Leveraging Double-Valued Neutrosophic Set for Real-Time Chronic Kidney Disease Detection and Classification

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Abstract

Chronic kidney disease (CKD) is a non-communicable disease that has made a significant contribution to admission, morbidity, and mortality rates of patients globally. CKD is a common kidney disease that happens when both kidneys fail, and the CKD patient suffers from these conditions for a long time. Machine learning (ML) is becoming more crucial in medical diagnoses as it allows detailed examination, thus reducing human error and optimizing prediction accuracy. Now, ML classifiers and algorithms are highly dependable techniques for the diagnoses of diverse diseases such as diabetes, heart disease, liver disease, and tumor disease predictions. A neutrosophic set (NS) is especially suitable in applications where information is vague, incomplete, or inconsistent, which provides an effective means for analyzing and modeling intricate mechanisms. A NS is a mathematical approach to handle indeterminacy, uncertainty, and imprecision. It expands IF sets, classical sets, and fuzzy sets by introducing three degrees: truth (T), indeterminacy (I), and false (F). This manuscript offers a Double-Valued Neutrosophic Set for Chronic Kidney Disease Detection and Classification (DVNS-CKDDC) technique. In the DVNS-CKDDC technique, three major processes are involved. At the primary phase, the DVNS-CKDDC technique performs a linear scaling normalization (LSN) model. Next, the DVNS-CKDDC technique makes use of the DVNS model for the identification of CKD. Finally, the beluga whale optimization (BWO) algorithm is employed for the parameter tuning of the DVNS method. To ensure the supremacy of the DVNS-CKDDC technique, a widespread simulation analysis is involved. The experimental values stated that the DVNS-CKDDC approach attains improved performance over other models

Keywords: Neutrosophic Set; Chronic Kidney Disease; Beluga Whale Optimization; Double-Valued Neutrosophic Set; Machine Learning

1. Introduction

Neutrosophy (neutron-sophic theory) is utilized to describe inconsistent, uncertain, and indeterminate data presented in the actual world [1]. Handling uncertainty and inconsistency has become important to the matters of scholars who studied mathematic models [2]. Research workers have been proposing various estimations to mark mathematical models for some difficulties containing inconsistent and uncertain data [3]. Forever as the structure of NSs and theory, numerous researchers and professionals have established and enhanced the neutrosophic set (NS) logic with various phases namely image processing, data measures, extensions, decision-making methods, etc., along with a good deal of expressive educational function are presents in the earlier two eras [4]. Chronic kidney disease (CKD) is a syndrome that happens once a patient's kidney function weakens. That results in affecting the complete value of life. CKD influences 1 out of every 10 persons globally [5]. CKD is in the rising stage, and by 2040, it is predicted to be the 5th important reason for death all over the world and the main reason

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for higher medical prices. CKD is categorized as an advanced and long-standing failure in kidney functions, prominent to helplessness to efficiently strain the excess and uphold fluids and electrolyte stability, resultant in the collection of waste products and fluid retaining [6]. Early diagnosis and appropriate supervision of CKD are essential to preserve kidney functions, slow down the infection progress, and improve patient results. A standard technique for CKD recognition, like urine tests and blood check-ups, can have limits in classifying the initial stage of kidney impairment and may not arrest variabilities in kidney fitness eventually. Offensive actions similar to kidney surgery were improper for regular selection, and image tests could be either time-consuming or expensive [7].

The machine learning (ML) method provides logical decision-making techniques to identify computer-supported automated diseases [8]. ML is applied to logically understand obtained information and translate it into valuable information to improve diagnostic procedures effectively. ML is previously employed to measure the condition of the human physique, examine disease-related views, and identify a range of complaints [9]. One solution to decrease chronic disease (CD) mortality rate is to identify it in the starting stage and then deal with it efficiently. Two different techniques involved in standard ML models are feature extraction and classification procedure. Hence, regular ML methodologies are time-consuming to calculate [10]. As a result, the traditional models are not more feasible for current diagnostic applications.

This manuscript offers a Double-Valued Neutrosophic Set for Chronic Kidney Disease Detection and Classification (DVNS-CKDDC) technique. In the DVNS-CKDDC technique, three major processes are involved. At the primary phase, the DVNS-CKDDC technique performs a linear scaling normalization (LSN) model. Next, the DVNS-CKDDC technique makes use of the DVNS model for the identification of CKD. Finally, the beluga whale optimization (BWO) algorithm is employed for the parameter tuning of the DVNS method. The experimental values stated that the DVNS-CKDDC system attains improved performance over other models.

