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Software Requirements Engineering and User Experience Design Modeling of Big Data Analysis using Convolution-Bidirectional Temporal Convolutional Network

Abstract: - The study of user perception and interaction with applications is referred to as user experience, or UX. The intricacy and versatility of software products, from requirements engineering to product functionality are well recognized. UX evaluations are often depends on prototypes, but it's important to consider the semantics embedded in software requirements to ensure project success. In this manuscript, Software Requirements Engineering and User Experience Design Modeling of Big Data Analysis using Convolution-Bidirectional Temporal Convolutional Network (SRE-UEDM-BDA-CBTCN) is proposed. The input data are collected from Requirements dataset. The collected data are given to the Convolution-Bidirectional Temporal Convolutional Network (CBTCN) to Design Modeling of Big Data Analysis user experience based on the dataset. In general, CBTCN does not express any adaption of optimization techniques for determining the ideal parameters to accurate Design user experience. Hence, African Vultures Optimization Algorithm (AVOA) is proposed in this work to improve the weight parameter of CBTCN. The proposed model is implemented and the efficiency is evaluated utilizing some performance metrics like accuracy, precision, specificity, sensitivity and F1-Score. The proposed SRE-UEDM-BDA-CBTCN method provides 28.46%, 21.34 and 33.81% higher accuracy, 22.88%, 26.52% and 34.63% higher Precision and 28.46%, 21.34 and 33.81% higher specificity compared with the existing techniques like Holistic big data integrated artificial intelligent modeling to improve privacy and safety in data management of smart cities (AIM-BDI-SDM), Exploring the factors that affect user experience in mobile-health applications: A text-mining and machine-learning approach (MHA-UED-MLA) and Towards Measuring User Experience based on Software Requirements (TM-UEB-SR).

Keywords: African Vultures Optimization Algorithm, Big Data Analysis, Convolution-Bidirectional Temporal Convolutional Network, Requirements dataset, User Experience.

I. INTRODUCTION

The User Experience (UX) refers to how people perceive and feel about systems or services. Quality in Use (QinU) encompasses UX concepts, as user perceptions can be influenced by both hedonic and pragmatic qualities of a system or software. Software UX often focuses on non-functional requirements and usability [1]. UX encompasses user satisfaction, usability, sentiments and a perception throughout the interaction. The user interface (UI) plays a crucial role in functionality, usability, reliability, satisfaction [2, 3]. Two separate factors affect usability: GUI and UX. This paper focuses on evaluating the user experience without a pre-built UI [4]. Therefore, post-release evaluations of user experience are not considered. Software UX Developed the UX-aware framework, which combines software and UX requirements [5, 6]. Based on the degree to which users are fulfilled with the program, the UX-aware framework defines UX criteria as quality requirements. Since prototypes and releases are usually used to evaluate UX, effective UX evaluation methods are applied early in the requirements development process [7]. The preliminary analysis is hampered by the lack of measuring measures or a benchmark dataset. UX measurement automation is a complex process that is frequently disregarded. These days, it has been suggested to use an agent to automate UX testing for certain tasks, like object recognition in game apps [8-10].To estimate and predict target variables, machine learning is widely applied in many fields. Reliable datasets are necessary for machine learning models to function well, albeit [11]. For UX based on software needs, there aren't any specific datasets available now. The lack of automated UX evaluation methods creates a research gap, requiring significant effort from UX evaluators [12, 13]. UX evaluators regret conducting manual evaluations like surveys. Unfortunately, evaluators must evaluate the UX utilizing an existing prototype and assessment methods. It is possible that requirements designers are not entirely aware of the early needs for UX software prior to obtaining prototypes. [14].Large datasets in requirements for software remain an important obstacle to cost-effective and quick app creation. Eliminating UX-compliant demands can lead to UX disregard in the end result as well as poor resource planning [15]. Automation of UX evaluation is limited by a lack of datasets and suitable evaluation models [16].

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The study intends to generate a dataset based on textual requirements for machine learning-based UX evaluation before software development. Use the User Experience Survey, a commonly used measure, to analyze user requirements [17]. The non-commercial requirements dataset, Requirements, serves as the foundation for the suggested benchmark datset. The research makes use of the most recent expanded Requirements dataset, which is part of the Requirements dataset repository that was recently upgraded [18].

A. Problem statement and Motivation

Requirements engineers may not fully understand early UX software requirements before creating prototypes. The timely and economic development of applications is still hampered by the need to manage large datasets of software needs. Eliminating UX-compliant demands can lead to poor product design and resource planning. These problems could lead to insufficient analysis results. These are motivated to do us this research work.

