International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 5
DOI: https://doi.org/10.17762/ijritcc.v11i5.6624
***Article Received**: 04 March 2023 **Revised**: 26 April 2023 **Accepted**: 05 May 2023*

Enhanced Grey Wolf Optimization based Hyper-parameter optimized Convolution Neural Network for Kidney Image Classification

Priyanka[1], Narender Kumar[2], Dr. Dharmender Kumar[3]
[1]Assistant Professor, Department of Computer Sciene,
MNS Government College, Bhiwani
priyankajndl.1991@gmail.com
[2]Assistant Professor, Department of Computer Sciene and Engineering,
Guru Jambheshwar University of Science and Technology (GJU S&T), Hisar, Haryana
narenderster@gmail.com
[3]Professor, Department of Computer Sciene and Engineering,
Guru Jambheshwar University of Science and Technology (GJU S&T), Hisar, Haryana
dharmindia24@gmail.com

Abstract— Over the last few years, Convolution Neural Networks (CNN) have shown dominant performance over real world applications due to their ability to find good solutions and deal with image data. However their performance is highly dependent on the network architecture and methods for optimizing their hyper parameters especially number and size of filters. Designing a good CNN architecture requires human expertise and domain knowledge. So, it is difficult in CNN to find sufficient number and size of filters for classification problems. The standard GWO algorithm used for any optimization purpose suffers from some issues such as slow convergence speed, trapping in local minima and unable to maintain balance between exploration and exploitation. In order to have proper balance between these phases, two modifications in GWO are introduced in this paper. A technique for finding optimum CNN architecture using methods based on Enhanced Grey Wolf Optimization (E-GWO) is proposed. The paper presents optimization of hyper parameters (numbers and size of filters in convolution layer) of CNN using E-GWO to improve the performance of the model. Kidney ultrasound images dataset collected from ultrasound centre is used to evaluate the performance of the proposed algorithm. Experimental results showed that optimization of CNN with E-GWO outperformed CNN optimized with traditional GA, PSO and GWO and conventional CNN yielding 97.01% accuracy. At last, the obtained results are statistically validated using t-test.

Keywords- Convolution Neural Network (CNN); Optimization; Kidney Image Classification; Hyper-parameters, Enhanced Grey Wolf Optimization (E-GWO)

I. INTRODUCTION

In computer vision field, deep learning models especially convolution neural networks have emerged as a powerful tool for classification and segmentation of images. Many recent publications have shown their incredible performance in health and clinical field to find out presence and absence of disease in patients and also the criticality of those diseases [1]. Accuracy and real time processing of medical images is of utmost importance as a small error in diagnosis can put someone's life in danger [2].

CNNs are special cases of Artificial Neural Networks (ANNs) which are biologically inspired architectures consisting of neurons as processing elements, that are arranged in layered fashion and interact with each other using weighted connections. The 'Neocognitron' origin of CNN architecture was introduced by [3] in 1980. Inspired by the work of Fukushima, LeCunn in 1998 further developed first CNN named 'LeNet-5' trained by back propagation [4] to teach computer system how to recognize different hand written digits. Later on, the concept felt favorable for many image processing tasks and gained popularity. CNN consists of a number and types of different layers to carry out the task of feature extraction and classification. In CNN convolution layer, pooling layer, ReLu layer does the work of feature extraction. These layers detect the existence probability of certain attributes of the input images and reduce the dimensions of the images by eliminating the least useful or redundant attributes and extract meaningful data for classification section to classify. Further fully connected layer (FCL), Softmax and classification layers classify the input images into different categories based on the attribute values produced by feature extraction part. Figure 1 below provides the basic idea of convolution neural network.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 5
DOI: https://doi.org/10.17762/ijritcc.v11i5.6624
***Article Received**: 04 March 2023 **Revised**: 26 April 2023 **Accepted**: 05 May 2023*

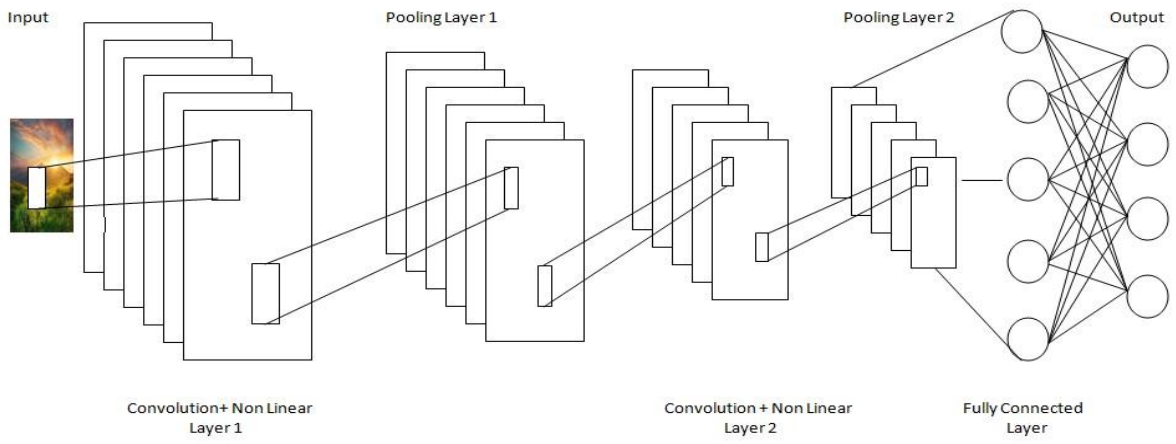


Figure 1. Basic CNN Architecture

It is known that the performance of CNN heavily resides upon their architecture. However designing an optimum architecture manually is very cumbersome task as it requires expertise which is not necessarily held by particular user. A user with data in hand may not have knowledge to design suitable architecture for his/her problem. Thus, there is need to design algorithms which automate the process of finding optimum architecture by optimizing hyper parameters of CNN. Keeping this view in mind in the proposed research work, an optimization technique using E-GWO is used for the purpose of optimization of hyper-parameters of CNN for obtaining optimal architecture for the chosen dataset.

A. Hyper-parameter optimization in CNN

The most important task in Deep CNN design for a certain problem is selecting the best hyper-parameter value during training. It may have an impact on the model's performance. Learning rate, training epochs, number of filters and filter size in convolution layers, batch size and dropout value are the most common hyper-parameters in deep CNN that can be optimized using optimization strategies. In this paper, number of filters and filter size in convolution layers of CNN are optimized.

Convolution filters are multi-dimensional data used in convolution layers which help in extracting particular features from input data. Convolution of filters with input image results in new spatially filtered image. For the operation of the convolution layer, the filter of a specified size is applied to an input image. The input values of the input image are multiplied with the corresponding filter values and then adding everything together. After then, the filter goes through the entire image, extracting the most important features. Figure 2 shows how a convolution filter works.

