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Chimp optimization algorithm to optimize a convolution neural network for skin detection in HVS and RGB images

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Abstract

Skin detection is a useful and popular method to identify and recognize human body parts, faces, naked people, and skin diseases and retrieve people in multimedia databases. Therefore, finding a suitable method to divide the pixels of an image into different skin groups can be very important. One of the most common methods is based on convolutional neural networks (CNN). However, the process of training a CNN is a challenging issue. Various optimization strategies have recently been used to optimize CNN biases and weights, such as the firefly algorithm (FA) and ant colony optimization (ACO). In this study, we use a well-known nature-inspired technique called Chimp optimization algorithm (ChOA) to train a classical LeNet-5 CNN structure for skin detection. The proposed skin classification algorithms operate directly on the RGB and HVS color space. The results clearly show that the proposed algorithm significantly improves the performance of a convolutional neural network.

Keywords: skin detection, segment the pixels, chimpanzee optimization algorithm, convolutional neural networks
2020 MSC: 78M32, 65K10

1 Introduction

Nowadays, it is important to identify different parts of the skin in a picture. This is useful for many types of computer applications and interactions between humans and computers. Skin recognition can be seen as a first step to getting needed information from bad websites, analyzing medical images, and other areas in image processing. There are computer programs that can recognize parts of human bodies, faces, and people who are not wearing clothes. They use something called "skin recognition." In simple words: Skin recognition can help improve how well pictures or videos are blocked on the internet based on skin tone. Recognizing someone's skin color can help identify their health, race, age, and determine if they have been exposed to the sun for too long.

Using skin color space instead of gray levels will be very helpful in identifying skin. These calculations are a part of preparing pictures for computer programs. To achieve this goal, they need special ways of analyzing what can be seen in the pictures.

There is a list called "color data" with seven items. Sometimes, two things can look different even if they have the same gray color in a certain color area. Human skin has the same color that most people recognize. So, no matter what the situation is, we can handle it well by making a plan and following it. When you use a system to recognize

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skin color, you need to do two main things: 1- Sort out the pixels in the picture based on their color. Choosing the right tool to sort things into groups. People think that [6, 14] are really good things used in this area. These two articles used math to tell apart the face and hands. They had to be really accurate and efficient in their calculations.

Because skin color can change and be influenced by many different things like ethnicity, lighting, personal features, makeup, and more. Many ways were suggested for recognizing skin [2]. The first thing to do when identifying skin in any method is to pick the right colors that match skin tones. This means that the parts of a picture that show skin and those that don't are separated into different groups. Then, they are analyzed to identify which parts are skin and which aren't. The RGB color space is used a lot in computers and pictures. It is very sensitive to certain things.

To choose the right colors, we need to separate skin and non-skin colors. We can do this using different methods like using specific skin color ranges, looking at the colors in a picture, or using computer programs. Reword this in an easier way [16, 19]: Every method has its advantages and disadvantages. For example, thresholding calculations require certain settings to be adjusted because of the kind of color space they use. When the lighting in a photo changes, the skin color might look different too. So, it's hard to judge a person's skin color in a photo. This makes it hard to use computer programs that depend on skin color. However, if we can find a way to predict skin color using a table and good data, then we can get better results.

Recognizing different skin colors can help computers interact better with humans and has many different uses. This means that it is important to have a good plan for dividing the little dots in a picture (called pixels) into different groups, like skin. This article talks about how a picture can have different colors in it. The article suggests using a new computer program that combines different methods to figure out which parts of the picture show skin. This text is incomplete, please provide the full text to rewrite in simple words.

ChOA is one of the foremost effective meta-heuristic calculations in building optimization issues [8, 9, 12]. This impact is related to the capable space investigation without affectability to the estimate of the look space. Fundamentally, ChOA is displayed based on three fundamental objectives (1) to discover an Optima arrangement speedier than other MOAs, (2) to unravel high-dimensional issues, and (3) to realize a strong arrangement to challenging issues. Our objective in this article is to optimize the introductory weights of the convolutional arrange or utilize ChOA for skin discovery. The comes about clearly appear that the proposed calculation altogether makes strides the execution of an MLP neural organize.

The rest of this paper is organized as follows: Section 2 presents a literature review of convolutional neural networks; Section 3 explains the Chimp Optimization Algorithm. In Section 4, the proposed method is comprehensively explained, Section 5 represents and discusses the experimental results and lastly Section 6 is the conclusion.