2. Related Works

In [11], a novel CKD recognition algorithm is presented. Enhanced Gaussian filtering (GF) is applied to pre-processing, and watershed-based segmentation has been performed. In addition, features such as the projected ROI, Local Vector Pattern (LVP), and mean intensity are recovered. The Long Short-Term Memory (LSTM) and enhanced neural network provide the outcome of the features. Moreover, by utilizing Self Updated Cat Swarm Optimizer (SU-CSO), the weightiness of NN is modified to recover the classifier estimation precision model. Khalid et al. [12] designed a fusion method to form the presented method. The following procedure uses the Pearson correlation for feature selection (FS). Initially, one of the top models is preferred based on critical literature research. Next, the amalgamation of this method is utilized in their presented hybrid method. Gradient boosting, Gaussian Naïve Bayes (GNB) and decision tree (DT) are applied as a base method, and the RF classifier is applied as meta-classifiers in the suggested hybrid model.

In [13], the recent hybrids TS over stochastic diffusion search (SDX)-based FS is applied. The adaptive back-propagation neural networka (ABPNNs) is categorized utilizing fuzzy logic (FL). FL can be utilized to associate the ABPNN outcomes. Subsequently, this method may help the specialists to determine the phases of chronic renal disease. Elkholy et al. [14] present an ML method to explore CKD. The adjusted deep belief networks (DBNs) derived from Grasshopper's Optimizer Algorithm (GOA) classifiers using the previous Density-based FS (DFS) algorithm for CKD, is named "DFS-ODBN." Before the DBN classifiers, limits are improved via GOA, the suggested model removes excessive or unrelated measurements using DFS.

In [15], a Local Search with Nearest Neighbour (LSNN) optimizer is offered to choose the best-related features to train the deep net method. The suggested LSNN optimization, a K-fold cross-validation is used to compute the mean square errors, it works on the fitness function of selecting better elements via local search optimization. Consequently, the chosen elements are used to train the planned Improved Deep Belief Networks (IDBNs). In IDBN, the presentation of a predictable DBN is upgraded by using a hybrid atom crow optimization in the learning stage. The authors [16] aimed to progress ML technique. This group of phases contains the appropriate attribution of lost data points, in addition to balancing the data using the SMOTE method and measuring the features. The mathematical model, likely, the chi-squared trial, is applied to extract the least-essential group of sufficient and extremely connected features to the result. On behalf of the model preparation, a store of superintended training methods can be utilized to develop a robust ML model.

3. The Proposed Model

In this manuscript, we focus on the design and progress of the DVNS-CKDDC system. In the DVNS-CKDDC technique, three major processes are involved data normalization, DVNS-based CKD detection, and BWO-based parameter tuning process. Fig. 1 exemplifies the entire process of the DVNS-CKDDC method.

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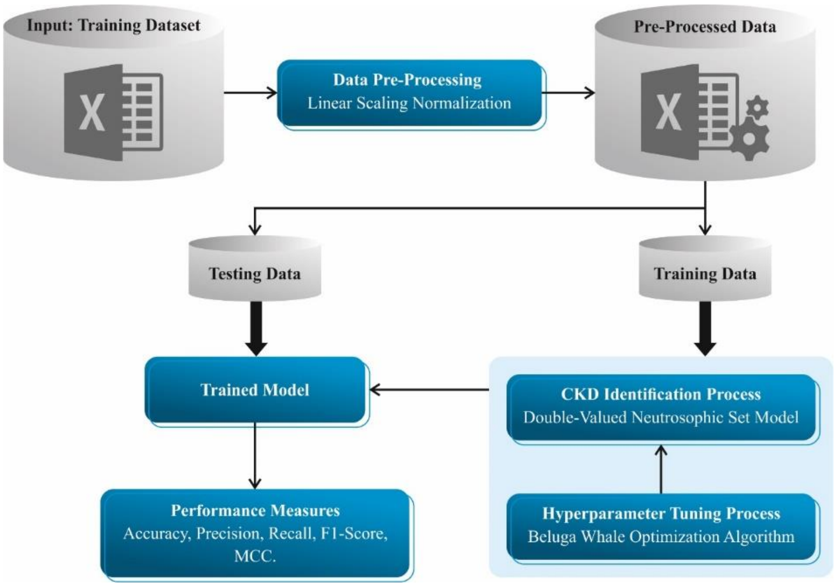

Figure 1: Overall process of DVNS-CKDDC technique

A. Data Normalization

At the primary phase, the DVNS-CKDDC technique performs the LSN model. Linear scaling normalization, a data normalization model, converts data to an exact range, normally [0, 1]. By using the formulation $x' = \frac{(x-min)}{(max-min)}$, every data point x is scaled relative to the dataset's maximum and minimum values, certifying that every value falls in the preferred range. This model upholds the relationships among data points, making it valuable for ML techniques subtle to the balance of input data, like gradient descent-based models.