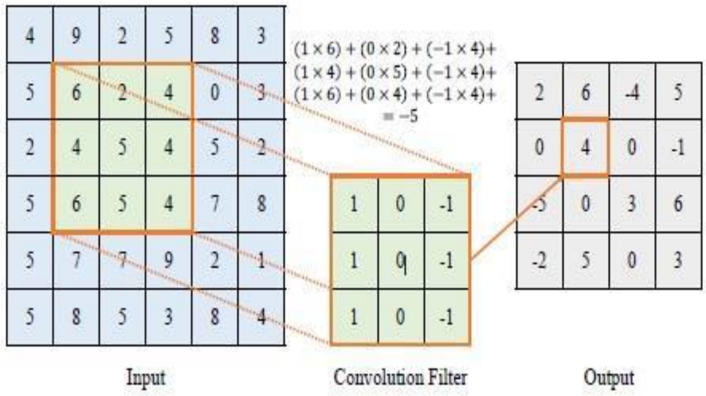


Figure 2. Convolution operation of filter with input image

The research work helps in finding presence of Kidney Disease in patients by classifying kidney images in four categories: Normal Kidney, Cystic Kidney, Kidney Stone and Hydronephrosis. By early detection of these diseases, suitable treatment can be given to patient and his/her life can be saved from worst diseases such as Hypertension, Cardiomyopathy etc.

The main contributions of the paper are:

1) First of all, the image dataset used for the research work is acquired from ultrasound centre and thereafter the raw dataset is pre-processed to enhance the quality of images.
2) The pre-processed images are used for classification purpose using Convolution Neural Network (CNN). To further optimize CNN hyper-parameters such as number and size of filters, an Enhanced Grey Wolf Optimization (E-GWO) algorithm is proposed for producing optimum architecture.
3) Performance of the proposed optimized architecture is calculated based on some classification indicators. Finally, a comparative analysis is done to compare the performance of the proposed algorithm with conventional CNN and other optimization algorithms.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 5
DOI: https://doi.org/10.17762/ijritcc.v11i5.6624
***Article Received**: 04 March 2023 **Revised**: 26 April 2023 **Accepted**: 05 May 2023*

The rest of the paper is arranged as follows: section 2 of the paper describes existing algorithms given by various researchers for optimizing CNN. Section 3 gives the overview of traditional GWO as well as provides modifications done in GWO in detail. Section 4 gives results of the work and finally section 5 provides the conclusions of the paper.

II. Related Work

The existing literature is rich with publications on optimization of CNN using meta-heuristic methods [5]–[8] , stochastic gradient descent method [9], [10] and Adam optimizer [8] etc. for providing better results. These optimization algorithms make use of different techniques for optimizing different combinations of CNN parameters and providing best architecture for classifying image dataset. This section discusses some of the papers published on optimization of CNN using different meta-heuristic techniques for tuning various parameters of network architecture to detect a number of diseases.

In [9], a technique is presented for optimizing hyper-parameters of CNN using variable length GA encoding paradigm of the networks. In [10], researcher optimized CNN using five algorithms such as Levenberg Marquardt (LM) GA, Back propagation and two GA hybrids GABP and GALM and found that GALM outperforms all other algorithms in terms of classification error.

Jayanthi in [11] developed a PSO-CNN model to classify color fundus images to detect diabetic retinopathy in three stages namely pre-processing, feature extraction and classification and achieved 98.63% specificity. Aslm in [12] developed a model to detect leukemia by classifying white blood cell images. In this model, CNN is used to extract features and then ACO is used to select best subset of features for classifying WBC images. Sameena in [13] developed an automated image analysis module for classifying covid 19 cases from chest x-ray images using an ensamble of Whale optimization and BAT algorithms.

In [14], Komanduri detected glucome patients from optimal coherence tomography image using firefly algorithm optimized CNN model and achieved high prediction rate and effected rate. To perform image de-noising and select optimal parameters for classification of medical images, [15] used a technique known as bilateral filter and a swarm intelligence algorithm Dragonfly to optimize CNN. In [16], researcher introduced a new approach for detecting skin cancer patients. The weights and biases of CNN are optimized using Whale Optimization algorithm leading to minimization of error rate. Further a disease diabetic retinopathy has been detected by Roshini in [17] by using adaptive filtering technique with fitness probability based CSO optimized CNN and achieved high accuracy and precision. A new optimization technique named Grey Wolf Optimization was further used by [18] to optimize CNN for detecting skin cancer in early stages. The cost effective CNN model developed by the researchers proved its efficacy by achieving high accuracy and less error rate.

Thus from the literature survey it can be concluded that GWO algorithm is superior to other optimization algorithms because:

- It has few parameters and is simple to implement.
- It has been successful in handling a variety of engineering optimization challenges.
- Because of its adaptability, it has been attempted to use it to address optimization problems.
- When combined with neural network, it outperforms all other evolutionary algorithms for classification challenges.

However, this algorithm faces many issues. The main issue to deal with is maintaining balance between exploration and exploitation processes. In literature, many research papers [19]-[25] address this issue and provide many solutions and modifications in GWO to solve this issue. This paper also provides some modifications in GWO algorithm to enhance its performance.

III. Proposed Work

In the proposed research work, hyper-parameters of CNN are optimized to find optimal number of filters and filter size in convolution layers of CNN. Figure 3 shows the summary of the research work done in this paper.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 5
DOI: https://doi.org/10.17762/ijritcc.v11i5.6624
***Article Received**: 04 March 2023 **Revised**: 26 April 2023 **Accepted**: 05 May 2023*

