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DESIGN AND EVALUATION OF A NEW TENT-SHAPED TRANSFER FUNCTION USING THE POLAR LIGHTS OPTIMIZER ALGORITHM FOR FEATURE SELECTION

Zaynab Ayham Almishlih[1], Omar Saber Qasim[1], Zakariya Yahya Algamal[2]

[1]University of Mosul, Department of Mathematics, Mosul, Iraq, [2]University of Mosul, Department of Statistics and Informatics, Mosul, Iraq

Abstract. *This research aims to develop a new transfer function to transform continuous space to binary space using the Polar Lights Optimizer (PLO) algorithm for the feature selection problem. The PLO algorithm relies on simulating the behaviour of the aurora borealis to achieve a balance in exploring and exploiting binary space. A new transfer function called the tent-shaped transfer function has been incorporated into the algorithm to improve its performance. The proposed function was tested on seven datasets, and compared with traditional transfer functions such as the S-shaped function family and the V-shaped function family. The results showed that the tent-shaped transfer function outperforms in terms of feature selection accuracy and reduces the number of features more effectively, which enhances the algorithm's ability to improve performance and reduce computational complexity.*

Keywords: feature selection, transfer function, Polar Lights Optimizer, tent-shaped transfer function

PROJEKTOWANIE I OCENA NOWEJ FUNKCJI PRZENOSZENIA W KSZTAŁCIE NAMIOTU PRZY UŻYCIU ALGORYTMU POLAR LIGHTS OPTIMIZER DO SELEKCJI CECH

Streszczenie. *Badania te mają na celu opracowanie nowej funkcji przenoszenia w celu przekształcenia przestrzeni ciągłej w przestrzeń binarną przy użyciu algorytmu Polar Lights Optimizer (PLO) dla problemu selekcji cech. Algorytm PLO opiera się na symulacji zachowania zorzy polarnej w celu osiągnięcia równowagi w eksploracji i wykorzystaniu przestrzeni binarnej. Nowa funkcja przenoszenia zwana funkcją przenoszenia w kształcie namiotu została włączona do algorytmu w celu poprawy jego wydajności. Proponowana funkcja została przetestowana na siedmiu zestawach danych i porównana z tradycyjnymi funkcjami przenoszenia, takimi jak rodzina funkcji w kształcie litery S i rodzina funkcji w kształcie litery V. Wyniki pokazały, że funkcja przenoszenia w kształcie namiotu jest lepsza pod względem dokładności wyboru cech i skuteczniej zmniejsza liczbę cech, co zwiększa zdolność algorytmu do poprawy wydajności i zmniejszenia złożoności obliczeniowej.*

Słowa kluczowe: selekcja cech, funkcja przenoszenia, Polar Lights Optimizer, funkcja przenoszenia w kształcie namiotu

Introduction

Binary optimization problems (BOPs) are a fundamental category in the field of combinatorial optimization, with wide applications such as the 0-1 Knapsack Problem (0-1KP), the Maximum Coverage Problem (MCP), the Feature Selection Problem (FSP), and others [2, 3, 6]. In recent years, the feature selection problem has become pivotal due to its importance in improving the performance of analysis and classification models. With the significant increase in the volume and diversity of data, the presence of unnecessary or irrelevant features poses a major challenge, leading to increased computational complexity and reduced efficiency of systems [10, 18].

As a result, it has become necessary to use effective techniques to select essential features that contribute to improving performance and reducing dimensionality [5]. One of the methods used in feature selection is metaheuristic optimization techniques, which include algorithms based on mathematical models inspired by nature. The Polar Lights Algorithm (PLO) is one of these algorithms, as it relies on the principle of mathematical simulation of the behavior of natural phenomena, such as the aurora phenomenon, to explore the binary space and find optimal solutions [7, 16].

Transfer functions play a pivotal role in this framework, transforming continuous space into binary space, allowing binary algorithms to be applied to problems that require discrete solutions. Several transfer functions such as S- and V-shaped functions have been developed, and are effective in transforming continuous values into binary [17, 19]. However, the scope of optimizing these functions remains open, especially in large-dimensional optimization problems, where traditional transfer functions may lead to substandard results [1, 4]. This paper aims to explore a new transfer function in the context of the Polar Lights (PLO) algorithm for feature selection, comparing its results with traditional transfer functions. The research addresses how to strike a balance between exploitation and exploration to improve the accuracy of computational performance and select features more effectively.

