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Original Article

Whale Optimization Algorithm with Deep Learning-Based Usability Recommendation Model for Medical Mobile

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Abstract *- Mobile applications or 'apps' assist people in managing health and chronic illnesses have become common and gained significant attention. But in-depth analysis is needed to know about the acceptability and usability for low-income, ethnically/nationally different populations who face a disproportionate chronic disease problem and its complications. The study intends to examine the usability of mobile medical applications to avail development and tailoring of patient-facing apps for various populations. In this view, this study develops a novel Whale Optimization Algorithm with long short-term memory (WOA-LSTM) Based Usability Recommendation Model for Medical Mobile Applications. A survey was conducted using a set of questionnaires for software quality assurance and software quality management practices. In this case, the LSTM model is employed for the recommendation process. The hyperparameters involved in the LSTM model are optimally tuned by WOA, resulting in improved performance. The WOA-LSTM model produces context-specific judgment and generalized suggestions for App recommendation in related extreme samples. A series of experiments were carried out to determine the effective performance of the WOA-LSTM model, and the results pointed out the efficient outcomes on user recommendation.*

Keywords *- Deep learning, Usability recommendation, Medical mobile application, Recommendation model, Whale optimization.*

1. Introduction

Extensive Usage of smartphone techniques has been adapted for upgrading health and healthcare conveyance. Also, a massive number of healthcare applications were proposed with the help of a massive number of healthcare applications. To monitor, plan and attain healthcare objectives, several healthcare applications might be taken into account as beneficial and effective in the area [1]. The smartphone progressively creates a position in day-to-day life and has greater value in day-to-day routine work. Nowadays, they serve a wide-ranging function and features compared to the previous one. IOS applications and Android are widely employed [2, 3]. Over the last few decades, the adaptability of smartphones has led to a noteworthy development in the healthcare field. At present, in the Google Play store (operating system: Android, developer: Google), over 700,000 applications are presented, and in Apple App Store (operating system: IOS, developer: Apple), more than 900,000 applications are presented. The smartphone technique has made lots of lives quick and easy worldwide, as an entertaining device and a life-saving technique, from implanted medicinal gadgets to the instrument that tracks major signs of smartphones, namely smartwatches [4]. Usage of health care application as a game modifier in the health care field. At first, considerably improving patient knowledge and then boosting the productivity are the two major fields of health care that require instantaneous consideration [5, 6]; efficiency and Speed play a major part in determining health care organization, as well as trying to enhance the patient knowledge for higher-quality treatment.

Specialists have recommended that mobile technology is pervasive, applications reduce barriers to engaging in positive healthcare behavior, and self-manage chronic conditions [7, 8]. But there are concerns regarding the technology widening the digital division when privileged populations take advantage of them. Especially, it might be significant to tailor this technology to different collections to make it advantageous for varied viewers, reduce costs, and progress healthcare quality. Furthermore, there is growing attention amongst underserved or vulnerable populations in exploiting mobile healthcare for managing diabetes [9]. Earlier indication has recognized very poor usability of healthcare system internet-based patient portal websites amongst an elder, ethnically or racially different patient population. Furthermore, researchers have recognized mobile healthcare application usability barriers for elder patients [10]. When studies have estimated the usability of diabetes application, some researchers have inspected the usability of commercially presented mobile applications amongst end-users—particularly amongst largely low-income countries.

Overdijkink et al. [11] aim to estimate the usability, acceptability, feasibility, and efficiency of mHealth lifestyle and medicinal applications to assist health care during pregnancy in higher-income nations. Acceptability was evaluated by appreciation, client fulfillment, and the reference of the application. Feasibility is determined by the continued use, intention, interest, and actual use; apparent correctness; and capacity of the user to perform the application's activity. Cruz Zapata et al. [12] presented a software requirement catalog for usable smartphone applications to expand new applications or assess present ones. The presented method depends on the recognized source in research on usability and mobile healthcare application. The presented method was prepared based on the ISO/IEC/IEEE 29148:2011 standard and following the SIREN method to construct a reusable catalog.