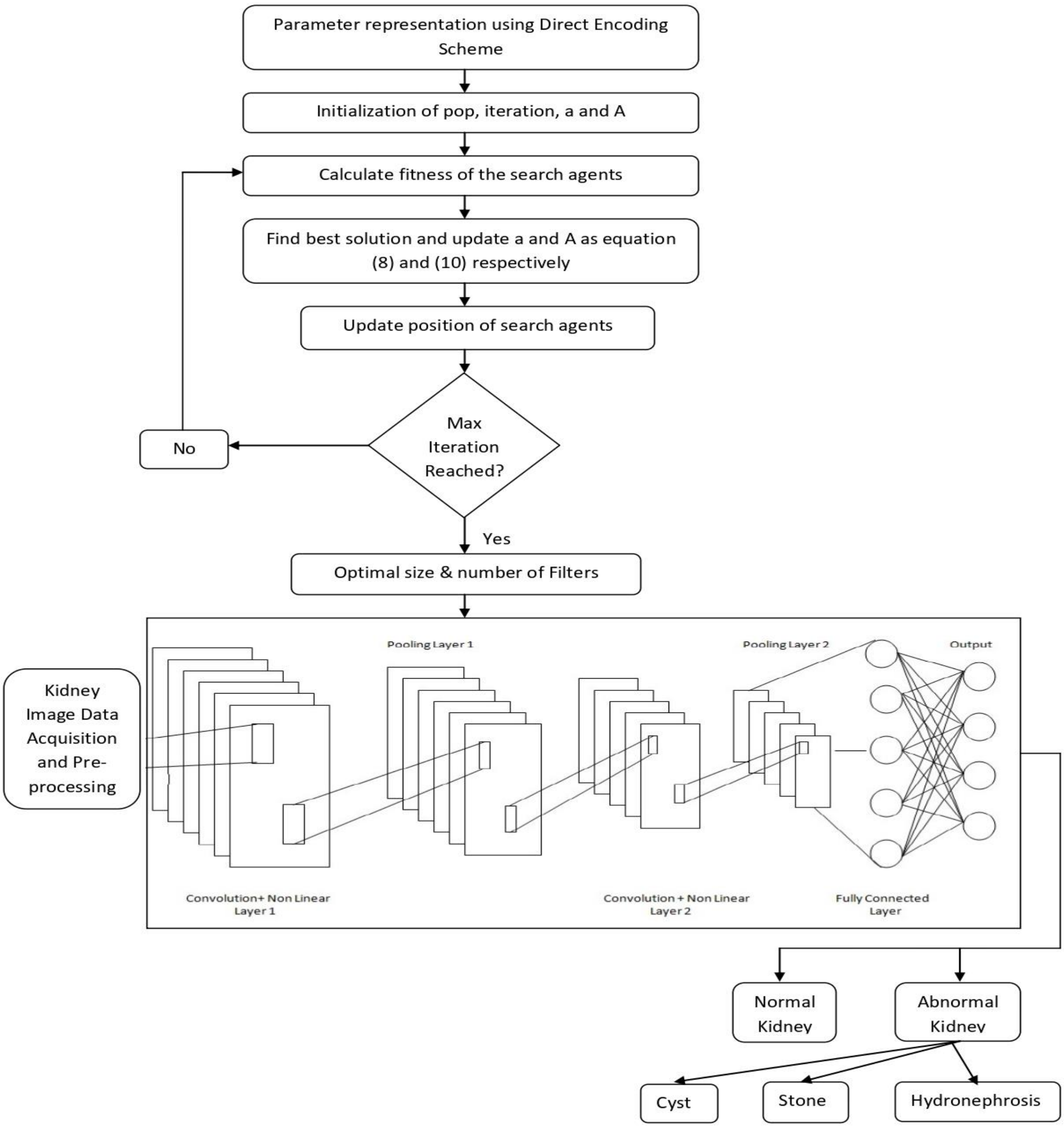


Figure 3. Overview of Proposed Research Work

The collected image dataset is of low quality and distorted with many unwanted artifacts such as noise etc. To enhance the quality of images, the data needs to be pre-processed before further processing.

First, confirm that you have the correct template for your paper size. This template has been tailored for output on the US-letter paper size. If you are using A4-sized paper, please close this template and download the file for A4 paper format called “CPS_A4_format”.

A. Pre-processing

The raw images obtained are of different dimensions. They are resized to 550*730 pixel resolutions to get systematic view. After resizing, cropping is done to remove unwanted details such as patient- doctor’s information and images of 250*230 dimensions are obtained. The cropped images are then interpolated to get bigger images having same clarity as previous one. Thereafter image rotation is performed to rotate the images to zero degree axes. At last, background of images is removed to obtain pixels of interest. Figure 4 shows the resultant images after applying these pre-processing methods.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 5
DOI: https://doi.org/10.17762/ijritcc.v11i5.6624
Article Received: 04 March 2023 Revised: 26 April 2023 Accepted: 05 May 2023

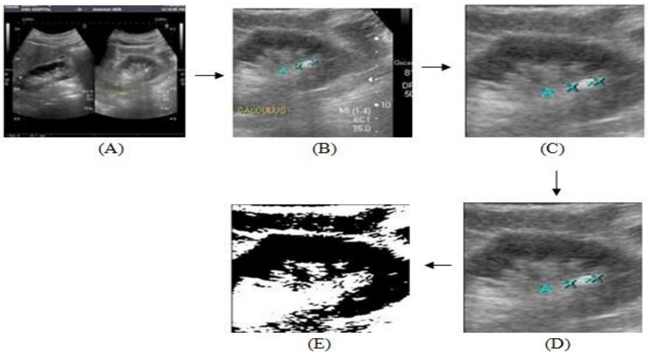


Figure 4. Preprocessing methods (A) Originally Acquired Image (B) Image after Cropping Operation (C) Enlarged Image after applying Interpolation (D) Rotated Image (E) Background Image, this is the final preprocessed image.

This preprocessed image dataset is used as input for Convolution Neural Network for classification purpose. More details about CNN can be found in [26]. As described in section1, CNN is further optimized using Grey Wolf Optimization (GWO) algorithm to get better results.

B. Grey Wolf Optimization

Seyedali Mirjalili [27] gave the basic concept of grey wolf optimization (GWO) algorithm, which simulates the leadership structure (alpha (α), beta (β), delta (δ), or omega (ω)) and hunting mechanism of grey wolves in nature. Encircling, hunting, and attacking the prey are essential behaviors in GWO, and they may be mathematically represented as an optimization tool for finding the best solution to any problem [28].

To construct GWO and execute optimization, the hunting skills and social structure of wolves are mathematically modeled in three steps as:

1) Encircling

The behaviour of grey wolves is modelled by

$$D=|C.X_{(prey)}(t)-X_{(wolf)}(t)| \quad (1)$$

$$X_{(wolf)}(t+1)=X_{(prey)}(t)-A.D \quad (2)$$

Where t represents current iteration, A and C are the coefficient vectors, $X_{(prey)}$ represents the position vector of the prey and $X_{(wolf)}$ indicates the position of grey wolf.

According to the prey's theory, the vectors "A" and "C" are critical in updating a wolf's position when a two-dimensional position vector and certain probable neighbours are taken into account. Eqs. (3) And (4) are used to calculate these coefficients, with factor "a" decreasing linearly from 2 to 0 throughout the process. The range of random vectors r_1 and r_2 is [0, 1].

$$A= 2a.r_1-a \quad (3)$$

$$C=2.r_2 \quad (4)$$

2) Hunting

The alpha wolf, together with the beta and delta wolves, usually oversees the hunting. During the iteration, three of the best candidate solutions, alpha, beta, and delta wolves, are considered initially. Other search agents adjust their places in accordance with the top three search agents. This behaviour has been represented mathematically by eq. (5).

$$X(t+1)=(X_1(t)+X_2(t)+X_3(t))/3 \quad (5)$$

Where

$$X_1=X_{alpha}-A_1.D_{alpha}$$
$$X_2=X_{beta}-A_2.D_{beta}$$
$$X_3=X_{delta}-A_3.D_{delta}$$

And

$$D_{alpha}=|C_1.X_{alpha}-X|$$
$$D_{beta}=|C_1.X_{beta}-X|$$
$$D_{delta}=|C_1.X_{delta}-X|$$

Where X (t+1) indicates the updated position of the prey in next iteration, $X_1(t)$, $X_2(t)$ and $X_3(t)$ are the position vectors of the search agents at any time t and X is the position of the prey.

