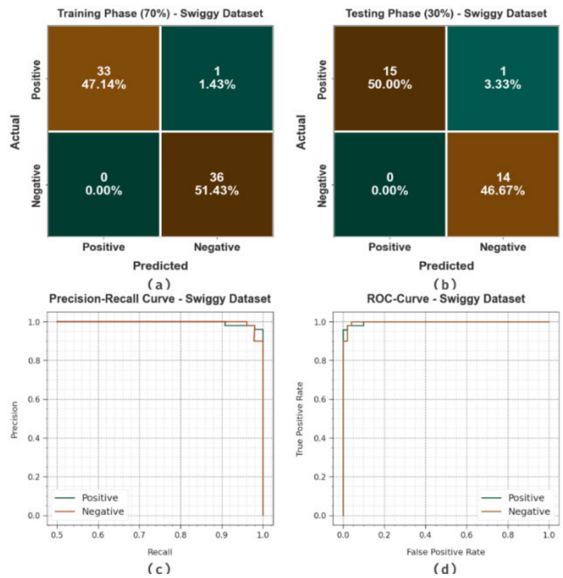

FIGURE 3. Swiggy dataset (a-b) confusion matrices and (c-d) PR and ROC curves.

Fig. 3 determines the classifier results of the RSAHDL-UXD model below Swiggy's dataset. Figs. 3a-3b describes the confusion matrices provided by the RSAHDL-UXD system on 70%:30% of TRPH/TSPH. The figure indicated that the RSAHDL-UXD model has identified and classified positive and negative classes. Also, Fig. 3c validates the PR study of the RSAHDL-UXD system. The figure stated that the RSAHDL-UXD approach has gained the highest PR result, below all class labels. Lastly, Fig. 3d validates the ROC study of the RSAHDL-UXD technique. The figure shows that the RSAHDL-UXD methodology has shown proficient results with high ROC values below disparate class labels.

In Table 4, the overall detection outcome of the RSAHDL-UXD algorithm is demonstrated with 70%:30% of TRPH/TSPH on the Swiggy dataset. The outcomes imply that the RSAHDL-UXD methodology accurately recognized the positive and negative instances. With 70% of TRPH, the RSAHDL-UXD methodology offers an average $accu_y$ of 98.57%, $prec_n$ of 98.65%, $reca_l$ of 98.53%, F_{score} of 98.57%, and MCC of 97.18%. Also, with 30% of TSPH, the RSAHDL-UXD methodology provides an average $accu_y$ of 96.67%, $prec_n$ of 96.67%, $reca_l$ of 96.88%, F_{score} of 96.66%, and MCC of 93.54%.

The $accu_y$ curves for training (TR) and validation (VL) projected in Fig. 4 for the RSAHDL-UXD model on the Swiggy dataset provide respected insights into its solution below several epochs. Mostly, there is a constant improvement in both $accu_y$ to rising epochs, signifying the method's capability to study and classify designs from both data. The increasing development in TS $accu_y$ highlights the methods given to the TR data and its ability to make detailed forecasts on unknown data, underscoring generalised solid processes.

Fig. 5 delivers a wide-ranging overview of the TR and TS loss values for the RSAHDL-UXD algorithm on the Swiggy

TABLE 4. The detection result of the RSAHDL-UXD technique on the Swiggy dataset.

Classes	$Accu_y$	$Prec_n$	$Reca_l$	F_{Score}	MCC
TRPH (70%)					
Positive	98.57	100.00	97.06	98.51	97.18
Negative	98.57	97.30	100.00	98.63	97.18
Average	98.57	98.65	98.53	98.57	97.18
TSPH (30%)					
Positive	96.67	100.00	93.75	96.77	93.54
Negative	96.67	93.33	100.00	96.55	93.54
Average	96.67	96.67	96.88	96.66	93.54