This study develops a novel Whale Optimization Algorithm with long short-term memory (WOA-LSTM) Based Usability Recommendation Model for Medical Mobile Applications. A survey was conducted using a set of questionnaires for software quality assurance and software quality management practices. In this case, the LSTM model is employed for the recommendation process. The hyperparameters involved in the LSTM model are optimally tuned by WOA, resulting in improved performance. The WOA-LSTM model produces context-specific judgment and generalized suggestions for App recommendation in related extreme samples. A series of experiments were carried out to determine the effective performance of the WOA-LSTM model

2. Materials and Methods

This study has developed a novel WOA-LSTM model for mobile medical applications as a usability recommendation model. In this case, the LSTM model is employed for the recommendation process.

2.1. Selection Stage

App advertised as health-based needs to experience peer view beforehand to overview, like a medicinal survey. Other approaches to get responses from professional and normal users such that software engineers might discuss, extrapolate, and recommend modification. Health assurance accountability needs to be measured in electronic record security, health information privacy, insurance portability, and administrative simplification. App source needs to be scrutinized frequently for systematic derivation.

2.2. Review Assessment (RA) Stage

Review Assessment of SQA and SQM Practices is a portion of the Review Assessment Phase. The process for MMA - Software Quality Management and Software Quality Assurance [13]. Then, guarantee that the question is appropriate to the embedded software sector and captures the vital data related to the survey purpose and RQ when creating the assessment questions.

2.3. Data Inference Analysis (DIA) Stage

The mobile device captures a massive amount of information on user behavior, preference, and habit because of the recurrent communication with them in day-to-day life, making them an attractive resource for ML applications. GRA is a subdivision of the grey concept developed for handling partial and imprecise information in grey systems and has proven effective in defining the optimal solution [14]. The fundamental operation of GRA is to construct the grey linking, offer the sequential reference, and calculate the grey relation coefficient and grey relation grade

2.4. WOA-LSTM based Integration Stage

LSTM is a special kind of RNN, where the hidden layer is comprised of more than one memory cell, and every memory cell comprises output, forget, and input gates [15]; (1) Forget gate:

The forget gate f_t is accountable for controlling the long-term state c continues to be retained and is defined as the input x_t of the existing moment t and the output h_{t-1} of preceding moment $t-1$ and mathematically expressed in the following

$$f_t = \sigma\left(W_f \times [h_{t-1}, x_t] + B_f\right) \tag{1}$$

In which w_f denotes the weight matrix of the forgetting gate; B_f characterizes the bias term, and $\sigma(\cdot)$ characterizes the sigmoid function.

(2) Input gate:

The function of the input gate is to determine a new unit state $\tilde{c}$ and control how much data is added, and it is defined by [16]:

$$i_t = \sigma(W_i \times [h_{t-1}, x_t] + B_i) \tag{2}$$

$$\tilde{c} = tanh(W_c \times [h_{t-1}, x_t] + B_c) \tag{3}$$

Whereas W_i denotes the weight matrix of the input gate; i_t represents the input gate result; $\cdot\ \tilde{c}$ signifies the present input cell state; B_i indicates the bias of the input gate; B_c characterizes the bias of cell state, and W_c embodies the weight matrix. The matrix $[h_{t-1}, x_t]$ comprises two vectors, the output h_{t-1}at the preceding moment $t-1$ and the input x_t at the present moment. $\tanh(\cdot)$ denotes a double tangent function, and $\sigma(\cdot)$ shows the sigmoid activation.

(3) Output gate:

In the output gate, the output h_{t-1} of the preceding moment $t-1$ and the input x_t of the present moment, t, are utilized for output f_t by a sigmoid function $\sigma(\cdot)$:

$$O_t = \sigma(W_0 \times [h_{t-1}, x_t] + B_0) \quad (4)$$

$$c_t = f_t \times c_{t-1} + i_t \circ \tilde{c}_t \quad (5)$$

$$h_t = 0_t \times tanh(c_t) \quad (6)$$

Now B_0 characterizes the bias of the output gate, and W_0 characterizes the weight matrix of the output gate.