3) Attacking

The wolves charge in to attack the prey during this phase. The coefficient vector "a" plays an important part in showing the wolf's movement towards the victim and its oscillation range is reduced by vector "a". The following position of a candidate solution can be anywhere between its current location and the prey's location. If the magnitude of vector "A" fulfils eq. (6), the candidate solution converges. If the measure matches eq. (7), it diverges from the victim, indicating that a better prey has been discovered.

$$|A|<1 \quad (6)$$

$$|A|>1 \quad (7)$$

The hunt process is usually guided by alpha wolves. Finally the hunt process is finished by attacking the prey by alpha wolves.

Every optimization algorithm such as PSO, CSO, GA, ABC, GWO, Bat, Firefly and many others have exploration and exploitation phases. Exploration defines the ability of an algorithm to explore new regions in the search space whereas exploitation applies the information of individuals to generate better individuals. For any algorithm to be successful there must be a balance between the two phases. These phases are two conflicting concepts. Mere exploration results in preventing an algorithm to approximate global optimum accurately. On the other hand, mere exploitation results in local optima stagnation as well as poor quality solution. Therefore, there must be a right balance between the two in order to find global optimum with fast convergence speed. For the above said purpose, some modifications are proposed in traditional GWO to get enhanced GWO in this research work.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 5
DOI: https://doi.org/10.17762/ijritcc.v11i5.6624
***Article Received**: 04 March 2023 **Revised**: 26 April 2023 **Accepted**: 05 May 2023*

C. Enhanced GWO (E-GWO)

The main problem with GWO is its position-update equation which is suitable for exploitation but performs poor at exploration. According to this equation, the new candidate is generated by moving the old candidate towards best candidates' i.e. alpha, beta and delta wolves leading to their premature convergence without exploring enough search space. This proves that the algorithm is poor at exploration.

1) Updating the Value of random Parameter A:

A is a coefficient vector in GWO whose adaptive value allows a smooth transition between the two phases. With decreasing 'A' as in eq. (6) half of the iterations are dedicated to exploitation and other half are dedicated to exploration as in eq. (7). So, with fine adjusting the values of random parameter 'A' both the phases can be balanced. As it is known that more randomness will result in more exploration. In the proposed work, the value of A is modified to increase randomness which will ultimately increase exploration as shown in eq. (8):

$$A=A+C \qquad (8)$$

The value of C is calculated as shown in Eq. (4).

2) Adding Non Linearity in 'a':

GWO search process is non-linear and complex. In conventional GWO, the control parameter 'a' is linearly decreasing which does not truly reflect GWO search process. Adding non linearity in 'a' will help in achieving better performance of GWO.

In GWO, 'a' is linearly decreasing from 2 to 0 according to the equation:

$$a=2(1-t/T) \qquad (9)$$

where t is current iteration and T is total number of iterations.

The proposed work adds non linearity by using exponential function to control parameter 'a' over more number of iterations. The value of 'a' is modified as:

$$a=2(1-t/T)^2 \qquad (10)$$

. The effect of these modifications will be proved by experimental results later. Figure 5 provides the framework of proposed algorithm.

Algorithm 1: GWO algorithm

Input: The predefined building blocks of CNN, Number of search agents X= (1,2,3,4………n), Maximum iteration number, the image dataset for classification

Output: The discovered optimal CNN architecture

1. Initialize the population with the given number of search agents using the encoding strategy.
2. Initialize the vectors a, A, and C.
3. Calculate the fitness value 'f' of each search agent using the fitness function and rank the agents having best three fitness value as

   X_α=The best candidate search agent

   X_β= The second best candidate search agent

   X_δ= The third best candidate search agent
4. **While** i < maximum number of iteration ***do***

   Renew the location of current agent using the equation (5)

   $$X(T+1) = X_1(T) + X_2(T) + X_3(T)/3;$$

   Update the positions of X_α, X_β and X_δ.

   Update the values of a, A and C according to equations (10), (8) and (4) respectively.

   i ← i+1

   end

Return Sα having best fitness value f.

Figure 5. The proposed algorithm

IV. Result and Discussion

The main motive of this paper is to apply Enhanced GWO algorithm to optimize the size and numbers of filters in convolution layer of CNN to achieve more accurate results for the chosen kidney dataset.

A. Dataset Description

For this study, a total of 294 ultrasound images of healthy or unhealthy kidneys are acquired from Adarsh ultrasound center in Hisar (Haryana). MATLAB 9.4.0.813654 (R2018a) is used for implementing the proposed algorithm. Other configuration of machine includes windows 10 (64 bit), 12 GB RAM and Intel i5 processor having 2.5 GHz clock speed. Figure 6 shows each type of kidney image acquired initially from ultrasound centers.

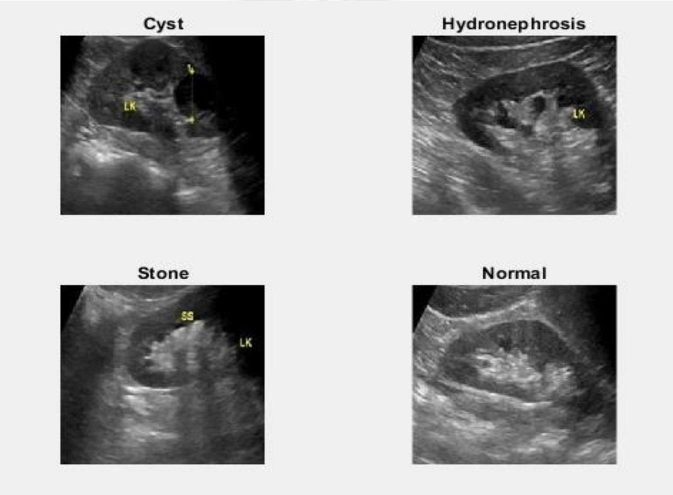


Figure 6. Types of kidney images in dataset

B. System Architecture Configuration

Before applying any optimization algorithm, it is necessary to define the configuration of the network initially taken by choosing the hyper parameters values associated with each layer. The proposed architecture contains four convolution layers each followed by ReLU layer and pooling layer. Some of the parameters such as padding, stride size, pooling operation, number of epochs, batch size are taken as constant. The values for these parameters are 2*2, 1*1, max, 50 and 25 respectively. These values are chosen based on manual experience about CNN. Figure 7 below shows the architecture of CNN used for the research work.

Figure 7. Proposed CNN architecture

Table 1 below defines the ranges of various CNN parameters considered in the proposed scheme.

Table 1. Various CNN parameters with their ranges

CNN hyper parameters	Ranges
Number of convolution layer	(3, 4)
Padding	2*2
Stride size	1*1
Pooling operation	Max
No. of epochs	(25, 50, 75)
Number of filters	(0-100)
Size of filters	(0-20)
Batch size	32
Activation functions used	ReLU, SoftMax

C. Parameters of GWO

The values of some parameters of GWO taken for optimizing CNN architecture are as shown in table 2.

