DOI: 10.4149/BLL_2024_020

Bratisl Med J 2024; 125 (2)

117 – 124

SCREENING AND MANAGEMENT

Binary fire hawks optimizer with deep learning driven non-invasive diabetes detection and classification

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ABSTRACT

Non-invasive diabetes detection refers to the utilization and development of technologies and methods that can monitor and diagnose diabetes without requiring invasive procedures, namely invasive glucose monitoring or blood sampling. The objective is to provide a more convenient and less burdensome approach to screening and management of diabetes. It is noteworthy that while non-invasive method offers promising avenues for diabetes detection, they frequently require validation through clinical studies and might have limitation in terms of reliability and accuracy than classical invasive approaches. In recent times, deep learning (DL) and feature selection (FS) are used to monitor and diagnose diabetes accurately without requiring invasive procedures. This technique combines the FS method with the DL algorithm for making accurate predictions and extracting relevant features from non-invasive data. This article introduces a new Binary Fire Hawks Optimizer with Deep Learning-Driven Non-Invasive Diabetes Detection and Classification (BFHODL-NIDDC) technique. The major intention of the BFHODL-NIDDC technique focuses on the involvement of non-invasive procedures for the detection of diabetes. In the BFHODL-NIDDC technique, data preprocessing is initially performed to preprocess the input data. Next, the BFHO algorithm chooses an optimal subset of features and improves the classifier results. For the identification of diabetes, multichannel convolutional bidirectional long short-term memory (MC-BLSTM) model is used. At last, the beetle antenna search (BAS) algorithm is used for the hyperparameter selection of the MC-BLSTM method which in turn enhances the detection performance of the MC-BLSTM model. A series of simulations were conducted on the diabetes dataset to assess the diabetes detection performance of the BFHODL-NIDDC technique. The experimental outcomes illustrated better performance of the BFHODL-NIDDC method over other recent approaches in terms of different metrics *(Tab. 4, Fig. 9, Ref. 23). Text in PDF www.elis.sk*

KEY WORDS: diabetes, non-invasive detection, binary fire hawks optimizer, deep learning, hyperparameter tuning.

Introduction

Data-driven and data science methods are transforming the healthcare industry and chronic diseases were controlled, that includes the utility of treatment technologies, monitoring, and detection (1). This can be supported by the adoption of wearable gadgets with sensing abilities. Using existing studies on the quantified self and health tracking, it is possible to offer live analysis of personal healthcare data (2). Diabetes management was an interesting use case in this context, given the significance of presenting timely and precise feedback, observing and diagnostic tool to healthcare providers and patients (3). Indeed, various researches have solved the difficulties of controlling the various aspects of diabetic conditions, by utilizing wearable gadgets as sources of datasets. But the growth of data-driven methods relies on the presence of a dataset that is utilized for training, automated learning or validation (4). Such a dataset is required not just in controlled and clinical environments (for example monitoring during a hospital stay), but even in day-to-day living conditions.

In the past, various works were conducted for glucose measurement (5). It is minimally invasive, invasive, or non-invasive. There were numerous attempts for continuous glucose monitoring depending on the non-invasive method (6). It depends on non-optical and optical approaches. Few optical approaches used depend on the PPG method, Raman Spectroscopy, NIR spectroscopy etc. After the data acquisition from sensors, various scholars focused to devise the optimized computing method for forecasting the glucose level accurately (7). Non-invasive diabetes recognition utilizing deep learning (DL) and machine learning (ML) algorithms has acquired significant attention as a promising algorithm for convenient and accurate recognition and monitoring of diabetes. By examining non-invasive measurements and using the power of advanced methods, this algorithm has the potential for minimizing the reliance on invasive processes, like blood sampling, while presenting timely and reliable diabetes assessments (8). ML methods like RF, DT, or SVM can be implemented for training methods with the use of the collected non-invasive dataset. Such

