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Urinary Bladder Inflammation Prediction with the Gray Wolf Optimization Algorithm and Multi-Layer Perceptron-Based Hybrid Architecture

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Abstract
This study presents a decision-support system for predicting bladder inflammation. The proposed decision support system is built by establishing a hybrid architecture with the Gray Wolf Optimization algorithm (GWO) and Multi-Layer Perceptron (MLP). In addition to optimizing the hyperparameters in the MLP structure with GWO, the hybrid architecture also optimizes the order of input values to be presented to the MLP structure. The Acute Inflammations data set in the UCI Machine Learning repository was used as the data set in the study. Classification operations were carried out on this data set with the models obtained with hybrid architecture, Decision trees, k-Nearest Neighbors, and Support Vector Machines methods. The controversial findings from experimental studies have shown that the proposed hybrid architecture produces more successful results than other machine learning methods used in the study. In addition, the MLP structure optimized with the hybrid architecture offers a new diagnostic method for patient decision support systems.

1. Introduction

Inflammation is a defense mechanism that recognizes cell damage and aims to repair it. It also acts to clear damaged cells. There are two basic types: Acute inflammation is generally characterized by dilation of blood vessels, accumulation of fluid between cells, movement of neutrophils, and sometimes activation of the coagulation process [1]. One of the acute inflammations seen in the human body is urinary bladder inflammation. In later stages, the inflammation in the body damages organs and tissues. Early diagnosis and treatment are extremely important to minimize this damage.

Decision support systems developed in the field of health in recent years play an important role in the early prediction and diagnosis of many diseases [2], [3]. Adem et al. [4] used a stacked autoencoder and softmax classification for the classification and diagnosis of cervical cancer. In the study, machine learning methods such as Rotation Forest (RF), Support Vector Machines (SVM), Feed Forward Neural Network, and k-Nearest Neighbors (kNN) were also used. All machine learning methods used in the study were tested on data taken from the UCI database. The findings show that the presented model performs classification more successfully than other machine learning methods.

Giorgio et al. [5] implemented the ECG signal processing chain for arrhythmia detection, QT segment prolongation assessment, and pulmonary embolism risk assessment. The decision support system developed using programmable logic devices (PLDs) and field programmable gate arrays (FPGAs) is also wearable. As a result of the studies, successful results were obtained in ECG signal processing.

Kim et al. [6] have developed a rules-based speech analysis diagnostic system to evaluate the risk of stroke due to neurogenic bladder disease in elderly individuals. The created model was evaluated in real-time on 30 abnormal data points and 30 normal data points. The findings demonstrated a high test

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accuracy of 98.7% for normal data and 99.6% for abnormal data.

Casal-Guisande et al. [7] developed a decision support system using the Synthetic Minority Oversampling Technique for Nominal and Continuous (SMOTE-NC) and Fuzzy logic methods for the diagnosis of sleep apnea. The proposed decision support system has achieved successful results in experimental studies on a dataset of 4400 patients.

Javed et al. [8] used RF and SMOTE to predict heart failure. In the study, techniques such as Navian Bayes (NB), Logistic Regression (LR), Decision Trees (DT), and SVM, which are frequently used in the literature, were used, and more successful results were produced with the proposed method.

For the developed systems to produce better results, many machine learning methods are used in studies. These methods are part of a continuous improvement effort. One of the most prominent techniques in this continuous improvement effort is optimization algorithms [9], [10]. One of the optimization algorithms frequently used in the literature is the Gray Wolf Optimization (GWO) algorithm. When we look at the studies using GWO, Jeyafzam et al. [11] used the Grey Wolf Optimization algorithm to optimize the hyperparameters in the SVM model they used for the prediction of diabetes. Classification methods such as DT, Multilayer Perceptron Neural Network, Simple Bayes, and Temporal Fuzzy Min-Max Neural Network were also used in the study. The model optimized with GWO produced more successful results than other ML methods.