In the LSTM model, because of a hidden layer with a storage function and unique three-gate structure, it could better reveal previous long-term information, thus solving the problem of long-term dependency. Firstly, the hidden layer C_t of the present moment, t employs the forget gate to control that data in the hidden layer C_{t-1} of the latter moment $t-1$ should be rejected and that data continues to be preserved. Next, the model rejects data in the hidden layer C_t and the forget gate and learns new data using the input gate. Afterward, after a sequence of calculations, the cell state $C_t$is upgraded. LSTM employs the output gate, cell state C_t, and a tanh layer to define the last output value h_t. Fig. 1 illustrates the LSTM framework.

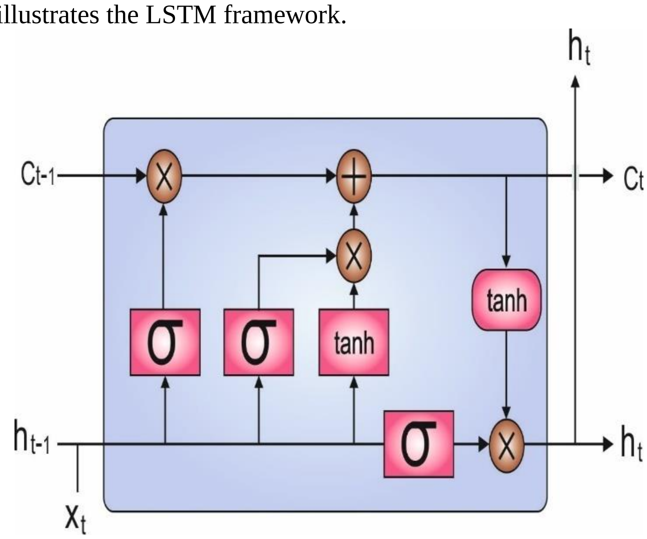

Fig. 1 LSTM structure

For adjusting the hyperparameters involved in the LSTM model, the WOA has been employed. The humpback whale hunting behavior is modeled in the WOA [17-20]. They mostly consider the predator that surrounds and captures the prey with the bubble-net hunting approach. Now, the optimal location exposed until now is developed as the prey location X^*, which guides another searching agent towards a potential region at the exploitation stage. Encircling prey, spiral bubble-net attacks to improve local searching, and searching for prey to improve global searching are the three approaches of whales expressed in the WOA approach according to the subsequent definition.

Encircling prey: Humpback whale detects and surrounds the location of prey. Considering the WOA, the present optimal whaleX^* is closer to the targeted prey as it is not possible to define the position of the optimal global solution. Then, the position of other whales is altered the X^* according to the following formula,

$$Dis(X^*, X_i) = |C_i(t) \times X^*(t) - X_i(t)| \quad (7)$$

$$X_i(t+1) = X^*(t) - A_i(t) \times Dis(X^*, X_i) \quad (8)$$

In $the\ existing\ iteration, dis$ (X^*, X_i) denotes the distance between the prey and the i-th whale. A and C denote coefficient values calculated according to the following equations. Fig. 2 showcase the process flow of WOA.