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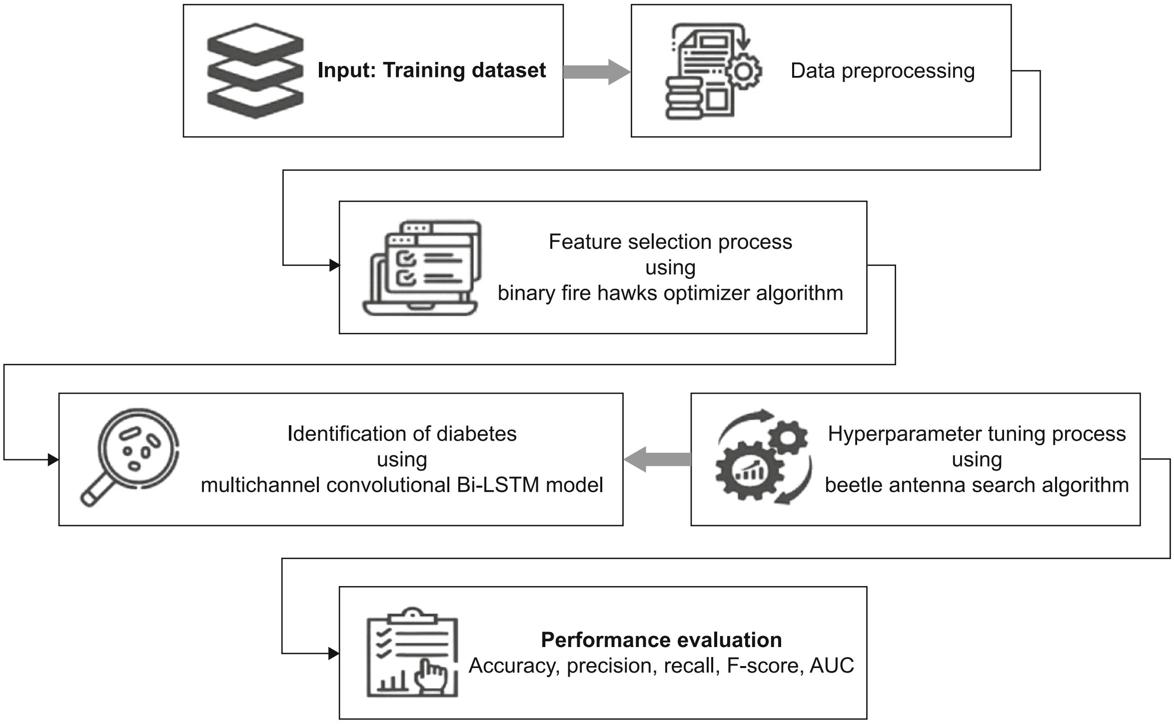


Fig. 1. Overall process of BFHODL-NIDDC approach.

methods learn relationships and patterns in the data, allowing the classification of individuals into non-diabetic or diabetic groups (9). DL approaches that include deep neural network (DNN), convolutional neural networks (CNN), or recurrent neural network (RNN), were utilized to further enhance diabetes detection. DL approaches can capture intricate patterns and learn complicated representations in the non-invasive dataset, resulting in improved performance and accuracy (10).

This article introduces a new Binary Fire Hawks Optimizer with Deep Learning-Driven Non-Invasive Diabetes Detection and Classification (BFHODL-NIDDC) technique. In the BFHODL-NIDDC technique, data preprocessing is initially performed to preprocess the input data. Next, the BFHO algorithm chooses an optimal subset of features and improves the classifier results. For the identification of diabetes, multichannel convolutional bidirectional long short-term memory (MC-BLSTM) model is used. At last, the beetle antenna search (BAS) algorithm is used for the hyperparameter selection of the MC-BLSTM method which in turn enhances the detection performance of the MC-BLSTM model.

Related works

In (11), the concentration of acetone in the exhaled breath was examined to find type 2 diabetes. A novel sensing module containing an array of sensors was applied to monitor the acetone concentration for detecting diseases. DL methods like CNN are utilized to automatically inspect clinical data to make predictions. A deep hybrid Correlational NN (CORNN) was applied and devised in this study for analysing the sensor signals for generating predictions. In (12), the authors developed CSA-driven DBN for DME classification. In this technique, OCT images were considered for the potential classification of the DME process. Likewise, the DBN method was implemented for categorizing the DME-affected region or images of OCT as normal ones. The GAN method was trained by CSA such that the efficacy of classification was improved.

Reddy et al (13) presented a new method to identify DM that can be non-invasive. The presented work considers the digital imageries of the retina as inputs. The concentration is on finding the chaotic geometric attributes formed during feature extraction, because of the numerous non-uniform alignments of thin blood vessels in the images. Islam et al (14) introduce an autonomous software module with a GUI that depends on ANN and digital signal processing (DSP) to distinguish, process, and categorize BGL signs from ultra-wideband (UWB) signals captured using human blood medium.