Magdy et al. [12] used various machine-learning methods for skin cancer classification in their study. They used the gray wolf optimization algorithm to optimize AlexNet hyperparameters and achieved successful results in skin cancer classification.

The ML methods used in the studies in the literature contain many hyperparameters. The success of the methods depends on these hyperparameters [13]. It is almost impossible to adjust these parameters using trial-and-error methods to produce successful results. Problem-specific tuning of these hyperparameters will only be possible with the development of hybrid models [14], [15].

In this study, a hybrid architecture using the GWO algorithm and Multi-Layer Perceptron (MLP) Networks is proposed for the prediction of urinary bladder inflammation. The hyperparameters in the MLP structure in the proposed architecture are optimized with GWO. In the study, DT, KNN, and SVM methods, which are frequently used in classification problems in the literature, are also used. All the methods are tested on the Acute Inflammation dataset in the UCI database, and the findings are presented comparatively.

2. Material and Method

In this part of the study, GWO, MLP, and other ML methods used to predict urinary bladder inflammation are mentioned in detail.

2.1. Multi-Layer Perceptron (MLP)

MLP is a kind of artificial neural network [16], which has several advantages such as simple structure, intuitive model parameters, and fast model training speed. In the MLP structure, there are an input layer, hidden layers, and an output layer. A simple MLP structure is shown in Figure 1.

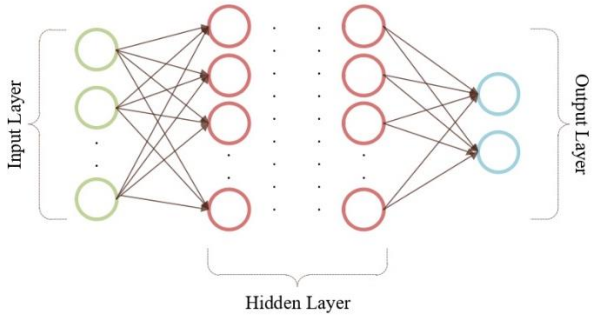


Figure 1. MLP structure.

In the MLP structure presented in Figure 1, information flow is transmitted from the input layer to the output layer. Each layer consists of neuron cells. The incoming data in the neuron cells is multiplied by the weights determined by the network and sent to an aggregation function. A bias value determined by the network is added to the data coming out of the aggregation function [14]. The data is translated by passing it through the activation function within the neuron cell, and the net output for that neuron cell is produced. In MLP structures, the output of one neuron cell is used as input for the neuron cell in the next layer. At the end of the network, the error rate between the generated output and the target output is calculated, and this error rate is reflected to the network by back propagation [15].

2.2. Gray Wolf Optimization Algorithm (GWO)

Proposed in 2014 by Faris et al., GWO is a metaheuristic algorithm and has been used in different optimization domains [17]. Gray wolves live in packs

in nature. There is a hierarchy in gray wolf packs. This hierarchy is shown in Figure 2.

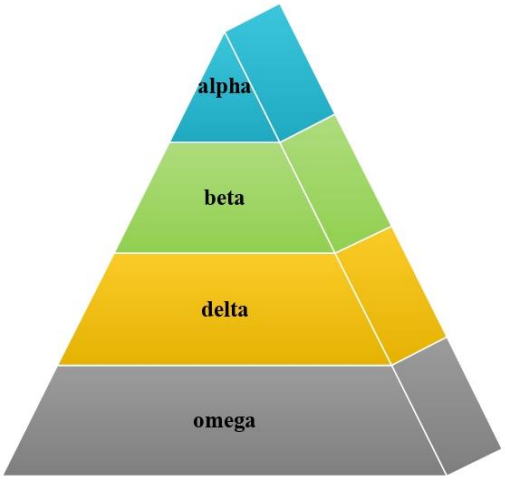


Figure 2. Gray wolf pack hierarchy.