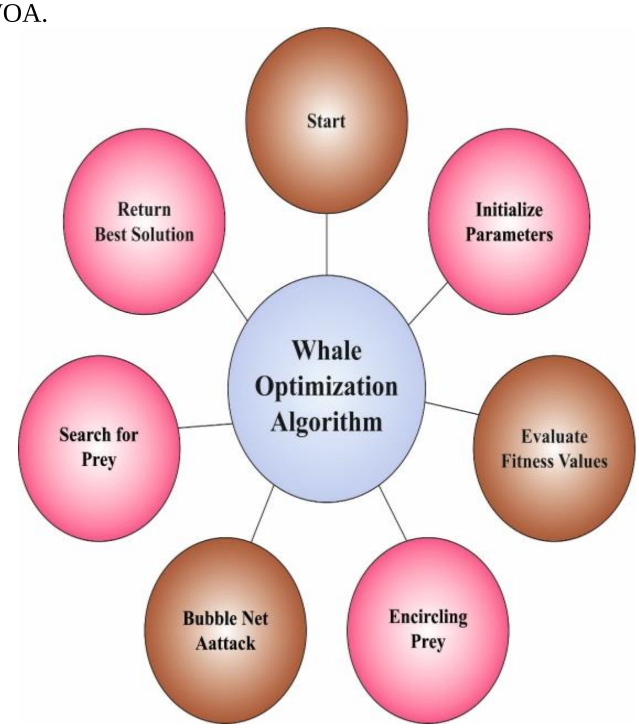

Fig. 2 Process flow of WOA

$$A(t) = 2 \times a(t) \times r - a(t) \quad (9)$$

$$C_i(t) = 2 \times r \quad (10)$$

Whereas a reduces from 2 to 0 through the iteration. Furthermore, r creates an arbitrary value within [0,1].

$$a(t) = 2 - t \times (\frac{2}{\text{Max } It}) \quad (11)$$

Bubble-net attacking: A arithmetical method of humpback whale bubble-net approach (exploitation) was designed by two methods called shrinking encircling model and spiral update location that is equated by,

$$X_i(t+1) = \begin{cases} X^*(t) - A(t) \times Dis(X_r, X_i) & if p < 0.5 \\ Dis(X^*, X_i) \times e^{bl} \times \cos(2\pi l) + X^*(t) & if p \geq 0.5 \end{cases} \quad (12)$$

Whereas p represents an arbitrary number within [0,1]. When the value of p is small compared to 0.5, the location of X_i changes by shrinking the encircling model; alternatively, a spiral updating approach is utilized when the value of p is great than or equivalent to 0.5. A represents an arbitrary parameter created within $[-a, a]$, whereas a reduces from 2 to 0 all over the iterations. $Dis(X^*, X_i)$ represents the distance between the i-th searching agent and the prey in a spiral updating location, b represents a constant value, and l represents an arbitrary number [1, 1].

Search for prey: To highlight the exploration capability (if $|A| \geq 1$), a whale position is upgraded, where a random whale is selected instead of the optimal whale exposed until now.

$$X_i(t+1) = X_r(t) - A \times Dis(X_r, X_i) \quad (13)$$

Whereas, $X_r(t)$ denotes the location of arbitrarily elected whale in the existing iteration and $Dis(X_r, X_i)$ shows the distance among i-th whale and $X_r X_r$.

2.5. External Validation and Optimization (EVO) Phase

According to the expected and required outputs, the last stage is to assess the system efficiency with the testing dataset or exterior dataset. Other contributor samples, collected by additional methods and then compared with the novel information, are suitable for precision assessment. When this process yields better results, the scheme would be prepared for using a production environment. The whole procedure needs to be re-estimated. Also, it's likely to have the procedure upgrading themselves since a new contributor record is included.

2.6. MMA Recommendation for Utilization (MMA-RU)

End-user (patient) receives the product (app+WOA-LSTM) as a separate application with a common update according to an external validation result or public web page, e.g., involving a web-based scheme with the WOA-LSTM. Moreover, adversarial attacks need to be utilized for testing the novel scheme for weakness to guarantee that private information, the main information associated with medicinal records, is not unprotected. That uncommon patterns or unanticipated anomalies do not twist the technique.

3. Results and Discussion

The performance of the WOA-LSTM model has been validated in this section using a set of factors depending upon Software Quality Assurance (SQA) and Software Quality Management (SQM) practices. 9 and 7 questionnaires are used to analyze SQA and SQM. Table 1 provides the conventional method's usability recommendation results in terms of different measures. The conventional method has recognized class 1 with $accu_y$ $prec_n reca_l F_{score}$ and of 89.50%, 88.13%, 88.01%, and 89.82%, respectively.