In (15), the authors present a potential prediction method for diabetes mellitus classification via Deep 1D-CNN values. The outlier detection has been leveraged to remove missing values. Next, SMOTE was utilized to minimize the effect of the imbalance class on predictive outcomes. Eventually, forecasts are made utilizing a DCNN method and can be assessed through a particular set of evaluation indicators. Munadi et al (16) introduce a new structure for DFU classification that depends on thermal imaging utilizing decision fusion and DNN.

Abdulhadi and Al-Mousa (17) mainly forecast the existence of diabetes especially in females-at an initial phase via various ML approaches. Early recognition of diabetes could prevent the development of the disease and lessen the risk of severe complications like kidney and heart diseases, which makes the proper lifestyle variations timely and can help avoid diabetes. So, there comes a vital demand for tools that could better help clinicians for identifying this disease at an initial stage and thus stop its development. In (18), the authors presented a new diabetes categorizing method that depends on Conv-LSTM that was not implemented. The author implemented another three popular methods like CNN-LSTM, and Traditional LSTM (T-LSTM), and the performance was compared with the advanced method over Pima Indians Diabetes Database (PIDD).

The proposed model

In this study, an automated non-invasive diabetes detection model, named the BFHODL-NIDDC technique has been developed. The major intention of the BFHODL-NIDDC technique focuses on the involvement of non-invasive procedures for detecting diabetes. In the BFHODL-NIDDC technique, several stages of operations were carried out namely preprocessing, BFHO-based feature selection, MC-BLSTM-based classification, and BAS-based parameter tuning. Figure 1 represents the overall process of the BFHODL-NIDDC approach.

Feature selection using BFHO algorithm

At this stage, the BFHO technique is used to select an optimal set of features. In this stage, the proposed FS technique based on an improved version of FHO is presented (19). The proposed FS model termed BFHO begins by splitting the datasets into testing and training sets. Next, it makes use of the training sets to search for the applicable features, and the procedure starts by constructing the population of *N* solutions to calculate the fitness values (FV). Then, it assigns the fittest solution and exploits it with operator of FHO for updating the population *X*. The next stage was to choose the applicable attributes from the testing sets. The steps of the FS approach are shown below.

Initially, the social data is split into testing and training instances. Next, the population *X* with *N* solutions was produced, and solution $X_i, i = 1,2,..., N$ has *D* dimensional, and X_i value is represented as follows:

$$X_{ij} = Lj + r1\ x\ (uj - Lj),\ i = 1,2, ...,D \quad (1)$$

In Eq. (1), u_j and L_j signify the maximal and minimal values at the j^{th} dimensions in the search space.

The operator of adapted FHO updated the population *X*. The process initiates by transforming all the X_i into Boolean form based on Eq. (2):

$$BX_{ij} = \begin{cases} 1\ if X_{ij} > 0.5 \\ 0\ otherwise \end{cases} \quad (2)$$

Later, the feature of the training set that is respective to one in BX_{ij} is chosen and estimated by the subsequent FV (Fit_i).

$$Fit_i = \rho \times \gamma + (1-\rho) \times \left(\frac{|BX_{ij}|}{D}\right) \quad (3)$$

Where $\rho \in [0,1]$ - indicates the weighted parameter to balance among the dual parts of Eq. (3),γ shows the classifier error attained by the KNN classifiers with trained set. $|BX_{i,j}|$ and D denote the amount of FSs and the overall amount features from the database, correspondingly. The next procedure is to define the fittest solution Xb that has optimum Fitb. Next, update solution X by the operator of the FHO. The updating step was performed until the stopping condition is met. Figure 2 represents the steps involved in BFHO.

Here, the feature of the testing set that corresponds to one in the better solution X_b is chosen for evaluating the quality. This can be attained by the similar FV determined in Eq. (3). Next, calculate the quality of estimated output by performance measure. The proposed FS method based on BFHO is shown in Algorithm 1.

Algorithm 1: The FS based on the BFHO technique

Input: iteration counts, number of solutions (N), and social data has D features, (tmax), and parameters of FHO.
First Stage
Divide the data as training and testing sets.
Produce population *X*
Second Stage
Allocate T = 1.
while (t < tmax) do
  Produce the Boolean form of X_i by using Eq. (2).
  Compute FV of X_i depends on training sample shown in Eq. (3).
  Determine the fittest solution X_b that has small FV.
  Upgrade *X*.
  $t = t + 1$.
End while
Third Stage
Choose the feature of the testing set that is equivalent to one in X_b.
Calculate the quality of estimated outcome.

