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An Optimized Machine Learning Models by Metaheuristic Corona Virus Optimization Algorithm for Precise Iris Recognition

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Abstract

Human iris' identification is a constantly developing technology and it has it's own significant in many commonplace applications such as financial sector, identity verification, evidence analysis, law enforcement, and security standards. Several obstacles face the recognition of the iris and the high variation in its captured image is one the most highly affected that is brought on by many factors including aging, illumination, and occlusion. Furthermore, there are some issues with the computing time and complexity of systems concerned in recognizing iris that require attention. In this research, a proposed Iris recognition system that can show a high recognition accuracy and a reduced time is presented. The Corona Virus Optimization Algorithm is a sophisticated bioinspired algorithm that serves as the foundation for the suggested system. The main objective of the suggested approach is to increase the iris identification accuracy rate by fi-ne-tuning the hyperparameter of six conventional Machine Learning models and selecting as well refining the most useful features. Four versions of

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Iris Image Database known as of CASIA (i.e., 1.0, 2.0, 3.0, 4.0), have been employed to test the system. The evaluation experiment outcomes findings proven the system's efficiency in catching the high recognition accuracy in uncontrolled environments when compared to current methods. This is accomplished in a through a recognition time ranging from 1564.16 to 13.97 milliseconds, requiring extraordinarily little processing complexity and effort to attain 94%–100% accuracy.

Keywords: Machine Learning (ML), Feature Extraction, Optimization, Corona Virus Optimization Algorithm (CVOA), Iris Recognition

1. INTRODUCTION

Many kinds of services that need identity verification are now using computers for human authentication and the concept of personal identity has gained significance in our connected society. Modern identification techniques mostly rely on a person's biometrics traits; this is not the case with conventional methods, which have several drawbacks and may not always offer the right degree of identity authentication [1]. The biometric features of an individual are used as a common component in biometric-based identification method[2]. Identity verification using a person's biometrics are employed in a variety of fields and applications, such as national identification cards, the criminal justice system, commercial (for example, access to the internet, logging in to a networked computer, electronic security of information and data), and cardholder registration [3]. An eye's capacity to identify people and other things in its surroundings is comparable to that of a camera, but with unique qualities that make it a potential doorway to the soul[4]. The iris in the eye is a collection of muscles resembling round discs, containing pigments that define an. The iris' main job is to regulate how much light enters the eye by dilatation or constriction of the pupil [5]. Systems that use iris recognition provide a very efficient and safe way to identify and authenticate people due to their unique properties even for twins and their randomization [6], also it can be observed at a distance [7]. Several considerations make the design of an iris-based recognition system regarded as complicated. First, iris scanning necessitates an expensive sensor, second, challenges related to the eye movement, eye blinking, poor light, and capture distance, which can lead to iris reflections, aging effects, occlusion, and orientation [8]. As well, eye components like lenses, eyelashes, and spectacles can hide the iris [9]. Feature-based algorithms comprise the bulk of iris identification methods [10], which relies on identifying and extracting key features that faithfully acquire the image's included patterns while minimizing the loss of the details with the high significance [11]. For classification, these extracted features are used as inputs for Machine Learning (ML) algorithms. To train these models effectively, however, a sizable collection of annotated training data and strong processing capabilities are occasionally necessary[12]. many biometric recognition systems use an additional process known as feature selection or optimization to enhance the feature set and calculation time as a result maximize the quality of the features used in ML models, which will improve the models' accuracy, generalization, and overall effectiveness [13]. Building a robust system requires careful consideration of feature selection and optimization, especially when dealing with duplicate values [14]. In the context of ML models, optimization techniques, for example the gradient descent are applied iteratively to improve and validate the model's parameters until a workable solution is obtained [15]. Swarm intelligence is the most well-known optimization algorithm, which draws inspiration from the group behaviors of insects and other animals. These techniques are used for many different problems in many domains, including feature selection and machine learning parameter tuning.

The new iris identification system presented in this work uses six different popular machine learning model categories and a recently invented Corona Virus Optimization Algorithm (CVOA). By adjusting the hyper-parameters of traditional machine learning algorithm, the CVOA method will generate new classifiers and improve the feature set. Accurately identifying each unique iris in a variety of environmental circumstances, positions, ages, and occlusions, the system has successfully surmounted the hurdles presented by complexity and time.

The afterward sections of this work are structured as follows; in Section 2 a brief discussion about some previous related literatures are presented, while Section 3 describe the details of the used CVOA algorithm. Section 4 introduces the suggested system of iris recognition. Sections 5 and 6 exhibit all the evaluation results obtained of the proposed system and contain an overview of the findings and recommendations for further investigation sequentially.