Table 1. Analysis of Usability Recommendation Model using the conventional method

No. of Classes	Classes of MMA	Accuracy	Precision	F-Score
Class-1	AliveCor Heart Monitor	89.50	88.13	89.82
Class-2	Mobile MIM	89.60	89.04	89.66
Class-3	Mobius Ultrasound Imaging System	89.80	89.26	88.60
Class-4	Customized Sound Therapy(CST)	82.10	88.22	89.71
Class-5	Electronic Stethoscope System E	91.70	89.59	88.74
Class-6	MyFitnessPal	89.30	90.08	89.99
Class-7	Lexicomp	90.60	89.30	88.03
Class-8	Epocrates	90.60	88.66	88.95
Class-9	Micromedex	92.40	88.55	89.43
Class-10	OneTouch RevealTM	90.00	88.26	88.18
Class-11	RxmindMe	91.20	90.32	89.12
Average		**89.71**	**89.04**	**89.11**

Besides, the conventional technique has recognized class 4 with $accu_y$, $prec_n$, $reca_l$, and F_{-score}s of 82.10%, 88.22%, 90.89%, and 89.71%, respectively. In addition, the conventional system has recognized class 7 with $accu_y$, $prec_n$, $reca_l$, and F_{-score}s of 90.60%, 89.30%, 90.95%, and 88.03% correspondingly. Moreover, the conventional scheme has recognized class 9 with $accu_y$, $prec_n$, $reca_l$, and F_{-score}s of 92.40%, 88.55%, 89.28%, and 89.43%. Furthermore, the conventional method has recognized class 11 with $accu_y$, $prec_n$, $reca_l$, and F_{-score}s of 91.20%, 90.32%, 90.96%, and 89.12%. By observing the table, it is noticed that the DLBTDC-MRI model has accomplished maximum precision-recall performance under all classes.

Table 2 offers the usability recommendation outcomes presented by the LSTM system in terms of dissimilar measures. The LSTM technique has recognized class 1 with $accu_y$, $prec_n$, $reca_l$, and F_{-score}s of 99.80%, 97.87%, 100%, and 98.92%. In addition, the LSTM technique has recognized class 4 with $accu_y$, $prec_n$, $reca_l$, and F_{-score}s of 99.70%, 97.80%, 98.89%, and 98.92% correspondingly. Moreover, the LSTM technique has recognized class 7 with $accu_y$, $prec_n$, $reca_l$, and F_{-score} of 99.80%, 98.90%, 98.90%, and 98.90%, correspondingly. Furthermore, the LSTM technique has recognized class 9 with $accu_y$, $prec_n$, $reca_l$, and F_{-score}s of 99.80%, 97.78%, 100%, and 98.88%. The LSTM technique has recognized class 11 with $accu_y$, $prec_n$, $reca_l$, and F_{-score}s of 99.90%, 98.89%100%, and 99.44%, respectively.

Table 2. Analysis of Usability Recommendation Model using LSTM Model

No. of Classes	Classes of MMA	Accuracy	Precision	Recall	F-Score
Class-1	AliveCor Heart Monitor	99.80	97.87	100.00	98.92
Class-2	Mobile MIM	99.80	97.85	100.00	98.91
Class-3	Mobius Ultrasound Imaging System	99.80	98.92	98.92	98.92
Class-4	Customized Sound Therapy(CST)	99.70	97.80	98.89	98.34
Class-5	Exo Electronic Stethoscope System	99.50	98.89	95.70	97.27
Class-6	MyFitnessPal	99.40	100.00	93.48	96.63
Class-7	Lexicomp	99.80	98.90	98.90	98.90
Class-8	Epocrates	99.90	98.90	100.00	99.45
Class-9	Micromedex	99.80	97.78	100.00	98.88
Class-10	OneTouch RevealTM	99.80	98.90	98.90	98.90
Class-11	RxmindMe	99.90	98.89	100.00	99.44
Average		**99.75**	**98.61**	**98.62**	**98.60**

Table 3 offers the usability recommendation outcomes presented by the WOA-LSTM technique in terms of diverse measures. The WOA-LSTM technique has recognized class 1 with $accu_y$, $prec_n$, $reca_l$, and F_{-score}s of 99.90%, 100%, 98.91%,
and 99.45%. In addition, the WOA-LSTM system has recognized class 4 with $accu_y$, $prec_n$, $reca_l$, and F_{-score}s of 99.80%, 97.83%, 100%, and 98.90%, correspondingly.