2 Convolutional neural organize

Convolutional neural organize (CNN) may be a category of models dedicated to extricating highlights from 2D inputs (e.g., pictures). CNN served in numerous applications such as picture preparing, design acknowledgment, and a few other sorts of cognitive errands [1, 7, 13, 15]. A ordinary CNN incorporates three sorts of layers: the convolutional layer, the max-pooling layer, and the completely associated layer. In this ponder, CNN has been utilized effectively as a skin classifier. The preparing procedure utilized in this work is based on skin and non-skin patches since of its quick merging time compared with entirety image-based preparing. They go through a stack of different convolutions, one max-pooling layer taken after by two completely associated layers and an yield layer.

The convolution layers (1, 2, 3) are convolved with their particular kernel number (16, 32, and 64). After the block of convolution layers, the max-pooling layer, moreover known as a down-sampling layer, is applied to the feature maps. It was utilized to play down computational complexity and administer overfitting.

The walk for past layers is set at 1. Padding was utilized after the primary convolution layer, and it was set at 1. Nonlinearity is displayed within the demonstrate by offering all layers with the rectified linear unit (ReLU) enactment work. ReLU does not immerse, subsequently superior slope proliferation compared to sigmoid and hyperbolic tan activation functions.

1×1 channels are utilized within the to begin with and the third convolutional layers and 2×2 channel within the moment one since skin patches from 1×1 to 35×35 are utilized, which is distinctive from most of the past models that utilized bigger channels. For preparing this design, a huge dataset SFA is utilized, comprising of roughly 160,992 skin and no skin patches.

Positive tests coincide with skin picture patches, and negative ones compare to non-skin picture patches. We were persuaded that the SFA dataset is expansive and differing sufficient to identify skin pixels due to the variety in races and colors of these tests. The points of interest of each layer parameters of the proposed skin discovery CNN show are displayed in Table 1. Since we are confronting a parallel classification issue (skin or non-skin) and the yield of our demonstrate could be a likelihood (we conclusion our arrange with a single-unit layer with a sigmoid actuation), the leading choice was to design the demonstrate with the rmsprop optimizer and the parallel cross entropy misfortune work.

Dropout [18] could be a regularization show with moo calculation fetched and solid profound learning capacity. In dropout, a hyper-parameter of neuron inspecting likelihood (p) is chosen. Whereas the default value is set as 0.5, it isn't a standard, and hence, it must be always tried with diverse information and systems. To avoid the issue of overfitting, we infuse dropout a few times; especially, each covered up unit within the demonstrate must learn to participate with diverse examined neurons, which renders the neurons more overwhelming and leads them to secure valuable highlights, instead of relying on other neurons to amend their mistakes. At long last, the preparing and testing of the CNN were wiped out 100 ages and a bunch measure of 128 tests.

Table 1: The architecture of the proposed skin detection CNN model

Layers No.	**Type**	**Kernel size**	**No. kernels**	**Stride**	**Output shape**
Layer 1	Conv 1	1×1	16	1	$1 \times 1 \times 16$
Layer 2	Conv 2	2×2	32	1	$2 \times 2 \times 32$
Layer 3	Conv 3	1×1	16	1	$2 \times 2 \times 64$
Layer 4	Max pooling 1	2×2		0	$1 \times 1 \times 64$
Layer 5	Flatten 1		128		64
Layer 6	Dense 1		64		128
Layer 7	Dense 2		1		64
Layer 8	Dense 3				1

3 Chimp optimization algorithm

Machine Intelligence/ blochchain/internet of things methods have a wide range of applications [17, 5, 4].The chimp optimization algorithm could be a modern MOA proposed by Khisheh and Mousavi in 2020 [9] for high-dimensional issues, with the point of speeding up merging conjointly to anticipate catching in nearby minima. This algorithm is determined from chimpanzees' hunting behavior. Chimpanzees are a species of large African apes that closely takes after people. A chimpanzee colony could be a fission-fusion sort community. In this respect, four free bunches of chimpanzees, called attackers, barriers, chasers and drivers, are proposed to mimic distinctive shrewd and perform assignments that investigate the look space based upon their particular methodology. The driver takes after the prey but does nothing to capture it. The barrier places trees as its deterrents to avoid the prey from getting away. The chaser moves quick towards the prey; and at last, the attacker who needs more mindfulness to foresee the following development of the prey, identifies the way of the prey and strengths it to withdraw. At long last, all the chimpanzees set aside their obligations independently to acquire meat. In outline, the social hunting behavior of chimpanzees comprises two stages: exploration and exploitation. Within the exploration stage, chimpanzees drive, chase, and square the prey as outlined in Fig. 1 to put themselves in a great position for the another stage. Within the abuse stage, chimpanzees wrap up the chase by attacking the prey as appeared in Fig. 2.

