Optimized Deep Belief Networks Based Categorization of Type 2 Diabetes using Tabu Search Optimization

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***Abstract*—Diabetics mellitus has the potential to result in numerous challenges. Based on the increasing morbidity rates in recent years, it is projected that the global diabetic population will surpass 642 million by 2040, indicating that approximately one in every ten individuals will have diabetes. Undoubtedly, this alarming statistic necessitates urgent focus from both academics as well as industry to foster novelty and advancement in prediction of diabetics, with the aim of preserving patients' lives. Deep learning (DL) was employed to forecast a multitude of ailments as a result of its swift advancement. Nevertheless, DL approaches continue to face challenges in achieving optimal prediction performance as a result of the selection of hyper-parameters and tuning of parameters. Hence, the careful choice of hyper-parameters plays a crucial role in enhancing classification performance. This paper introduces TSO-DBN, a Tabu Search Optimization method (TSO) that is based on Deep Belief Network (DBN). TSO-DBN has demonstrated exceptional performance in several medical fields. The Tabu Search Optimization algorithm (TSO) has been used to pick hyper-parameters and optimize parameters. During the experiment, two problems were tackled in order to improve the findings. The TSO-DBN model exhibited exceptional performance, surpassing other models with an accuracy of 96.23%, an F1-score of 0.8749, and a Matthews Correlation Coefficient (MCC) of 0.88.63.**

Keywords*—*Deep belief network; Tabu search; diabetics mellitus; hyper-parameters; optimization

I. Introduction

Diabetes mellitus, also known as human diabetes, is a prevalent and chronic disease that is rapidly spreading [1,2] and has a substantial impact on modern society [3]. Individuals with diabetes mellitus experience impaired meal absorption, resulting in elevated blood glucose levels [4,5]. Diabetes is a medical disorder characterized by either insufficient production of insulin (type 1 diabetes) or impaired utilization of hormones (type 2 diabetes) [6–8]. In type 1 diabetes, the body ceases the production of insulin. This occurs because to the inadvertent assault and subsequent destruction of a segment of the digestive tract by the body's autoimmune system. Type 1 diabetes generally impacts those who are young, predominantly those who are under the age of 30. Conversely, type 2 diabetes is a chronic condition that cannot be cured and usually impacts persons in their middle and later stages of life. These criteria jointly contribute to evaluating and identifying persons who are at risk of acquiring type 2 diabetes.

In recent studies, deep learning and machine learning algorithms have consistently shown a high level of efficiency in categorization, when compared to existing methods [9]. Enhancing the precision of diabetes prediction is crucial, as is the timely identification of diabetes mellitus. In order to forecast diabetes mellitus, the researchers are integrating various machine learning and deep learning methodologies. Categorizing diabetes is a challenging task. Moreover, the precision of the implemented technique's forecasts may be influenced by the absence of data points in the datasets. This issue has been demonstrated to be a notable concern in the databases used for predicting the risk of diabetes. The objective of this study is to create a computer model that utilizes DBN Classification to effectively identify diabetes in its first phases, perhaps leading to life-saving interventions. By utilizing a collection of real diabetes mellitus data, the technique of DBN is utilized to predict the occurrence of diabetes mellitus. DBN, or Deep Belief Network, is a form of artificial intelligence that use computational methods to acquire knowledge from a vast amount of samples and autonomously program itself, eliminating the necessity for explicit rule definitions. The combination of substantial amounts of data and advancements in computational capabilities has led to this phenomenon [10].

Despite the widespread adoption of deep learning techniques by many academics for their strong empirical results, this approach nevertheless possesses significant limitations. The selection and optimization of hyper-parameters is a highly demanding part of deep learning. Model Parameter has a significant impact on every dataset, particularly for datasets with a large number of dimensions, and greatly affects training performance. Hence, the careful choice of hyper-parameters plays a vital role in enhancing the classification accuracy for predicting the risk of type 2 diabetes [11]. Therefore, this study introduces an enhanced diabetes risk prediction method by proposing an optimized deep belief network based TSO for selecting hyper-parameters and optimizing DBN parameters. In contrast to prior research in the field, which incorporate deep learning techniques alongside traditional optimization methods such as grid or random search. This work involved constructing and examining the effectiveness of fourteen widely-used machine learning classifiers that are routinely employed in research on predicting the risk of diabetes. The assessment of the TSO-DBN model and fourteen machine learning classifiers on a shared dataset demonstrates that the optimized DCNN model outperforms the aforementioned classifiers from previous studies, with logistic regression (LR) displaying superior performance among the thirteen other classifiers utilized in this investigation.

Thus, the findings of this study can be categorized into four main contributions:

- We conducted a thorough examination of high-quality research papers that focused on predicting the risk of diabetes using both traditional machine learning and advanced deep learning techniques.
- We conducted an assessment of the effectiveness and user-friendliness of nine machine learning classifiers using a large and diverse dataset. The purpose of this assessment was to predict the risk of type 2 diabetes. We used well-established evaluation criteria to measure the performance of these classifiers.
- Combining SMOTE data sampling and TSO-DBN to address the underlying issue of class imbalance.
- We have suggested a model for a deep belief network that relies on the selection of hyper-parameters and the optimization of attributes.