In this paper, the content is organized according to the following structure. Section 1 presents the polar lights optimization algorithm, while section 2 presents the binary polar light optimization algorithm. Section 3 comes up with a new proposal, which is an innovative transfer function. In section 4, experimental results are evaluated and discussed by performing them on seven benchmark datasets. Finally, section 5 summarizes the entire.

1. Polar Lights Optimization algorithm (PLO)

It is one of the nature-inspired algorithms used in the field of optimization. This algorithm is inspired by the behaviour of the northern and southern polar lights (aurora borealis) [20], which is caused by interactions between charged grains from the sun with the Earth's magnetic field at the poles. This phenomenon results in luminescence as shown in Fig. 1. The goal of developing this algorithm is to provide a new mechanism for exploring and exploiting optimal solutions in complex optimization problems.

The Polar Lights Algorithm simulates the motion of grains representing solutions in the search space, as charged particles interact during the natural celestial lights phenomenon (aurora borealis). The algorithm relies on two main methods:

Exploration: The ability to search extensively in the solution space in search of new and undiscovered solutions.

Exploitation: The ability to improve existing solutions to get closer to the optimal solution.

2. Binary Polar Lights Optimization algorithm (BPLO)

The original Polar Lights Algorithm has been modified into a binary form to handle optimization problems in the binary domain such as feature selection. In the binary form, solutions must take values 0 or 1, making the algorithm suitable for applications that require binary decisions [9].

In the BPLO algorithm, the motion of particles in continuous space is transformed into binary space using transfer functions, which are functions that convert continuous values into binary values. The position of each particle is updated using specific mathematical equations, and decisions about updating the positions are made based on the results of the transfer function.

BPLO generates randomly initial solutions represented by $X_i = [X_i^1, X_i^2, ..., X_i^d]$, $i = \{1, 2, \ldots, N\}$ in a d-dimensional search space, using Eq. (1).

$$X = \begin{bmatrix} X_1^1 & \cdots & X_1^d \\ \vdots & \ddots & \vdots \\ X_N^1 & \cdots & X_N^d \end{bmatrix} \quad (1)$$

where N represents the population size, X_i represents the i^{th} solution, where each solution represents a binary string (0 or 1) representing the selected features in the problem.

The algorithm is based on an equation to update the position:

$$X_i^{(t+1)} = Transfer(V_i^{(t+1)}) \quad (2)$$

where $X_i^{(t+1)}$ is the new position of particle i at time $t+1$, $Transfer$ is the transfer function used to convert velocity values from a continuous field to binary probability values between 0 and 1. The speed is adjusted based on the location of the current solution and the best solutions discovered:

$$V_i^{(t+1)} = \omega * V_i^t + c_1 * r_1 (P_{best} - X_i^t) + c_2 * r_2 (G_{best} - X_i^t) \quad (3)$$

where ω is the inertia factor, which helps in controlling the wide search, c_1 and c_2 are the accelerating factors that control the trend toward the best local and global location, r_1 and r_2 are random values between 0 and 1, P_{best} is the best solution for the current particle, and G_{best} is the best global solution discovered.

Here, the new location is determined based on a random value r as follows:

$$X_i^{(t+1)} = \begin{cases} 1 & if \quad r < Transfer(V_i^{(t+1)}) \\ 0 & if \quad r \geq Transfer(V_i^{(t+1)}) \end{cases} \quad (4)$$

Exploration refers to the ability of the algorithm to search different areas of the solution space to find diverse solutions and explore new regions. Exploration in BPLO is enhanced by assigning high values to the inertia factor ω and acceleration factors c_1 and c_2, which allow particles to move to new areas of the solution space. When higher exploration is achieved: A larger value of the inertia factor ω is assigned (usually in the early stages of the process), which forces particles to move further in the search space away from the best location found. Exploitation, in contrast, refers to the ability of the algorithm to improve existing solutions by focusing on a particular region or solution to obtain the best possible result near that solution. Exploitation is enhanced when the inertia factor ω values are low, leading to the solutions converging towards the best discovered locations, whether locally or globally. When higher exploitation is achieved: the ω value is gradually reduced in later stages of the process, reducing the movement of particles and driving them towards the optimal solution. Also, the effect of c_1 and c_2 is increased to increase the concentration of particles on regions containing the best local and global solutions. Over time, the value of ω decreases dynamically according to the following equation to achieve an automatic balance between exploration and exploitation:

$$\omega = \omega_{\max} - \left(\frac{\omega_{\max} - \omega_{\min}}{Max_{Iter}} \right) * t \quad (5)$$

where $\omega_{\max}$ is initial inertia (highest value at the beginning of the search), $\omega_{\min}$ is final inertia (lowest value at the end of the search), Max_{Iter} is maximum number of repetitions, and t is current iteration. Pseudo-code of BPLO is summarized in Algorithm 1.