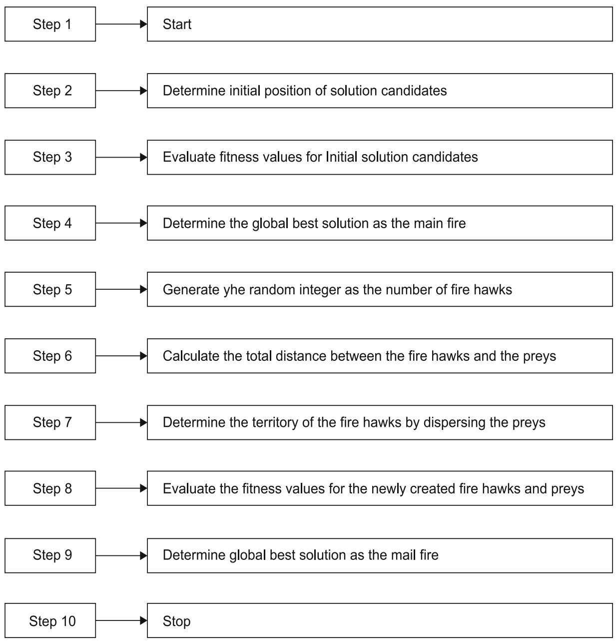


Fig. 2. Steps involved in BFHO.

Diabetes detection using MC-BLSTM model

In this work, the MC-BLSTM approach was utilized for diabetes detection. The dual-channel convolution was provided by the normalized trained sample as part of pretraining. In the earlier stage of pretraining, the predictive model creates a huge loss (20). As a result, an optimizer is used for mitigating these losses and also improving the accuracy that changes the module features. Therefore, the module becomes updated after all the iterations of the pretraining. But the basic element of the dual channel convolution BLSTM model is "Conv Block" which comprises 2 successive 1 - D Conv, Max - poollayer, and dropout layers, along with "BLSTM Block", which comprises of BLSTM, max -pooling, and dropout layer. Furthermore, concatenation, flattening, and dense layers are used in this work.

In the dual-channel convolutional BLSTM model, four successive "Conv Blocks" are applied for all the data channels to remove spatial features. The Max pooling layer with a pooling size of 2 is utilized for pooling higher contrasting data in the mapping feature that results in the down-sampling of the mapping feature sizes. During training a dropout layer with 0.2 is utilized for resolving the over-fitting problems. In the entire 1D convolution layer, the ReLu function is used. Here, four BLSTM block was used for extracting and learning temporal features. Furthermore, a dropout layer and Max pool layer with similar dimensions is inserted in the "BLSTM Block". But BLSTM layers are the expanded version of classical LSTM layers but both LSTMs are used for extracting temporal features in forward (from past to future) or backward (from future to past) directions. The respective output *h* (*t*) of the LSTM layer was evaluated for the concatenated multi-feature signal *x* (*t*) at *t* time, as follows:

$$f(t) = \sigma\left(\omega_f \cdot [h(t-1), x(t)] + \beta_f\right) \quad (4)$$
$$i(t) = \sigma(\omega_i \cdot [h(t-1), x(t)] + \beta_i) \quad (5)$$
$$o(t) = \sigma(\omega_0 \cdot [h(t-1), x(t)] + \beta_0) \quad (6)$$
$$(t) = f(t) \odot c(t-1) + i(t) \odot tanh(\omega_c \cdot [h(t-1), x(t)] + \beta_c) \quad (7)$$
$$h(t) = o(t) \odot tanh\left(c(t)\right) \quad (8)$$

Where *c*(*t*) shows the internal state of LSTM. *f*(*t*), *i*(*t*), and *o*(*t*) represent the forget, input, and output gates of the LSTM cells, correspondingly. Here, *h*(*t*) and *h*(*t*) indicate the cell state value of both LSTMs generated in *N* sequential input and are functioned in both directions, correspondingly, the output response of BLSTM was formulated by Eq. (9):

$$y_t = concat\left[g\left(\overrightarrow{h(t)}\right), g\left(h(\leftarrow t)\right)\right] \quad (9)$$

Where *g*(·) represent respective activation function.