This paper aims to create a dataset for evaluating UX using Convolution-Bidirectional Temporal Convolutional Network and textual requirements before developing software. UX experts annotated user needs by utilizing a widely accepted scale, the User Experience Questionnaire. The non-commercial requirements datasets is utilized in the UX evaluation process for software applications in the proposed requirements dataset.

B. Contribution

- The major concepts of this research work is abridged below,
- Essential factors are necessary for successful software requirements engineering and user acceptance. The Requirements dataset facilitates UX evaluation through CBTCN models, rather than traditional methods like questionnaires or heuristic models.
- The research presented here helps software developers track software quality throughout its life cycle. Automated UX systems benefit software consumers and builders.
- This saves time and effort for software developers while also providing early feedback to consumers.
- In this paper is structured as: part 2 outlines literature review, part 3describes proposed method, part 4 proves result and discussions, part 5 offers conclusion.
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II. LITERATURE REVIEW

Among the frequent research studies on deep learning based User Experience Design Modeling of Big Data Analysis; some of the latest investigations were assessed in this part.

Chen et al. [19] have suggested comprehensive big data integrated artificial intelligence modelling to enhance security and privacy in smart city data management. To enhance the privacy and safety elements of data management interfaces across numerous applications for smart cities, the term holistic Big Data Integrated Artificial Intelligent Modelling was presented as part of the proposed solution to solve these problems. The differential evolutionary method was recently implemented in HBDIAIM to ensure sufficient safety for the personally identifiable information administration connected to applications for smart cities. In addition, the Big Data analytics assisted selection privacy method was utilized in the different evolutionary methods to improve the scalability and accessibility of information in a data managing interaction depend upon their respective place of storage. It provides high sensitivity and it provides low F1-score.

Pal et al. [20] have presented Utilizing machine learning and text mining to investigate the elements that impact user experience in mobile health applications. The suggested technology described analyzes user comments from popular mobile health platforms that weren't controlled. The variables that have an impact were found and separated into two main dimensions, such as strategic adoption and motivational membership, using topic modelling techniques. Findings indicate that time and cash, simplicity, adaptability, and accessibility are significant indicators of offering a positive user experience on mobile health systems. Then, it found that review polarity had significant influencing effects on indicators related to brand connection and hedonic drives like bookings via the internet and video discussion. I t provides high precision and low specificity.

Atoum et al. [21] have presented towards measuring user experience based on Software Requirements. Initially the method as provided builds a benchmark dataset for user experience (UX) using textual software requirements from multiple UX specialists. Second, a machine learning model to gauge user experience was developed by the study using the dataset. The presented study evaluates the statistical internal consistency and dependability of the dataset in addition to describing its features. The dataset has a low mean square root error and a high Cronbach Alpha, according to the results. It was shown that unique benchmark dataset was utilized to approximate UX immediately, doing away with the subjective evaluation necessities. Using the dataset, machine learning models based on UX elements were constructed. It provides high precision and it provides low accuracy.

Sadigov et al. [22] have presented deep learning-based user experience estimation in distance learning. In the presented method the efficacy of online education throughout the Covid-19 pandemic was assessed by employing posted tweets, analysis of sentiment, as well as topic modeling methods. Nearly 160,000 tweets describing circumstances connected to a significant change in the educational system were collected from the Twitter social network using deep learning-based sentiment analysis techniques. A long short term memory-based sentiment analysis model with word2vec embedding was used to evaluate the opinions of Twitter users during remote education, and the LDA method was utilized to create a topic model that identified the most discussed subjects on the platform. It provides high accuracy and low sensitivity.

Li et al. [23] have presented massive data analysis of the Internet of Things using deep learning in digital twins of smart cities. The proposed method seeks to perform big data analysis (BDA) on the enormous amount of data generated by the Internet of Things (IoT) in smart cities, resulting in a change toward fine management and secure, effective, and efficient data processing in the smart city. The research offers the deep learning (DL) algorithm with BDA and proposes a way for a convolutional neural network's distributed analogy strategy. According to DL, the DTs multi-hop dissemination IoT-BDA scheme was being used to construct a smart city, and technological advancements in multi-hop transmission are being utilized to both simulate and analyze the system's performance. It provides high precision and it provides low specificity.