B. CKD Detection of DVNS

Next, the DVNS-CKDDC technique makes use of the DVNS model for the identification of CKD. Indeterminacy handles vagueness that is confronted in all globes of existence by everybody [17]. It makes science or research further sensitive and realistic by presenting the unknown feature of a lifetime as a perception. There are periods in the reality from which the indeterminacy I is detected to be indeterminacy, which contain many truth than the false values then it could not be categorized as truth. Sometimes, the indeterminacy has several false values than the truth values then it could not be categorized as false. This type of indeterminacy can be categorized into two for providing high sensitivity to indeterminacy. Once the indeterminacy I is known as indeterminacy then it has several truth values than the false values then it could not be categorized as truth, it is assumed as an indeterminacy inclined to trust (I_T). Sometimes, indeterminacy has several false values than the truth values then it could not be categorized as false, it is known as indeterminacy inclined to false (I_F). Truth inclined towards false and indeterminacy inclined to indeterminacy making the indeterminacy included in the setup to be further precise and correct. It offers a detailed and better interpretation of the present indeterminacy.

The description of DVNS is given below:

Consider X as an object with common components in X represented as x. The DVNS A in X is represented as the truth degree $T_A(x)$, indeterminacy inclined to the truth degree $I_{TA}(x)$, indeterminacy inclined to a false degree $I_{FA}(x)$, and false degree $F_A(x)$. For all the generic components $x \in X$, there is

$$T_A(x), I_{TA}(x), I_{FA}(x), F_A(x) \in [0,1],$$

and

$$0 \leq T_A(x) + I_{TA}(x) + I_{FA}(x) + F_A(x) \leq 4.$$

As a result, a DVNS A is formulated as follows:

$$A = \{\langle x, T_A(x), I_{TA}(x), I_{FA}(x), F_A(x)\rangle | x \in X\}.$$

The DVNS A is given below

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$$A = \int_X \{ \langle T(x), I_T(x), I_F(x), F(x) \rangle / dx, x \in X \} \quad (1)$$

While X is constant then the term can be given as

$$A = \sum_{i=1}^{n} \{ \langle T(x_i), I_T(x_i), I_F(x_i), F(x_i) \rangle | x_i, x_i \in X \} \quad (2)$$

While X is distinct.

To demonstrate the DVNS solicitations in real time, assume the constraints that frequently describe the service quality of systematic web services, such as dependability, cost, and ability for illustrative purposes. The service quality evaluation of systematic services is used for illustrating the set-theoretic function of DVNS.

Assume $X = [x_1, x_2, x_3]$ where x_1 denotes ability, x_2 is dependability, and x_3 is cost and values range from zero to one. They are attained from the survey of some field specialists; their possibility can be best service degree, indeterminacy inclined to the best service degree, or indeterminacy inclined to the poor service degree.

$$A = \langle 0.3,0.4,0.2,0.5 \rangle / x_1 + \langle 0.5,0.1,0.3,0.3 \rangle / x_2 + \langle 0.7,0.2,0.1,0.2 \rangle / x_3.$$

B defined by a DVNS of$X$ is

$$B = \langle 0.6,0.1,0.3,0.2 \rangle / x_1 + \langle 0.2,0.1,0.2,0.4 \rangle / x_2 + \langle 0.4,0.1,0.1,0.3 \rangle / x_3.$$

The accompaniment of DVNS A defined as $c(A)$ is denoted by

1. $T_{c(A)}(x) = F_A(x)$,

2. $I_{Tc(A)}(x) = 1 - I_{TA}(x)$,

3. $I_{Fc(A)}(x) = 1 - I_{FA(A)}(x)$,

4. $F_{c(A)}(x) = T_A(x)$,

for x in X.

Assume the DVNS A as

$$c(A) = \langle 0.5,0.6,0.8,0.3 \rangle / x_1 + \langle 0.3,0.9,0.7,0.5 \rangle / x_2 + \langle 0.2,0.8,0.9,0.7 \rangle / x_3.$$

DVNS A is controlled in DVNS, $AsubseteqB$, thus

1. $T_A(x) \leq T_B(x)$,

2. $I_{TA}(x) \leq I_{TB}(x)$,

3. $I_{FA}(x) \leq I_{FB}(x)$,

4. $F_A(x) \geq F_B(x)$,

for all x in X.

X refers to a partial well-ordered set.

Assume A and B as the DVNSs, then A is not in B and B is not in A.

Both DVNSs A and B are equivalent, represented by $A = B$, as long as $A \subseteq B$ and $B \subseteq A$.

$$A \subseteq B \Leftrightarrow T_A \leq T_B, I_{TA} \leq I_{TB}, I_{FA} \leq I_{FB}, F_B \geq F_A$$

$$\Leftrightarrow F_A \leq F_B, 1 - I_{TB} \leq 1 - I_{TA}, 1 - I_{FB} \leq 1 - I_{FA}, T_B \geq T_A$$

$\Leftrightarrow c(B) \subseteq c(A)$.