As shown in Figure 2, there are 4 different groups in the hierarchy: α (apha) wolves, β (beta) wolves, δ (delta) wolves, and ω (omega) wolves. The alpha wolves in the pack are responsible for hunting, resting, and other group movements and the other gray wolves follow the alpha. Therefore, alpha gray wolves are seen as leaders in the pack [18].

When gray wolves hunt, they first calculate the distance between their current position and the prey to encircle it. They then update their position according to this distance. This is how gray wolves' hunting behavior is described. The mathematical representation of gray wolves surrounding their prey is shown in Equation 1 [19].

$$X(t+1) = X_p(t) - A * D \qquad (1)$$

In Equation 1, the position of the gray wolf is updated. Where t is the current iteration number, $X_p(t)$ and $X(t)$ are the current position vectors of the prey and gray wolf at iteration *t*, respectively. D represents the distance between the gray wolf and the prey and is calculated as shown in Equation 2 [20].

$$D = |C * X_p(t) - X(t)| \qquad (2)$$

A and C are the coefficient vectors presented in Equation 1 and Equation 2. These coefficient vectors are calculated as presented in Equations 3 and 4 [21].

$$A = 2 * a * r_1 - a \qquad (3)$$

$$C = 2 * r_2 \qquad (4)$$

The values r_1 and r_2 in the equations are random vectors. In Equation 3, a represents the convergence factor. The value of a converges linearly from two to zero as the iteration increases. The value of a is calculated as shown in Equation 5.

$$A = 2 - 2 * \frac{t}{t_{max}'} \qquad (5)$$

In the gray wolf model of hunting behavior, α (alpha), β (beta), and δ (delta) wolves are considered to have a better understanding of the potential location of prey. In this hierarchy, the α wolf represents the most optimal solution, the β wolf represents a suboptimal solution, and the δ wolf represents the third-best solution. The other gray wolves use computational formulas to update their position relative to the α, β, and δ wolves, which are shown in Equations 6-8 [22].

$$\begin{aligned} D_\alpha &= |C_1 * X_\alpha - X(t)| \\ D_\beta &= |C_2 * X_\beta - X(t)| \\ D_\delta &= |C_3 * X_\delta - X(t)| \end{aligned} \qquad (6)$$

$$\begin{aligned} X_1 &= |X_\alpha * A_1 * D_a| \\ X_2 &= |X_\beta * A_1 * D_\beta| \\ X_3 &= |X_\delta * A_1 * D_\delta| \end{aligned} \qquad (7)$$

$$X(t+1) = (X_1 + X_2 + X_3)/3 \qquad (8)$$

In the equations, D_α represents the distance between the current gray wolf and α gray wolf. D_β represents the distance between the current gray wolf and the β gray wolf. D_δ represents the distance between the current gray wolf and the δ gray wolf. X_α represents the α gray wolf position vector. X_β represents the β gray wolf location vector. X_δ, δ represents the gray wolf position vector. *X(t)* represents the position of the gray wolf at iteration *t*. C_1, C_2, and C_3 are random vectors and are calculated as presented in Equation 4. The position of the gray wolves is updated with Equation 8.

The flow diagram of the gray wolf optimization algorithm is shown in Figure 3.

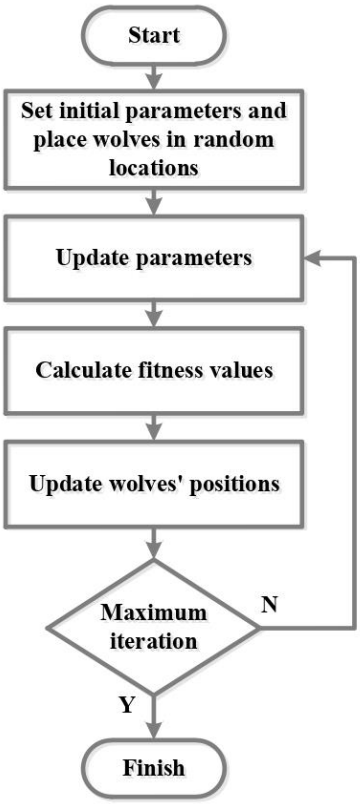


Figure 3. GWO flowchart.