2. RELATED WORKS

Iris recognition has been the subject of several studies, in which researchers have proven the accuracy with which their systems can reliably identify people. However, these algorithms tend to ignore some problems and have limited relevance to real-world scenarios. Certain aspects of them, such as their complexity, precision, error rate, calculation time, and capacity to manage different environmental fluctuations in iris images, can be enhanced. An extensive review of the literature on several iris identification methods is presented in this work. A novel technique for obtaining iris features presented in [16], and it primarily relies on the integration of 1-D Wavelet Transform, Sobel Operator, and one-dimensional Circular Profiles. Producing the best Probabilistic Neural Network (PNN) model and shows a 99.35% accuracy. However, this cannot be adapted to changes in the surrounding conditions, also shows a degree of computational difficulty. In [17], the author describes a technique for optimizing Gabor filters for iris identification using Particle Swarm Optimization (PSO) and Boolean PSO (BPSO) algorithms. The Support Vector Regression (SVR) model was used to integrate many local feature representations in order to increase the iris detection's precision and reliability. It was applied to three datasets and yielded an astounding 100% Recognition Rate. Consequently, other challenges to iris identification, such as lighting invariances, noise and occlusions, were not addressed in this work. The features were extracted using the Gabor Wavelet Transform along with an optimization algorithm named Teaching Learning (TL) in [18] to handle many obstacles in the environment (i.e., lighting, orientation, position, occlusion, nationality, motion) higher than 97 % accuracy. It is important to keep in mind, nevertheless, that the TL algorithm could show a slower rate of convergence than other optimization techniques, especially in scenarios involving complicated and high-dimensional optimization. The Feed Forward Back Propagation Neural Network (FFBNN) is adopted in [19] for iris identification, along with the Adaptive Central Force Optimization (ACFO) algorithm. The complexity reduced, and the accuracy under different lighting situations increased and achieves a 98% accuracy. Nevertheless, it lacks stability because of the ACFO method. By using the PSO in conjunction with the Gravitational Search Algorithm (GSA) to train the Feedforward Neural Network (FFNN) and identify the ideal weights and biases, the authors in [20] increase the identification rate of the iris. It shows a100% accuracy, however, it is unstable and requires a lot of resources. In [21],the Granular Approach

Optimization (GNN) and Firefly Optimization Algorithm (FOA) in conjunction with the Modular Neural Network (MNN), have been used and exhibit a 99.13% accuracy. Because the FOA requires an assessment of fitness functions for each particle in each iteration, this technique suffers from significant processing costs when used to large datasets. To tackle the issues of noise and segmentation, an optimization method applied in [22], which utilizes the Haralick features obtained by the Gray Level Co-occurrence Matrix (GLCM), before using the fuzzy logic driven PSO technique. A 0.193 seconds of identification time and 100% accuracy are achieved, but this study lacks universality and yields unsatisfactory results on a variety of datasets. The authors in [23] suggest a hybrid technique that combines the Neural Network of Multi-Layer Perceptron and PSO algorithm (MLPNN–PSO) with an accuracy of 95.36%. However, this approach has limited generalizability due to its lack of evaluation of the system on varied datasets and complexity and time restrictions. The authors of [24] provide a method for determining the best parameter combinations that will improve accuracy and consistency. The Moment Space Transformation is used to gather the features, and a variety of optimization techniques are employed to modify the weights of the Self-Organizing Map (SOM). A 99.3% accuracy obtained, but utilizing every one of these optimization strategies can make recognition time more difficult and resource-intensive. A Modified Chaotic Binary PSO (MCBPSO) technique for adjusting the Extreme Learning Machine's (ELM) parameters has been introduced in [25]. The Curvelet is used to extract the iris properties and shows accuracy of 99.78%. On the other hand, the inclusion of chaotic sequences and longer convergence times may result in the expense of greater computing complexity. The solution outlined in [26] depends on maximizing the iris detection ability by utilizing a feature selection technique using the optimization algorithm named Variable Length Black Hole. Two datasets were used to evaluate the model of 99.107% highest result, however, it is quite complicated and unsteady, even though it is beneficial.

Considering the problems mentioned in the literature, a novel Iris image recognition method is presented in this study. Machine learning classifiers and the recently created Corona Virus Optimization (CVOA) algorithm are used in the system. In addition to achieving accurate recognition results in various situations and changes in iris image appearance, it tackles the difficulties of complexity, time, and low-resolution images. Given the substantial influence of the proposed model.

- Apply CVOA method to the features retrieved through FLD to obtain the optimal few features that can solely describe the most significant parts of the iris image with minimum amount of data.
- Create six machine learning classifiers by utilizing the best configured hyperparameters that the CVOA algorithm yielded. In uncontrolled environments, these classifiers can effectively identify individual iris images.
- Utilize a variety of metrics on four publicly accessible datasets with variations to evaluate the program's performance and demonstrate its ability to handle huge datasets.