The combination of DVNSs A and B is a DVNS C, represented by $C = A \cup B$, whose truth degree, indeterminacy inclined to truth degree, indeterminacy inclined to false degree, and false degree are inclined to A and B as below:

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1. $T_c(x) = \max(T_A(x), T_B(x))$,

2. $I_{TC}(x) = \max(I_{TA}(x), I_{TB}(x))$,

3. $I_{FC}(x) = \max(I_{FA}(x), I_{FB}(x))$,

4. $(x) = \min(F(x), F(x))$,

for = x in X.

Assume the DVNSs A and B as

$$A \cup B = \langle 0.6,0.4,0.3,0.2\rangle/x_1 + \langle 0.5,0.1,0.3,0.3\rangle/x_2 + \langle 0.7,0.2,0.1,0.2\rangle/x_3.$$

$A \cup B$ refers to the smaller DVNS encompassing A and B.

The intersection of A and B is a DVNS C, are $C = A \cap B$, where truth degree, indeterminacy inclined to truth degree, indeterminacy inclined to false degree, and false degree are inclined to A and B as follows:

1. $(x) = \min(T(x), T(x))$,

2. $(x) = \min(I(x), I(x))$,

3. $(x) = \min(I(x), I(x))$,

4. $F_c(x) = \max(F_A(x), F_B(x))$,

for $x \in X$.

Assume the DVNSs A and B as

$$A \cap B = \langle 0.3,0.1,0.2,0.5\rangle/x_1 + \langle 0.2,0.1,0.2,0.4\rangle/x_2 + \langle 0.4,0.1,0.1,0.3\rangle/x_3.$$

$A \cap B$ is the biggest DVNS in A and B.

The variance of two DVNSs D, are $D = A\backslash B$, truth degree, indeterminacy inclined to truth degree, indeterminacy inclined to false degree, and false degree are include A and B as follows:

1. $(x) = \min(T(x), F(x))$,

2. $(x) = \min(I(x), 1 - I_{TB}(x))$,

3. $(x) = \min(I(x), 1 - I_{FB}(x))$,

4. $(x) = \min(F(x), T(x))$,

for x in X.

Assume A and B the DVNSs as

$$A\backslash B = \langle 0.2,0.4,0.2,0.5\rangle/x_1 + \langle 0.4,0.1,0.3,0.2\rangle/x_2 + \langle 0.3,0.2,0.1,0.2\rangle/x_3.$$

The truth favorite (Δ), falsity favorite (∇), and indeterminacy neutral (∇), are described by DVNS. The truth favorite (Δ) and false favorite (∇), eliminate the indeterminacy and convert it into a paraconsistent set or IFSs. Likewise, a DVNS is converted into an SVNS through the indeterminacy neutral (∇), which integrates the indeterminacy value of DVNS.

The truth favorite of a DVNS A is $B = \Delta A$, where truth and falsity degrees are given below:

1. $T_B(x) = \min(T_A(x) + I_{TA}(x), 1)$,

2. $I_{TB}(x) = 0$,

3. $I_{FB}(x) = 0$,

4. $F_B(x) = F_A(x)$,

for x in X.

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The truth favorite of DVNS A as $B = \Delta A$,

$$B = \langle 0.7,0,0,0.5\rangle/x_1 + \langle 0.6,0,0,0.2\rangle/x_2 + \langle 0.9,0,0,0.2\rangle/x_3.$$

C. Parameter Tuning Process

Lastly, the BWO model is utilized for the parameter tuning of DVNS method. BWO is a novel metaheuristic approach stimulated by the behaviors of beluga whales [18]. Balance factor B_f defines the shift from exploration to exploitation stage.

$$B_f = B_0\left(1 - \frac{T}{2T_{\max}}\right) \quad (3)$$

In Eq. (3), T and $T_{\max}$ are the existing and the maximum iterations, and B_0 changes randomly within [0,1]. Fig. 2 illustrates the steps involved in BWO.

Exploration Stage

The exploration stage includes a pair of swimming beluga whales and updating the position using the following equation.

$$\begin{cases} X_{i,j}^{T+1} = X_{i,p_j}^{T} + \left(X_{r,p_1}^{T} - X_{i,p_j}^{T}\right)(1 + r_1)\sin(2\pi r_2)\; j = even \\ X_{i,j}^{T+1} = X_{i,p_j}^{T} + \left(X_{r,p_1}^{T} - X_{i,p_j}^{T}\right)(1 + r_1)\cos(2\pi r_2)\; j = odd \end{cases} \quad (4)$$

In Eq. (4), $X_{i,j}^{T+1}$ indicates the new location for the i^{th} beluga whales at j^{th} dimension. P_j shows the random integer chosen from d-dimension $(j = 1,2, \dots, d)$. $X_{i,Pj}^{T}$ and $X_{r,P1}^{T}$ shows the location of i^{th} and r^{th} beluga whales. r_1 to r_7 is a random value within [0,1].

