



HAL
open science

A Novel Feature Selection Algorithm Based on Aquila Optimizer for COVID-19 Classification

Ling Li, Jeng-Shyang Pan, Zhongjie Zhuang, Shu-Chuan Chu

► **To cite this version:**

Ling Li, Jeng-Shyang Pan, Zhongjie Zhuang, Shu-Chuan Chu. A Novel Feature Selection Algorithm Based on Aquila Optimizer for COVID-19 Classification. 12th International Conference on Intelligent Information Processing (IIP), May 2022, Qingdao, China. pp.30-41, 10.1007/978-3-031-03948-5_3. hal-04178744

HAL Id: hal-04178744

<https://inria.hal.science/hal-04178744v1>

Submitted on 8 Aug 2023

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Distributed under a Creative Commons Attribution 4.0 International License



This document is the original author manuscript of a paper submitted to an IFIP conference proceedings or other IFIP publication by Springer Nature. As such, there may be some differences in the official published version of the paper. Such differences, if any, are usually due to reformatting during preparation for publication or minor corrections made by the author(s) during final proofreading of the publication manuscript.

A Novel Feature Selection Algorithm Based on Aquila Optimizer for COVID-19 Classification

Ling Li¹[0000-0001-9289-3544], Jeng-Shyang Pan^{1,2}[0000-0002-3128-9025], Zhongjie Zhuang¹[0000-0002-6209-9574], and Shu-Chuan Chu^{1,3}(✉)[0000-0003-2117-0618]

¹ College of Computer Science and Engineering, Shandong University of Science and Technology, Qingdao 266590, China

² Department of Information Management, Chaoyang University of Technology, Taichung, Taiwan

³ College of Science and Engineering, Flinders University, 1284 South Road, Clovelly Park SA 5042, Australia
scchu0803@gmail.com

Abstract. To this day, the prevention of coronavirus disease is still an arduous battle. Medical imaging technology has played an important role in the fight against the epidemic. This paper is to perform feature selection on the CT image feature sets used for COVID-19 detection to improve the speed and accuracy of detection. In this work, the population-based intelligent optimization algorithm Aquila optimizer is used for feature selection. This feature selection method uses an S-shaped transfer function to process continuous values and convert them into binary form. And when the performance of the updated solution is not good, a new mutation strategy is proposed to enhance the convergence effect of the solution. Through the verification of two CT image sets, the experimental results show that the use of the S-shaped transfer function and the proposed mutation strategy can effectively improve the effect of feature selection. The prediction accuracy of the features selected by this method on the two open datasets is 99.67% and 99.28%, respectively.

Keywords: COVID-19 · Aquila optimizer · Feature selection · CT image.

1 Introduction

Since the discovery of Severe Acute Respiratory Syndrome coronavirus 2 (SARS-CoV-2) in 2019, it has caused an unprecedented situation worldwide. As of December 17, 2021, there have been 271,963,258 confirmed cases of coronavirus disease (COVID-19) worldwide, including 5,331,019 deaths [1]. Thousands of people are infected with this dangerous virus every day. Although many people have been vaccinated, the coronavirus continues to mutate. By December 18th, 2021, a new variety of SARS-CoV-2, Omicron, had been found in 89 countries [2]. Preventing and diagnosing COVID-19 remains a daunting task. For the diagnosis of coronavirus, Reverse Transcription Polymerase Chain Reaction (RT-PCR) is

the preferred method for detecting COVID-19, but false negatives will still occur. People infected with the virus may even need to undergo multiple tests before they can be detected. According to [3], chest X-ray and CT scan images may play an important role in accurately diagnosing this disease. Some radiologists recommend using chest X-ray images to diagnose COVID-19 cases. Although nucleic acid testing has become the benchmark for the diagnosis of coronavirus infections, medical imaging diagnosis continues to play an important role.