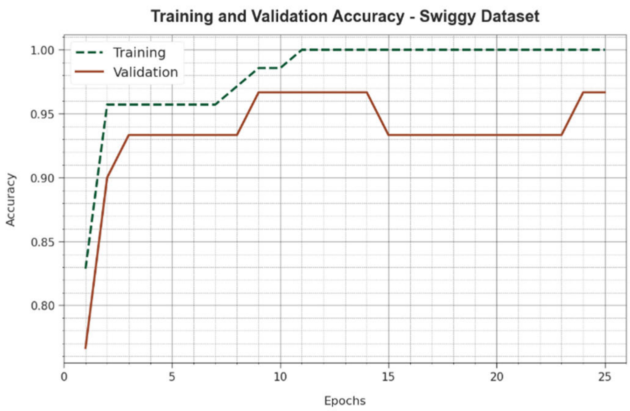

FIGURE 4. ***$Accu_y$* curve of RSAHDL-UXD technique on Swiggy dataset.**

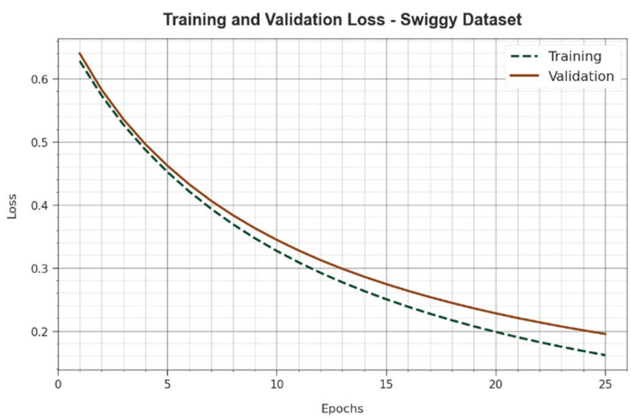

FIGURE 5. Loss curve of RSAHDL-UXD technique on Swiggy dataset.

database across various epochs. The TR loss reliably declines as the model upsurges its weights to decrease classification faults on both data. The loss curve outperformed the system's position with the TR data, underscoring its ability to capture outlines efficiently in both data. The constant adjustment of parameters in the RSAHDL-UXD algorithm is notable and projected to reduce variances among predictions and correct TR classes.

Table 5 provides a comparison study of the RSAHDL-UXD approach on the Swiggy dataset [16]. The results suggest that

TABLE 5. Comparative outcome of RSAHDL-UXD technique with other methods on SWIGGY dataset [16].

Swiggy Dataset				
Methods	$Accu_y$	$Prec_n$	$Reca_l$	F_{Score}
NN	87.51	87.63	87.51	87.50
LR	86.15	86.67	86.15	86.10
CNN	94.92	94.92	94.92	94.92
BiLSTM	96.96	97.00	97.00	97.00
BiLSTM-EHO	94.89	94.87	94.87	94.87
Conv-BiLSTM-EHO	98.08	98.09	98.08	98.08
RSAHDL-UXD	98.57	98.65	98.53	98.57

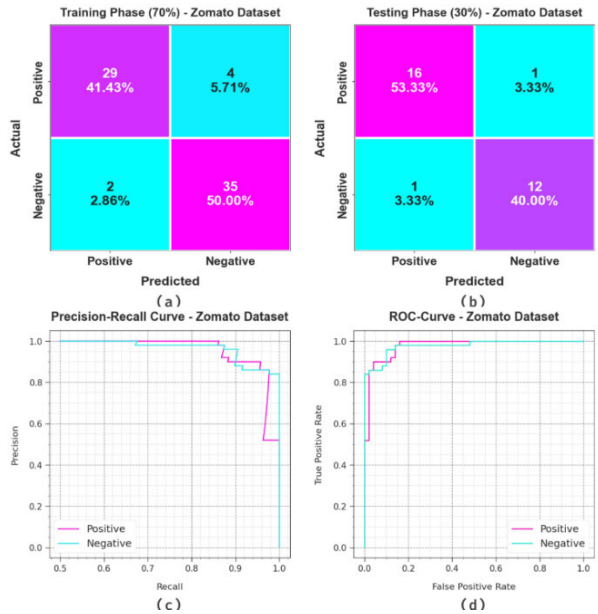

FIGURE 6. Zomato dataset (a-b) confusion matrices and (c-d) PR and ROC curves.