Benzidia et al. [24] have suggested the effects of intelligence along big data analytics on hospital environmental performance and green supply chain process integration. The technology of big data analytics and artificial intelligence (BDA-AI) was increasingly prevalent in the approach presented. Expanded organizational processing of data theory was used to close this gap by introducing BDA-AI and presenting digital learning as a step in between the green manufacturing procedure. The study demonstrated that the integration of ecological processes and the cooperation of green supply chains were significantly impacted by the application of BDA-AI technology. The environment was another finding of the study. Environmental performance was significantly impacted by collaboration in green supply chains and process integration. It provides greater accuracy and less precision.

Ahmed et al. [25] have presented A Framework for Pandemic Prediction utilizing Big Data Analytics. The presented method indicates a health tracking structure for COVID-19 evaluation and forecasting. The structure makes use of Big Data analytics and IoT. It uses massive amounts of data to perform descriptive, diagnostic, predictive, and prescriptive analyses on an unusual real data set, with a focus on multiple global epidemic indications. The neural network-basis technique was intended to identify and forecast the global epidemic that benefits medical personnel. Make pandemic predictions with neural networks and equate the outcomes with those of other machine learning techniques. It provides high specificity and it provides low accuracy.

III. PROPOSED METHODOLOGY

In this section, Software Requirements Engineering and User Experience Design Modeling of Big Data Analysis using Convolution-Bidirectional Temporal Convolutional Network (SRE-UEDM-BDA-CBTCN) is proposed. The block diagram of proposed SRE-UEDM-BDA-CBTCN approach is illustrated in Figure 1. This process contains three steps including data Acquisition, classification and optimization. Accordingly, detailed description of all step given as below,

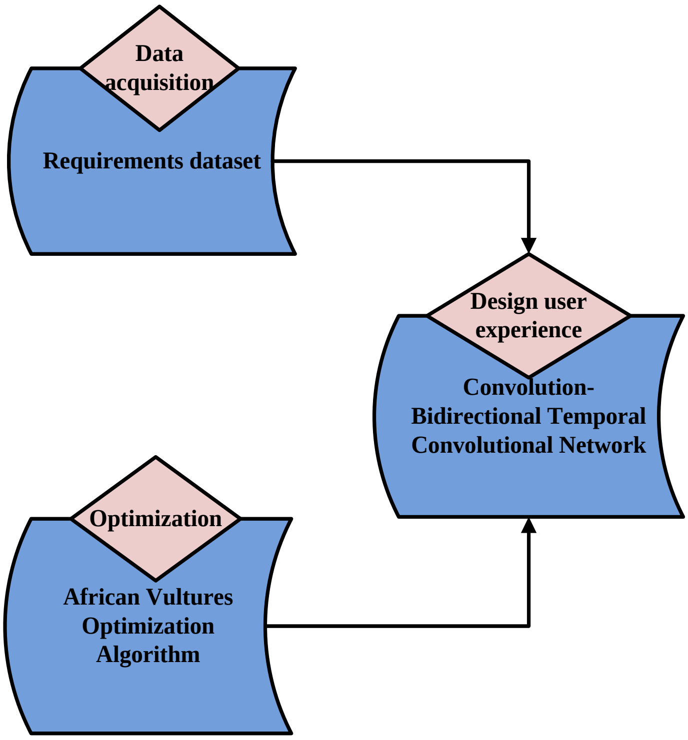

Figure 1: Block Diagram for proposed SRE-UEDM-BDA-CBTCN method

A. Data Acquisition

The data is gathered from Requirements dataset [26].It includes collection of 22 dataset of 50+ requirements each, expressed as user stories. All of these are available online or obtained from software companies with permission to be shared. Then, the Convolution Bidirectional Temporal Convolutional Network receives the gathered data as input.

B. Design of user experience using Convolution Bidirectional Temporal Convolutional Network

In this section, Convolution-Bidirectional Temporal Convolutional Network (CBTCN) [27] model is proposed for the Design Modeling of Big Data Analysis user experience. Establishing the user experience (UX) for a Big Data Analysis system that uses a Convolution-Bidirectional Temporal Convolutional Network (CBTCN) requires taking into account both the functionality provided by the model that underlies it and the interface that is used through which users interact with the system. The CBTCN is trained using appropriate techniques based on the available Big Data Analysis problem. Create a user experience interface for users to enter and upload their data. The complex features of the CBTCN model are abstracted from the user interface, resulting in a basic understanding of the model's objective and abilities. Design the user experience to be flexible, permitting users to connect and communicate with the Big Data Analysis system from a variety of devices and screens. Then, the Big Data Analysis of system is calculated in equation (1).

$$S^{j} = (S_1^{j}, S_2^{j}, \ldots, S_t^{j}, \ldots, S_{W-1}^{j}, S_W^{j}) \tag{1}$$