In population-based optimization algorithms, the arrangement space is regularly explored through local or global looks performed by a number of particles. In these looks, particles can be educating to act as a single gather with a common technique. On the other hand, particles can be made to act in different free bunches with a common objective. This arrangement is valuable for making beyond any doubt that irregular look continues at the same time with coordinate look. The ChOA look prepare starts with the era of free communities of chimpanzees with different techniques to explore for a look space. The numerical definitions proposed for the driving and chasing stage of the hunt are given in Equations (3.1) and (3.2) [9, 10, 11].

$$d = |c_1 x_{prey} - m_1 x_{chimp}| \tag{3.1}$$

$$x_{chimp}(t+1)d = x_{prey}(t) - ad \tag{3.2}$$

in these details, x_{prey} and x_{chimp} signify the position vector of the prey and the chimpanzee separately, t signifies the number of iterations, and a, m and c are coefficient vectors, which are given by Equations (3.3), (3.4) and (3.5).

$$a = 2.f.r_1 - f \tag{3.3}$$

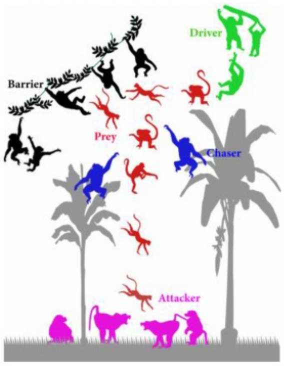


Figure 1: The exploration phase of chimpanzees' hunting behaviour [9].

Figure 2: The exploitation phase of chimpanzees' hunting behaviour [9].

$$c = 2.r_2 \tag{3.4}$$

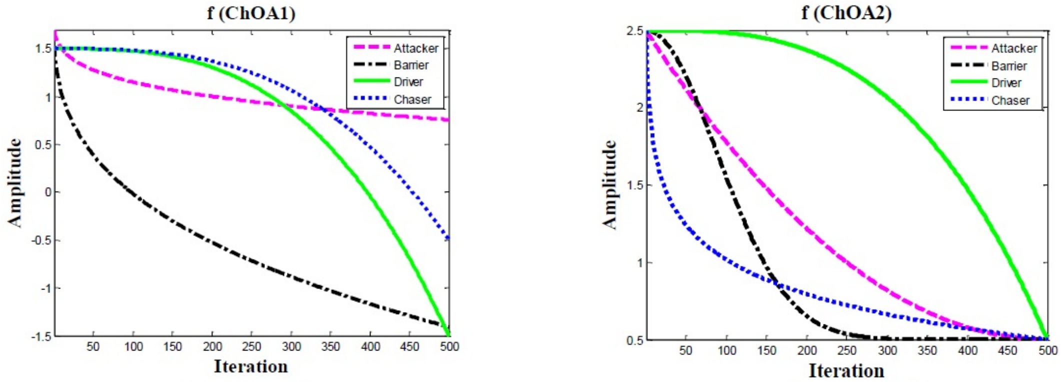
$$m = Chaotic\_value \tag{3.5}$$

Autonomous bunches of chimpanzees are scientifically modeled utilizing distinctive techniques to upgrade f (in both stages of abuse and investigation). These capacities ought to be chosen so that f diminishes nonlinearly from 2.5 to amid each emphasis. The energetic coefficients of f, with distinctive bends and slants, in two diverse chosen forms as ChOA1 and ChOA2, are displayed in Table 1 and Fig. 3. In this Table 2, T speaks to the most extreme number of cycles and t demonstrates the current iteration.

Table 2: The dynamic coefficients of f vector [9].

Groups	**ChOA1**	**ChOA2**
Group 1	$1.95 - 2t^{\frac{1}{4}}/T^{\frac{1}{3}}$	$2.5 - (2log(t)/log(T))$
Group 2	$1.95 - 2t^{\frac{1}{3}}/T^{\frac{1}{4}}$	$(-2t^3/T^3) + 2.5$
Group 3	$(-3t^3/T^3) + 1.5$	$0.5 + 2\exp[-(4t/T)^2]$
Group 4	$(-2t^3/T^3) + 1.5$	$2.5 + 2(t/T)^2 - 2(2t/T)$

$r1$ and $r2$ are irregular vectors within the range $[0, 1]$. a may be a arbitrary variable within the interim $[-2f, 2f]$, and whereas f's esteem diminishes from 2.5 to within the cycle period, the domain of a's assortments diminishes by f. As Fig. 4 appears, when the irregular values of a are within the extend $[-1-1]$, the following position of a chimpanzee can be anyplace between the current position and the position of the prey, driving the chimpanzees to assault the prey. In this demonstrate, $a > 1$ or $a < -1$ triggers the chimpanzees' disparity behavior, which could be a component driving them to take off the prey. This component upgrades the exploration stage by progressing the worldwide look of the arrangement space.