The subsequent sections of the paper are organized in the following manner. Section I provided an overview of the context around the prediction of diabetes. Section II offers a comprehensive examination and analysis of the most advanced approaches for predicting diabetes. The proposed methodology discussed in Section III. Section IV provides a comprehensive presentation of the findings and examination of this study. The discussion of the study is provided Section V and Section VI ultimately finishes the study and offers valuable lessons for future endeavors.

II. Literature Study

The neural network is a fundamental concept that consists of interconnected neurons joined together through synapses, forming a biological neural network. Dendrites are the main processing units in a synapse, responsible for receiving axon input and producing output. An artificial neural network, comprising numerous processing units, has emerged as a result of emulating the biological mechanism of data processing, where information is transmitted from one node in the input layer to other nodes in the output layer. Within a network, a cluster of nodes or neurons serves as a singular entity or intermediate processing component. The PID dataset has been utilized in several studies investigating the classification of Diabetes Disease (DD) data [12–14]. In recent years, DD categorization research has presented several approaches and taxonomies, leading to a complex blend of imprecise and comprehensive terminology. Retinal fundus imaging and conventional assessment serve as the fundamental basis for current procedures used in screening for diabetic retinopathy (DR). However, these methods are expensive and time-consuming due to the requirement of highly qualified experts for evaluation [15].

In [16] the authors employed machine learning techniques, specifically ten-fold cross validation, to analyze individuals with a history of non-diabetes and heart issues. The authors enhanced the accuracy of clinical prediction for early detection of diabetes type 2 mellitus by employing advanced machine learning forecasting algorithms like Glmnet, RF, XGBoost, and LightGBM. While it demonstrates efficacy with one dataset, it is unsuitable for another.

In their study, the researchers in [17] devised an innovative technique for detecting DD using the LS-SVM and GDA methodologies. A novel cascading learning system was implemented, utilizing the methodologies previously outlined. The constructed system comprised of two stages: firstly, GDA was utilized; secondly, LS-SVM was implemented to categorize the datasets connected to diabetes. Compared to previous findings obtained using alternative categorization techniques, the results demonstrated a favorable accuracy rate of 82.05% for classification.

In [18] the authors introduced multilayer feedforward network techniques using DL for efficient early prediction. The model has a success rate of 98.07% in analyzing diabetes. The authors of reference [19] proposed a diabetes forecasting model based on an enhanced deep neural network (DNN) technique. The framework has the capability to both predict and ascertain of disease in the future. A hybrid model, developed by [20], has been designed to accurately detect type 2 diabetes with a precision rate of 97.5%. This model combines an Advanced Learning Machine algorithm with a genetic algorithm.

In [21], a hybrid model could be employed for diabetics prediction. The initial step was data cleansing to ensure consistency, followed by RF and XGB classifiers for selection of a subset of features. Subsequently, erroneous data were eliminated by the utilization of K-means clustering.

According to [22], the PIDD dataset was used to train seven distinct machine learning models, each with its own set of features. Two features were excluded in the feature selection process of this technique. SVM and LR showed strong predictive performance for diabetes; a complex neural network was trained with multiple hidden layers and epochs. The authors demonstrate that a neural network with two hidden layers has superior performance in comparison to previous methodologies.

A review in [23] indicates that machine learning is robust enough to aid doctors in predicting the likelihood of future type 2 diabetes development. Machine learning (ML) was employed in a study [24] to conduct a comprehensive evaluation of predicting methods for diabetes. The Prediction Model Risk of Bias Assessment Tool (PROBAST) evaluated bias in machine learning models, whereas Meta-DiSc measured variability in a systematic review, demonstrating the greater effectiveness of machine learning compared to traditional methods.

The ensemble approaches utilized various supplemental machine learning techniques, such as SVM and Convolutional Neural Networks (CNN), to evaluate improvements in performance. However, the primary algorithm used in reference [25] was Logistic Regression (LR). The experiment utilized two distinct feature selection methods in conjunction with two datasets. The first dataset was chosen from the Pima Indians dataset, which comprises nine unique features. The subsequent dataset employed was the Vanderbilt dataset, which consisted of 16 features. The study's findings demonstrated that the LR algorithm ranks among the most efficacious methods for developing predictive models.

In addition, the authors in [26] presented a successful methodology for accurately categorizing and predicting diabetes. The researchers utilized a variety of machine learning algorithms, such as Gaussian process classifier (GPC), Gaussian Naive Bayes (GNB), LR, RF, SVM, DT, KNN, and AB. The evaluation of these models was conducted using the metrics of precision, accuracy, recall, F-measure, and error.

The authors employed deep neural networks [27] for the investigation. Deep learning has led to substantial advancements in data processing [28], computer vision [29–30], and several other domains [31–33]. In recent decades, experts have started recognizing the promise of deep learning approaches in effectively managing massive datasets [34]. DL approaches have successfully enabled the prediction of diabetes.

III. Methods and Materials

This section elucidates the methodology employed in the study, delineating four pivotal stages in the prediction pipelines: benchmark data collecting, pre-processing, modelling prediction, and result analysis. The subcategories provide a comprehensive explanation of each stage and methodology employed.