Where, S^{j} denotes the calculation of Big Data, S_1^{j} denotes value calculation of Big Data, S_t^{j} denotes value calculation of Big Data in time, S_{W-1}^{j} is the calculation of weight Big Data, S_W^{j} is the Big Data weight. Designing the user experience of a Big Data Analysis system is critical to ensure that users are able to communicate with and derive insights from the analyzed data. Then, the Big Data Analysis user experience is calculated in equation (2).

$$I_t^{j} = e(\sum_d N_w^{j-1} * S_t^{j} + a_t) \tag{2}$$

Where, I_t^{j} denotes the value calculation in user experience, e is the applied data, $\sum_d$ is the data in communication analyzed, N_w^{j-1} denotes number of weights in Big Data, S_t^{j} denotes value calculation of Big Data in time, a_t denotes time taken in the Big Data. Achieving an effective Big Data Analysis user experience requires striking a balance among strong statistical capabilities and an interface that is easy to use. Regularly including users in the design and testing process is critical to ensuring that the system Then the Design of Big Data Analysis is calculated by the equation (3).

$$\sum_{j=1}^{2} q_j = 1 \; j\xi(G, f * S) \tag{3}$$

Where, $\sum_{j=1}^{2} q_j$ denotes the Design of Big Data Analysis, j denotes consideration of Big Data value, ξ is the sigmoid value calculation, G is the general state of information, f denotes feature value in Big Data Analysis, $*S$ denotes multiple calculation of Big Data Analysis. By tackling these aspects during the design process, it is possible to create systems for Big Data Analysis system that is scalable, safe, user-friendly, as well as capable of extracting valuable insights from large and complex datasets. Then the Modeling of Big Data Analysis calculation is given in equation (4).

$$\sum_{j=1}^{2} q_j = 1 \; j\xi(G, f, j, a, k, s, l) \tag{4}$$

Where $\sum_{j=1}^{2} q_j$ denotes the Modeling of Big Data Analysis, ξ denotes sigmoid value calculation, G denotes general state of information, f implies feature value in Big Data Analysis, a is the analyze data, k denotes weight parameter value of data, l denotes length of data. Then the Design Modeling of Big Data Analysis user experience is given in equation (5).

$$e(c) = (Y * re)(c) = \sum_{j=1}^{t-1} e(j) * Y_{c-r.j} \tag{5}$$

Where, $e(c)$ denotes the applied data Modeling Analysis, $Y * re$ signifies represented applied data modelling, $\sum_{j=1}^{t-1}$ is the time taken consideration of Big Data Analysis user experience, $e(j)$ signifies the denotes the applied data consideration Modeling value, $Y_{c-r.j}$ denotes Design Modeling of Big Data Analysis. Allow users to customize model parameters and settings according to their specific analysis requirements. Create a clear and intuitive visual representation of the analysis results. Use data visualization methods to present knowledge obtained from the CBTCN model in a meaningful manner. Consider adding interactive components to ensure users are able to engage with the findings from the analysis. Finally, CBTCN is effectively Designed Modeling of Big Data Analysis user experience. In this work, AVOA is utilized to optimize the CBTCN. Here, AVOA is used for tuning the weight and bias parameter of CBTCN.

C. Optimization using African Vultures Optimization Algorithm

In this section, AVOA [28] is utilized to enhance the weight parameter of CBTCN. AVOA used to optimize CBTCN weight parameters which effectively analyze Design Modeling of Big Data Analysis user experience. The optimized weight parameters obtained through the AVOA driven optimization process are then applied within the CBTCN model to improve Big Data Analysis user experience. The AVOA algorithm principle is divided to five major stages, which are includes in the following steps.

Step 1: *Initialization*

In the initialization weight parameter is using the model is expressed in the form of Big Data Analysis which is used to calculate the Design Modeling in weight parameters of CBTCN is calculated in the equation (6).

$$b = \begin{bmatrix} b_{1,1} & b_{1,2} & \ldots & b_{1,b} \\ b_{2,1} & b_{2,2} & \ldots & b_{2,b} \\ \vdots & \vdots & \vdots & \vdots \\ b_{b,1} & b_{b,2} & \ldots & b_{a,b} \end{bmatrix} \tag{6}$$

Where, b denotes the parameter weight calculation in the Big Data Analysis user experience, $b_{a,b}$ is the number of parameter weight calculation in the user experience.

Step 2: *Random generation*

The $S^j, e(c)$ weight parameter is created at random through CBTCN method after initialization.