Algorithm 1: Pseudo code of BPLO

Start
Load dataset, split into training and testing sets
PLO' parameters initialization ω, Max_{Iter}, c_1, c_2, r_1, r_2 and population size (number of initial solutions) N
Generate a random set of initial solutions (I = 1, . . ., n)
while (t < Max_{Iter}) do
Evaluate the objective function (fitness)
Identify the best solution (best polar light) in the set
for i=1 to solutions do
Evaluate the new velocity of the solution using eq. (3)
Switch the continuous velocity to binary values using eq. (2)
Update the location of the solution to the new binary location using eq. (4) and calculate its fitness
if $fit_{new} > fit_{current}$
$X_i^t = X_i^{(t+1)}$
end if
end for
t=t+1
end while
Return the solution of finest (maximum accuracy, minimum features).

3. Proposed family of Tent-shaped transfer functions

Given the vital role of transfer functions in the discretization of binary optimization problems, it highlights the importance of exploring and discussing the design of transfer functions in their diversity and practical effectiveness. And for this reason, the existing V-shaped transfer functions and S-shaped transfer functions [12–15] are firstly reviewed in this section. Then a new class of transfer functions is proposed, which are known as tent-shaped transfer functions. Based on this idea, a new binary polar lights optimization algorithm BPLO is proposed.

Table 1. V-Shaped and S-Shaped transfer functions

	Name	Transfer Function
V-shaped	V_1	$V_1(x) = \left\| erf\left(\left(\sqrt{\pi}/2\right)x\right)\right\|$
	V_2	$V_2(x) = \left\|\tanh(x)\right\|$
	V_3	$V_3(x) = \left\| x/\sqrt{1+x^2} \right\|$
	V_4	$V_4(x) = \left\|(2/\pi)\arctan\left((\pi/2)x\right)\right\|$
S-shaped	S_1	$S_1(x) = 1/\left(1+e^{-2x}\right)$
	S_2	$S_2(x) = 1/\left(1+e^{-x}\right)$
	S_3	$S_3(x) = 1/\left(1+e^{-x/2}\right)$
	S_4	$S_4(x) = 1/\left(1+e^{-x/3}\right)$

Basically, The most common and widely used transfer functions are the V and S-shaped functions [14, 15]. Among these functions, the most representative V-shaped functions are V1 to V4, while the most representative S-shaped functions include the functions S1 to S4. The mathematical formulas of these functions are shown in table 1, while their curves are shown in Fig. 1 and 2. They make it clear that S-shaped functions are a class of fundamental functions that are derived from the exponential function. They contain a single calculation formula, which is $S(x)=1/(1+e^{(bx+a)})$, where b and a are real numbers, and $b \neq 0$. It is generally referred to as the S-shaped transfer function since this kind of function has a "S"-shaped curve. Also, V-shaped transfer functions, their curves show a "V" shape, so they are called "V-shaped transfer functions", even though there is no unified mathematical formula for them, and they are not all elementary functions.