A. *Dataset*

The diabetes dataset being analysed consists of 768 female patients, obtained from the UCI [38]. Out of the total number of participants, 500 do not have diabetes, but 268 have received a diagnosis for the ailment. The goal is to determine whether diabetes is present or not by examining specific diagnostic parameters in the dataset. The trial specifically targets individuals of Pima Indian ancestry, all of whom are at least 21 years old. Curiously, some patients display zero readings for crucial metrics. Significantly, there are 374 patients with a serum insulin level of zero, 27 with a body mass index of zero, 35 with a diastolic blood pressure of zero, 227 with a skinfold thickness of zero, and 5 with a glucose level of zero. These zero values are classified as null values and, in accordance with WHO criteria, function as crucial markers for forecasting diabetes. The goal variable in the dataset is dichotomous, representing the presence (1) or absence (0) of diabetes in a patient. By employing machine learning methods, this binary classification allows for the prediction of diabetes using particular criteria. The dataset's demographic attributes, specifically for patients diagnosed with diabetes, are displayed in Table I. This dataset has been crucial in studies focused on predicting diabetes. Scientists utilise the extensive data in this dataset to find key indicators that lead to precise predictions of diabetes. Due to its large sample size of female patients, this dataset is particularly valuable for comprehending and tackling the intricacies related to diabetes in this specific group. Scientists and professionals are still investigating and expanding upon the knowledge gained from this dataset, which is leading to progress in the prediction and treatment of diabetes.

B. *Data Pre-processing*

The data has been standardized in pre-processing using the Min-Max normalization approach, resulting in values ranging from 0 to 1. Consequently, we have employed the isnull() and notnull() procedures to verify the presence of any missing values. The data exhibited class imbalance difficulties, prompting us to employ SMOTE as a means to rectify the class imbalance. Resampling is a commonly used technique for addressing the issue of imbalanced datasets. Undersampling and oversampling are the two predominant techniques [35]. Generally, oversampling methods tend to be more effective than undersampling techniques [36, 37]. SMOTE is a widely recognized method for oversampling. SMOTE is a method of oversampling that produces artificial samples for the underrepresented class. We have conducted important feature ranking, as depicted in Fig. 1. The data preprocessed to ensure its compatibility with the TSO-DBN model training. The implementation of the TSO-DBN model is explained in the following section.

C. *Tabu Search Optimization (TSO)*

TSO is a metaheuristic approach that, in its fundamental form, involves a process for searching neighboring solutions. At each step, a thorough examination is conducted to evaluate all potential actions that can be taken from the current answer, and the optimal action is chosen. The approach enables transitions to solutions that do not enhance the existing solution. In addition, in order to avoid the algorithm from repeating the same actions, certain movements are designated as "null" and are initially excluded from consideration. We examined three categories of motion:

- Inserting an element $u'_j \in \mathrm{U} - \mathrm{T}$;
- Eliminating an element $u_j \in \mathrm{T}$; and
- Swapping of u_j With u'_j where $u_j \in \mathrm{T}$ and $u'_j \in \mathrm{U} - \mathrm{T}$.

TABLE I. Description of Attributes of Diabetics Dataset

Sl No	Attribute	Description	SD Vs Mean
1	Pregn.	Number of times Pregnancy	3.36 / 3.84
2	Plasm	PlasmaGlucose level(2h)	30.46 / 121.67
3	Press.	BloodPressure(mm Hg)	12.10 / 72.38
4	Skin	Skinfold Thichness(mm)	8.89 / 29.08
5	Insulin	SerumInsulin in two hours(µU/mL)	89.10 / 141.76
6	BMI	Body Mass Index(Kg/M)	6.88 / 32.43
7	Pedigree	DiabeticsPedigree Function	0.33 / 0.47
8	Age	Age(Years)	11.76 / 33.24
9	O/p Class	Yes or No class for Diabetics	

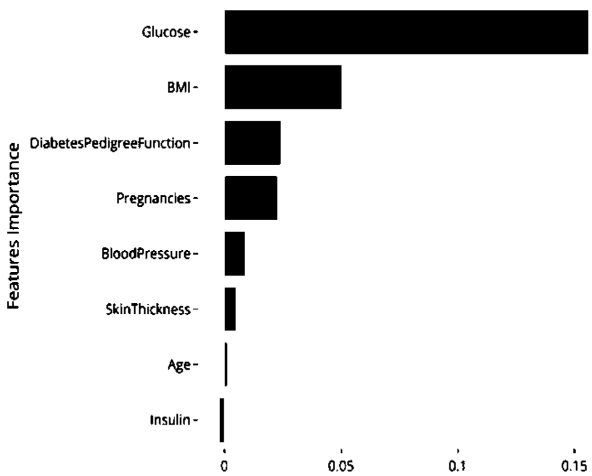

Fig. 1. Feature ranking for type 2 diabetics.

The set of neighboring solutions T (i.e., solutions that can be reached through these motions) is defined as $N(T)$.

To avoid cycles, the output from T and the input into T for elements recently entered or left are labeled "tabu." The current tabu state is determined by tracking the entry or exit of an element $u_j \in$ U.

VectIn (j) - : Represents the iteration number at the element u_j entered T.

VectOut (j) -: Represents the iteration number at the element u_j left T.