Step 3: *Fitness Function*

A random solution is generated using initialized evaluations. Using parameter optimization value, fitness function is evaluated for optimizing weight parameter $S^j, e(c)$ of the design. This is given in the equation (7),

$$Fitness\ Function = [optimizing\ S^j, e(c)] \tag{7}$$

Step 4: *Exploration phase*

Exploration phase is used to evaluate the weight parameter in optimization. The CBTCN weight parameter can be used to improve the calculation. Then, calculates the evaluation of each optimization vector is given in the equation (8).

$$q(j+1) = D(j) - |r(k)| * e * com(r)\ \ q_2 < d_{\max} \tag{8}$$

Where $q(j+1)$ denotes the quality of Big Data value consideration, $D(j)$ denotes design of user experience, $r(k)$ is the weight parameter of data, $com(r)$ denotes requirements of data, $q_2 < d_{\max}$ is the calculation of maximum quality. Then the user experience value is calculated in equation (9).

$$c_1 = D(j) * (\frac{d * q(j)}{2\eta}) * \cos(q(j))\ \ q_2 d \tag{9}$$

Where, c_1 signifies user experience value, $D(j)$ signifies design of user experience, d signifies data, 2η denotes value calculated in user, $\cos(q(j)$ denotes analyzing the value of data, $q_2 d$ quality of data value in user experience. Then the software requirements efficiency is calculated in equation (10).

$$c_2 = D(j) * (\frac{d * q(j)}{2\eta}) * \sin(q(j))\ \ q_2 d \tag{10}$$

Where, c_2 denotes the user experience second value, $D(j)$ denotes design of user experience, d implies data, $\sin(q(j)$ denotes software requirements efficiency.

Step 5: Exploitation phase for optimizing $S^j, e(c)$

The term exploitation of weight parameter calculation refers to the process of optimizing the model's weights to improve its accuracy in Design Modeling of Big Data Analysis user experience using CBTCN models proposed method is mathematically expressed in equation (11)

$$q(j+1) = d(j) - h(j) * E\ \ q_1 \geq d_{q_1} \tag{11}$$

Where, $q(j+1)$ denotes the denotes the quality of Big Data value consideration, $h(j)$ implies hyper parameter of user experience, E signifies energy efficiency, $q_1 \geq d_{q_1}$ denotes quality of value analyzed in software requirements. Then the quality of Big Data second value consideration is mathematically expressed equation (12).

$$q(j+2) = d(j)S^j - E + d_{q_1} * (va - ha) * d_{q_1} + ha \tag{12}$$

Where, $q(j+1)$ denotes the quality of Big Data second value consideration, $d(j)$ implies data value consideration, va signifies parameter value of data, ha denotes parameter value of optimized data, d_{q_1} quality of value analyzed. Then, the weight parameter value of data is calculated in equation (13).

$$k = g * (\sin^k(\frac{\eta}{2} * \frac{j}{j_{\max}}) + \cos(\frac{\eta}{2} * \frac{j}{j_{\max}}) - 1) \tag{13}$$

Where k denotes the weight parameter value of data, $g*$ is the multiplication value of modeling big data, $\sin^k$ is the optimized weight parameter, $\frac{\eta}{2}$ is the number of value calculated in big data analysis, $\frac{j}{j_{\max}}$ is the maximum value of user data.