Deep learning is considered to be one of the best methods for processing medical images, but the network architecture of deep learning is often more suitable for large data sets. On the other hand, some of the features extracted through deep learning can be too sufficient, with redundant and irrelevant features, which can lead to poor classification accuracy. The purpose of the feature selection is to select the most appropriate portion of the many original features to improve the accuracy of the classification. At the same time, removing irrelevant features can also reduce the dimension of the data and the cost of model training.

Metaheuristic algorithms [4] have shown good performance in many fields [5, 6] and have been widely applied to feature selection problems in recent years [7–11]. Aquila Optimizer (AO) [12] is a newly proposed metaheuristic algorithm for solving continuous optimization problems. AO simulates the four behaviors of Aquila hunting to search for the optimal solution. It has two different exploration strategies and two exploitation strategies, which can efficiently search in space. AO algorithm has been successfully used for feature selection. Abd Elaziz et al. [13] used MoblieNetV3 [14] to extract image features and used AO to perform feature selection on the extracted features. However, this method only uses 0.5 as thresholds to convert continuous values into binary form. Once the solution value is 0, it is easy to fall into the local optimum. Therefore, an improved binary version of the AO algorithm is proposed for feature selection in this paper. And a new mutation strategy is used to speed up the convergence when the update method does not work well. The main work of this paper is listed as follows.

- (1) Analyze the change of the solution value in the binary AO algorithm. Before using the update operator, change the 0 of the solution value to -1 to prevent the effect of the update operator from weakening.
- (2) An S-shaped transfer function is introduced to convert continuous values into binary form, instead of the previous conversion method of a fixed threshold.
- (3) A new mutation strategy is used when the solution performance is not good.

The rest of this paper will be organized as follows: Section 2 briefly introduces AO algorithm and the fitness function for feature selection. In Section 3, a new binary version AO algorithm is proposed, and a new mutation strategy is proposed. In Section 4, the comparative results of the experiments are given, and the results are analyzed. Corresponding conclusions are drawn in Section 5.

2 Related work

2.1 Aquila Optimizer(AO)

AO algorithm is a newly proposed population-based optimization [15–18] method, which is inspired by the prey behavior of Aquila in nature. The mathematical model of AO is as follows.

The first step is the process of expanded exploration, which mathematical formula is as follows.

$$X_i^{t+1} = X_{best} \times \left(1 - \frac{t}{T}\right) + X_M^t - X_{best} * rand \quad (1)$$

$$X_M^t = \frac{1}{N} \sum_{i=1}^N X_i^t \quad (2)$$

where T represents the total number of iterations, and t represents the current number of iterations. X_{best} is the best solution in the previous t iterations. X_M^t represents the average value of the solutions in the current solution space. The calculation formula is shown in Eq.(2). $rand$ represents a random number between 0 and 1. N is the number of agents in the population.

The second step is narrowed exploration. In this process, levy flight is used to perturb X_{best} . The author of the AO algorithm calls it a contour flight with a short glide attack. This strategy is mathematically formulated as follows.

$$X_i^{t+1} = X_{best} \times Levy(D) + X_R^t + (y - x) * rand \quad (3)$$

where X_R represents a randomly selected agent in the population. D is the dimension space. $Levy(D)$ is calculated using Eq.(4-5). y and x represent the search of the spiral shape, which are calculated using the Eq.(6-7).

$$Levy(D) = s \times \frac{\mu \times \sigma}{|v|^{\frac{1}{\beta}}} \quad (4)$$

$$\sigma = \left(\frac{\Gamma(1 + \beta) \times \sin(\frac{\pi\beta}{2})}{\Gamma(\frac{1+\beta}{2}) \times \beta \times 2^{\frac{\beta-1}{2}}} \right) \quad (5)$$

where $s = 0.01$ and $\beta = 1.5$. μ and v are random numbers between 0 and 1.

$$y = r \times \cos(\theta), \quad x = r \times \sin(\theta) \quad (6)$$

$$r = r_1 + U + D_1, \quad \theta = -\omega \times D_1 + \theta_1, \quad \theta_1 = \frac{3 \times \pi}{2} \quad (7)$$

where $U = 0.00565$ and $\omega = 0.005$. r_1 is a random number between 1 and 20. D_1 is an integer that gradually increases from 1 to D .