Exploitation Stage

The preying behavior stimulates the exploitation stage, as follows.

$$X_i^{T+1} = r_3 X_{best}^{T} - r_4 X_i^{T} + C_1 \cdot L_F \cdot (X_r^T - X_i^T) \quad (5)$$

In Eq. (5), X_i^T and X_r^T are the locations for i^{th} and r^{th} beluga whales, X_i^{T+1} and X_{best^T} are the new and the best locations. C_1 shows the strength of random jumps, L_F implies the Levy fight function.

$$C_1 = 2r_4\left(1 - \frac{T}{T_{\max}}\right) \quad (6)$$

$$L_F = 0.05 \times u \times \sigma/|v|^{\frac{1}{\beta}} \quad (7)$$

Where $\sigma = \left(\frac{\Gamma(1+\beta)\times\sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left[\frac{1+\beta}{2}\right]\times\beta\times\frac{2(\beta-1)}{2}}\right)^{1/\beta}$, u and v are uniformly distributed random numbers.

Whale Fall

A limited amount of beluga whales fell to the deep seabed and did not survive during foraging and migration. X_{tep} shows the step size of the whale fall.

$$X_i^{T+1} = r_5 X_i^T - r_6 X_r^T + r_7 X_{step} \quad (8)$$

$$L_F = 0.05 \times u \times \sigma/|v|^{\frac{1}{\beta}} \quad (9)$$

Let u_b and l_b be the upper and lower bounds, respectively, C_2 indicates the step factor, and $C_2 = 2W_f \times n$. W_f denotes the whale fall probability, $w_f = 0.1 - 0.05T/T_{\max}$.

The fitness range is the extensive feature inducing the efficiency of BWO technique. The hyperparameter range process includes the solution-encoded method to calculate the performance of the candidate solution.

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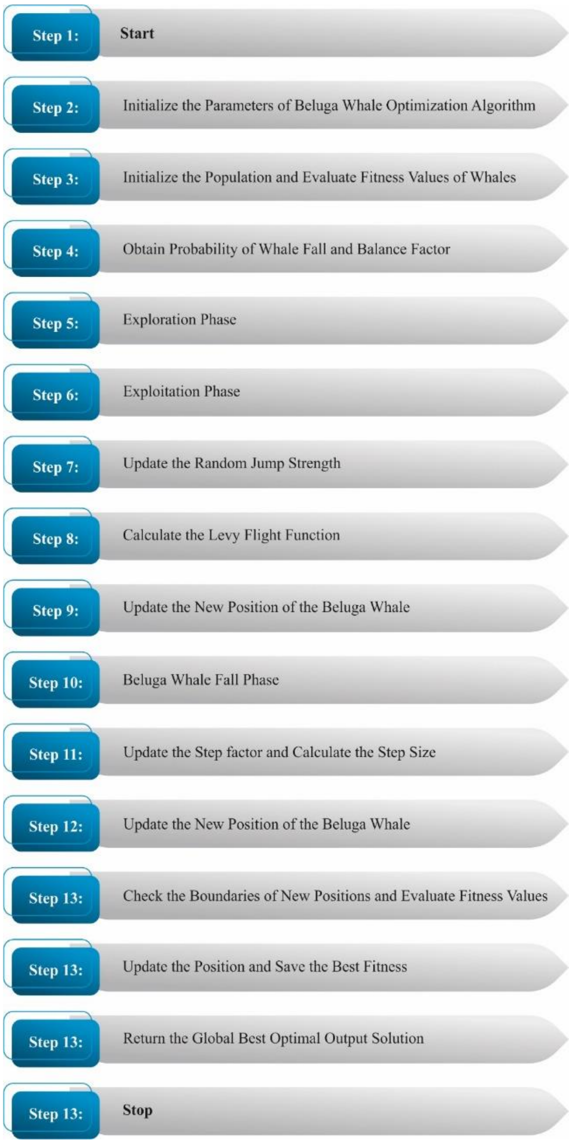

Figure 2: Steps involved in BWO

ere, the BWO technique takes accuracy as the core measure to design FF as stated below:

$$Fitness = \max(P) \tag{10}$$

$$P = \frac{TP}{TP + FP} \tag{11}$$

Whereas, TP and FP indicates the positive values of true and false, respectively.

4. Performance Validation

In this part, the performance validation of the DVNS-CKDDC technique is examined using the CKD dataset.