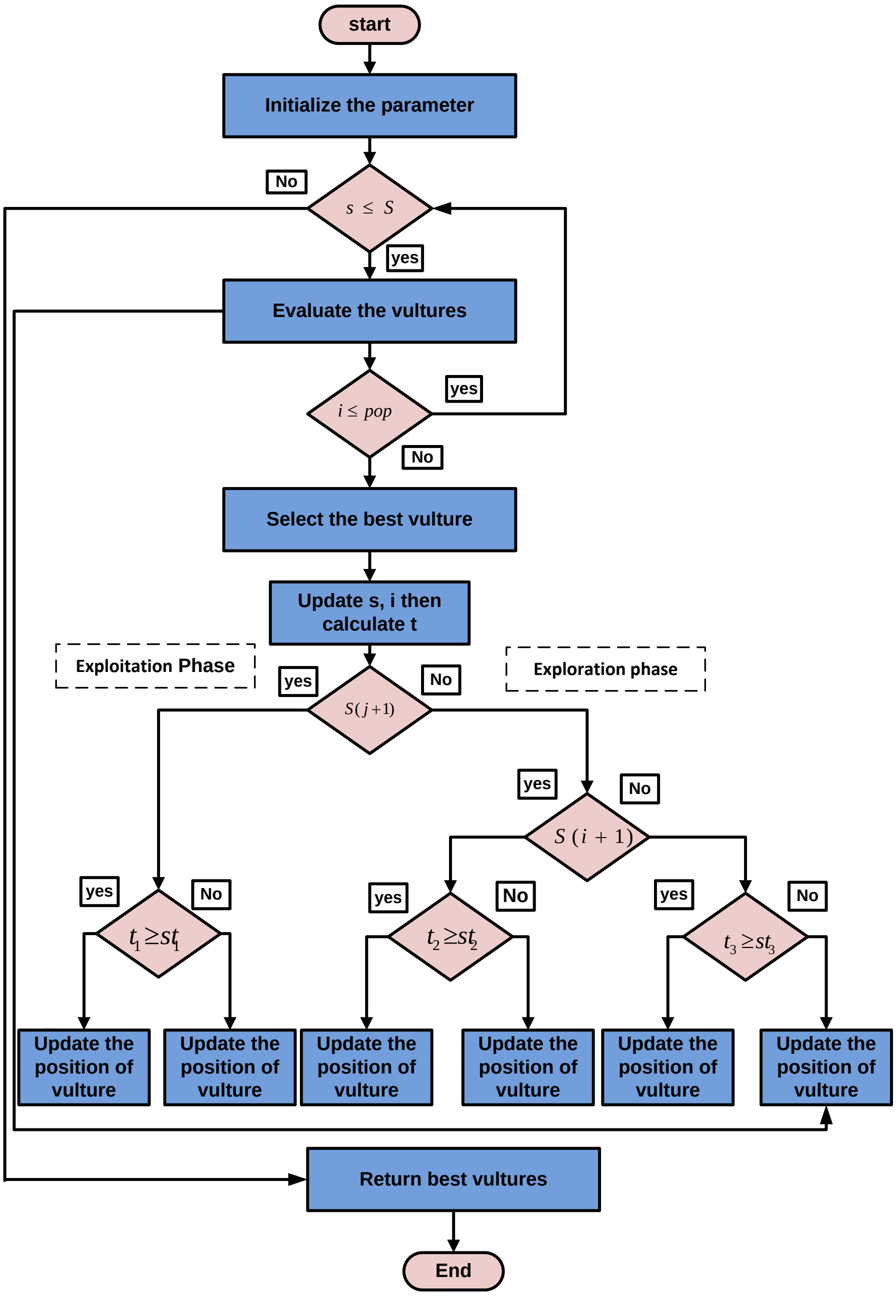

Figure 2: Flowchart of AVOA for optimizing CBTCN parameter

Step 6: Termination

Finally, the factor $S^j, e(c)$ is optimized by AVOA; will repeat step 3 till it reaches halting criteria $b = b + 1$ is met. CBTCN is optimized with AVOA effectively for better accuracy. Thus the proposed SRE-UEDM-BDA-CBTCN methods effectively design the user experience with greater accuracy with lesser computation time.

IV. RESULT AND DISCUSSION

The experimental outcomes of proposed SRE-UEDM-BDA-CBTCN are discussed. The proposed technique is implemented in python. The performance of proposed technique is comparing to the existing AIM-BDI-SDM [19], MHA-UED-MLA [20], and TM-UEB-SR [21] methods respectively.

A. Performance Metrics

It is assessed to scale the efficacy of the proposed technique. It is an important task for ideal classifier selection. The performance is evaluated using several performance metrics including accuracy, precision, specificity, sensitivity and F1-Scoreareexamined.

1) Accuracy

The Accuracy is a metric used to evaluate a detection system's performance in correctly identifying instances within a given dataset, categorized as design the user experience. Then the calculation of Accuracy is given in eqn (14).

$$Accuracy = \frac{(TP+TN)}{(TP+FP+TN+FN)} \tag{14}$$

Here, TP denotes true positive, TN signifies true negative, FP symbolizes false positive, FN represents false negative.