The third step is extended exploitation. In this process, Aquila uses the selected target area to approach the prey and attack. This method is mathematically shown in Eq.(8).

$$X_i^{t+1} = (X_{best} - X_M^t) \times \alpha - rand \times ((UB - LB) \times rand + LB) \times \delta \quad (8)$$

where α and δ are the adjustment parameters of the exploitation process, which are fixed at 0.1. UB and LB respectively represent the upper and lower bounds of a given problem.

The fourth step is narrowed exploitation. When Aquila approaches its prey, it attacks the target based on its random movement. It is mathematically formulated as follows.

$$X_i^{t+1} = QF \times X_{best} - G_1 \times X_i^t \times rand - G_2 \times Levy(D) + rand \times G_1 \quad (9)$$

where QF represents the value of the quality function of the t -th iteration, and its definition is shown in Eq.(10).

$$QF = t^{\frac{2 \times rand - 1}{(1-T)^2}} \quad (10)$$

$$G_1 = 2 \times rand - 1, \quad G_2 = 2 \times \left(1 - \frac{t}{T}\right) \quad (11)$$

where G_1 in Eq.(9) represents various actions of AO during the tracking of the best solution. It is calculated by Eq.(11). G_2 represents a factor decreasing from 2 to 0.

2.2 Fitness function

For the feature selection problem, the two elements of classification error and the number of selected features are generally considered comprehensively and strive to achieve the goal of fewer features selected and high classification accuracy. In this work, the objective function shown below is used.

$$fitness = \alpha * \gamma_R(D) + \beta * \frac{|S|}{|D|} \quad (12)$$

where $|S|$ represents the number of features selected, $|D|$ represents the number of features in the original dataset. $\gamma_R(D)$ is the error rate of the classifier. In this work, Support Vector Machine (SVM) [19] is used as the classifier. α and β are weight coefficients, generally speaking, $\alpha=0.99$, $\beta=0.01$ [8, 20].

3 A New Improved Binary Aquila Optimizer

3.1 Analysis and Advancement for Binary Aquila Optimizer

Abd Elaziz et al. [13] proposed a binary version of the AO algorithm for feature selection. Its method of converting continuous values into binary form is shown in Eq.(13).

$$BX_{ij} = \begin{cases} 1, & X_{ij} > 0.5 \\ 0, & X_{ij} \leq 0.5. \end{cases} \quad (13)$$

where i is the i -th agent in the population, and j represents the j -th dimension. This method can quickly convert continuous values into binary form, but when

BX_{ij} is 0, the effect of the update method shown in Eq.(1-11) will be greatly reduced. The two pie charts in Fig. 1 show the changes in subsequent solutions when the solution value is 0 and 1, respectively. It can be found that when $BX_{ij} = 0$, after the subsequent update process, the agent in the population has a probability of more than 87% that it will not change its value, and its value will always be 0. The probability of the agent changing the value is only 12.36%. When $BX_{ij} = 1$, there is a 56.15% probability that the agent will not change its value, and a 43.85% probability that it will change its value.