Hyperparameter tuning using BAS

The BAS is used to adjust the hyperparameter value of the MC-BLSTM network. The BAS method stimulates these processes, and it could accomplish effective optimization, without prior knowledge regarding the certain procedure of function and its gradient (21). Also, it needs only one individual which has a significant effect on reducing the computation difficulty. This method is used for enhancing the computational efficacy of the backpropagation (BP) method in NNs and helps it discover the global optimum solution with highest probability, by defining the hyperparameter.

This new metaheuristic has proved promising outcomes on real-time optimization problems. It is used to enhance the BPNN model for predicting gas explosion pressure. Also, it is used to resolve other optimization problems including path planning for intelligent fault diagnoses of wind turbine rolling bearings, and conditioning optimization of extreme learning machines and mobile robots with collision-free ability.

Consider the location of beetles as a vector x^t at time (t = 1,2,...) and determines the odor intensity at location *x* using FF (*x*). The maximal value of the *f*(*x*) marks the odor source. Then, BAS model exploits 2 rules stimulated by beetle utilizing antennae to randomly explore and search an unfamiliar environment.

$$\vec{b} = \frac{rnd(k,1)}{\left||rnd(k,1)|\right|} \quad (10)$$

In Eq. (10), *k* shows the dimension of the location and *rnd* refers to the random function. Then, the search behavior of the left and right antenna correspondingly is modelled using Eqs. (11) & (12)

$$x_r = x^t + d^t\vec{b} \quad (11)$$

$$x_l = x^t - d^t\vec{b} \quad (12)$$

Where x_l and x_r represent the position positioned on the left and right side of the search space, correspondingly. *d* denotes the sensing range of antenna and relates to the exploit capability that should be larger to cover a sufficient search space to escape from the local minimal point at the beginning and later attenuates as time elapse.

The detection behaviors are expressed by the iteration method that relates the recognition of odor by considering the search behaviours:

$$x^t = x^{t-1} + \delta\vec{b}sign(f(x_r) - f \quad (13)$$

In Eq. (13), *sign*() denotes the sign function, and δ signifies the step size of all the iterations. The search parameters including antenna length *d* and step size δ, are upgraded based on the rule provided by the following equations:

$$d^t = 0.95d^{t-1} + 0.01 \quad (14)$$
$$\delta^t = 0.95\delta^{t-1} \quad (15)$$

Fitness choice is a major aspect of the BAS methodology. An encoder solution can be utilized for measuring better candidate outcomes. The accuracy value is the crucial condition used to propose the FF.

$$Fitness = \max(P) \quad (16)$$

$$P = \frac{TP}{TP + FP} \tag{17}$$

Where TP and FP exemplify the true and false positive values.

Results and discussion

In this section, the diabetic detection outcomes of the BFHODL-NIDDC method can be validated using the non-invasive diabetes dataset. It includes 768 samples with two classes as defined in Table 1.

In Figure 3, the confusion matrices of the BFHODL-NIDDC method are clearly illustrated for diabetic classification. The outcomes highlighted that the BFHODL-NIDDC method properly identified the diabetic and non-diabetic samples.

Tab. 1. Details of datasets.

Class	No. of Samples
Diabetic	268
Non-Diabetic	500
Total Samples	768

In Table 2 and Figure 4, a comprehensive diabetes detection result of the BFHODL-NIDDC technique is provided. The results implied that the BFHODL-NIDDC technique effectually classifies the diabetic and non-diabetic samples. On 80 % of TRP, the BFHODL-NIDDC technique provides average $accu_y$ of 94.92 %, $prec_n$ of 97.09 %, $reca_l$ of 94.92 %, F_{score} of 95.85 %, and AUC_{score} of 94.92 %. At the same time, on 20 % of TSP, the BFHODL-NIDDC method provides average $accu_y$ of 93.48 %, $prec_n$ of 97.37 %, $reca_l$ of 93.48 %, F_{score} of 95.16 %, and AUC_{score} of 93.48 %.

Figure 5 examines the $accu_y$ of the SCSOFS-HDL system in the training and validation procedure on 80:20 of TRP/TSP. The figure indicates that the SCSOFS-HDL method attains maximum $accu_y$ values over the highest epochs. Furthermore, the maximum validation $accu_y$ over training $accu_y$ shows that the SCSOFS-HDL system efficiently learns on 80:20 of TRP/TSP.