(a) ChOA1 (b) ChOA2

Figure 3: Mathematical models of dynamic coefficients (f) related to independent groups for (a) ChOA1 and (b) ChOA2 [9].

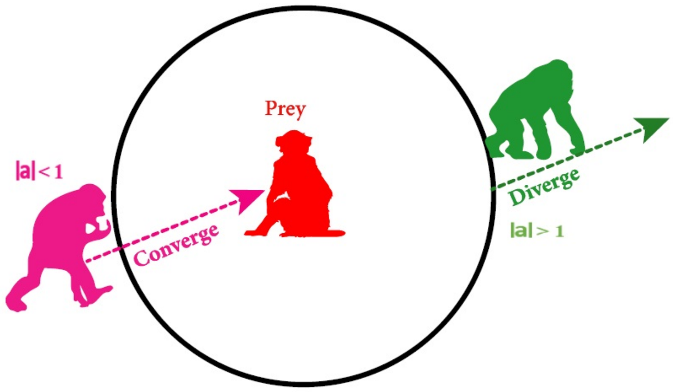


Figure 4: Position updating mechanism of chimps and effects of $|a|$ on it [9, 11].

As appeared in Condition (4), c is other component influencing the investigation organize. The components of vector c are irregular factors within the remove $[0, 2]$. With this instrument in put, the calculation is less vulnerable to getting stuck in local minima, which might be especially risky in last emphases. In this definition, vector c speaks to the impact of boundaries that moderate down the chimpanzees' development toward the prey. Vector c can designate a arbitrary weight to the prey to form chasing harder or easier by expanding ($c > 1$) or diminishing ($c < 1$), depending on the position of the chimpanzee. m may be a chaotic vector that demonstrates the impact of chimpanzees' sexual inspiration on the chasing prepare, and is calculated based upon different chaotic maps appeared in Table 3 and Fig. 5. The sexual inspiration within the final arrange causes the chimpanzees to donate up their obligation for chasing and attempt to urge the meat in a jumbled way. This chaotic behavior eventually makes a difference chimpanzees diminish both issues of catching in neighborhood optimums and moderate joining speeds in arrange to illuminate high-dimensional issues. The individual numerical demonstrate is communicated by Equation (3.6).

Table 3: Chaotic maps [9, 11].

No	Name	Chaotic map	Range
1	Quadratic	$x_{i+1} = x_i^2 - c, \quad c = 1$	$(0, 1)$
2	Gauss/mouse	$x_{i+1} = \begin{cases} 1, & x_i = 0 \\ \frac{1}{mod(x_i, 1)}, & otherwise \end{cases}$	$(0, 1)$
3	Logistic	$x_{i+1} = \alpha x_i(1 - x_i), \quad \alpha = 4$	$(0, 1)$
4	Singer	$x_{i+1} = \mu(7.86x_i - 23.31x_i^2 + 28.75x_i^3 - 13.302875x_i^4), \quad \mu = 1.07$	$(0, 1)$
5	Bernoulli	$x_{i+1} = 2x_i(mod\ 1)$	$(0, 1)$
6	Tent	$x_{i+1} = \begin{cases} \frac{x_i}{0.7}, & x_i < 0.7 \\ \frac{10}{3}(1 - x_i), & 0.7 \leq x_i \end{cases}$	$(0, 1)$

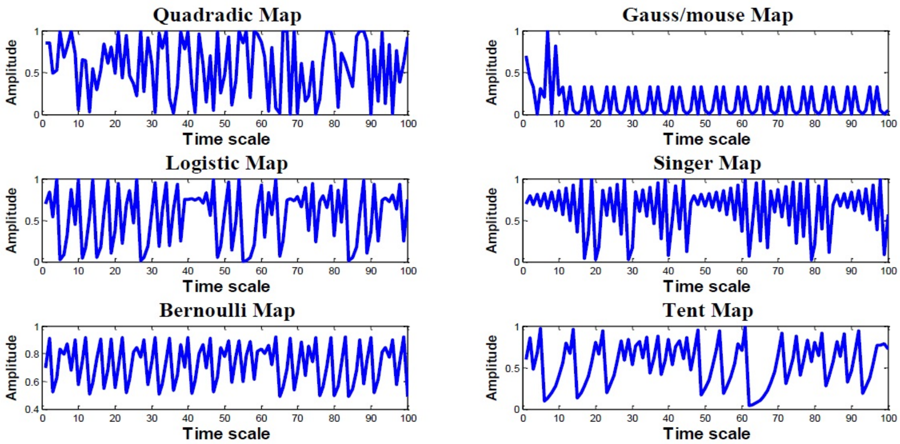


Figure 5: The chaotic maps used in the article [9, 11].