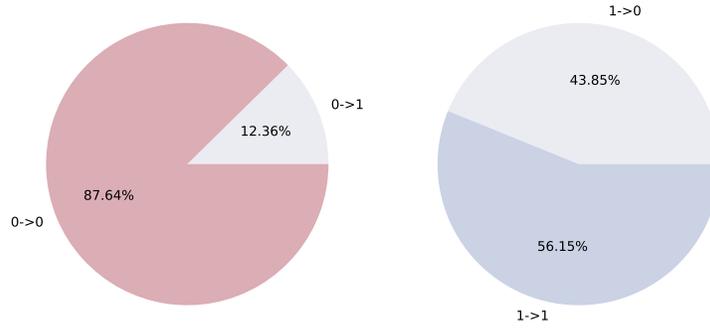


Fig. 1. The probability of change in solution value

In consideration of the above situation, when the position is updated using Eq.(1-11), the solution value is changed from 0 to -1. And the S-shaped transfer function [20, 21] shown in Eq.(14-15) is used to convert continuous values into binary form. Fig. 2 shows the probability of whether the subsequent solution changes after using the S-shaped transfer function and changing the solution value from 0 to -1. It can be seen that after using these two methods, when $X_{ij} = 0$, the probability of the individual changing the value is increased by 4.06% than before. When $X_{ij} = 1$, the probability of the individual changing the value is 18.12% higher than before.

$$S(x) = \frac{1}{1 + e^{-10(x-0.5)}} \quad (14)$$

$$X_{ij} = \begin{cases} 1, & S(X_{ij}) \geq rand \\ 0, & S(X_{ij}) < rand \end{cases} \quad (15)$$

3.2 A New Mutation Strategy for Binary Aquila Optimizer

A new binary mutation strategy to improve the convergence of the algorithm is proposed in this section when the update effect is not good. Fig. 3 shows

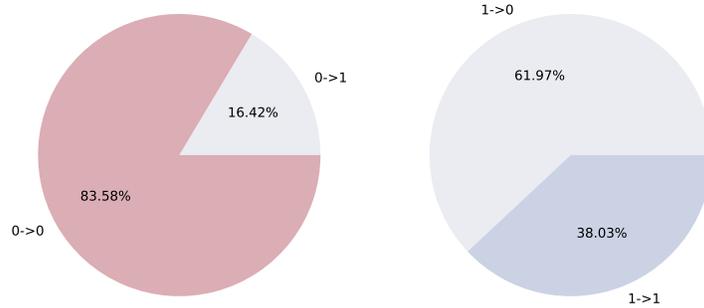


Fig. 2. The probability of the solution value changing after using the method described in Section 3.1

the comparison of fitness value between the updated solution and the previous solution during the first 20 iterations. It can be found that 82% of the updated solutions are worse than the previous solution, and only 18% of the solutions have a better effect after the update. In this case, a mutation strategy is proposed. This strategy is used when the updated solution does not converge well. It is mathematically formulated as follows.

$$XA = ((1 - X_{worst}) \cup X_{best}) + X_i^t \quad (16)$$

$$X_{ij}^{t+1} = \begin{cases} 1, & XA_j * 0.5 \geq rand \\ 0, & XA_j * 0.5 < rand \end{cases} \quad (17)$$

where \cup represents the bitwise OR operation, and j represents the j th dimension in a solution. $rand$ is a random number between 0 and 1. X_{worst} is the worst-performing individual in the population. The mutation strategy uses the idea of the opposition-based learning [22] and considers the opposite position of X_{worst} . Since the effect of X_i^t itself is better than that after the update, the position of X_i^t also is considered. Table 1 shows the influence of X_{worst} , X_{best} , and X_i^t on the position of the individual in the next iteration.

4 Experimental Results

4.1 Dataset Description

This section introduces the two datasets used in the work, both of which are CT image sets for COVID-19. The open-source Densnet121 [23] network is used to extract features from images. After extracting image features from each dataset, we keep the same data split, and these split data are fed to the feature selection process. The two CT image sets used are described in detail below. Fig. 4 (a) and (b) show sample images from Dataset1 and Dataset2, respectively.