Table 2. GWO parameters

GWO parameters	Ranges
Number of search agents	20
Maximum iterations	50

Based on the parameters taken, the proposed algorithm is implemented on CNN architecture having 3 and 4 convolution layers on varying number of epochs such as 25, 50 and 75. The results are taken in terms of some parameters such as accuracy. Table 3 below shows the results obtained by implementing the algorithm on CNN having 3 convolution layers and by taking number of epochs as 25 in MATLAB. The obtained results are compared with various other optimization algorithms.

Table 3. Accuracies of 3 layer CNN, GA-CNN and GWO-CNN

Architecture used	Accuracy (%)	Sensitivity (%)	Specificity (%)
CNN	68.9	70.5	68.6
GA-CNN	77	77.6	80.5
GWO- CNN	80.3	79.97	85.57
(E-GWO)-CNN	87.4	86.3	90.2

Figure 8 below demonstrate the comparative analysis of the classification indicators for the proposed algorithm. Seeing the figures, it can be concluded that E-GWO optimized CNN (87.4% accuracy) provides better results than traditional GWO optimized CNN (80.3% accuracy) on 3 layers CNN. Also both the algorithms provide better results than non optimized CNN structure.

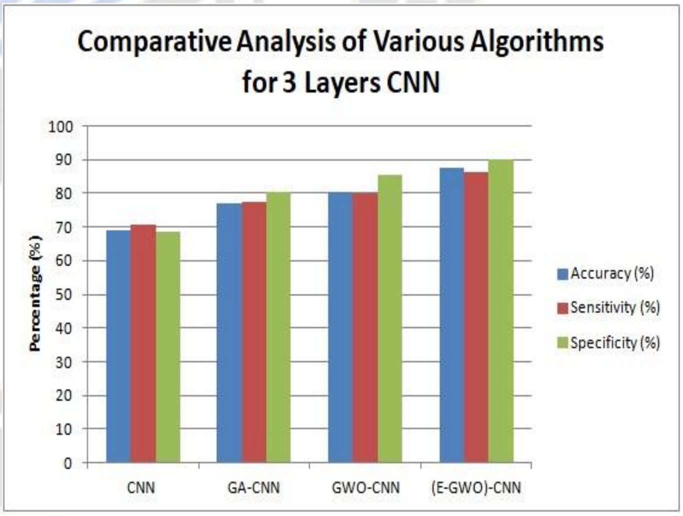


Figure 8. Comparison of classification parameters for 3 layers CNN

Further, experiments are performed taking varying number of epochs and number of convolution layers is increased to 4 this time. All other parameters are considered same as in 3 layers CNN. At first, implementation is performed for GWO optimized CNN taking number of epochs as 25, 50 and 75. Table 4 and figure 9 below show the results for classification indicators such as accuracy etc in mathematical and graphical form respectively.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 5
DOI: https://doi.org/10.17762/ijritcc.v11i5.6624
***Article Received**: 04 March 2023 **Revised**: 26 April 2023 **Accepted**: 05 May 2023*

Table 4. Accuracies of GWO optimized CNN for 25, 50 and 75 epochs

Number of Epochs	Accuracy (%)	Sensitivity (%)	Specificity (%)
25	87.50	86.9	88.10
50	90.28	91.10	89.43
75	94.20	93.35	95.20

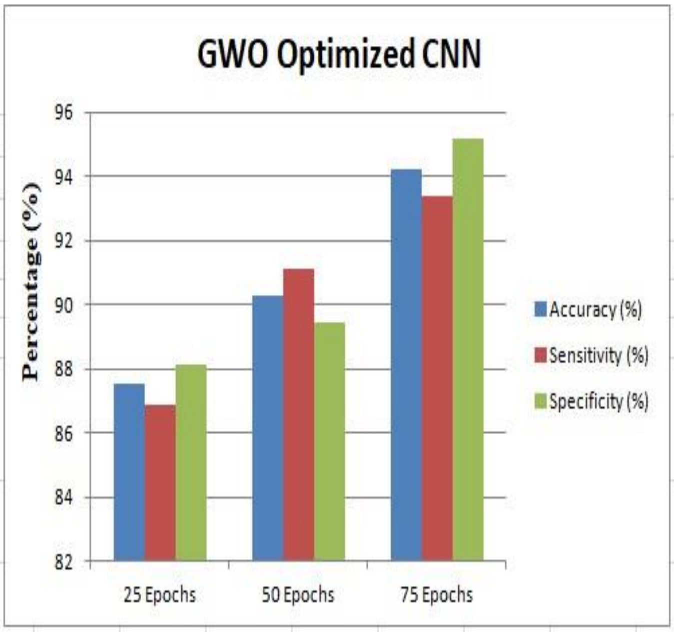


Figure 9. Comparison of classification parameters for GWO optimized CNN taking varying number of epochs

As clear from the graph when the number of epochs is less lowest accuracy (i.e. 87.50%) is achieved. The accuracy goes on increasing and provides highest accuracy at 75 epochs (94.20%). Hence it can be concluded here that GWO optimized CNN shows direct behavior in reference to number of epochs/iterations.

After that, experimental work is done for E-GWO optimized CNN taking varying number of epochs. Modifying the value of ‘A’ and changing ‘a’ from linear to non-linear value result in more randomness i.e. exploration. The more the search space explored, more accurate results will be obtained as this will truly reflect the positions of search agents. This will further result in decrease in loss curve which can be seen from training-loss curve. Table 5 and figure 10 below shows the accuracies achieved in tabular and graphical form.

Table 5. Accuracies of E-GWO optimized CNN for 25, 50 and 75 epochs

Number of Epochs	Accuracy (%)	Sensitivity (%)	Specificity (%)
25	88.20	86.8	89.02
50	95.52	95.70	92.45
75	97.01	96.10	98.92