$$x_{chimp}(t+1) = \begin{cases} x_{prey}(t) - a.d, & \text{if } \mu < 0.5 \\ \text{Chatic\_value}, & \text{if } \mu > 0.5 \end{cases} \tag{3.6}$$

where μ is a random number in $[0, 1]$. As the Fig. 6 outlines, the ultimate position could be an arbitrary point in a circle that's decided by the positions of assailant, chaser, and driver chimpanzees and the boundaries. The position of the prey is estimated by the most excellent gather, and the other chimpanzees arbitrarily overhaul their positions within the region. Fig. 6 appears the update process a chimpanzee's area in a 2D look space. For a numerical reenactment of the chimpanzees' behavior, it is accepted that the aggressor (the most excellent arrangement accessible), the driver, the deterrent and the pursuer are possibly way better educated of the position of the prey. Hence, four of the finest gotten arrangements are as of now put away, and other chimpanzees are constrained to upgrade their position agreeing to the finest area of the chimpanzee. This relationship is communicated by Equations (3.7), (3.8), and (3.9).

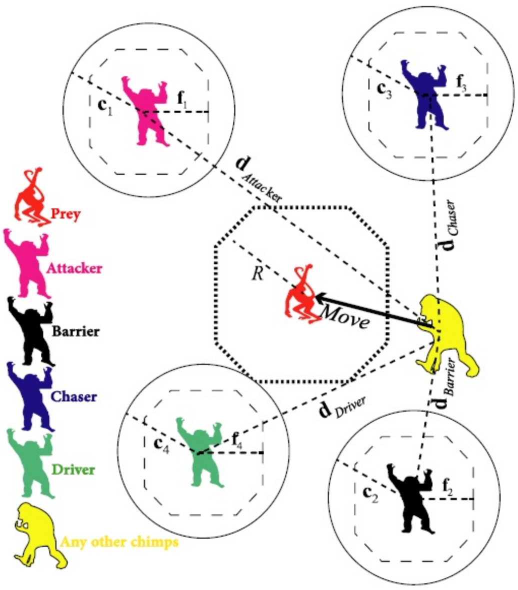


Figure 6: Position updating in ChOA [9, 11].

$$\begin{aligned} d_{Attacker} &= |c_1 x_{Attacker} - m_1 x|, \quad d_{Barrier} = |c_2 x_{Barrier} - m_2 x|, \\ d_{Chaser} &= |c_3 x_{Chaser} - m_3 x|, \quad d_{Driver} = |c_4 x_{Driver} - m_4 x|. \end{aligned} \tag{3.7}$$

$$x_1 = x_{Attacker} - a_1(d_{Attacker}), \quad x_2 = x_{Barrier} - a_2(d_{Barrier}),$$
$$x_3 = x_{Chaser} - a_3(d_{Chaser}), \quad x_4 = x_{Driver} - a_4(d_{Driver}). \tag{3.8}$$

$$x(t+1) = \frac{x_1 + x_2 + x_3 + x_4}{4}. \tag{3.9}$$

In common, the ChOA look prepare starts with the era of an irregular populace of chimpanzees (candidate arrangements), and after that all of the chimpanzees are haphazardly isolated into four free bunches: aggressor, deterrent, follower, and driver. Amid the cycle period, these diverse bunches gauge the conceivable areas of the prey, and each candidate arrangement overhauls its separate from the prey. Each chimpanzee employments its bunch procedure to overhaul its f coefficients. A versatile alteration of vectors c and m, at the same time dodges nearby optimization and moderate merging speed.