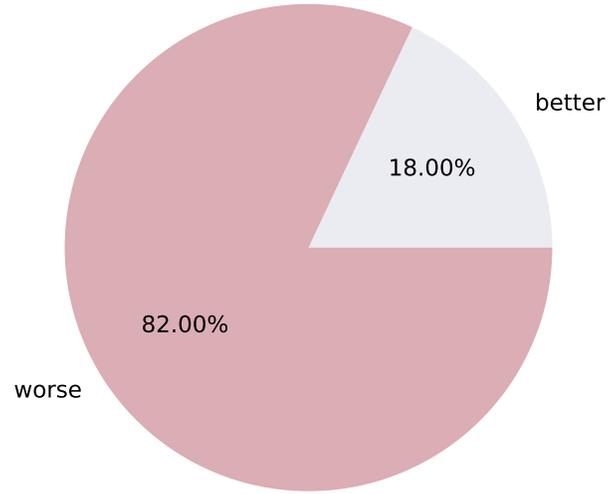


Fig. 3. The result of comparing the updated solution with the previous solution in terms of fitness

Table 1. The influence of X_{worst} , X_{best} , X_i^t on X_i^{t+1}

X_{worst}	X_{best}	$(1 - X_{worst}) \cup X_{best}$	X_i^t	X_i^{t+1}
0	0	1	0	0 or 1
0	1	1	0	0 or 1
1	0	0	0	0
1	1	1	0	0 or 1
0	0	1	1	1
0	1	1	1	1
1	0	0	1	0 or 1
1	1	1	1	1

- (1) Dataset1: COVID-CT dataset [24]: The images in this database are collected from hospitalized patients in Sao Paulo, Brazil. It contains 349 CT images of COVID-19 patients and 463 CT images of uninfected persons.
- (2) Dataset2: SARS-CoV-2 CT image dataset [25]: This dataset is an open-source dataset, containing 1252 (COVID-19) positive CT images and 1230 CT images of uninfected patients, a total of 2482 CT images. These data are collected from real patients at the Sao Paulo Hospital in Brazil.

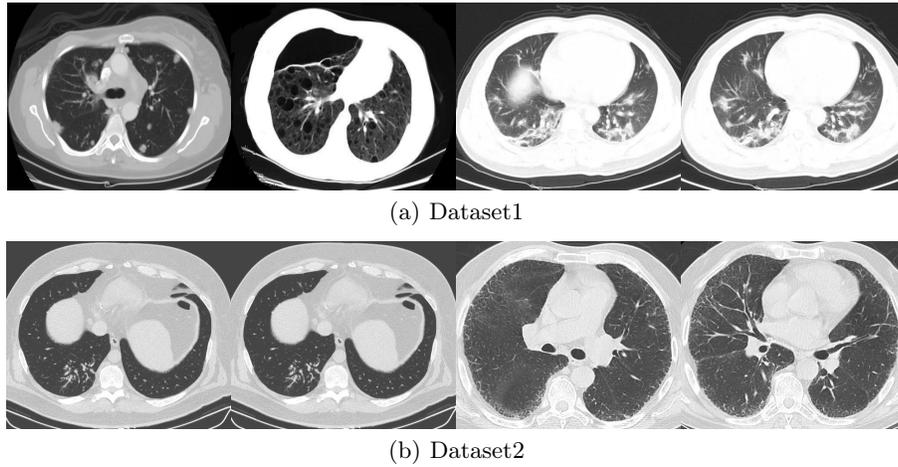


Fig. 4. Sample images taken from two datasets

4.2 Experiments Setting

For the convenience of representation, the AO algorithm using the methods described in Section 3.1 is called IBAO. When it adds the mutation strategy described in Section 3.2, it is called IMBAO. They perform 90 iterations on each dataset, running 15 times independently. Each population has 40 agents.

4.3 Comparison of the Proposed Algorithms with existing AO

In this section, the proposed IBAO and IMBAO are compared to the existing AO algorithm [13]. Table 2 and Table 3 provide detailed performance metrics of the three feature selection methods applied to COVID-19 prediction on two image sets.