What is remarkable about GWO is its ability to strike a simple balance between global search and local exploration, even though several parameters need to be tuned to achieve efficient convergence [17]. For this reason, it has been widely used in the literature in recent years [23].

2.3. Other Machine Learning Methods Used in This Study

In this study, ML methods, which are commonly used in classification problems in the literature, were also used for bladder inflammation prediction. The methods used are shown in Table 1.

ML methods presented in Table 1 produce successful results in classification problems [28]–[30].

Table 1. Other machine learning methods used in this study

ML Methods	Description
DT	Decision trees consisting of a root node, sub-branches, and nodes use multiple features and labels. A node with no sub-branches belongs to a class [24].
KNN	When classifying, KNN determines which class a new data point belongs to based on its distance from other data points [25].
SVM	SVM is a classifier that separates data placed in a given coordinate plane by drawing the best-discriminating hyperplane [26], [27].

2.4. Dataset

In this study, we used the Acute Inflammations dataset from the UCI Machine Learning repository for urinary bladder inflammation prediction [31]. This dataset was created by Dr. Jacek Czerniak at the Laboratory of Intelligent Systems of the Polish Academy of Sciences, Systems Research Institute in Warszawa, Poland [32]. The attributes in the dataset and the types of values they receive are shown in Table 2 [32].

Table 2. Data set description

No	Parameters	Data Type	Values
1	Temperature of patient	Input	35C-42C
2	Occurrence of nausea	Input	No, Yes
3	Lumbar pain	Input	No, Yes
4	Urine pushing (continuous need for urination)	Input	No, Yes
5	Micturition pains	Input	No, Yes
6	Burning of urethra, itch, swelling of urethra outlet	Input	No, Yes
7	Inflammation of uthe rinary bladder	Output	No, Yes

There are a total of 120 people in the dataset whose attributes are presented in Table 2. The dataset is randomly divided into two parts; 70% for training and 30% for testing.

2.4. Evaluation Metrics

In this study, we will calculate the recall, precision, f-score, and accuracy values used in the literature to measure the performance of urinary bladder

inflammation classifiers [33]. There are two classes in the dataset for bladder inflammation prediction. In order to calculate these evaluation criteria for the two classes, the results obtained from the classifiers must first be placed in the complexity matrix [34]. The complexity matrix for the two classes is shown in Figure 4.

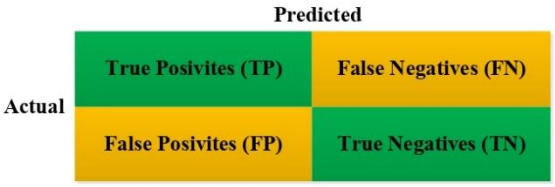


Figure 4. Confusion matrix

In the complexity matrix given in Figure 4, TP (True Positive) represents the number of people who are not actually sick and are classified as not sick. FN (False Negative) represents the number of people who are not actually sick and are classified as sick. FP (False Positive) represents the number of people who are actually sick and healthy. TN (True Negative) represents the number of people who are actually sick and classified as sick [35]. Based on these values in the complexity matrix, recall, precision, F-score, and accuracy values are calculated as presented in Equations 9-12 [36].

$$\text{Recall}(R) = \frac{TP}{TP + FN} \tag{9}$$

$$\text{Precision(P)} = \frac{TP}{TP + FP} \tag{10}$$

$$\text{F-score} = \frac{2 * P * R}{P + R} \tag{11}$$

$$\text{Accuracy(A)} = \frac{TP + TN}{TP + TN + FN + FP} \tag{12}$$

2.4. Hybrid GWO-MLP Model

In this part of the study, a hybrid architecture was created using the GWO algorithm and MLP for the prediction of urinary bladder inflammation. With this architecture, is aimed at optimizing the ranking of MLP parameters that will make the best classification and the parameters to be given as input to the MLP structure. The GWO-MLP architecture is shown in Figure 5.