The loss outcome of the SCSOFS-HDL algorithm in training and validation is shown on 80:20 of TRP/TSP in Figure 6. The out-

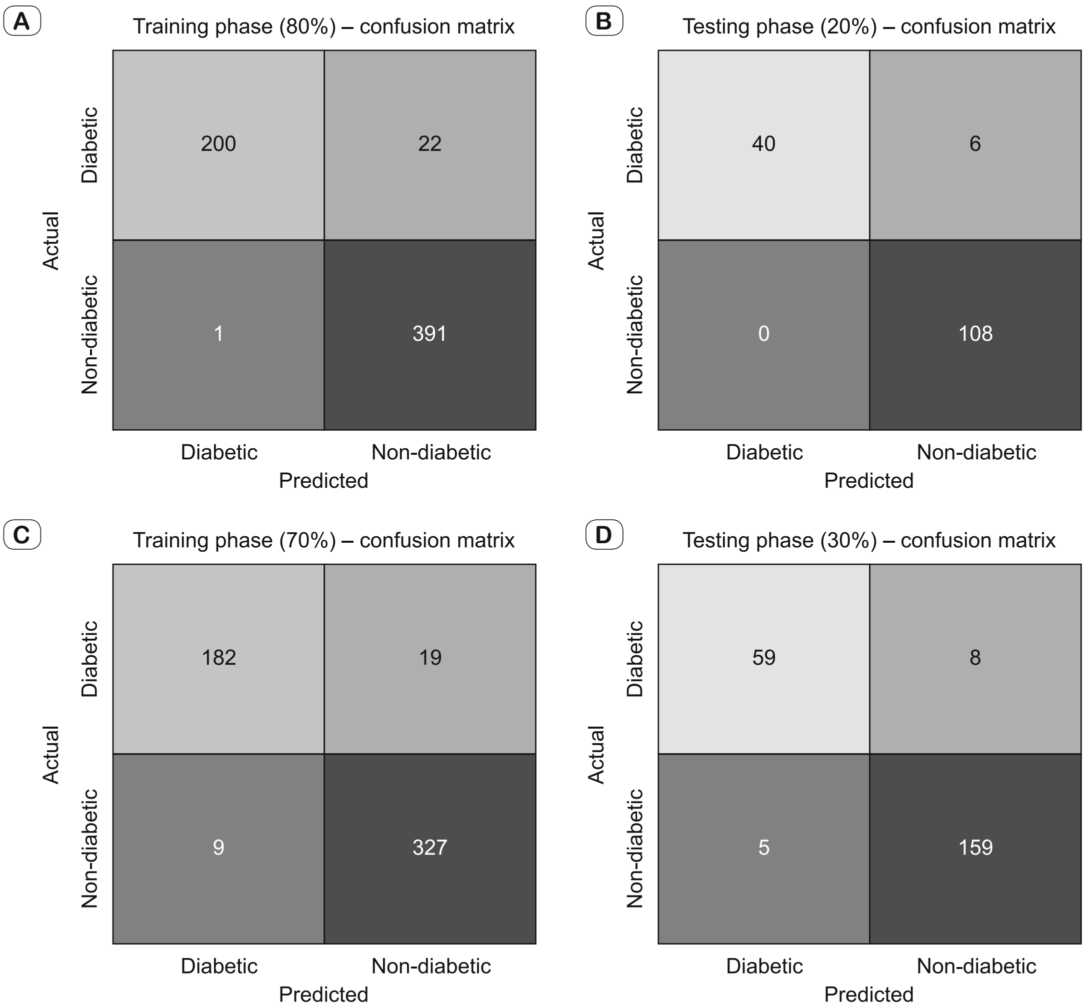


Fig. 3. Confusion matrices of BFHODL-NIDDC approach (A–B) 80:20 of TRP/TSP and (C–D) 70:30 of TRP/TSP.

Tab. 2. Diabetes detection outcome of BFHODL-NIDDC method on 80:20 of TRP/TSP.

Class	$Accu_y$	$Prec_n$	$Reca_l$	F_{score}	AUC_{score}
Training Phase (80%)					
Diabetic	90.09	99.50	90.09	94.56	94.92
Non-Diabetic	99.74	94.67	99.74	97.14	94.92
Average	94.92	97.09	94.92	95.85	94.92
Testing Phase (20%)					
Diabetic	86.96	100.00	86.96	93.02	93.48
Non-Diabetic	100.00	94.74	100.00	97.30	93.48
Average	93.48	97.37	93.48	95.16	93.48

come shows that the SCSOFS-HDL methodology obtains nearby values of training and validation loss. The SCSOFS-HDL system efficiently achieves 80:20 of TRP/TSP.