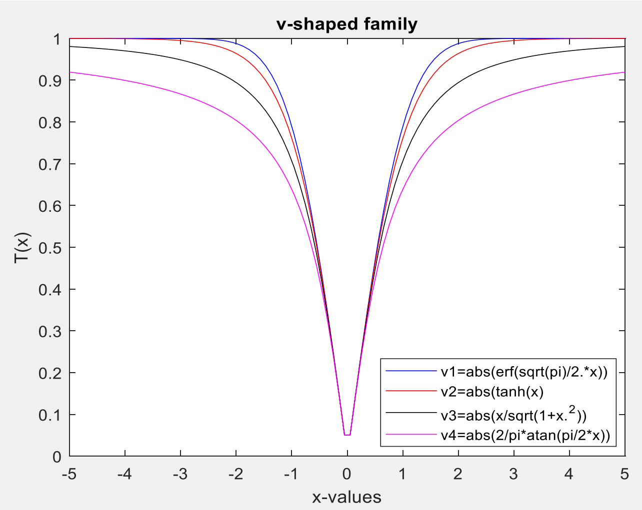

Fig. 1. V-shaped transfer function

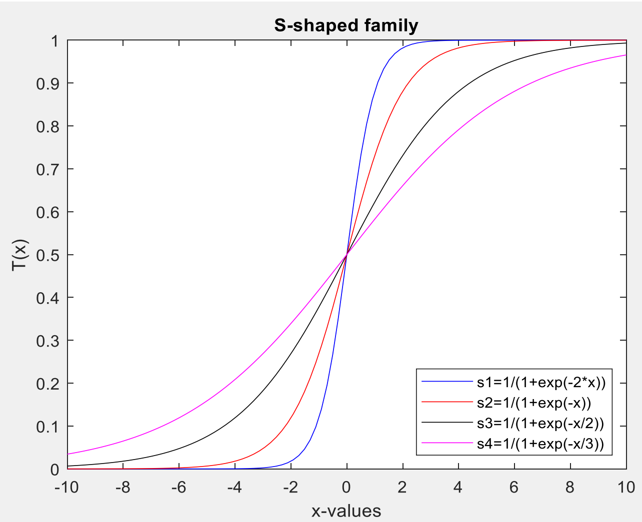

Fig. 2. S-shaped transfer function

As we know, there are an infinite number of transformations from the real dimensional space R^n or its subspace to the discrete space $\{0,1\}^n$, This transformation is often used as transfer functions for discretizing BOPs that still lack associated theoretical results. Hence, individuals usually design and apply a transfer function based on their experience to discretize BOPs. This is a way to reconfigure using the available transfer functions, however, has a reference role and guiding importance. Nowadays, existing transfer functions and their applicability [8, 13–15] are evaluated mainly based on results obtained when solving BOPs. Based on this fact, it becomes clear that trying to develop a variety of transfer functions can be very beneficial, not only does this provide more options for the discretization of BOPs, but it also contributes to the accumulation of experience required to build a comprehensive theory for evaluating those functions. Since V-shaped transfer functions and S-shaped transfer functions [12–15] consist of a trigonometric function, an anti-trigonometric function, an exponential function, or a non-elementary function, their calculations require relatively more. This will have a negative impact on the execution time of BOPs. For this purpose, a new transfer function is proposed. Since the function curve of the new transfer function resembles the shape of a tent, it is called a tent-shaped transfer function and is defined as follows:

$$T(x)=1/(1+|x|)^R \tag{6}$$

where R is a positive real number. By changing the value of R, a set of Tent-shaped functions family is obtained, their expressions and figures appear in table 2 and figure 3, respectively.

It is clear from figures 2 and 3 that the properties of the tent-shaped functions are completely different from the S-shaped transfer functions. But if we compare our function with the V-shaped transfer functions, we see that they are similar only in that they are symmetrical about the Y-axis, but they are very different in several properties, including: The V-shaped transfer function decreases monotonically over (-∞,0] and increases monotonically over [0,∞), while exactly the opposite occurs for the tent-shaped transfer function, it is clear from looking at Figures 1 and 3 that the tent-shaped function curve is inverted V-shaped. This difference may not be as important as the following:

First, all tent-shaped transfer functions have a unified calculation formula $T(x)=1/(1+|x|)^R$, R is a positive real number, and their calculations are very simple. While the V-shaped transfer functions do not have a unified calculation formula, in addition, the calculation formula for functions V2 and V4 are relatively complex.

Second, the decrease or increase in the curvature of the tent-shaped transfer functions is much more gradual than the curvature of the V-shaped transfer functions. This difference in mathematical properties is the most important factor among the different properties between tent-shaped transfer functions and V-shaped transfer functions.

From the above two points, the computational difficulty of tent-shaped transfer functions is much less than that of V-shaped transfer functions.

Table 2. T-Shaped transfer functions

Name	Transfer Function
T_1	$T_1(x)=(1/(1+\lvert x\rvert))^{1/2}$
T_2	$T_2(x)=1/(1+\lvert x\rvert)$
T_3	$T_3(x)=(1/(1+\lvert x\rvert))^2$
T_4	$T_4(x)=(1/(1+\lvert x\rvert))^3$