Therefore, the presence of an element $u_j' \in \mathrm{U} - \mathrm{T}$ is $tabu$ if

$$itr \leq \text{VectOut} \tag{1}$$

Furthermore, the departure of an element $u_j \in$ T is $tabu$ if

$$itr \leq \text{VectIn} \tag{2}$$

Ultimately, the substitution of an element $u_j \in$ T with another $u_j' \in \mathrm{U} - \mathrm{T}$ occurs $tabu$ only if any of the two previously specified conditions is verified to be present.

As shown in Algorithm, each iteration takes into account all the arrangements that are not $tabu$ prohibited or that satisfy the ambition requirement. The optimal neighbor solution is stored in the variable T^b. This change is implemented ($g^b = g(T')\ and\ T = T^b$), and the values of VectIn and/or VectOut are modified based on the type of movement conducted and the elements implicated. After each iteration T^* and g^*, the best solution obtained during the search and its corresponding objective function g value, denoted as and , are updated. The operation terminates once a predetermined number of iterations ($\max_{itr} TSO$) have occurred without any enhancement of g^*. The parameter no_{itr} is a crucial factor in this technique. Higher values of tenure lead to a larger number of movements being designated $tabu$, which in turn reduces the flexibility of the process. On the other hand, lower values of tenure may not effectively avoid cycles. Hence, the process of choosing appropriately is of utmost importance.

Algorithm: $TSO(no_{itr}, \max_{itr} TSO\ ,\ o/p,\ T^*)$

1. Compute $T^* = T, g^* = g(T), itr = 0, itr_{best} = 0$
2. Compute
$$VectIn(j) = -no_{itr}, VectOut(j) = -no_{itr}, for\ all\ j = 1,2, \ldots\ldots, n$$
3. Do
    - Compute $itr = itr + 1$
    - Compute $g^b = -\infty$
    - ∀ ′ ∈ ( ) Execute:
      Begin
    - Find out the $tabu$ status of the associated movement
    - Find out if the “aspiraon criterion” is met or not, i.e., verify whether $g(T') > g^*$
    - If the movement is $not\ tabu$ or meets the aspiraon criterion, then if $g(T') > g^b$
    - Compute: = $g^b = g(T')\ and\ T^b = T'$
      End
4. Compute: $T = T^b$
5. Update VectIn and/or VectOut
6. If $g(T) > g^*\ then\ , T^* = T, g^* = g(T)\ and\ itr_{best} = itr$
7. Until $itr > itr_{best} + \max_{itr} TSO$

D. DBN Technique

The DBN (Deep Belief Network) was developed by Hinton et al. with the aim of addressing the problem of the vanishing gradient observed in previous studies. The DBN is a resilient and complex generative design that is built using pre-trained layers. It falls under the category of deep neural network (DNN) approaches. DBN consists of numerous RBMs, each consisting of a Visible Layer (VL) and a Hidden Layer (HL). The Visible Layer is the input element, while the Hidden Layer is the output element. The nodes in various levels are fully connected, whereas the nodes within each internal layer are not interconnected. The Restricted Boltzmann Machine (RBM) aims to model the probability distribution from the visible layer (VL) to the hidden layer (HL) by utilizing an Energy Function (EF). DBN involves two steps: pretraining, which is unsupervised and involves training deep RBMs, and fine-tuning, which is supervised and involves training the classification layer. The utilization of Deep Belief Networks (DBN) for weight initialization in artificial intelligence has proven to be highly efficient across various disciplines. The DBN demonstrates a favorable outcome in feature extraction, making it well-suited for recognizing the characteristics inside the data. Due to its fully connected structure, DBN facilitates data analysis more effectively than any other DNN. Fig. 2 illustrates the organization of each Restricted Boltzmann Machine (RBM), which consists of a VL containing the V-units $v = \{vl_1, vl_2, \ldots\ldots, vl_i\}$, and a Hidden Layer (HL) containing the H-units $hl = \{hl_1, hl_2, \ldots\ldots, hl_j\}$.

Subsequently, the unsupervised training process is carried out between each layer, allowing the Deep Belief Network

(DBN) to acquire knowledge from the provided input. Once the features have been learned, they are then passed on to the classifier layer of the DBN. Ultimately, the classification layer undergoes fine-tuning to enhance the performance of the DBN.

E. Proposed TSO-DBN Model

Fig. 3 depicts the block diagram of the settings required to conduct various tests. The dataset was obtained from clinical sources and is derived from the diagnostic reports of individuals with diabetes. The clinical data was preprocessed using several filters. Following the preprocessing stage, the features were extracted according to their significance. Subsequently, the data was divided into two segments, namely for training and testing purposes. The dataset exhibits a class imbalance issue, with the negative class prevailing over the positive class. To address this problem, we employed a synthetic minority oversampling technique (SMOTE). After resolving all the dataset-related concerns, we proceeded to train and validate the data using the proposed TSO-DBN model. Afterwards, the model underwent testing with test data in order to classify the type of diabetes. The performance accuracy was determined by employing various accuracy metrics. Ultimately, a performance comparison between the suggested model and state-of-the-art models was presented. Hence, the pertinent information is depicted in Fig. 3.