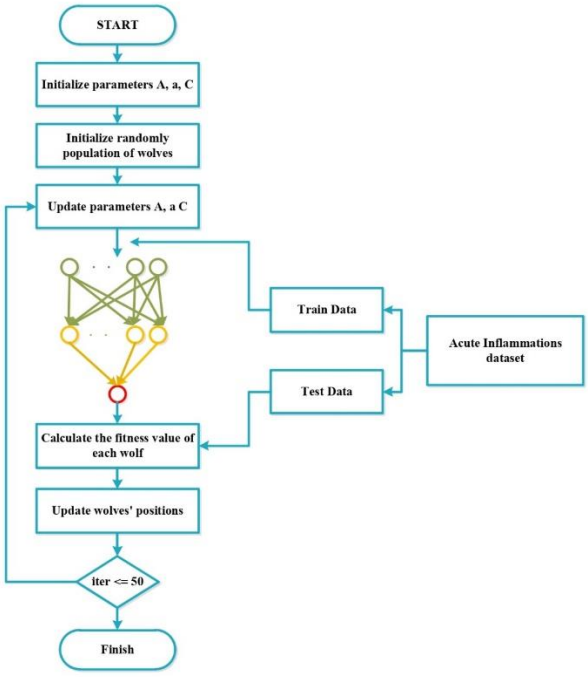


Figure 5. GWO-MLP architecture

As a first step in the hybrid architecture presented in Figure 5, GWO initial parameters were determined as a result of experimental studies. These values are shown in Table 3.

Table 3. GWO parameters

Parameters	Values
Number of Gray Wolves (n)	20
İteration Number (t)	50

In the proposed hybrid architecture, gray wolves will hunt in 6 dimensions: the input data sequence, the number of hidden layers in the MLP structure, the number of neurons in these hidden layers, the activation functions in the structure of neuron cells, the activation function in the output layer, and the learning function of the MLP. While creating a random population in these 6 dimensions, the representation and boundary values of these dimensions were determined as presented in Table 4.

The activation functions corresponding to each AFN and OLAF value in Table 4 are shown in Table.

The learning function corresponding to each LFMLP value in Table 4 is shown in Table 6.

Table 4. Solution space and boundary values

Representation	Description	Minimum Value	Maximum Value
IS	Input data sequence	6	6
NH	Number of hidden layers in the MLP structure	2	8
NN	Number of neurons in hidden layers	2	8
AFN	Activation functions used in neurons	1	6
OLAF	Output layer activation function	1	6
LFMLP	Learning function of MLP structure	6	6

Table 5. AFN and OLAF values

Representation	Corresponding Activation Function
1	radbas
2	purelin
3	logsig
4	hardlim
5	tansig
6	hardlims

Table 6. LFMLP values

Representation	Corresponding Activation Function
1	traingda
2	trainrp
3	trainbr
4	trainscg
5	traincgp
6	traingd
7	trainc
8	traingdm
9	traingdx
10	trainoss
11	traincgb
12	traincgf
13	trainb
14	trainbfg
15	trainr

The fitness function presented in Equation 13 was used to identify alpha, beta, and delta wolves in the gray wolf pack randomly generated by the number of populations given in Table 3.

$$FitF(W_i) = Test - Accuracy(MLP_i) \quad (13)$$

In Equation 13, $FitF(W_i)$ represents the fitness value of the i. gray wolf. MLP_i i. represents the MLP structure generated with the parameters of the gray wolf positions. The MLP structure obtained with the parameters of each gray wolf location performs classification on the test data.