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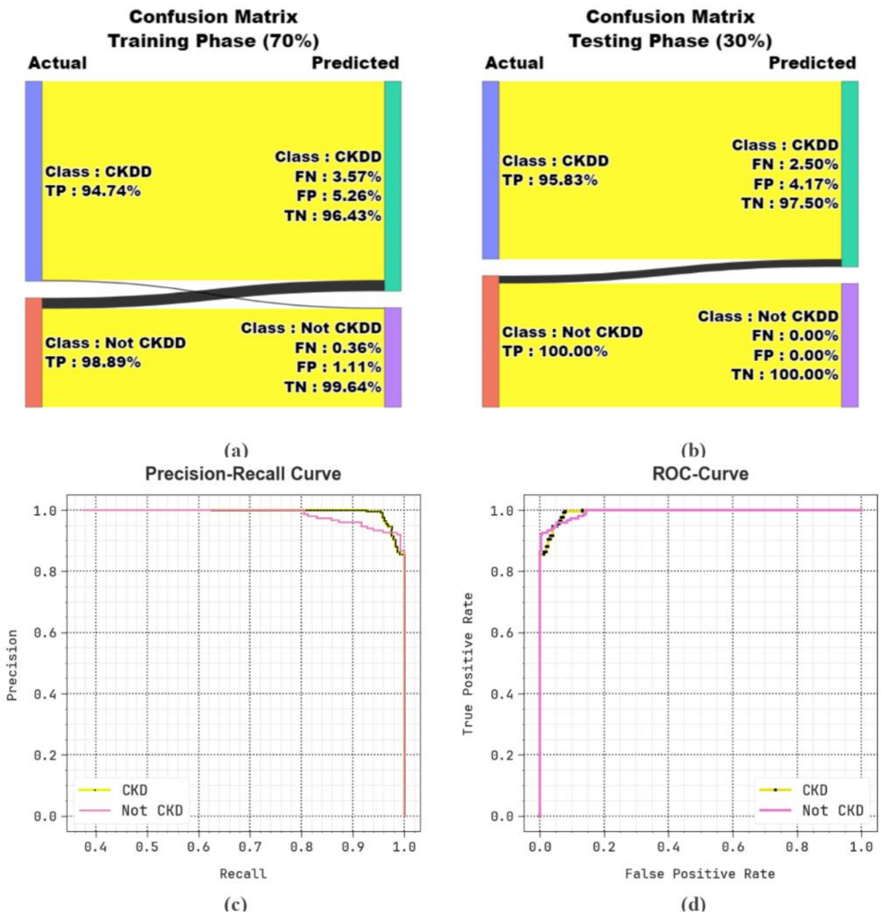

Figure 3: Classifier outcome of (a-b) 70% and 30% confusion matrices and (c-d) PR and ROC curves

Fig. 3 establishes the classifier results of the DVNS-CKDDC technique under the test dataset. Figs. 3a-3b portrays the confusion matrices offered by the DVNS-CKDDC system on 70:30 of TRAS/TESS. The outcome indicated that the DVNS-CKDDC method has recognized and classified all 2 class labels accurately. Similarly, Fig. 3c validates the PR study of DVNS-CKDDC technique. The outcome stated that the DVNS-CKDDC system has increased maximum PR performance under every classes. Finally, Fig. 3d shows the ROC investigation of the DVNS-CKDDC technique. The result represented that the DVNS-CKDDC technique has resulted in proficient outcomes with maximum ROC values under different class labels.

In Table 1 and Fig. 4, the entire result analysis of the DVNS-CKDDC system under 70%TRAS and 30%TESS is reported. The figure demonstrates that the DVNS-CKDDC system reaches proficient outcomes. With 70%TRP, the DVNS-CKDDC technique gains an average $accu_y$ of 96.07%, $prec_n$ of 96.81%, $reca_l$ of 94.67%, $F_{measure}$ of 95.61%, and AUC_{score} of 94.67%. In addition, with 30%TSP, the DVNS-CKDDC technique gains average $accu_y$ of 97.50%, $prec_n$ of 97.92%, $reca_l$ of 97.06%, $F_{measure}$ of 97.42%, and AUC_{score} of 97.06%.

Table 1: Classifier outcome of DVNS-CKDDC technique under 70%TRP and 30%TSP

Class Labels	$Accu_y$	$Prec_n$	$Reca_l$	$F_{Measure}$	AUC_{Score}
TRAS (70%)					
CKD	96.07	94.74	99.45	97.04	94.67
Not CKD	96.07	98.89	89.90	94.18	94.67
Average	96.07	96.81	94.67	95.61	94.67
TESS (30%)					
CKD	97.50	95.83	100.00	97.87	97.06
Not CKD	97.50	100.00	94.12	96.97	97.06
Average	97.50	97.92	97.06	97.42	97.06

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In Fig. 5, the training and validation accuracy outcomes of the DVNS-CKDDC method are established. The accuracy values are calculated over a range of 0-25 epochs. The outcome emphasized that the training and validation accuracy values display a rising tendency which notified the skill of the DVNS-CKDDC system with enhanced performance over numerous iterations. Moreover, the training and validation accuracy remains nearer over the epochs, which designates the lowest minimal overfitting and exhibits the improved performance of the DVNS-CKDDC system, assuring consistent prediction on unseen samples.