4 Design of proposed technique

Neural networks use weights and biases to learn, and these are improved with optimization techniques. There is a type of computer program called deep learning-based classifiers that work really well in this field. You can find some examples of these in sources numbered 51 to 54. Another good choice is an algorithm called Gradient Descent (GD). It works by trying to make the gradient error as small as possible. Basically, if the derivative of a function exists, GD finds the lowest point of that function. In simple terms, when adjusting the parameters of a neural network, GD takes into account how the error changes based on changes made to the weights. There are three types of GD: batch, mini-batch, and stochastic that are very important. In deep learning, we usually use stochastic gradient descent because it's faster than other types. GD-trained neural networks have a big issue where they can get stuck in one solution which is not the best. One issue with using this method is that the strength of the network relies on the starting values of the weights. This paper suggests a new way to find better ways to detect skin tone using two computer algorithms called ChOA and "gradient descent". They found that by combining the best parts of both algorithms, they can do a more efficient search and get better results. The ChOA algorithm helps start the network weights well, and the gradient descent algorithm helps the network learn without getting too overfitting.

One vital prerequisite for the preparing of CNNs is to define the issue or the objective into an fitting organize. CNNs work based on their weights and biases, which are variables that can be changed. If you alter these variables, it can affect all the layers in the network and cause the output to be different. The weights and biases in the CNN can be changed to make it work better, just like in other neural networks. To optimize parameters using ChOA, the parameters of CNN must be formulated as Equation (4.1).

$$\vec{V} = \{\vec{W}, \vec{\theta}\} = \{W_{1,1}, W_{1,2}, ..., W_{n,n}, \theta_1, \theta_2, ..., \theta_h\} \tag{4.1}$$

here, we use different letters to represent different things. θ means bias, n means the number of samples, and w represents the weight of the connection. This starting point gets changed using a special method to make it better at correctly sorting things. This process is just like how we usually train a CNN using the gradient descent method. The only difference is that in the traditional method, we start with random values for the parameters and then update them during the process. The usual way of training a neural network, called the gradient descent algorithm, is affected a lot by how the network's weights are set in the beginning. If the weights are not set well, the algorithm might get stuck in a bad spot and not be able to find the best solution. This study used the ChOA algorithm to find the best solution. They started by making a list of parameters equal to the number of chimps they were studying. Then, they kept choosing the best answer in each round to improve their chances of finding the best overall answer. We use two methods called ChOA and GD to help us find the best starting weights for a network. This helps us get better results and makes the search process faster.

5 Experiments and results

This part explains how we plan to do something. First, we explain the approach we are using. In this paper, we are trying to solve the problem of finding skin in two stages. Our first step is to teach a computer program called a convolutional neural network whit ChOA. It uses pictures of skin and pictures of not skin to learn what skin looks like. We made a new set of information from the SFA set so that we could teach our computer system. You can see how we did this in the picture. Next, we suggest using a skin detection program to look through the entire picture once the model has been set up and trained.

A Hewlett-Packard (hp) computer was utilized to evaluate our approach with the 64-bit Windows 10 Home Operating System, installed memory (RAM) of 8.00 GB, and Intel (R) Core (TM) i7-6500U CPU. For data processing, the MATLAB and Statistics Toolbox Release 2021a were employed. The proposed approach was tried on SFA dataset. SFA dataset [3] is based on pictures of FERET and AR confront datasets. SFA is made up of the initial pictures, the ground truths for benchmark the skin discovery, and the patches of skin and non-skin. The measurements of patches change from 1×1 pixels to 35×35 pixels. This dataset combines photographs of individuals from different ethnic bunches and contains a few photographs with brightening variety. In expansion, there are a few photographs with complex non-skin but skin-colored locales.

A two range classification (as skin or non-skin exclusively) is utilized for skin location; pixel-based classification is chosen to classify each skin and non-skin pixel, autonomously from its neighbors. To this conclusion, skin division is exceptionally successful since it ordinarily includes a little sum of computation and can be done in any case of posture. In arrange to create a skin color location framework, a combination of neural systems and ChOA can be utilized. In numerous issues, this calculation has appeared to be fittingly quick and precise in accomplishing ideal arrangements. In neural network training, it is pivotal to avoid getting stuck in local minima. Besides, the ratio of input vector length to meta-heuristic calculation is generally a huge value. Hence, an algorithm ought to be utilized to avoid local minima conjointly have an suitable convergence speed. ChOA has both of these features. Later on, we taught a computer program using different techniques including gradient descent, back propagation, and an algorithm called Imperialist competitive algorithm. We looked at three different ways of doing things and compared them. We set up three ways to check if the new method worked well. The first thing to look at is how often things are correctly detected. This is called correct detection rate (CDR). False acceptance rate (FAR) is when something is accepted even though it's not right, and false rejection rate (FAR) is when something is rejected even though it is right. Equation (5.2) and (5.3) show how FAR and FRR are measured.

$$CDR = \frac{\text{No. of Pixels Correctly Classified}}{\text{Total Pixels in the Test Dataset}} \tag{5.1}$$

$$FAR = \frac{\text{No. of Non-Skin Pixels Classified as Skin Pixels}}{\text{Total Pixels in the Test Dataset}} \tag{5.2}$$

$$FRR = \frac{\text{No. of Skin Pixels Classified as Non-Skin Pixels}}{\text{Total Pixels in the Test Dataset}} \tag{5.3}$$

The parameters corresponding to ICA,CGA, ACO and ChOA algorithm are shown in Table 4.