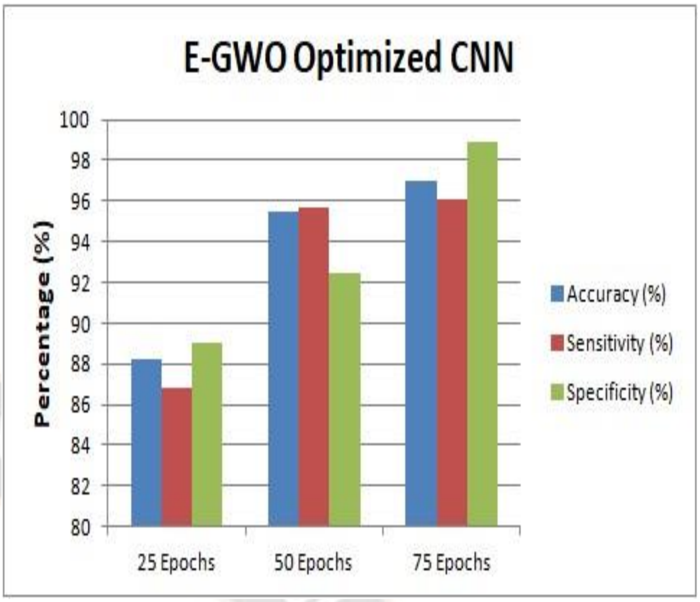
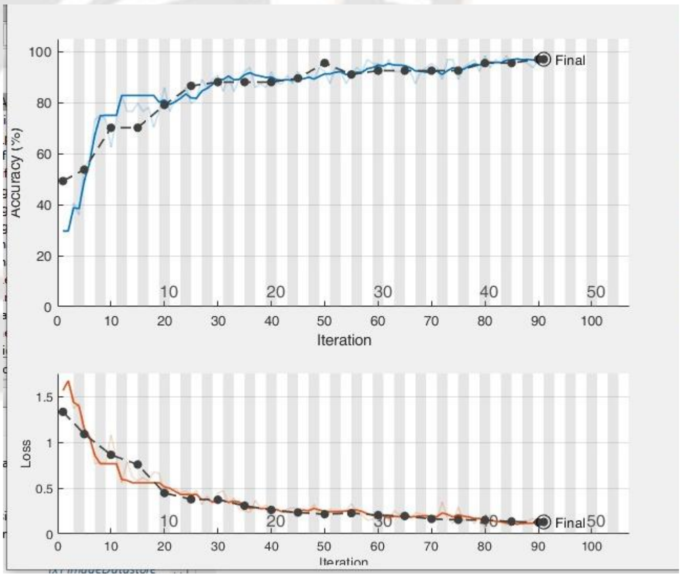


Figure 10. Comparison of classification parameters for E-GWO optimized CNN taking varying number of epochs

As clear from the graph when the number of epochs is less, lowest accuracy (i.e. 88.20%) is yielded. The accuracy goes on increasing and provides highest accuracy at 75 epochs (97.01%). Hence it can be concluded here that E-GWO optimized CNN also shows direct behavior in reference to number of epochs/iterations. Figure 11 below shows the training progress and loss function of E-GWO when number of epochs are 75.



International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 5
DOI: https://doi.org/10.17762/ijritcc.v11i5.6624
***Article Received**: 04 March 2023 **Revised**: 26 April 2023 **Accepted**: 05 May 2023*

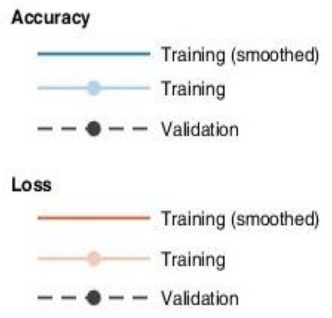


Figure 11. Training and loss progress of E-GWO

D. Statistical Validation of the Results

To statistically validate the results, t-test is applied on the algorithms at significance level of 0.01. The t-test is a non parametric statistical test applicable for comparing two algorithms and single domain. This test determines the significant difference between the means of two samples. It considers a null hypothesis that the mean of the two groups are equal. Based on some formulas, the obtained values are compared against standard values, and the hypothesis is found to be accepted or rejected.

If the hypothesis is found to be rejected, one can say that the results are not obtained by chance, there is significant difference between them.

Here, the t-test is applied on traditional CNN and GWO-CNN and thereafter the test is applied on GWO-CNN and (E-GWO)-CNN to find significant difference between them. Tables 6 and 7 show the results obtained using t-test for both groups.

Table 6. t-test Results for CNN and GWO-CNN

Parameters	**Degree of freedom**	**p-value**	**Null hypothesis Accepted/Rejected**
Accuracy	10	0.0000007245	Rejected
Sensitivity	10	0.0000007482	Rejected
Specificity	10	0.00002466	Rejected

Table 7. t-test Results for GWO-CNN and (E-GWO)-CNN

Parameters	**Degree of freedom**	**p-value**	**Null hypothesis Accepted/Rejected**
Accuracy	10	0.000001619	Rejected
Sensitivity	10	0.000006793	Rejected
Specificity	10	0.0003052	Rejected

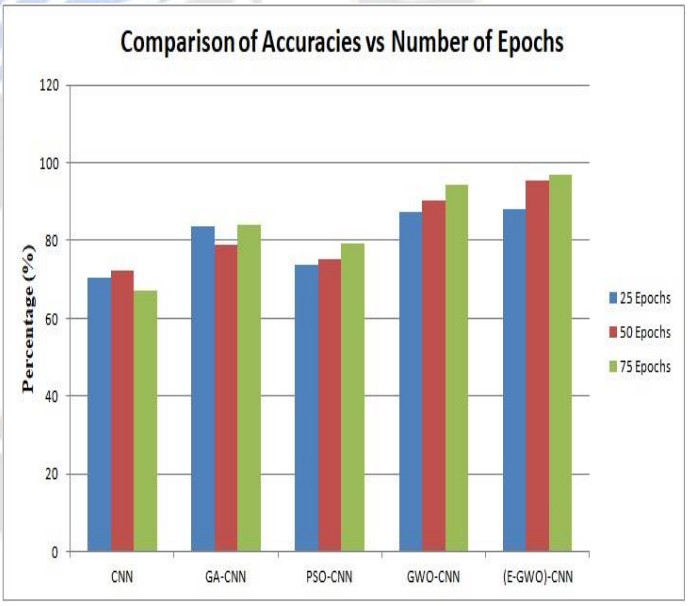
The table values statistically validate the experimental results that performance of (E-GWO)-CNN is significantly better than performance of other classifiers on all the chosen classification parameters as p-value is less than 0.005 in all cases.

E. Comparative analysis of proposed algorithm with other optimization algorithms

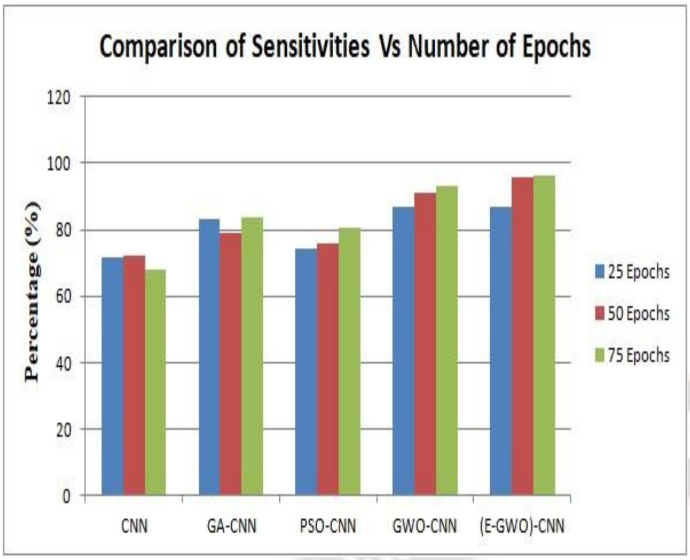
Finally, to summarize, the significance of the proposed algorithm is proved by comparing with conventional CNN, GA-CNN, PSO-CNN and traditional GWO. The comparison is done on the basis of accuracy obtained on varying number of epochs considering all other parameters as constant. Table 8 and figure 12 shows the comparative analysis of algorithms on various parameters.