2) *Precision*

Precision measures the ability of system to detect positive cases correctly out of all predicted positive cases. It is the ratio of true positives to the total false and true positives. This is determined by equation (15),

$$\Pr ecision = \frac{TP}{(TP+FP)} \tag{15}$$

3) Sensitivity

The ratio of accurately predicted positive (true positives) among the actual positive instances is sensitivity. It is assesses the capacity to detect positive instances correctly which is computed by eqn (16).

$$sensitivity = \frac{TP}{TP+FN} \tag{16}$$

4**)** *Specificity*

It weights the efficacy of the approach on one class by approximating the probability that the expression is given the specificity in the equation (17).

$$Specificity = \frac{(TN)}{(FP+TN)} \tag{17}$$

5) F1-*Score*

The harmonic mean of precision and sensitivity is F1-score. It is widely used as an evaluation metric that combines precision and sensitivity to a single metric to gain a better understanding the model performance. It can be computed by equation (18).

$$F1-score = \frac{TP}{TP+FN} \tag{18}$$

B. *Performance* Analysis

Figure 3 to 7 depicts the experimental results of accuracy, precision, specificity, sensitivity and F1-Scoreare analyzed for the proposed SRE-UEDM-BDA-CBTCN method is compared with existing AIM-BDI-SDM, MHA-UED-MLA and TM-UEB-SR methods respectively.

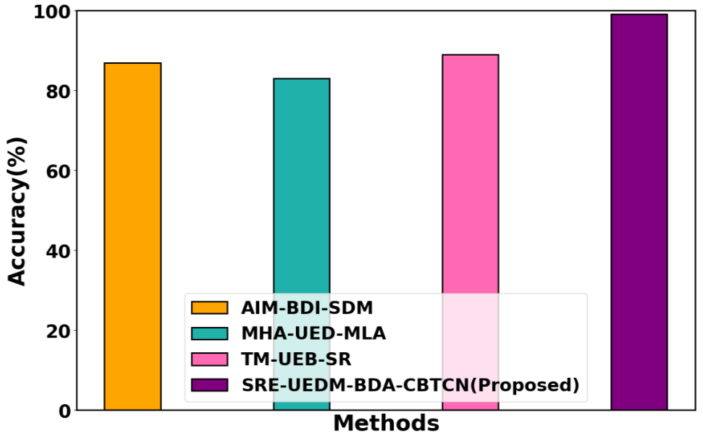

Figure 3: Performances analysis of accuracy

Figure 3 depicts accuracy. The proposed SRE-UEDM-BDA-CBTCN method Design user experience provides 28.46%, 21.34 and 33.81% greater accuracy compared with existing AIM-BDI-SDM, MHA-UED-MLA and TM-UEB-SR methods respectively.

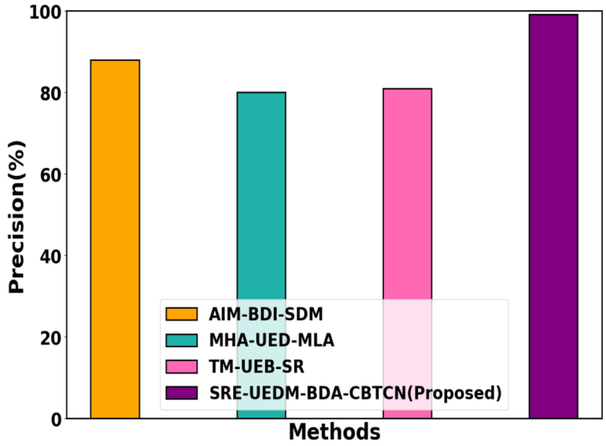

Figure 4: Performances analysis of Precision

Figure 4 depicts Precision. The proposed SRE-UEDM-BDA-CBTCN method Design user experience provides 22.88%, 26.52%, 34. 63% greater Precision compared with the existing AIM-BDI-SDM, MHA-UED-MLA and TM-UEB-SR methods respectively.

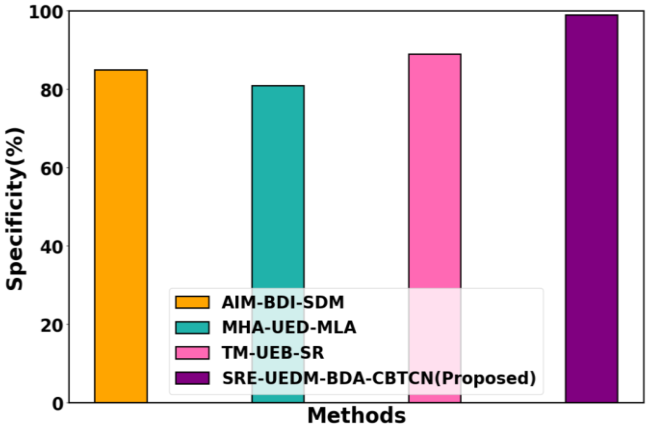

Figure 5: Performances analysis of specificity

Figure 5 depicts specificity. The proposed SRE-UEDM-BDA-CBTCN method Design user experience provides the 28.46%, 21.34 and 33.81% higher specificity compared with existing AIM-BDI-SDM, MHA-UED-MLA and TM-UEB-SR methods respectively.