Table 4: Parameters Corresponding To ICA, CGA, ACO and ChOA Algorithm.

Algorithm	**Number of populations**	**Iterations**	**Other Parameters**
CGA	nAnts: 200	1000	$pc = 0.8$, $Pm = 0.3$
ICA	nParticles: 200	1000	$nImp = 25$, $P_{rev} = 0.3$, $Zeta = 0.2$
ACO	nAnts: 200	100	$q = 0.5$, $\zeta = 1$
ChOA	nChimps: 200	1000	f, m, c, a, d: dynamic parameters according to section 2

Table 5 shows the performance of the CNN classifier by initializing weights with evolutionary algorithms before and after training with gradient descent, as well as training with gradient descent with random initial values. It is concluded that the initialization of weights using evolutionary algorithms and training with gradient descent has a better performance and the performance of the ChOA algorithm is better. Also, the case where the CNN has not received any training only uses the initial weights determined by the proposed algorithm, it is less accurate than the case where the initial weight is randomly determined and trained with a decreasing gradient. Each algorithm was run for three times. The average of Their output values are given in Table 6.

As shown in Table 6, the best results in RGB and HVS images were obtained by improved CNN with ChOA. The output of ChOA algorithm and gradient reduction for some sample images in HVS and RGB color space are shown in Table 7. In the first column, images from the SFA database are shown. In the second and fourth columns of Behnranib, the results of HVS and RNG images with the CNN network without using the evolutionary algorithms of Faghaz are shown using deductive gradients. In the third and fifth columns of Behnranib, the results of HVS and RNG images with improved CNN network or ChOA algorithm are shown.

6 Conclusion

Skin color detection is a useful and popular method in human-computer interaction as well as in content analysis. In this article, convolutional network and chimpanzee evolutionary algorithm were used for skin detection. First,

Table 5: Comparison of our proposed method in different modes of training.

M	Image Type	Initialization Technique	Training Technique	Accuracy
CGA	RNG	CGA	–	70.21
		random	Gradient descent	91.13
		CGA	Gradient descent	98.27
ICA	RNG	ICA	–	73.81
		random	Gradient descent	91.13
		ICA	Gradient descent	96.14
ACO	RNG	ACO	–	67.89
		random	Gradient descent	91.13
		ACO	Gradient descent	95.28
ChOA	RNG	ChOA	–	76.28
		random	Gradient descent	91.13
		ChOA	Gradient descent	99.51

Table 6: Output Of Various Algorithms Simulations

		BP	ACO	ICA	genetic	ChOA
RGB	MSE	0.1	0.07	0.01	0.009	0.002
	CDR	91.13	95.28	96.14	98.27	99.51
	FAR	4.05	3.06	3.03	2.55	2.05
	FRR	4.35	3.25	3.05	2.95	2.25
HVS	MSE	0.18	0.082	0.021	0.009	0.003
	CDR	92.23	94.08	95.32	98.27	99.01
	FAR	4.52	4.06	3.53	2.75	2.32
	FRR	4.87	3.95	3.12	2.99	2.29

Table 7: Output of three algorithms for a sample image is shown.

Original Image	HVS with GD	HVS with ChOA	RGB with GD	RGB with ChOA
				
				

the initial weights and biases of CNN were improved by using ChOA, then gradient descent was used to train the ChOA-based CNN network, and their performance was tested on images in RGB and HVS color spaces. In order to prove the validity of the ChOA technique, the results were compared with three recently published methods and three other stochastic optimization approaches (ACO, PSO and ICA). The results showed that ChOA strategy can effectively train CNN. This approach develops the probability of finding optimal values for weights and biases in a CNN model.

References

[1] J. Ahmad, K. Muhammad, S. Bakshi, and S.W. Baik, *Object-oriented convolutional features for fine-grained image retrieval in large surveillance datasets*, Future Gener. Comput. Syst. **81** (2018), 314–330.

[2] Z. Al-Tairi, R. Wirza, M.I. Saripan, and P. Sulaiman, *Skin segmentation using YUV and RGB color spaces*, J. Inf. Process. Syst. **10** (2014), 283–299.