Table 8. Comparative analysis of various approaches

Architecture used	**Number of Epochs**	**Accuracy (%)**	**Sensitivity (%)**	**Specificity (%)**
Conventional CNN	25	70.5	71.5	71.9
	50	72.1	72.02	74.2
	75	67.2	67.87	67.5
GA-CNN	25	83.6	83.05	88.72
	50	78.7	79.05	78.32
	75	84.2	83.72	89.22
PSO-CNN	25	73.8	74.3	74.1
	50	75.2	76	75
	75	79.3	80.7	79.1
GWO-CNN	25	87.5	86.9	88.10
	50	90.28	91.10	89.43
	75	94.2	93.35	95.20
(E-GWO)-CNN	25	88.20	86.8	89.02
	50	95.52	95.70	92.45
	75	97.01	96.10	98.92



International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 5
DOI: https://doi.org/10.17762/ijritcc.v11i5.6624
***Article Received**: 04 March 2023 **Revised**: 26 April 2023 **Accepted**: 05 May 2023*



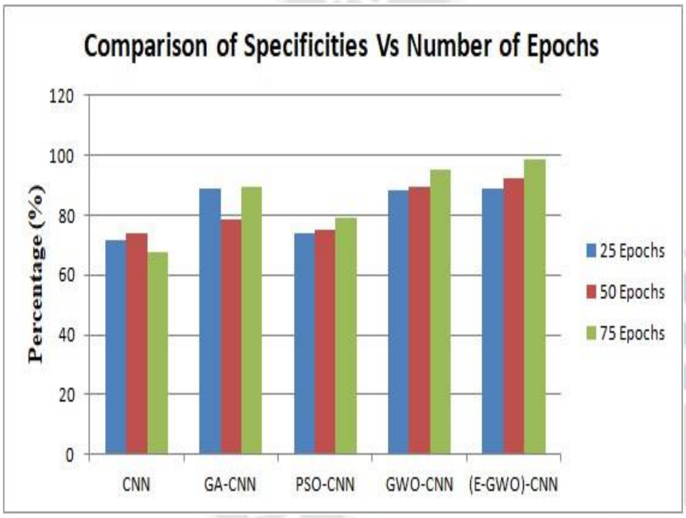


Figure 12. Comparison of existing algorithm with proposed algorithm on varying number of epochs for parameters a) Accuracy b) Specificity c) Sensitivity

It can be seen from the graphs that among all algorithms E-GWO provides more optimized architecture on kidney dataset. It provides highest accuracy (i.e. 97.01%) when the number of epochs are 75. Also it has highest sensitivity and specificity values 96.10% and 98.92% respectively. The non optimized CNN architecture has highest accuracy value (72.1%) on 50 epochs.

CONCLUSION

Kidney diseases lead to severe diseases such as heart attack, cardiomyopathy, pulmonary attack etc. So, early detection of these diseases is of utmost importance in clinical practices. For this purpose, researchers started developing automated systems or optimizing available systems avoiding the need of human interference in detection and treatment of diseases, thus achieving high accuracy and more refined decisions. In this paper, novel method for optimizing convolution neural network using enhanced GWO (E-GWO) has been proposed. A number of experiments have been performed for different optimization algorithms using kidney dataset and various indicators such as accuracy, sensitivity and specificity are calculated. Based on the experimental results, it is concluded that E-GWO optimized CNN shows direct behavior in terms of number of epochs yielding 97.01% accuracy and outperforms many algorithms such as GWO-CNN, PSO-CNN, GA-CNN and conventional CNN. Finally the results are statistically validated using t-test to show that these results are not obtained by chance.

REFERENCES

[1] S. M. Anwar et al., “Medical Image Analysis using Convolutional Neural Networks: A Review,” *Journal of Medical Systems*, vol. 42, no. 11, pp. 1-13, 2018, https://doi.org/10.1007/s10916-018-1088-1

[2] S. S. Yadav, and S. M. Jadhav, “Deep Convolutional Neural Network based Medical Image Classification for Disease Diagnosis,” Journal of Big Data, vol. 6, no. 1, pp. 1-18, 2019, https://doi.org/10.1186/s40537-019-0276-2

[3] K. Fukushima, “A Self-Organizing Neural Network Model for a Mechanism of Pattern Recognition Unaffected by Shift in Position,” Biological Cybernetics, vol. 36, pp. 193-202, 1980, https://doi.org/10.1007/BF00344251

[4] P. Sermanet, S. Chintala, and Y. LeCun, “Convolutional Neural Networks Applied to House Numbers Digit Classification,” In Proceedings of the 21st international conference on pattern recognition (ICPR2012), IEEE, pp. 3288-3291, Nov. 2012

[5] E. Byla, and W. Pang, “Deepswarm: Optimizing Convolutional Neural Networks Using Swarm Intelligence,” In UK Workshop on Computational Intelligence, Springer, pp. 119-130, Sept. 2019, https://doi.org/10.1007/978-3-030-29933-0_10

[6] Q. Zheng, X. Tian, N. Jiang, and M. Yang, “Layer-wise Learning based Stochastic Gradient Descent Method for the Optimization of Deep Convolutional Neural Network,” Journal of Intelligent & Fuzzy Systems, vol. 37, no. 4, pp. 5641-5654, 2019, 10.3233/JIFS-190861

[7] A. Ratre, “Stochastic Gradient Descent–Whale Optimization Algorithm-based Deep Convolutional Neural Network to Crowd Emotion Understanding,” The Computer Journal, vol. 63, no. 2, pp. 267-282, 2020, https://doi.org/10.1093/comjnl/bxz103

[8] D. O. Melinte, and L. Vladareanu, “Facial Expressions Recognition for Human–Robot Interaction Using Deep Convolutional Neural Networks with Rectified Adam Optimizer,” Sensors, vol. 20, no. 8, pp. 2393, 2020, https://doi.org/10.3390/s20082393

[9] Q. Zhang et al., “Optimization of Culture Conditions for Differentiation of Melon Based on Artificial Neural Network and Genetic Algorithm,” Scientific Reports, vol. 10, no. 1, pp. 1-8, 2020, doi: 10.1038/s41598-020-60278-x

[10] Y. Sun et al., “Automatically Designing CNN Architectures Using the Genetic Algorithm for Image Classification,” IEEE

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 5
DOI: https://doi.org/10.17762/ijritcc.v11i5.6624
***Article Received**: 04 March 2023 **Revised**: 26 April 2023 **Accepted**: 05 May 2023*

Transactions on Cybernetics, vol. 50, no. 9, pp. 3840-3854, 2020, 10.1109/TCYB.2020.2983860