In Table 3 and Figure 7, comprehensive diabetes detection outcomes of the BFHODL-NIDDC technique are provided. The results implied that the BFHODL-NIDDC technique effectually classifies the diabetic and non-diabetic samples. On 70 % of TRP, the BFHODL-NIDDC method provides average $accu_y$ of 93.93 %, $prec_n$ of 94.90 %, $reca_l$ of 93.93 %, F_{score} of 94.38 %, and AUC_{score} of 93.93 %. At the same time, on 30 % of TSP, the BFHODL-NIDDC method provides average $accu_y$ of 92.51 %, $prec_n$ of 93.70 %, $reca_l$ of 92.51 %, F_{score} of 93.07 %, and AUC_{score} of 92.51 %.

Figure 8 examines the $accu_y$ of the SCSOFS-HDL system in the training and validation method at 70:30 of TRP/TSP. The figure indicates that the SCSOFS-HDL system attains maximum $accu_y$ values over the highest epochs. Furthermore, the maximum validation $accu_y$ overtraining $accu_y$ shows that the SCSOFS-HDL method efficiently learns at70:30 of TRP/TSP.

The loss outcome of the SCSOFS-HDL algorithm in training and validation is on 70:30 of TRP/TSP. The outcome indicates that the SCSOFS-HDL approach accomplishes nearby values of training and validation loss. The SCSOFS-HDL system efficiently gains at70:30 of TRP/TSP.

Finally, an extensive comparative study of the BFHODL-NIDDC technique with existing approaches in Table 4 and Figure 9

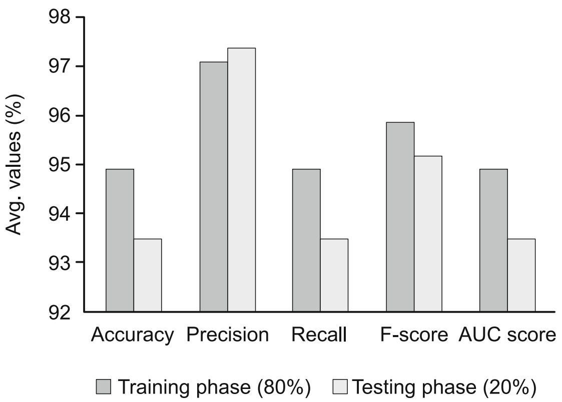


Fig. 4. Average outcome of BFHODL-NIDDC methodology on 80:20 of TRP/TSP.

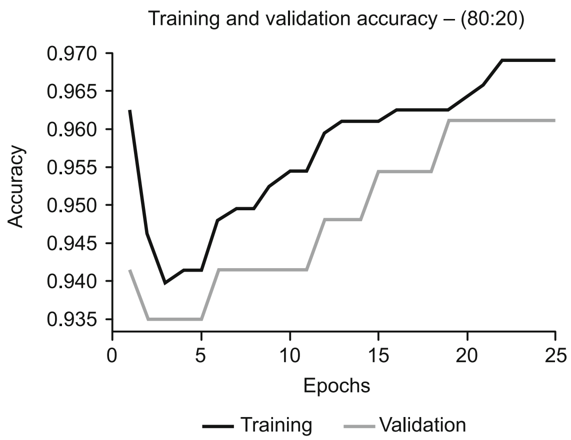


Fig. 5. $Accu_y$ curve of BFHODL-NIDDC approach on 80:20 of TRP/TSP.

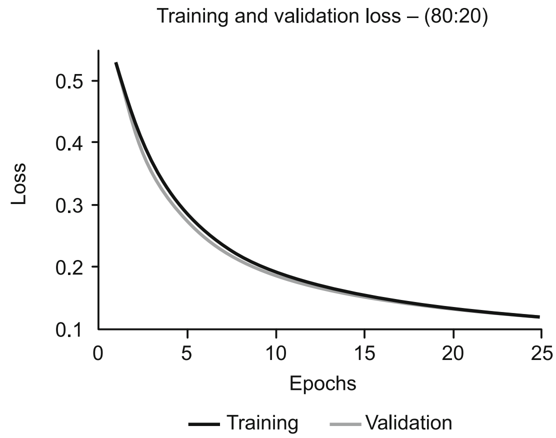


Fig. 6. Loss curve of BFHODL-NIDDC method on 80:20 of TRP/TSP.