From the comparison result of IBAO and AO in Table 2 that the use of the S-shaped transfer function and the conversion of the solution value from 0 to -1 slightly improve the fitness value. It is worth noting that the smaller the fitness value, the better the feature selection method. It can be seen from Table 3

Table 2. Comparison of three methods on Dataset1

Method	Dataset1				
	Fitness	Accuracy	Precision	Recall	F1-score
AO	0.0369	0.9667	0.9595	0.9726	0.9660
IBAO	0.0336	0.9667	0.9474	0.9863	0.9664
IMBAO	0.0275	0.9733	0.9726	0.9726	0.9726

Table 3. Comparison of three methods on Dataset2

Method	Dataset2				
	Fitness	Accuracy	Precision	Recall	F1-score
AO	0.0184	0.9859	0.9872	0.9831	0.9851
IBAO	0.0129	0.9879	0.9957	0.9788	0.9872
IMBAO	0.0080	0.9939	0.9957	0.9915	0.9936

that IBAO is better than AO in four aspects: Fitness, Accuracy, Precision, and F1-score. On the two datasets, IMBAO using the mutation strategy has a significant improvement in Fitness, Accuracy, and F1-score compared with IBAO. On Datasets2, the accuracy of the IMBAO method has even reached 0.9939. From the comparison results, it can be seen that the classification performance and the fitness value have undergone significant changes when the mutation strategy is used. The fitness value is significantly reduced, and the prediction accuracy and other performance are significantly improved. The comparison results prove the effectiveness of the proposed methods.

4.4 Comparison of the Proposed Method with Other Optimization Algorithms

In this section, IMBAO is compared with four feature selection methods based on optimization algorithm, namely DA [26], SSA [27], GWO [20] and SMA [7]. Table 4 and Table 5 show the comparison results of five feature selection methods on the two datasets.

Table 4. Comparison of five algorithms on Dataset1

Method	Dataset1				
	Fitness	Accuracy	Precision	Recall	F1-score
IMBAO	0.0050	0.9967	1.0000	0.9925	0.9962
DA	0.0277	0.9783	0.9674	0.9851	0.9760
SSA	0.0219	0.9833	0.9778	0.9851	0.9814
GWO	0.0250	0.9817	0.9814	0.9776	0.9795
SMA	0.0302	0.9400	0.9204	0.9478	0.9338

It can be seen from Table 4 and Table 5 that the proposed method IMBAO performs best on both datasets. In terms of Fitness, IMBAO is far superior to

Table 5. Comparison of five algorithms on Dataset2

Method	Dataset2				
	Fitness	Accuracy	Precision	Recall	F1-score
IMBAO	0.0092	0.9928	0.9917	0.9947	0.9931
DA	0.0178	0.9883	0.9856	0.9924	0.9890
SSA	0.0183	0.9871	0.9834	0.9924	0.9890
GWO	0.0197	0.9867	0.9819	0.9931	0.9875
SMA	0.0192	0.9839	0.9803	0.9893	0.9848

other methods. On Dataset1, according to Fitness, the rankings are IMBAO, SSA, GWO, DA, SMA. But on Dataset2, the rank according to the Fitness is IMBAO, DA, SSA, SMA, GWO. In terms of Accuracy, IMBAO has the best accuracy, and SMA has the worst accuracy on Dataset1. This is consistent with the situation on Dataset2. In terms of Precision, IMBAO performed the best on the two datasets, and the precision even reached 1.0 on Dataset1. IMBAO is also the best on the two evaluation indicators of Recall and F1-score. The comparison results powerfully illustrate the effectiveness of IMBAO in feature selection.

5 Conclusion

The analysis of medical images plays an important role in the diagnosis and treatment of diseases. Therefore, this paper proposes a feature selection method to improve the effectiveness of using CT images to predict COVID-19. This method uses AO algorithm as the optimizer and finds the best solution from 2^n solutions. S-shaped transfer function and a new mutation strategy proposed are used. And to prevent the effect of the update operator of the algorithm from decreasing, the solution value of 0 is changed to -1. Extensive evaluation experiments are performed on two CT image datasets, and the proposed method is compared with various feature selection methods. Experiments prove that the proposed method not only effectively improves the effect of AO algorithm for feature selection, but also has superior results compared with SMA, SSA, GWO, and other methods.