[3] J.P.B. Casati, D.R. Moraes, and E.L.L. Rodrigues, *SFA: A human skin image database based on FERET and AR facial images*, Anais, Rio de Janeiro: Escola de Engenharia de São Carlos, Universidade de São Paulo, 2013. Disponível em: http://iris.sel.eesc.usp.br/wvc/Anais_WVC2013/Poster/2/3.pdf. Acesso em: 27 maio 2023.

[4] H. Ghayoumi Zadeh, A. Fayazi, O. Rahmani Seryasat, and H. Rabiee, *A bidirectional long short-term neural network model to predict air pollutant concentrations: A case study of Tehran, Iran*, Trans. Machine Intell. **5** (2022), no. 2, 63–76.

[5] J. Haddadnia, O.R. Seryasat, and H. Rabiee, *Thyroid diseases diagnosis using probabilistic neural network and principal component analysis*, J. Basic Appl. Sci. Res. **3** (2013), no. 2, 593–598.

[6] J. Hartung, A. Jacquin, J. Pawlyk, J. Rosenberg, H. Okada, and P.E. Crouch, *Object-oriented H. 263 compatible video coding platform for conferencing applications*, IEEE J. Selected Areas Commun. **16** (1998), no. 1, 42–55.

[7] T.J. Hong, S.V. Bhandary, S. Sobha, H. Yuki, B. Akanksha, U. Raghavendra, A.K. Rao, B. Raju, N.S. Shetty, A. Gertych, and K.C. Chua, *Age-related macular degeneration detection using deep convolutional neural network*, Future Gener. Comput. Syst. **87** (2018), 127–135.

[8] M.A. Islam, D.T. Anderson, A.J. Pinar, T.C. Havens, G. Scott, and J.M. Keller, *Enabling explainable fusion in deep learning with fuzzy integral neural networks*, IEEE Trans. Fuzzy Syst. **28** (2019), no. 7, 1291–1300.

[9] M. Khishe and M.R. Mosavi, *Chimp optimization algorithm*, Expert Syst. Appl. **149** (2020), 113338.

[10] M. Khishe and M.R. Mosavi, *Classification of underwater acoustical dataset using neural network trained by chimp optimization algorithm*, Appl. Acoustics **157** (2020), 107005.

[11] S. Khosravi and A. Chalechale, *Chimp optimization algorithm to optimize a convolutional neural network for recognizing Persian/Arabic handwritten words*, Math. Prob. Engin. **2022** (2022).

[12] C.L. Kumari and V.K. Kamboj, *An effective solution to single-area dynamic dispatch using improved chimp optimizer*, In E3S Web of Conferences, EDP Sci. **184** (2020), 01069.

[13] Y. LeCun, Y. Bengio, and G. Hinton, *Deep learning*, Nature **521** (2015), no. 7553, 436–444.

[14] H. Luo, A. Eleftheriadis, and J. Kouloheris, *Statistical model-based video segmentation and its application to very low bit-rate video coding*, Signal Process.: Image Commun. **16** (2000), no. 3, 333–352.

[15] R. Mudassar, S. Muhammad, Y. Mussarat, K.M. Attique, S. Tanzila, and F.S. Lawrence, *Appearance based pedestrians' gender recognition by employing stacked autoencoders in deep learning*, Future Gener. Comput. Syst. **88** (2018), 28–39.

[16] K. Nikolskaia, N. Ezhova, A. Sinkov, and M. Medvedev, *Skin detection technique based on HSV color model and SLIC segmentation method*, Proc. 4th Ural Workshop on Parallel, Distributed, and Cloud Computing for Young Scientists, Ural-PDC 2018, CEUR Workshop Proc. **2281** (2018), 123–135.

[17] O. Rahmani-Seryasat, J. Haddadnia and H. Ghayoumi-Zadeh, *A new method to classify breast cancer tumors and their fractionation*, Ciência Natura **37** (2015), no. 4, 51–57.

[18] N. Srivastava, G. Hinton, A. Krizhevsky, I. Sutskever, and R. Salakhutdinov, *Dropout: A simple way to prevent neural networks from overfitting*, J. Mach. Learn. Res. **15** (2014), 1929–1958.

[19] M. Zafar, M.I. Sharif, M.I. Sharif, S. Kadry, S.A.C. Bukhari, and H.T. Rauf, *Skin lesion analysis and cancer detection based on machine/deep learning techniques: A comprehensive survey*, Life **13** (2023), no. 1, 146.