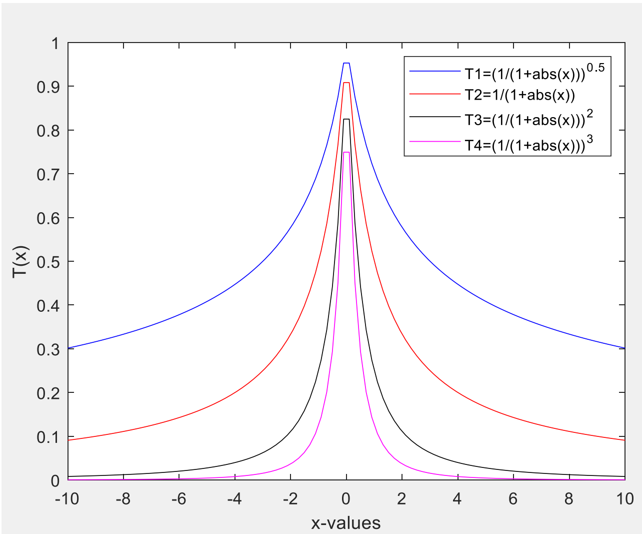

Fig. 3. T-shaped transfer function

4. Experimental results and discussion

This section provides precise details about the different data sets, the parameter settings used, and numerical results with statistical comparisons between them.

4.1. Datasets description

Tests of the proposed methods are conducted on seven benchmark datasets taken from the Kaggle repository [11]. The data includes a variety of instances from 349 to 338199, and a variety of features from 9 to 17 during the feature selection process. Each representation and detailed description of each dataset are shown in Table 3. Each data set is divided into 80% of the total samples as a training set, and 20% of the samples as a test set. All BPLO algorithms (S1–S4, V1–V4, and T1–T4) were implemented using MATLB and processed on a 4-core Intel Core i5 CPU (8 GB RAM, 4 GHz processor).

Table 3. Description of datasets used

No.	Name	Instances	Features
1	Bank	4521	17
2	Churn_Modelling	1000	14
3	diabetes_data_upload	520	17
4	Disease_symptom_and_patient_profile_dataset	349	10
5	Employee	4653	9
6	loan_approval_dataset	4269	13
7	nearest-earth-objects(1910-2024)	338199	9

4.2. Performance comparison of Tent-shaped transfer functions

Parameters for the tent-shaped transfer function are set for the purpose of testing the performance of the tent-shaped transfer function. These parameters are set to values of 0.5, 1, 2, and 3, respectively, and it analyzes how different parameter settings affect the results of virtual experiments. In BPLO, KNN classifier is used to achieve classification accuracy, where the K value is set as 5, and the fitness function is defined as follows:

$$fitness = 1 - ACC \qquad (7)$$

where ACC is the accuracy of the classification.

4.3. Evaluation of proposed Tent-shaped transfer function

In the first phase of the experiment, the performance of the BPLO algorithm was verified on seven datasets. Common evaluation criteria are measured, including classification accuracy and number of features identified (feature size). The 12 proposed BAOA methods (S1–S4, V1–V4, and T1–T4) were compared to study the best binary version of PLO in classification accuracy and feature selection. The following tables show the above, with the best results highlighted in bold.

Table 4 presents the averaged classification accuracy of the used and proposed transfer functions for all dataset. Table 5 presents the average number of selected features. According to the classification accuracy, as we can see from table 4, the proposed tent-shaped transfer functions, T1, T2, T3, and T4, achieve better results for all datasets. They almost achieved the highest classification accuracy compared to S1, S2, S3, S4, V1, V2, V3, and V4. From table 4, T1 function obtains the top classification accuracy at 88.7414% and 81.5387% in the Dataset1, and Dataset5, respectively. Further, T2 function had the highest classification accuracy at 81.97%, and 93.2536% in the Dataset2, and Dataset6, respectively. On the other hand, T3 obtained high classification accuracy at 94.8076%, 66.1891% and 99.5670% in the Dataset3, Dataset4 and Dataset7, respectively. While T4 was close to the best results in most datasets. As for the selected features, there is no doubt to say that with the proposed tent transfer functions for BAOA algorithm, they successfully addressed feature selection problems in all the datasets as shown in table 5. In the same manner, all these proposed tent transfer functions T1, T2, T3 and T4 took lesser number of features than S1, S2, S3, S4, V1, V2, V3 and V4 transfer functions meaning thereby that the insignificant impact information as well as other irrelevant impact features were rejected.