Acknowledgements. This work is supported by the National Natural Science Foundations of China (No. 61872085).

References

1. From WHO Coronavirus (COVID-19) Dashboard, <https://covid19.who.int/>
2. From the report of CBS NEWS, <https://www.cbsnews.com/news/omicron-89-countries-cases-doubling-fast-world-health-organization/>

3. Singh, D., Kumar, V., Kaur, M., et al.: Classification of COVID-19 patients from chest CT images using multi-objective differential evolution-based convolutional neural networks. *European Journal of Clinical Microbiology & Infectious Diseases* **39**(7), 1379–1389 (2020). <https://doi.org/10.1007/s10096-020-03901-z>
4. Wang, G.G., Tan, Y.: Improving metaheuristic algorithms with information feedback models. *IEEE transactions on cybernetics* **49**(2), 542–555 (2017). <https://doi.org/10.1109/TCYB.2017.2780274>
5. Xu, X.W., Pan, T.S., Song, P.C., Hu, C.C., Chu, S.C.: Multi-cluster based equilibrium optimizer algorithm with compact approach for power system network. *Journal of Network Intelligence* **6**(1), 117–142 (2021)
6. Wu, J., Xu, M., Liu, F.F., Huang, M., Ma, L., Lu, Z.M.: Solar wireless sensor network routing algorithm based on multi-objective particle swarm optimization. *J. Inf. Hiding Multim. Signal Process.* **12**(1), 1–11 (2021)
7. Abdel-Basset, M., Mohamed, R., Chakraborty, R.K., Ryan, M.J., Mirjalili, S.: An efficient binary slime mould algorithm integrated with a novel attacking-feeding strategy for feature selection. *Computers & Industrial Engineering* **153**, 107078 (2021). <https://doi.org/10.1016/j.cie.2020.107078>
8. Hu, P., Pan, J.S., Chu, S.C.: Improved binary grey wolf optimizer and its application for feature selection. *Knowledge-Based Systems* **195**, 105746 (2020). <https://doi.org/10.1016/j.knosys.2020.105746>
9. Zhang, Y., Gong, D.w., Gao, X.z., Tian, T., Sun, X.y.: Binary differential evolution with self-learning for multi-objective feature selection. *Information Sciences* **507**, 67–85 (2020). <https://doi.org/10.1016/j.ins.2019.08.040>
10. Pan, J.S., Tian, A.Q., Chu, S.C., Li, J.B.: Improved binary pigeon-inspired optimization and its application for feature selection. *Applied Intelligence* pp. 1–19 (2021). <https://doi.org/10.1007/s10489-021-02302-9>
11. Du, Z.G., Pan, T.S., Pan, J.S., Chu, S.C.: Quasi-affine transformation evolutionary algorithm for feature selection. In: *Advances in Smart Vehicular Technology, Transportation, Communication and Applications*, pp. 147–156. Springer (2022). https://doi.org/10.1007/978-981-16-4039-1_14
12. Abualigah, L., Yousri, D., Abd Elaziz, M., Ewees, A.A., Al-qaness, M.A., Gandomi, A.H.: Aquila optimizer: A novel meta-heuristic optimization algorithm. *Computers & Industrial Engineering* **157**, 107250 (2021). <https://doi.org/10.1016/j.cie.2021.107250>
13. Abd Elaziz, M., Dahou, A., Alsaleh, N.A., Elsheikh, A.H., Saba, A.I., Ahmadein, M.: Boosting covid-19 image classification using Mobilenetv3 and aquila optimizer algorithm. *Entropy* **23**(11) (2021). <https://doi.org/10.3390/e23111383>
14. Howard, A., Sandler, M., Chu, G., Chen, L.C., Chen, B., Tan, M., Wang, W., Zhu, Y., Pang, R., Vasudevan, V., et al.: Searching for Mobilenetv3. In: *Proceedings of the IEEE/CVF International Conference on Computer Vision*. pp. 1314–1324 (2019)
15. Pan, J.S., Tsai, P.W., Liao, Y.B.: Fish migration optimization based on the fishy biology. In: *2010 Fourth International Conference on Genetic and Evolutionary Computing*. pp. 783–786. IEEE (2010)
16. Chu, S.C., Tsai, P.W., Pan, J.S.: Cat swarm optimization. In: *Pacific Rim international conference on artificial intelligence*. pp. 854–858. Springer (2006). https://doi.org/10.1007/978-3-540-36668-3_94
17. Pan, J.S., Song, P.C., Pan, C.A., Abraham, A.: The phasmatodea population evolution algorithm and its application in 5g heterogeneous network downlink power allocation problem. *Journal of Internet Technology* **22**(6), 1199–1213 (2021)