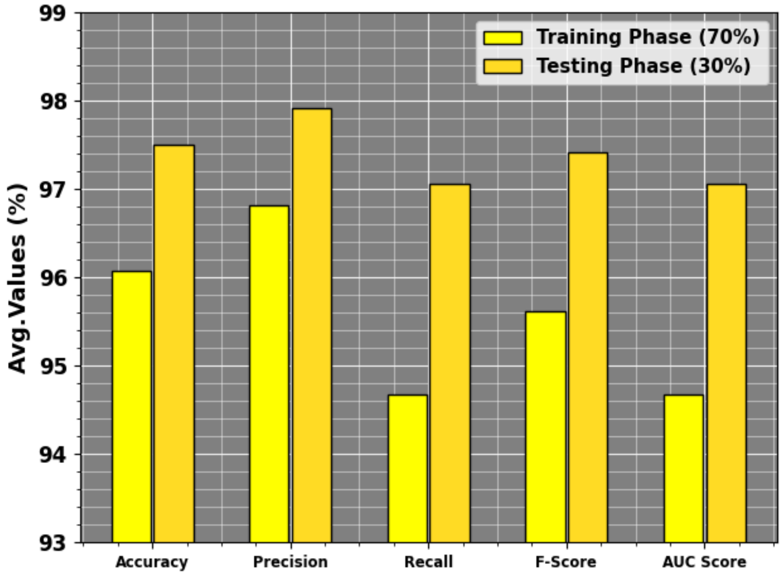

Figure 4: Average of DVNS-CKDDC technique under 70%TRP and 30%TSP

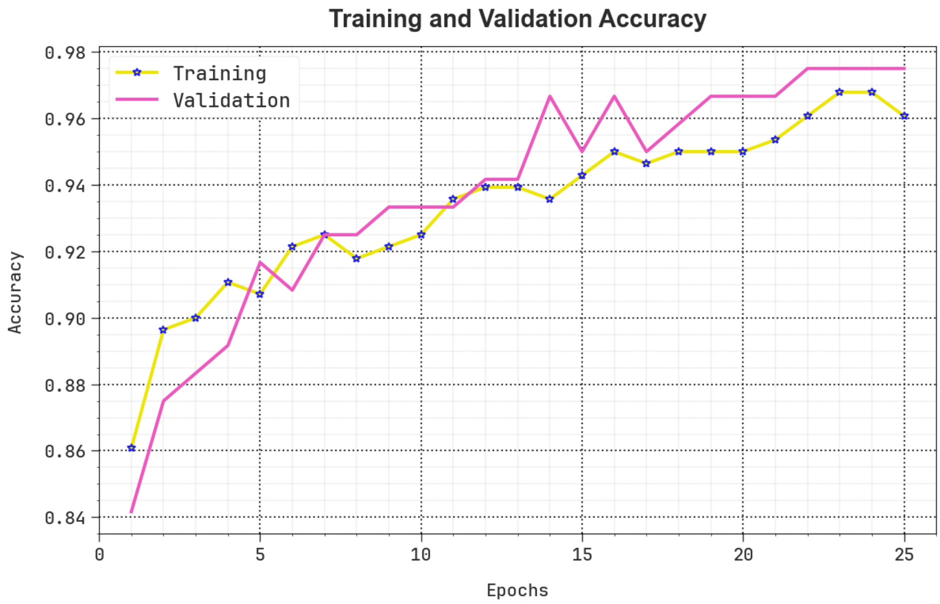

Figure 5: $Accu_y$ curve of the DVNS-CKDDC technique

In Fig. 6, the training and validation loss graph of the DVNS-CKDDC technique is displayed. The loss values are calculated over an interval of 0-25 epochs. It is embodied that the training and validation accuracy values demonstrate a decreasing tendency, which alerted the ability of the DVNS-CKDDC model to balance a trade-off between data fitting and generalization. The continual decrease in loss values furthermore guarantees the improved performance of the DVNS-CKDDC system and tunes the prediction outcomes over time.