the NN and LR techniques reveal worse performance. At the same time, the CNN and BiLSTM-EHO approaches show closer results. Moreover, the BiLSTM and Conv-BiLSTM-EHO techniques achieve reasonable performance. However, the RSAHDL-UXD method gains maximal performance over other methods with $a_{naccuracy}$ of 98.57%, $aprec_n$ of 98.65%, a $recal_l$ of 98.53%, and an F_{score} of 98.57%.

Fig. 6 defines the classifier outcomes of the RSAHDL-UXD model below the Zomato database. Figs. 6a-6b portrays the confusion matrices attained by the RSAHDL-UXD methodology on 70%:30% of TRPH/TSPH. The experimental validation signified that the RSAHDL-UXD method has detected and classified positive and negative class labels. Similarly, Fig. 6c reveals the PR curve of the RSAHDL-UXD methodology. The figure specified that the RSAHDL-UXD system has obtained the most outstanding PR values in all classes. But, Fig. 6d explains the ROC outcome of the RSAHDL-UXD model. The figure represented that the RSAHDL-UXD algorithm has an outcome in proficient effects with maximum values of ROC below dissimilar classes.

In Table 6, the inclusive detection outcomes of the RSAHDL-UXD model are verified with 70:30 of TRPH/TSPH on the Zomato dataset. The consequences suggest that the RSAHDL-UXD methodology correctly recognized the positive and negative samples. With 70% of TRPH, the RSAHDL-UXD model offers an average $accu_y$ of 91.43%, $prec_n$ of 91.65%, $reca_l$ of 91.24%, F_{score} of 91.37%, and MCC of 82.88%. In addition, with 30% of TSPH, the RSAHDL-UXD methodology delivers an average $accu_y$ of 93.33%, $prec_n$ of 93.21%, $reca_l$ of 93.21%, F_{score} of 93.21%, and MCC of 86.43%.

TABLE 6. The detection result of the RSAHDL-UXD technique on the Zomato dataset.

Classes	$Accu_y$	$Prec_n$	$Reca_l$	F_{Score}	MCC
TRPH (70%)					
Positive	91.43	93.55	87.88	90.62	82.88
Negative	91.43	89.74	94.59	92.11	82.88
Average	**91.43**	**91.65**	**91.24**	**91.37**	**82.88**
TSPH (30%)					
Positive	93.33	94.12	94.12	94.12	86.43
Negative	93.33	92.31	92.31	92.31	86.43
Average	**93.33**	**93.21**	**93.21**	**93.21**	**86.43**

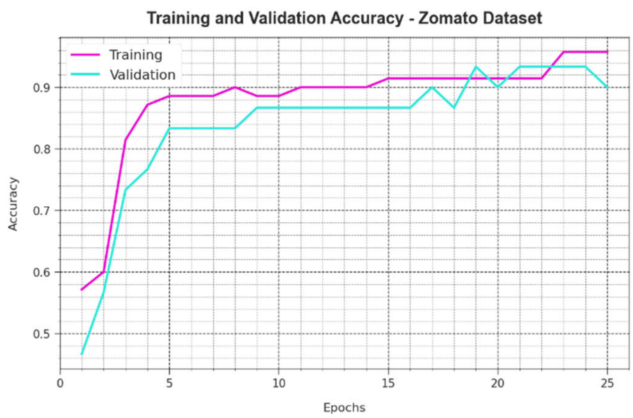

FIGURE 7. $Accu_y$ the curve of the RSAHDL-UXD technique on the Zomato dataset.