18. Pan, J.S., Meng, Z., Xu, H., Li, X.: Quasi-affine transformation evolution (QUATRE) algorithm: A new simple and accurate structure for global optimization. In: International Conference on Industrial, Engineering and Other Applications of Applied Intelligent Systems. pp. 657–667. Springer (2016). https://doi.org/10.1007/978-3-319-42007-3_57
19. Cortes, C., Vapnik, V.: Support-vector networks. *Machine learning* **20**(3), 273–297 (1995). <https://doi.org/10.1007/BF00994018>
20. Emary, E., Zawbaa, H.M., Hassanien, A.E.: Binary grey wolf optimization approaches for feature selection. *Neurocomputing* **172**, 371–381 (2016). <https://doi.org/10.1016/j.neucom.2015.06.083>
21. Li, L., Pan, T.S., Sun, X.X., Chu, S.C., Pan, J.S.: A novel binary slime mould algorithm with au strategy for cognitive radio spectrum allocation. *International Journal of Computational Intelligence Systems* **14**(1), 1–18 (2021). <https://doi.org/10.1007/s44196-021-00005-0>
22. Tizhoosh, H.R.: Opposition-based learning: a new scheme for machine intelligence. In: International conference on computational intelligence for modelling, control and automation and international conference on intelligent agents, web technologies and internet commerce (CIMCA-IAWTIC'06). vol. 1, pp. 695–701. IEEE (2005). <https://doi.org/10.1109/CIMCA.2005.1631345>
23. Maftouni, M., Law, A.C.C., Shen, B., Grado, Z.J.K., Zhou, Y., Yazdi, N.A.: A robust ensemble-deep learning model for COVID-19 diagnosis based on an integrated ct scan images database. In: IIE Annual Conference. Proceedings. pp. 632–637. Institute of Industrial and Systems Engineers (IISE) (2021)
24. Yang, X., He, X., Zhao, J., Zhang, Y., Zhang, S., Xie, P.: COVID-CT-dataset: A CT scan dataset about COVID-19 (2020)
25. Angelov, P., Almeida Soares, E.: SARS-CoV-2 CT-scan dataset: A large dataset of real patients CT scans for SARS-CoV-2 identification. *MedRxiv* (2020). <https://www.kaggle.com/plameneduardo/sarscov2-ctscan-dataset>
26. Sen, S., Saha, S., Chatterjee, S., Mirjalili, S., Sarkar, R.: A bi-stage feature selection approach for COVID-19 prediction using chest CT images. *Applied Intelligence* pp. 1–16 (2021). <https://doi.org/10.1007/s10489-021-02292-8>
27. Faris, H., Mafarja, M.M., Heidari, A.A., Aljarah, I., Ala'M, A.Z., Mirjalili, S., Fujita, H.: An efficient binary salp swarm algorithm with crossover scheme for feature selection problems. *Knowledge-Based Systems* **154**, 43–67 (2018). <https://doi.org/10.1016/j.knosys.2018.05.009>