Table 3 Analysis of Usability Recommendation Model using WOA-LSTM Model

No. of Classes	Classes of MMA	Accuracy	Precision	Recall	F-Score
Class-1	AliveCor Heart Monitor	99.90	100.00	98.91	99.45
Class-2	Mobile MIM	99.70	96.81	100.00	98.38
Class-3	Mobius Ultrasound Imaging System	99.90	100.00	98.92	99.46
Class-4	Customized Sound Therapy(CST)	99.80	97.83	100.00	98.90
Class-5	Exo Electronic Stethoscope System	99.50	97.83	96.77	97.30
Class-6	MyFitnessPal	99.50	100.00	94.57	97.21

Class-7	Lexicomp	100.00	100.00	100.00	100.00
Class-8	Epocrates	99.70	97.80	98.89	98.34
Class-9	Micromedex	100.00	100.00	100.00	100.00
Class-10	OneTouch RevealTM	99.80	97.85	100.00	98.91
Class-11	RxmindMe	99.80	98.88	98.88	98.88
Average		99.78	98.82	98.81	98.80

Furthermore, the WOA-LSTM technique has recognized class 7 with $accu_y$, $prec_n$, $reca_l$, and F_{-score} of 100%, 100%, 100%, and 100%. Furthermore, the WOA-LSTM system has recognized class 9 with $accu_y$, $prec_n$, $reca_l$, and F_{-score} of 100%, 100%, 100%, and 100%. Moreover, the WOA-LSTM technique has recognized class 11 with $accu_y$, $prec_n$, $reca_l$, and F_{-score} of 99.80%, 98.88%, 98.88%, and 98.88%, correspondingly. After examining the results and discussion, it is evident that the proposed WOA-LSTM model has exhibited better usability recommendation performance over the conventional and LSTM models.

4. Conclusion

This study has developed a novel WOA-LSTM model for mobile medical applications as a usability recommendation model. In this case, the LSTM model is employed for the recommendation process. The hyperparameters involved in the LSTM model are optimally tuned by WOA, resulting in improved performance. The WOA-LSTM model produces context-specific judgment and generalized suggestions for App recommendation in related extreme samples. A series of experiments were carried out to determine the effective performance of the WOA-LSTM model, and the results pointed out the efficient outcomes on user recommendation. In the future, hybrid DL models can be included to improve the recommendation performance of the LSTM model.

References

[1] Adesina N, Dogan H, Green S, and Tsofliou F, Effectiveness and Usability of Digital Tools to Support Dietary Self-Management of Gestational Diabetes Mellitus: A Systematic Review, Nutrients. 14(1) (2021) 10.

[2] Azad-Khaneghah P, Neubauer N, Miguel Cruz A, and Liu L, Mobile Health App Usability and Quality Rating Scales: A Systematic Review, Disability and Rehabilitation: Assistive Technology. 16(7) (2021) 712-721.

[3] Tiffany B, Blasi P, Catz S.L, and McClure J.B, Mobile Apps for Oral Health Promotion: Content Review and Heuristic Usability Analysis, JMIR mHealth and uHealth. 6(9) (2018) e11432.

[4] Jayamathi A, Jayasankar T, & Vinoth Kumar K, Novel Selective Mapping with Oppositional Hosted Cuckoo Optimization Algorithm for PAPR Reduction in 5G UFMC Systems, Technical Vjesnik. 29(2) (2022) 464-471.

[5] Liew M.S, Zhang J, Lee J, and Ong Y.L, Usability Challenges for Health and Wellness Mobile Apps: A Mixed-Methods Study among mhealth Experts and Consumers, JMIR mHealth and uHealth. 7(1) (2019) e12160.