The $accu_y$ curves for TR and VL projected in Fig. 7 for the RSAHDL-UXD model on the Zomato dataset provide appreciated visions into its solution at numerous epochs. Mainly, there is continued growth in both $accu_y$ to developing epochs, demonstrating the method's capability to acquire and diagnose forms from both data. The increasing development in TS $accu_y$ highpoints the model gives to the TR data and its capacity to make specific predictions on unknown data, underlining generalised solid abilities.

Fig. 8 suggests a complete analysis of the TR and TS loss values for the RSAHDL-UXD technique on the Zomato dataset across several epochs. The TR loss regularly declines

FIGURE 8. Loss curve of RSAHDL-UXD technique on Zomato dataset.

as the method refines its weights to decline classifier errors on both data. The loss curves show the method's position with TR data, emphasizing its proficiency in capturing designs well in both data. Notable is the continuous fine-tuning of parameters in the RSAHDL-UXD algorithm, intended to reduce differences among actual and forecasted TR classes.

Table 7 offers a comparison research of the RSAHDL-UXD technique on the Zomato dataset. The results suggest that the NN and LR techniques display worse performance. At the same time, the CNN and BiLSTM-EHO approaches determine nearby results. Furthermore, the BiLSTM and Conv-BiLSTM-EHO methods achieve reasonable performance. However, the RSAHDL-UXD technique attains maximal performance over other methods with $accu_y$ of 93.33%, $prec_n$ of 93.21%, $reca_l$ of 93.21%, and F_{score} of 93.21%.

TABLE 7. Comparative result of RSAHDL-UXD technique with other models on the Zomato dataset [16].

ZomatoDataset				
Methods	$Accu_y$	$Prec_n$	$Reca_l$	F_{Score}
NN	60.33	75.18	60.83	53.78
LR	78.78	80.44	78.91	78.60
CNN Model	87.83	87.83	87.83	87.83
BiLSTM	88.48	88.48	88.48	88.48
BiLSTM-EHO	91.22	92.07	91.99	91.99
Conv-BiLSTM-EHO	92.24	92.39	92.24	92.24
RSAHDL-UXD	93.33	93.21	93.21	93.21

To validate the effectiveness of the proposed method, we focused on conducting a detailed experimental analysis and investigation of two datasets. A brief experimental analysis ensures the performance improvement brought by optimizing hyperparameters. Table 8 reports the experimental values obtained by the RSAHDL-UXD and HDL without the hyperparameter tuning process. The experimental values highlighted that the proposed model performs better by including a hyperparameter tuning process on both datasets. Thus, the RSAHDL-UXD technique can be applied to identify and classify UX for OFDSs.

TABLE 8. Performance analysis of the proposed model before and after using hyperparameter optimization.

Measures	Swiggy Dataset		Zomato Dataset	
	RSAHDL-UXD	HDL without hyperparameter tuning	RSAHDL-UXD	HDL without hyperparameter tuning
$Accu_y$	98.57	96.87	93.33	91.65
$Prec_n$	98.65	96.54	93.21	92.17
$Reca_l$	98.53	97.45	93.21	91.96
F_{Score}	98.57	97.47	93.21	92.08

V. CONCLUSION

In this work, we focus on the designs and growth of the RSAHDL-UXD methodology on OFDSs. The primary objective of the RSAHDL-UXD algorithm is to identify and classify UX. To accomplish this, the RSAHDL-UXD technique undergoes data pre-processing to convert input data into the beneficial layout, and the word2vec system has been executed for the word embedding model. For UX detection, the classification uses the SMH-SASRNN algorithm. The hyperparameter tuning process was executed using RSA to enhance the recognition results of the SMH-SASRNN system. To validate the amended performance of the RSAHDL-UXD approach, a considerable extent of experimentation has been performed on multiple online food services datasets. The experimental outcomes stated that the RSAHDL-UXD model highlighted the superior performance of 98.57% and 93.33% over other techniques under diverse datasets.

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