Table 5. Average number of selected features

Datasets	S1	S2	S3	S4	V1	V2	V3	V4	T1	T2	T3	T4
Dataset1	7	7	9	8	7	7	11	6	**5**	6	10	7
Dataset2	7	9	6	5	10	6	6	7	7	**1**	6	11
Dataset3	9	**8**	10	12	13	**8**	**8**	10	9	**8**	12	9
Dataset4	5	7	5	**3**	5	6	4	4	4	**3**	4	7
Dataset5	6	6	**4**	**4**	6	**4**	**4**	**4**	6	**4**	5	6
Dataset6	6	**4**	6	6	5	8	7	7	7	**4**	8	5
Dataset7	2	3	5	5	4	5	**1**	3	**1**	5	2	5

Table 4. Average classification accuracy

Datasets	S1	S2	S3	S4	V1	V2	V3	V4	T1	T2	T3	T4
Dataset1	88.5202	88.5866	88.0115	88.1442	87.7018	87.4806	88.0999	87.6354	**88.7414**	88.6971	88.6750	88.3654
Dataset2	76.16	76.4	76.26	76.24	76.3	75.91	78.24	75.99	76.42	**81.97**	76	76.13
Dataset3	91.9230	82.3076	92.3076	93.0769	86.9230	91.9230	87.6923	84.8076	89.4230	88.4615	**94.8076**	86.5384
Dataset4	64.1833	59.3123	57.5931	54.1547	55.8739	57.8796	53.0086	63.0372	53.0086	55.5873	**66.1891**	56.7335
Dataset5	75.0268	78.5299	77.7562	76.6387	78.6159	77.09	70.4706	73.8448	**81.5387**	78.9168	75.8005	72.7057
Dataset6	57.4373	60.4825	56.5237	56.2192	56.5706	56.6174	56.4535	63.0592	57.7652	**93.2536**	56.2895	56.5940
Dataset7	99.4479	99.4343	88.4682	88.4960	99.4440	88.4975	86.5296	86.2693	86.4947	88.5191	**99.5670**	88.4398

5. Conclusions

In this study, a new tent-shaped transfer function is introduced to transform continuous space into binary space within the binary polar lights optimization (BPLO) algorithm to solve the feature selection problem. Extensive experiments were conducted using seven diverse datasets from Kaggle, where the performance of the proposed tent-shaped transfer function was tested and compared with previous transfer functions from the S-shaped and V-shaped families. The experimental results showed that BPLO with the tent-shaped transfer function achieved outstanding performance, proving its ability to achieve an ideal balance between global exploration and exploiting locally optimal solutions. This balance was reflected in reducing the number of selected features while maintaining or significantly improving the classification accuracy compared to traditional methods, which enhances its practical efficiency in real applications. These results demonstrate the effectiveness of the tent-shaped transfer function in improving the performance of feature selection algorithms, opening the way for future applications in complex optimization problems. It is recommended to continue research and develop new transfer functions based on this approach to explore its impact on more algorithms and application areas.

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M.Sc. Zaynab A. Almishlih
e-mail: zaynabayham92@uomosul.edu.iq

Zaynab A. Almishlih received her B.Sc. in mathematics from the University of Mosul, Mosul, Iraq, in 2014, and her M.Sc. degree in Mathematics from the University of Mosul, Mosul, Iraq, in 2020. She is currently a teacher of mathematics at the Nineveh Directorate of Education. Her research interests include applied mathematics, artificial intelligence techniques, and optimization algorithms.

https://orcid.org/0009-0007-0937-0875

Prof. Dr. Omar S. Qasim
e-mail: omar.saber@uomosul.edu.iq

Omar S. Qasim received his B.Sc. degree in mathematics from the University of Mosul, Mosul, Iraq, in 2003, and his M.Sc. degree in Mathematics from the University of Mosul, Mosul, Iraq, in 2006. He obtained his Ph.D. degree in Mathematical Science from the University of Mosul in 2010. He is currently a professor of Mathematics at the University of Mosul. His research interests include applied mathematics, deep learning, bioinformatics, fuzzy logic, and optimization algorithms.

https://orcid.org/0000-0003-3301-6271

Prof. Dr. Zakariya Y. Algamal
e-mail: zakariya.algamal@uomosul.edu.iq

Zakariya Y. Algamal received the B.Sc. degree in Statistics from University of Mosul, Mosul, Iraq, in 2001, the M.Sc. degree in Statistics from University of Mosul, Mosul, Iraq, in 2004, the Ph.D. degree in Mathematical Science/Statistics from Universiti Teknologi Malaysia (UTM), Malaysia, in 2016, and Post. Doctorate in Mathematical Science/Statistics from Universiti Teknologi Malaysia (UTM), Malaysia, in 2017. He is a professor in statistics in University of Mosul. His research interest includes the development of high dimensional data, generalized linear models, bioinformatics, chemoinformatics, and optimization algorithms.

https://orcid.org/ 0000-0002-0229-7958