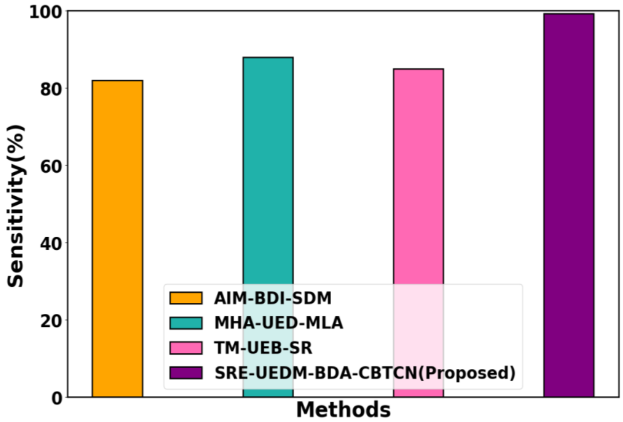

Figure 6: Performances analysis of sensitivity

Figure 6 depicts sensitivity. The proposed SRE-UEDM-BDA-CBTCN method Design user experience provides the 22.37%, 27.89%, and 31.37% greater sensitivity compared with existing AIM-BDI-SDM, MHA-UED-MLA and TM-UEB-SR methods respectively.

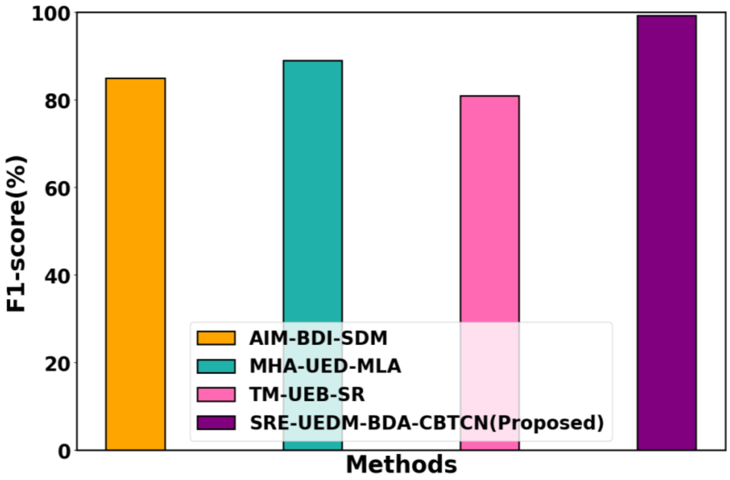

Figure 7: Performances analysis of F1-Score

Figure 7 depicts F1-Score. The proposed SRE-UEDM-BDA-CBTCN method Design user experience provides the 19.52%, 25.65%, and 29.82% greater F1-Score compared with the existing AIM-BDI-SDM, MHA-UED-MLA and TM-UEB-SR methods respectively.

C. Discussion

The various CBTCN models are trained and tested using cleaned the data approaches. During the experiment, changed the hyper parameters that shape the CBTCN Change a single parameter and the others will be fixed. It also successfully developed CBTCN-models that Design Modeling of Big Data Analysis by user experience. Design Modeling of Big Data Analysis in the proposed SRE-UEDM-BDA-CBTCN method accuracy is 28.46%, 21.34 and 33.81% higher than existing methods such as AIM-BDI-SDM, MHA-UED-MLA and TM-UEB-SR respectively. Similar to this, the precision of proposed method is 98.78% analyzed with sensitivity of comparison techniques of 88.67%. Therefore, the comparative methods are expensive than the proposed technique. As a result, the proposed technique Design Modeling of Big Data Analysis by user experience is effectively and efficiently.

V. CONCLUSION

In this manuscript, Software Requirements Engineering and User Experience Design Modeling of Big Data Analysis using Convolution-Bidirectional Temporal Convolutional Network (SRE-UEDM-BDA-CBTCN) is successfully implemented. The proposed method describes the User Experience Design Modeling of Big Data Analysis. The dataset enables software engineers to predict an application's user experience before creating a Data. Furthermore, the dataset can assist software engineers in creating UX-compliant and customer-specific requirements. The proposed SRE-UEDM-BDA-CBTCN method is executed in Python. The Performance metrics are analyzed. The proposed SRE-UEDM-BDA-CBTCN method provides 22.37%, 27.89%, and 31.37% higher sensitivity; 19.52%, 25.65%, and 29.82% higher F1-Score is compared with existing method such as AIM-BDI-SDM, MHA-UED-MLA and TM-UEB-SR methods respectively.

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