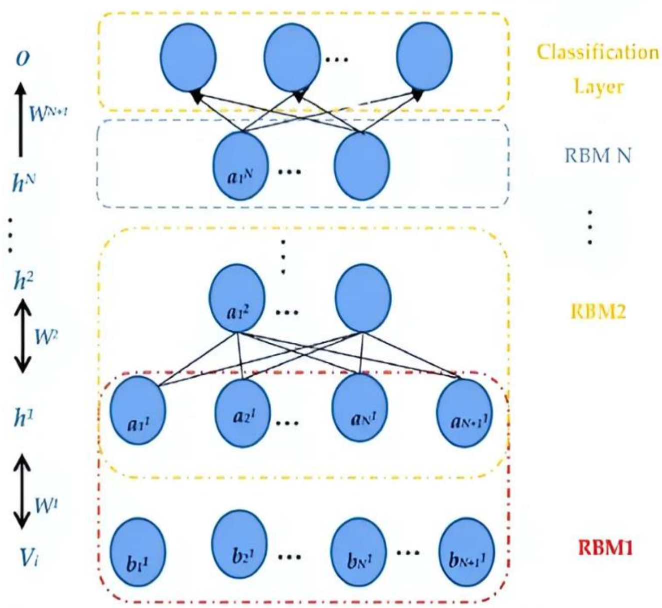

Fig. 2. DBN Architecture.

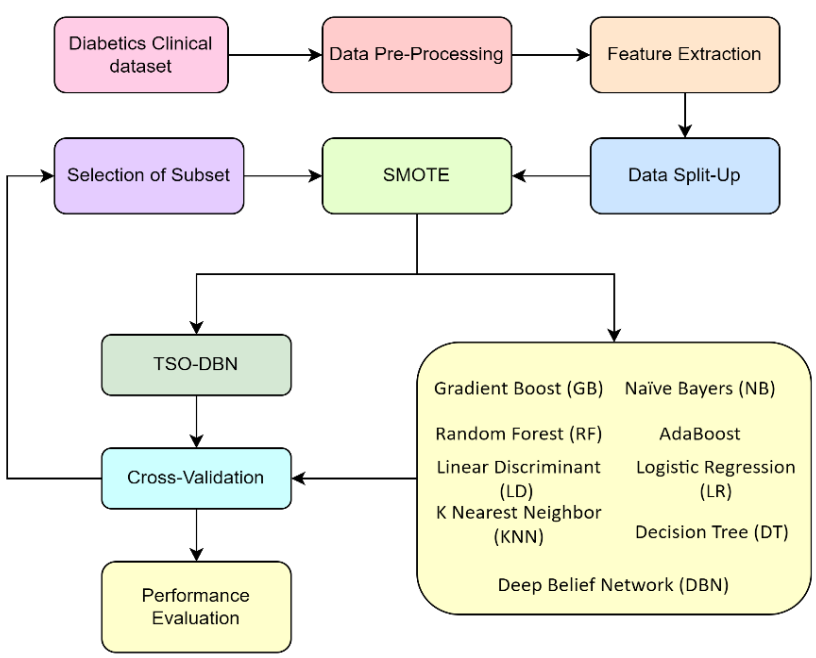

Fig. 3. TSO-DBN – The proposed model architecture.

IV. Experimental Results and Performance Evaluations

This section outlines the criteria for examining the obtained results, the computed outcomes, and performance evaluations. The early stages of the project take place in MATLAB 2021b, followed by the utilisation of Python with Keras and Tensorflow for testing purposes. The programmes are executed on a system equipped with an Intel i7 processor, 16 GB of DDR3 RAM, and an NVIDIA RTX 2060 graphics card.

A. *Hyper-Parameters Configurations*

To attain the best possible outcome when training the model and accomplish the desired outcomes for classifying diabetics, we conducted empirical experiments to fine-tune several hyperparameters. The hyperparameters encompass various factors like Learning Rate, No. of Hidden Layers, Number of iterations, Activation functions etc... Throughout training, the model trained for 130 epochs. Optimal hyperparameter values, determined post-fine-tuning and multiple experiments, are presented in Table II.

TABLE II. HYPERPARAMETERS

Hyper Parameters	**Values**
Hidden Layers	3
Activation Function	Sigmoid
Output Layer	Softmax
No of Epoch	130
N0. of Neurons	500
Learning Rate	0.003
Optimization	Adam

B. *Evaluation Metric*

The efficacy of the suggested model for predicting type 2 diabetes is assessed by employing various metrics to evaluate its accuracy in distinguishing between diabetic and non-diabetic patients. Understanding the performance of the diabetes-presented model requires a thorough examination of the standard assessment methods often used in the scientific research field. The evaluation measures most commonly used as follows:

- The accuracy of diabetes prediction models is commonly measured by calculating the ratio of correctly identified cases to the total number of cases, as defined by equation (1).

Consequently, it can be computed in the following manner:

$$\text{Αχχυραχψ} = \frac{TN+TP}{TP+TN+FN+FP} \qquad (3)$$

Binary classification utilizes the following terminology: TP for accurately identified positive instances, TN for accurately identified negative instances, FP for inaccurately identified positive instances, and FN for inaccurately identified negative instances.