[11] J. Jayanthi et al., "An Intelligent Particle Swarm Optimization with Convolutional Neural Network for Diabetic Retinopathy Classification Model," Journal of Medical Imaging and Health Informatics, vol. 11, no. 3, pp. 803-809 2021, https://doi.org/10.1166/jmihi.2021.3362

[12] A. Shahzad et al., "Categorizing White Blood Cells by Utilizing Deep Features of Proposed 4B-AdditionNet-based CNN Network with Ant Colony Optimization," Complex & Intelligent Systems, pp. 1-17, 2021, https://doi.org/10.1007/s40747-021-00564-x

[13] S. Pathan, P. C. Siddalingaswamy, and T. Ali, "Automated Detection of Covid-19 from Chest X-ray Scans Using an Optimized CNN Architecture," Applied Soft Computing, vol. 104, pp. 107238, 2021, https://doi.org/10.1016/j.asoc.2021.107238

[14] K. V. S. S. R. Krishna et al., "Classification of Glaucoma Optical Coherence Tomography (OCT) Images -Based on Blood Vessel Identification Using CNN and Firefly Optimization," Traitement du Signal, vol. 38, no. 1, 2021,

[15] M. Elhoseny, and K. Shankar, "Optimal Bilateral Filter and Convolutional Neural Network based Denoising Method of Medical Image Measurements," Measurement, vol. 143, pp. 125-135, 2019, https://doi.org/10.1016/j.measurement.2019.04.072

[16] L. Zhang, H. J. Gao, J. Zhang, and B. Badami, "Optimization of the Convolutional Neural Networks for Automatic Detection of Skin Cancer," Open Medicine, vol. 15, no. 1, pp. 27-37, 2019, doi: 10.1515/med-2020-0006.

[17] T. V. Roshini et al., "Automatic Diagnosis of Diabetic Retinopathy with the Aid of Adaptive Average Filtering with Optimized Deep Convolutional Neural Network," International Journal of Imaging Systems and Technology, vol. 30, no. 4, pp. 1173-1193, 2020, https://doi.org/10.1002/ima.22419

[18] R. Mohakud, and R. Dash, "Designing A Grey Wolf Optimization Based Hyper-parameter Optimized Convolutional Neural Network Classifier for Skin Cancer Detection," Journal of King Saud University-Computer and Information Sciences, 2021, https://doi.org/10.1016/j.jksuci.2021.05.012

[19] R. Ahmadi, G. Ekbatanifard, and P. Bayat, "A Modified Grey Wolf Optimizer Based Data Clustering Algorithm," Applied Artificial Intelligence, vol. 35, no. 1, pp. 63-79, 2021, https://doi.org/10.1080/08839514.2020.184210

[20] V. Kumar, and D. Kumar, "An Astrophysics-inspired Grey Wolf Algorithm for Numerical Optimization and its Application to Engineering Design Problems," Advances in Engineering Software, vol. 112, pp. 231-254, 2017, https://doi.org/10.1016/j.advengsoft.2017.05.008

[21] K. Luo, "Enhanced Grey Wolf Optimizer With a Model for Dynamically Estimating the Location of the Prey," Applied Soft Computing, vol. 77, pp. 225-235, 2019, https://doi.org/10.1016/j.asoc.2019.01.025

[22] W. Long, J. Jiao, X. Liang, and M. Tang, "An Exploration-enhanced Grey Wolf Optimizer to Solve High-dimensional Numerical Optimization," Engineering Applications of Artificial Intelligence, vol. 68, pp. 63-80, 2018, https://doi.org/10.1016/j.engappai.2017.10.024

[23] E. S. M. El-Kenawy, M. M. Eid, M. Saber, and A. Ibrahim, "MbGWO-SFS: Modified Binary Grey Wolf Optimizer Based on Stochastic Fractal Search for Feature Selection," IEEE Access, vol. 8, pp. 107635-107649, 2020, 10.1109/ACCESS.2020.3001151

[24] N. Mittal, U. Singh, and B. S. Sohi, "Modified Grey Wolf Optimizer for Global Engineering Optimization," Applied Computational Intelligence and Soft Computing, 2016, https://doi.org/10.1155/2016/7950348

[25] H. Joshi, and S. Arora, "Enhanced Grey Wolf Optimization Algorithm for Global Optimization," Fundamenta Informaticae, vol. 153, no. 3, pp. 235-264, 2017, 10.3233/FI-2017-1539

[26] Priyanka, and D. Kumar, "Kidney Image Classification Using Transfer Learning With Convolutional Neural Network," International Journal of Computational Vision and Robotics, vol. 12, no. 6, pp. 595-613, 2022, https://doi.org/10.1504/IJCVR.2022.126499

[27] Y. Sun, B. Xue, M. Zhang, and G. G. Yen, "Completely Automated CNN Architecture Design Based on Blocks," IEEE Transactions on Neural Networks and Learning Systems, vol. 31, no. 4, pp. 1242-1254, 2019, 10.1109/TNNLS.2019.2919608

[28] M. Pradhan, P. K. Roy, and T. Pal, "Grey Wolf Optimization Applied to Economic Load Dispatch Problems," International Journal of Electrical Power & Energy Systems, vol. 83, pp. 325-334, 2016, https://doi.org/10.1016/j.ijepes.2016.04.034

AUTHOR'S PROFILE

Priyanka is an Assistant Professor in department of Computer Science, MNS Government College, Bhiwani. She has done her Ph.D., M.Tech and B.Tech from Guru Jambheshwar University of Science & Technology (GJU S&T) Hisar, Haryana, India in 2022, 2014 and 2012 respectively. She is pursuing her Ph.D. in Department of CSE, GJU S&T Hisar Haryana. Her research work focuses on data mining, machine learning and image processing.

Narender Kumar is an Assistant Professor in the department of Computer Science and Engineering (CSE), Guru Jambheshwar University of Science and Technology (GJUS&T) Hisar, Haryana (India). He has done his Ph. D., M. Tech., and B. Tech. degree in CSE. He received his Ph.D. from GJUS&T Hisar, M. Tech. from Deenbandhu Chhotu Ram University of Science and Technology Murthal, Haryana (India) and B. Tech. from National Institute of Technology Hamirpur (India). His areas of interest are Data Mining, Machine Learning, Deep Learning and Metaheuristic Computations.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 5
DOI: https://doi.org/10.17762/ijritcc.v11i5.6624
***Article Received**: 04 March 2023 **Revised**: 26 April 2023 **Accepted**: 05 May 2023*

Dr. Dharmender Kumar completed his Bachelor of Technology in Computer Science and Engineering (CSE) from GJU S&T, Hisar, Haryana, Master of Technology in CSE from Kurukshetra University, Kurukshetra and Ph.D. in CSE from GJU S&T, Hisar, Haryana, India, Currently he is Chairman of Department of Computer Science and Engineering in GJU S&T, Hisar. His main research work focuses on artificial Intelligence, data mining and big data analytics.