[6] Vlachogianni P, and Tselios N, Perceived Usability Evaluation of Educational Technology Using the System Usability Scale (SUS): A Systematic Review, Journal of Research on Technology in Education. (2021) 1-18.

[7] Puig J, Echeverría P, Lluch T, Herms J, Estany C, Bonjoch A, Ornelas A, París D, Loste C, Sarquella M, and Clotet B, A Specific Mobile Health Application for Older HIV-Infected Patients: Usability and Patient's Satisfaction, Telemedicine and E-Health. 27(4) (2021) 432-440.

[8] Rasheedy D, Mohamed H.E, Saber H.G, and Hassanin H.I, Usability of a Self Administered Geriatric Assessment Mhealth: Cross Sectional Study in a Geriatric Clinic, Geriatrics & Gerontology International. 21(2) (2021) 222-228.

[9] Nwagwu W.E, Usability of Mobile Phones for Personal Health Care by People Living with HIV/AIDS, Health and Technology. 11(3) (2021) 491-504.

[10] Karita T, Carvajal T.M, Ho H.T, Lorena J.M.O, Regalado R.A, Sobrepeña G.D, and Watanabe K, Early Detection of Dengue Fever Outbreaks Using a Surveillance App (Mozzify): Cross-Sectional Mixed-Methods Usability Study, JMIR Public Health and Surveillance. 7(3) (2021) e19034.

[11] Overdijkink S.B, Velu A.V, Rosman A.N, Van Beukering M.D, Kok M, and Steegers-Theunissen R.P, The Usability and Effectiveness of Mobile Health Technology-Based Lifestyle and Medical Intervention Apps Supporting Health Care During Pregnancy: A Systematic Review, JMIR mHealth and uHealth. 6(4) (2018) e8834.

[12] Cruz Zapata B, Fernández-Alemán J.L, Toval A, and Idri A, Reusable Software Usability Specifications for mhealth Applications, Journal of Medical Systems. 42(3) (2018) 1-9.

[13] Cho H, Powell D, Pichon A, Thai J, Bruce J, Kuhns L.M, Garofalo R, and Schnall R, A Mobile Health Intervention for HIV Prevention Among Racially and Ethnically Diverse Young Men: Usability Evaluation, JMIR mHealth and uHealth. 6(9) (2018) e11450.

[14] Ormel I, Onu C.C, Magalhaes M, Tang T, Hughes J.B, and Law S, Using a Mobile App-Based Video Recommender System of Patient Narratives to Prepare Women for Breast Cancer Surgery: Development and Usability Study Informed by Qualitative Data, JMIR Formative Research. 5(6) (2021) e22970.

[15] Yu Y, Si X, Hu C, and Zhang J, A Review of Recurrent Neural Networks: LSTM Cells and Network Architectures, Neural Computation. 31(7) (2019) 1235-1270.

[16] Wang J, Li J, Wang X, Wang J, and Huang, M, Air Quality Prediction using CT-LSTM, Neural Computing and Applications. 33(10) (2021) 4779-4792.
[17] Mirjalili S, and Lewis A, The Whale Optimization Algorithm, Advances in Engineering Software. 95 (2016) 51-67.
[18] N B Arunekumar, K Suresh Joseph, A Novel Multi Social Communicative HHO Based Neural Networks with Quasi L1 – Regularization for ASD Bio Marker Identification, International Journal of Engineering Trends and Technology. 69(9) (2021) 220-229.
[19] U.Sivaji, Dr.P.Srinivasa Rao, An Improved Uniform Illustration Based Regression Testing by a Novel Heuristic Based Machine Learning Model, International Journal of Engineering Trends and Technology. 69(5) (2021) 177-185.
[20] Jayakumar Sadhasivam, Senthil Jayavel, Arpit Rathore, Survey of Genetic Algorithm Approach in Machine Learning, International Journal of Engineering Trends and Technology. 68(2) (2020) 115-133.