In the presented hybrid architecture, in the next step, the positions of the gray wolves are updated according to Equation 8.

As presented in Table 3, the hybrid architecture was run for 50 iterations. After 50 iterations, the parameters and corresponding values of the location of the alpha gray wolf are shown in Table 7.

Table 7. Alpha gray wolf location and values

Parameters	Values
IS	2-1-3-6-4-5 (Table 4 indices)
NH	1
NN	6
AFN	hardlims
OLAF	tansig
LFMLP	trainoss

The MLP classifier structure obtained with the alpha wolf position information presented in Table 7 is shown in Figure 6.

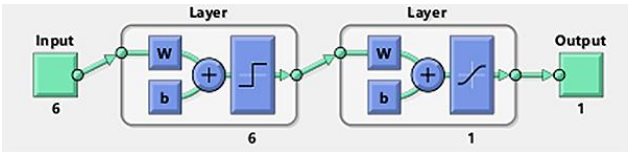
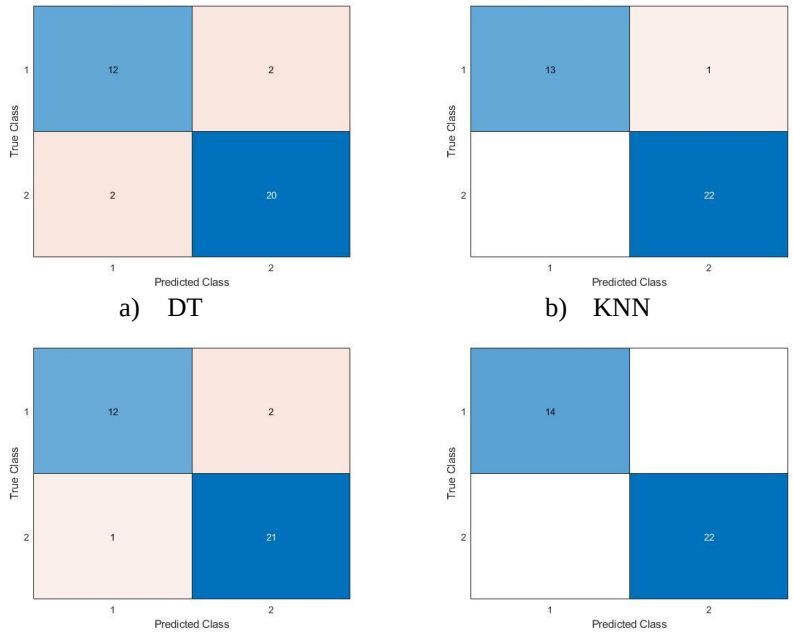


Figure 6. MLP structure formed by the alpha wolf position

3. Results and Discussion

In the experimental studies for bladder inflammation prediction, different machine-learning methods were used along with the presented hybrid architecture. The complexity matrices created by the classification processes in light of the experimental studies using DT, KNN, and SVM methods and the findings obtained as a result of the hybrid architecture are shown in Figure 7.