- Precision is a metric that calculates the ratio of accurate diabetes cases (true positives) to incorrect diabetes cases (false positives) within a particular category.

$$\text{Πρεχισιον} = \frac{TP}{TP+FP} \qquad (4)$$

- The recall metric calculates the proportion of relevant diabetes cases that were retrieved out of the overall amount of significant diabetes cases.

$$\text{Ρεχαλλ} = \frac{TP}{TP+FN} \qquad (5)$$

- The F-Measure is a composite statistic that encompasses both accuracy and recall, effectively capturing both features. Diabetes prediction algorithms have utilized assessment metrics to assess efficiency.

$$\text{Φ–Μεασυρε} = \frac{2*(Precision*Recall)}{Precision\ +Recall} \qquad (6)$$

- The Matthews correlation coefficient (MCC) is a statistical metric used to evaluate the performance of a classification model. It assigns a high score when all four classes in the confusion matrix show outstanding recognition outcomes, relative to the positive and negative classes in the dataset.

$$\text{MXX} = \frac{(TP*TN)-(FP+FN)}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \qquad (7)$$

The aforementioned assessment methods have been employed to assess the efficiency of the improved deep learning model in relation to the contributions made in the literature.

C. *Analysis of Results*

This section provides a clear explanation of the outcomes obtained from various traditional ML and DL classifiers and an optimised deep belief network-based TSO model. These models were utilized in the study to forecast the likelihood of developing type 2 diabetes. Evaluation matrices such as ROC and precision-recall curves depict the correlation between the rates of true positives and false positives. The models underwent testing utilising distinct data sets to assure impartiality and evaluate their capacity for generalisation.

There are two confusion matrices that display various model evaluation metrics depicted in Fig. 4. These metrics are derived from a matrix including four terms.

D. *Evaluation Metrics: Accuracy, F1-Measure, and Matthews Correlation Coefficient*

Accuracy and recall are essential metrics when assessing prediction models. While anticipating the most positive type of instances in the dataset is called as high recall. However, in scenarios where a perfect balance between accuracy and completeness is necessary, the F1 measure is commonly used. The F1 score represents the harmonic mean of a model's precision and recall ratings.

Table III presents a comparative comparison of ten traditional ML and DL classifiers that were thoroughly tested and assessed for their efficacy in predicting type 2 diabetes. The evaluation is done by comparing their accuracy, area under the curve (AUC), recall, precision, F1 score, and Matthews correlation coefficient (MCC) with the TSO-DBN model.

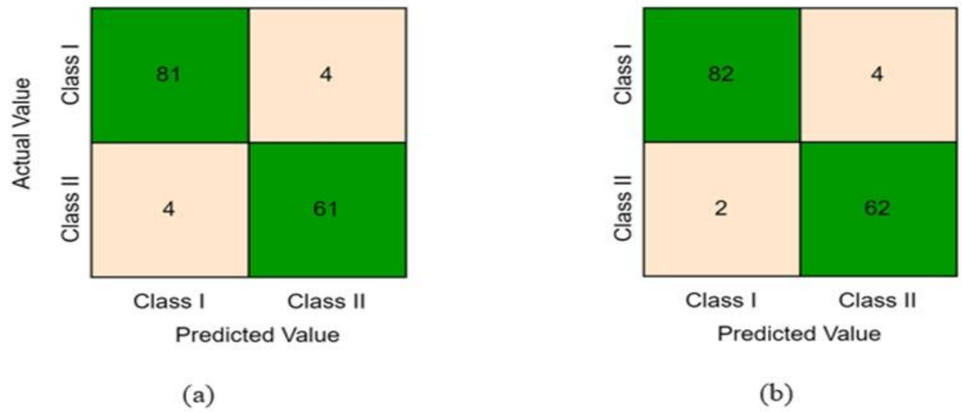

Fig. 4. Confusion matrix of (a) DBN model, (b) TSO-DBN model.

TABLE III. THE COMPARATIVE ANALYSIS OF PROPOSED WITH THE EXISTING ML TECHNIQUES

No	Model	Evaluation Matrices						Time Complexity (T) in sec
		Accuracy	AUC	Recall	Precision	F1	MCC	
1	Gradient Boost	0.8732	0.9374	0.7635	0.8676	0.8198	0.7642	0.7674
2	Random Forest	0.9132	0.8627	0.7247	0.4645	0.5196	0.6516	1.5443
3	Linear Discriminant	0.8607	0.8308	0.7693	0.8702	0.8513	0.5357	0.8542
4	K Nearest Neighbor	0.8981	0.8804	0.8325	0.4291	0.6624	0.6024	0.7127
5	Decision Tree	0.9046	0.9441	0.6619	0.7165	0.7312	0.6489	1.5364
6	Naïve Bayers	0.8873	0.8632	0.6612	0.5764	0.8089	0.4873	0.7645
7	Ada Boost	0.8765	0.9226	0.8354	0.8501	0.5583	0.7391	0.8469
8	Logistic Regression	0.9268	0.8797	0.7123	0.3969	0.4867	0.4334	1.7267
9	Deep Belief Network	0.9581	0.9754	0.8485	0.8091	0.8667	0.8348	1.0463
10	TSO-DBN	0.9623	0.9817	0.8819	0.8746	0.8749	0.8863	0.6438