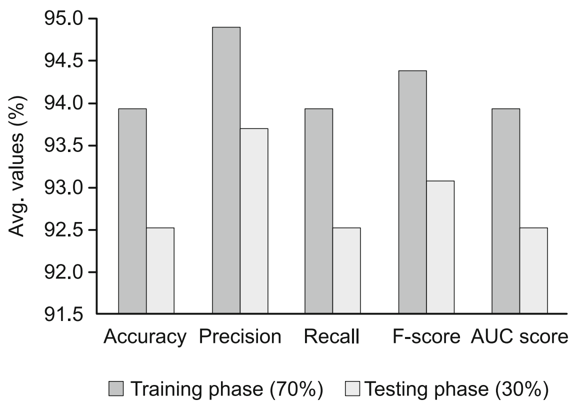


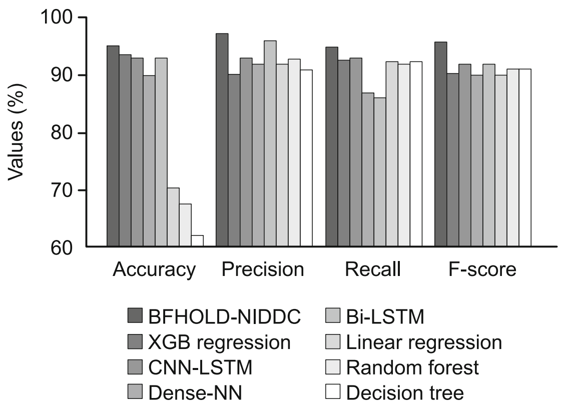
Fig. 7. Average outcome of BFHODL-NIDDC method on 70:30 of TRP/TSP.

Tab. 3. Diabetes detection outcome of BFHODL-NIDDC methodology on 70:30 of TRP/TSP.

Class	$Accu_y$	$Prec_n$	$Reca_l$	F_{score}	AUC_{score}
Training Phase (70%)					
Diabetic	90.55	95.29	90.55	92.86	93.93
Non-Diabetic	97.32	94.51	97.32	95.89	93.93
Average	93.93	94.90	93.93	94.38	93.93
Testing Phase (30%)					
Diabetic	88.06	92.19	88.06	90.08	92.51
Non-Diabetic	96.95	95.21	96.95	96.07	92.51
Average	92.51	93.70	92.51	93.07	92.51

Tab. 4. Comparative outcome of BFHODL-NIDDC system with other recent techniques.

Algorithm	$Accu_y$	$Prec_n$	$Reca_l$	F_{score}
BFHODL-NIDDC	94.92	97.09	94.92	95.85
XGB Regression	93.46	90.13	92.73	90.32
CNN-LSTM	93.00	93.00	93.00	92.00
Dense-NN	90.00	92.00	87.00	90.00
Bi-LSTM	93.02	96.00	86.00	92.00
Linear Regression	70.43	91.97	92.48	90.15
Random Forest	67.59	92.84	91.90	91.09
Decision Tree	62.05	91.00	92.28	91.03



(22, 23). The simulation values achieved enhanced performance over other models. The experimental values highlighted that the LR, RF, and DT models have gained poor performance. Along with that, the Dense-NN model attains improved results whereas the CNN-LSTM, XGB Regression, and Bi-LSTM models obtain decreased performance. However, the BFHODL-NIDDC technique confirms superiority with a maximum $accu_y$ of 94.92 %, $prec_n$ of 97.09 %, $reca_l$ of 94.92 %, and F_{score} of 95.85 %. These outcomes make sure the superior outcome of the BFHODL-NIDDC approach over other methods.

Conclusion

In this article, an automated non-invasive diabetes detection model, named the BFHODL-NIDDC technique has been developed. The major intention of the BFHODL-NIDDC technique concentrations on the involvement of non-invasive procedures for diabetes detection. In the BFHODL-NIDDC technique, several stages of operations were carried out namely preprocessing, BFHO-based feature selection, MC-BLSTM-based classification, and BAS-based parameter tuning. Finally, the BAS algorithm is used for the hyperparameter selection of the MC-BLSTM approach which in turn enhances the detection performance of the MC-BLSTM model. A sequence of simulations can be conducted on the diabetes dataset to assess the diabetes detection performance of the BFHODL-NIDDC technique. The experimental outcomes illustrated better performance of the BFHODL-NIDDC method over other recent approaches in terms of different metrics. In future, a data clustering procedure was incorporated to improve the outcome of the BFHODL-NIDDC technique.

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Received June 21, 2023.
Accepted August 18, 2023.