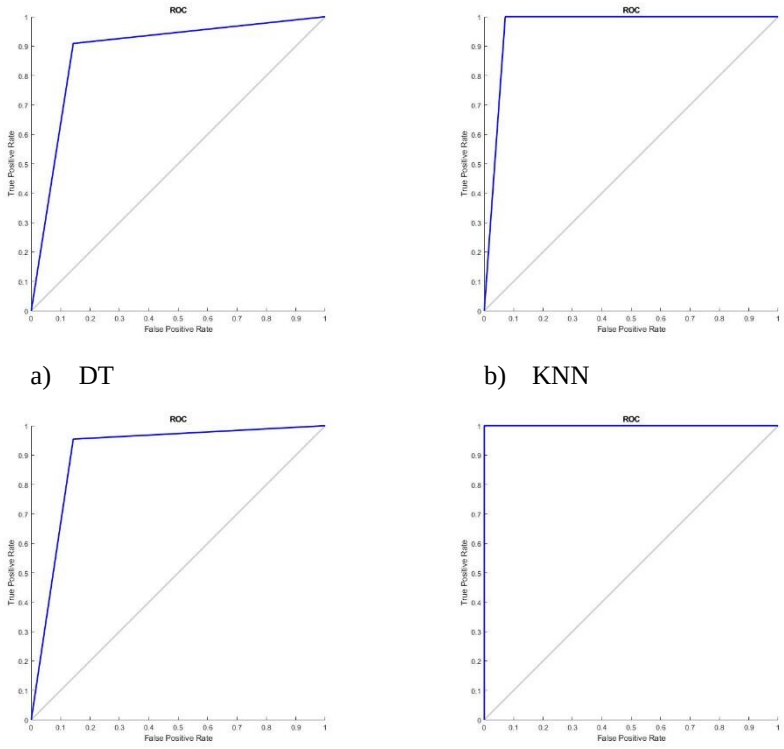
a) DT b) KNN

c) SVM d) Proposed Hybrid architecture

Figure 7. Confusion matrices of the classifiers used

According to the confusion matrices shown in Figure 7, the most successful classifier is the hybrid architecture that correctly predicts all test data.

A prominent criterion for evaluating the performance of ML models is the Receiver Operating Characteristic (ROC) curve [33]. ROC curves for each classifier are presented in Figure 8.



a) DT b) KNN

c) SVM d) Proposed Hybrid architecture

Figure 8. ROC curves of the classifiers

The ROC curve represents the false positive rate (FPR) on the x-axis and the true positive rate (TPR) on the y-axis. We refer to the area under the ROC curve as the AUC (Area Under the Curve). The AUC measures the classification ability of a model; the larger it is, the higher the success of the model. The most desirable value for AUC is 1, indicating that the area under the ROC curve of a perfect model is 1. Looking at the ROC curves given in Figure 8, the classification with the presented hybrid architecture produced more successful results than other ML methods.

The performance of the ML methods used in the classifications for bladder inflammation prediction is calculated according to Equations 9-12 and shown in Table 8.

Table 8. Experimental results for bladder inflammation classification

Models	Precision	Recall	F-scor	Accuracy
DT	0,86	0,86	0,86	0,89
KNN	**1**	0,93	0,96	0,97
SVM	0,92	0,86	0,89	0,92
Proposed model	**1**	**1**	**1**	**1**

According to the evaluation criteria shown in Table 8, the proposed hybrid architecture achieved high success compared to other classifiers.

4. Conclusion and Suggestions

Patient decision support systems designed with new-generation technologies realize early prediction and diagnosis of many health problems. Early diagnosis and treatment of diseases are of great importance for the protection of human health and to reduce or eliminate the negative effects caused by diseases. In this study, a GWO-MLP-based hybrid architecture is proposed to predict urinary bladder inflammation. With the proposed hybrid architecture, all hyperparameters that make up the MLP structure are optimized. In addition, the order of input information to be used as inputs in the MLP structure is also optimized by determining the order of input information within the architecture. The Acute Inflammation dataset in the UCI Machine Learning repository was used to measure the performance of the MLP structure established with the optimized parameters thanks to the hybrid architecture presented. Machine learning techniques commonly used in the literature were also used in the experimental studies on the dataset. The results of the studies showed that the hybrid GWO-MLP architecture provided accurate classification with 100% success on the test dataset for the prediction of urinary bladder inflammation. With the presented hybrid architecture, the parameters of an MLP architecture that should be created for bladder inflammation were determined, and the input data was sequenced.

The presented architecture can be easily used as an alternative method in health decision support systems. In future studies, mobile or web-based applications can be developed with these parameters.

Conflict of Interest Statement

There is no conflict of interest regarding the study.

Statement of Research and Publication Ethics

The study complies with research and publication ethics

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