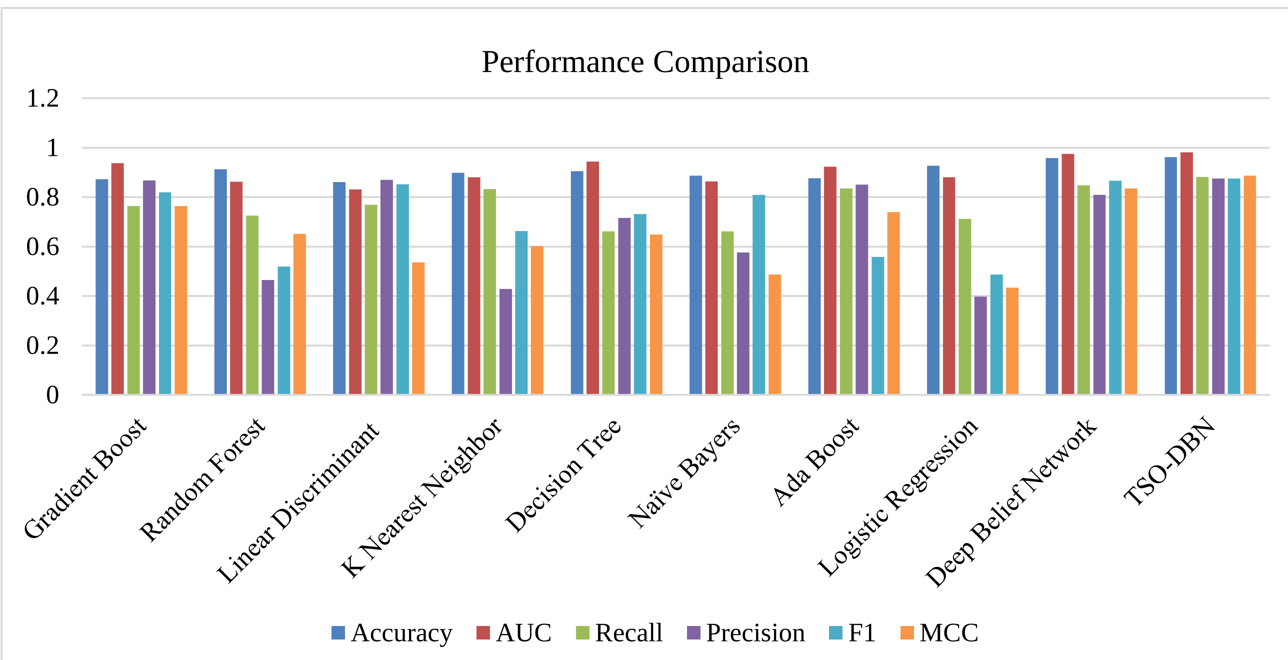

Fig. 5. Performance comparison of different classifiers.

Table III displays the F1 by utilizing the 10 predictors applied in this investigation. This table confirms the earlier results exhibited by the AUC and accuracy ratings. The TSO-DBN model attained a superior F1 score of 0.9623, whereas the LR predictor earned a significantly lower F1 score of 0.4867. We utilised a Linear Discriminant classifier and a Gradient Boosting Classifier, which yielded F1 scores of 0.8513 and 0.8198, accordingly.

Similarly, the Naïve Bayes Classifier achieved an F1 score of 0.8089, placing it in fifth position. Nevertheless, the Logistic Regression classifier exhibited the poorest performance, achieving a precision of 0.3969. Regarding the recall evaluation metric, the Naive Bayes model received a score of 0.6612, which was the lowest, while the TSO-DBN model acquired the highest score of 0.8819.

The results of the MCC (Matthews Correlation Coefficient) for all classical machine learning classifiers and TSO-DBN prediction models developed in this study are presented in Table III. The TSO-DBN model achieved a performance rate of 0.8863 according to MCC, while the classical DBN model achieved a performance rate of 0.8348. Following them, Gradient and Ada Boost achieved performance rates of 0.7642 and 0.7391, respectively. The random forest achieved an accuracy rate of 0.6516. In conclusion, the logistic regression model achieved a performance rate of around 0.4334, which is the lowest among the evaluation metrics measured by the Matthews correlation coefficient (MCC).

The findings of this study are summarised in Fig. 5, which shows that the TSO-DBN model performed better than all the commonly used ML classical classifiers in predicting the risk of type 2 diabetes. The suggested model yields near-optimal outcomes in terms of all measures.

E. Computational Complexity

The reported data in Table III compares the prediction and training timeframes of the most and least effective classical machine learning predictors for type 2 diabetes. Linear Discriminant is particularly noteworthy for its impressive training time of 0.3542s, while LR is notably slower with a training time of 1.8267s. The computational complexity comparison of different pre-trained models is shown in Fig. 6.

The classical DBN model exhibits a temporal complexity of 1.5463s, which can be attributed to its complex structure in comparison to simpler classical ML models. The TSO-DBN model, which has a temporal complexity of 1.6438s, corresponds to the difficulty of the DBN model. Surprisingly, although these models have intricate structures, there are slight variations in their time complexity when comparing Random Forest, Decision Tree, and DBN Network. The suggested model, with its complicated design, attains a time complexity of 1.6438s, demonstrating the balance between model intricacies and computing efficiency in forecasting type 2 diabetes.