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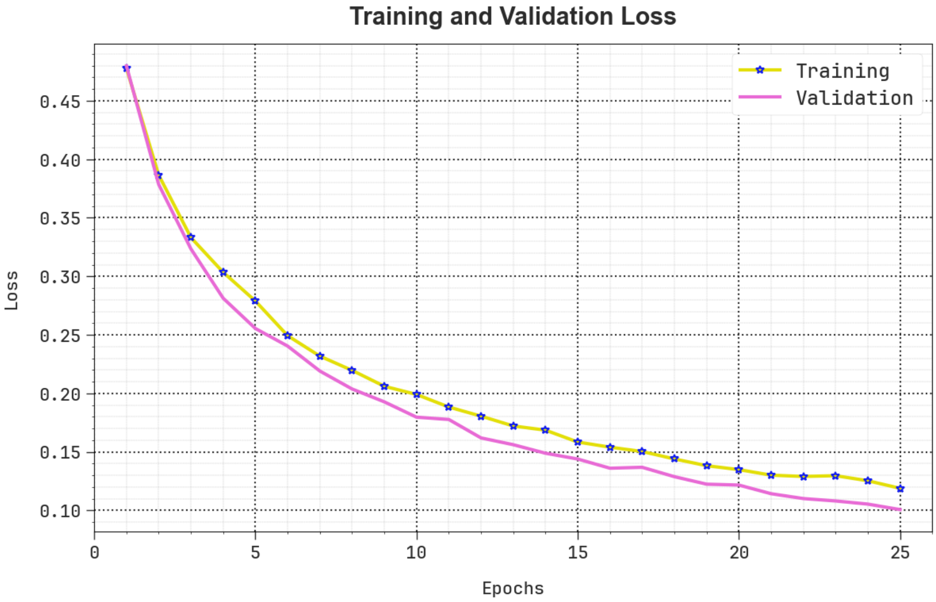

Figure 6: Loss curve of the DVNS-CKDDC technique

In Table 2 and Fig. 7, the effectual results of the DVNS-CKDDC system undergo comparison with existing models [16, 19, 20]. The results stated that the Autoencoder & NN model has shown poor results. At the same time, the GNB, NB, MLP, LR, SVM, and DT models have reported closer outcomes. But the DVNS-CKDDC technique managed to report supreme results with maximum $accu_y$, $prec_n$, $reca_l$, and $F_{measure}$ of 97.50%, 97.92%, 97.06%, and 97.42%, correspondingly. Thus, the DVNS-CKDDC technique can detect kidney disease efficaciously.

Table 2: Comparative outcome of DVNS-CKDDC technique with other models

Methodology	$Accu_y$	$Prec_n$	$Reca_l$	$F_{Measure}$
GNB Algorithm	94.00	92.07	94.51	92.89
Naïve Bayes	95.21	91.78	95.25	95.24
MLP Algorithm	94.00	91.76	96.28	92.60
Auto encoder & NN	93.00	95.90	94.84	94.87
Logistic Regression	96.00	95.85	91.25	95.98
SVM Classifier	96.00	91.58	96.80	91.87
Decision Tree	93.45	95.00	93.79	96.00
DVNS-CKDDC	97.50	97.92	97.06	97.42

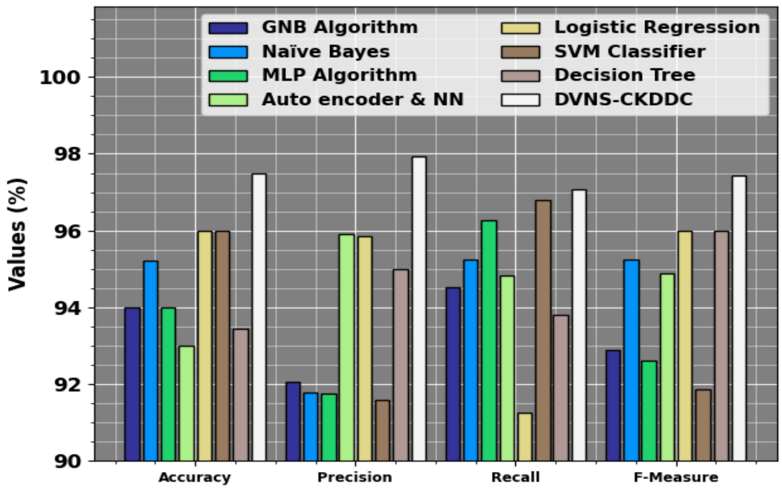

Figure 7: Comparative outcome of DVNS-CKDDC technique with other models

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5. Conclusion

In this manuscript, we focus on the design and growth of the DVNS-CKDDC model. In the DVNS-CKDDC method, three major processes are involved data normalization, DVNS-based CKD detection, and BWO-based parameter tuning process. At the primary phase, the DVNS-CKDDC technique performs the LSN model. Next, the DVNS-CKDDC technique makes use of the DVNS model for the identification of CKD. Lastly, the BWO technique is utilized for the parameter tuning of the DVNS system. To ensure the supremacy of the DVNS-CKDDC technique, a widespread simulation analysis is involved. The experimental values stated that the DVNS-CKDDC method attains improved performance over other models.

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