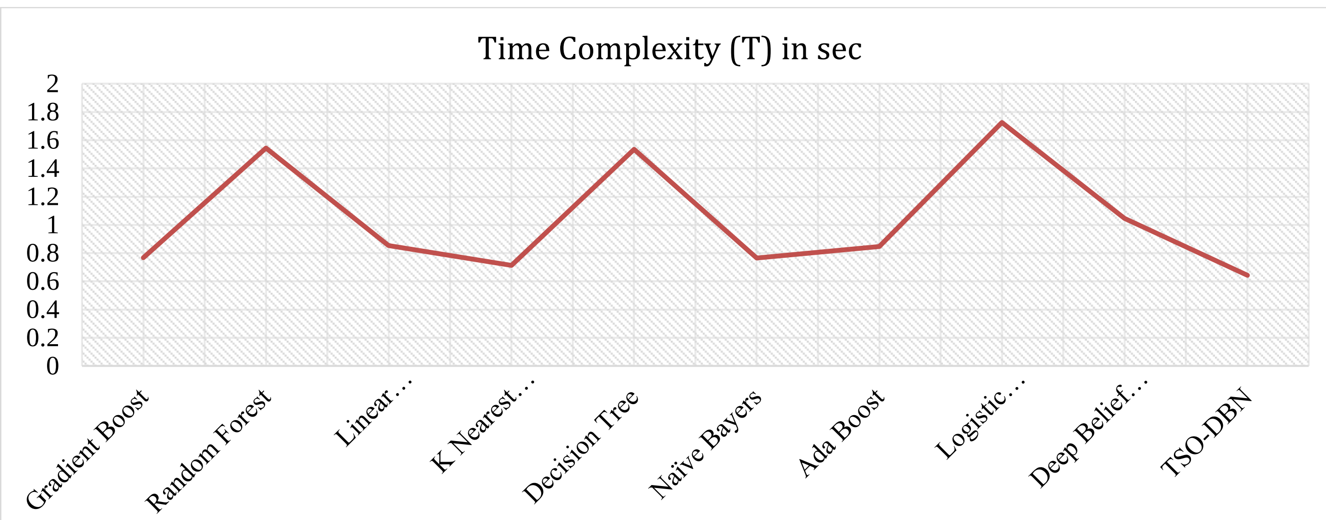

Fig. 6. Time complexity comparison of different pre-trained models.

V. Discussion

The assessment of prediction models for type 2 diabetes requires a careful consideration of metrics such as accuracy and recall, pivotal in evaluating model performance. While high recall is crucial for identifying positive instances accurately, achieving a balance between accuracy and completeness is often essential, leading to the common use of the F1 measure, representing the harmonic mean of precision and recall. In this study, Table III presents a comprehensive comparison of ten traditional machine learning (ML) and deep learning (DL) classifiers, evaluating their efficacy in predicting type 2 diabetes through metrics including accuracy, area under the curve (AUC), recall, precision, F1 score, and Matthews correlation coefficient (MCC), benchmarked against the TSO-DBN model. Notably, the TSO-DBN model demonstrates superior performance with an F1 score of 0.9623, surpassing other classifiers such as Logistic Regression (LR), which exhibited notably lower performance with an F1 score of 0.4867. Furthermore, the TSO-DBN model achieves the highest recall score of 0.8819, underscoring its effectiveness in identifying positive instances. MCC results further reinforce the TSO-DBN model's superiority, with a performance rate of 0.8863 compared to classical ML classifiers. These findings, summarized in Fig. 5, highlight the TSO-DBN model's effectiveness in predicting type 2 diabetes risk, yielding near-optimal outcomes across all evaluated measures. Additionally, the comparison of prediction and training timeframes reveals insights into the computational efficiency of different models, with Linear Discriminant standing out for its impressive training time, further emphasizing the balance between model intricacy and computing efficiency in diabetes forecasting.

VI. CONCLUSION

This study introduced a TSO-DBN to accurately forecast the occurrence of diabetes. The model was enhanced by integrating the Tabu Search optimization process. The TSO-DBN model is utilized on a database of diabetes health parameters, and predicted outcomes reveal that the suggested approach has attained the best accuracy of 96.23%. The diabetes prediction model was assessed using precision, recall, and F-measure, yielding scores of 0.8746, 0.8819, and 0.8749, respectively. Additionally, the Matthews correlation coefficient (MCC) result achieved was 0.8863. Hence, a comprehensive evaluation was carried out, and the model reported in this study shown commendable performance and yielded excellent outcomes. During the trial, it was noted that the TSO-DBN algorithm significantly improved the model's performance and prediction outputs. Therefore, one of the forthcoming tasks is to integrate and evaluate metaheuristic optimization techniques in place of Tabu Search optimization in order to enhance the efficiency of DBN classification. We are also addressing another constraint, which involves researching several other models for predicting diabetes mellitus. These models aim to accurately identify and prevent the occurrence of diabetes. Future research will explore and assess different deep neural network techniques to identify the most precise approach for predicting diabetes. This method can then be implemented in healthcare settings as an alternative to traditional tests performed in laboratories.

DECLARATIONS

Data Availability: The datasets used in the current study are available publicly.https://data.world/uci/pima-indians-diabetes (accessed on 25 January).

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