3. MATERIAL AND METHODS

3.1 Corona Virus Optimization Algorithm (CVOA)

Finding the best option or result from a variety of options is the process of optimization. It involves carefully analyzing and evaluating several options to determine which will result in the best situation while accounting for certain requirements or goals. Today's problems and situations cannot be effectively solved using traditional and simple search techniques in a reasonable amount of time or at a reasonable computational cost due to the presence of complex or numerous elements within the problem domain [27]. There are situations where the algorithm may need to be significantly altered to solve the issue. In computer science, optimization methodology has become a very interesting topic. These algorithms fall into a class of optimization techniques that help identify the best or almost best solution inside a problem space without significantly depending on conjectures on the mathematical characteristics of the problem [28]. Metaheuristics work incredibly well for problems with a large, non-convex solution space that is hard to fully investigate. It has been used in several fields, including scheduling, navigation, function optimization, machine learning parameter tweaking, and enhancement of features and selection [29]. These algorithms are typically impacted by physical, social, or biological phenomena [30]. The Corona Virus pandemic, starting in China, specifically in Whan was first reported on December 31, 2019. Thus, it has earned the appellation "pandemic" due to its extraordinary ability to rapidly spread and infect several countries worldwide [31]. The Corona Virus Optimization Algorithm (CVOA), a brand-new metaheuristic algorithm, has been released. The propagation and dispersal stage of the Corona Virus pandemic serves as an in-spiration for it. The steps in the CVOA method are easily explained by method (1) [32].

3.2 System Methodology

Using the CVOA algorithm, a novel iris identification system is presented in this paper, in which the CVOA will be employed in to precisely select and enhance the feature set, as well as to adjust the hyperparameters of six well-known ML architectures. As shown in FIGURE 1, a set of pre-processing operations followed by feature extraction will be employed before the utilization of the CVOA for feature optimization and hyperparameter tuning. The utilized dataset will be partitioned into two subsets: 70% for training the system, and 30% for evaluation .

3.2.1 Preprocessing stage

Grey Level Transform In the preprocessing stage, color transformation is the first step in the proposed system. The source images are transformed from RGB colored to a grayscale. Color transformation is a beneficial method in numerous ways as it decreases computational expenses and accelerates subsequent processing steps [33].

Contrast Enhancement based Histogram Equalization It is a method used in the spatial realm to create images with a uniform distribution of pixel intensity. This indicates consistent flattening and extending of the generated image's histogram. Since it successfully increases the image's overall contrast, it is frequently used to improve it, especially when the image data is represented

Algorithm 1 The Corona Virus Optimization (CVOAA)

Define:
$Initial\ infected\ group = X$ // Patient Zero starts as the infected group.
$\text{Best}_{\text{Individual}} = X$
$Iterations = 0$
$\text{Best}_{\text{Solution fitness}}$, $\text{Current}_{\text{highest fitness}}$ as real
while $Iterations < 1000\ AND\ Size\ of\ Initial\ infected\ group > 0$ **do**
  Step 1: Move individuals who are gone to the Dead set.
  $Dead = Initial\ infected\ group$
  Step 2: Process the $Initial\ infected\ group.$
  for $all\ j \in Initial\ infected\ group$ **do**
    $Fresh\ Disease = j$ IF $j \notin Dead\ AND\ j \notin Recovered\ AND\ j\ not\ isolated$
    $Retrieved = j$ IF $j \notin Dead\ AND\ j \notin Recovered\ AND\ j\ is\ isolated$
    $New\ disease\ transmission = j$ // $Occurs\ upon\ recovery.$
    $Remove\ j\ from\ Retrieved.$
    $newly\ infected\ group += j$ // $Add\ newly\ infected\ to\ the\ new\ group.$
  end for
  Step 3: Evaluate fitness for the newly infected group.
  for all j ∈ newly infected group **do**
    $\text{Best}_{\text{Individual}} = j\ IF\ fitness(j) > \text{Current}_{\text{highest fitness}}$
  end for
  Step 4: Compare and update the best individual.
  $New_{BetterIndividual} = \text{Best}_{\text{Individual}}$
  $\text{Best}_{\text{Individual}} = New_{BetterIndividual}$ IF fitness($New_{BetterIndividual}$) > fitness($\text{Best}_{\text{Individual}}$)
  Step 5: Update groups and iteration count.
  Retrieved $V = Initial\ infected\ group$
  Clear $Initial\ infected\ group$
  $Initial\ infected\ group = newly\ infected\ group$
  $Iterations = Iterations + 1$
end while // Output the best individual found.
Retrieve $\text{Best}_{\text{Individual}}$

by surrounding contrast values [34]. On the other hand, it is used to correct poor contrast values in digital iris images that result from things like uneven image lighting or insufficient illumination.

Blurring based Gaussian Filter: It is advantageous for the filter to eliminate noise in the image and highlight the features, such as lines and edges. Gaussian blur, also known as Gaussian smoothing, is the process of simulating the effect of blurring an image by using the Gaussian function to reduce the high-frequency components of the image [35]. The blurring technique creates an attractive visual effect that mimics the gentle blurring seen through a transparency screen. The research utilized a three*3 Gaussian blurring filter to create smooth images that retain the desired level of detail.

Image Rescaling The iris image has to be changed proportionately to make its complex features more visible for the extracting of features. The iris image scaling process is critical and aims to

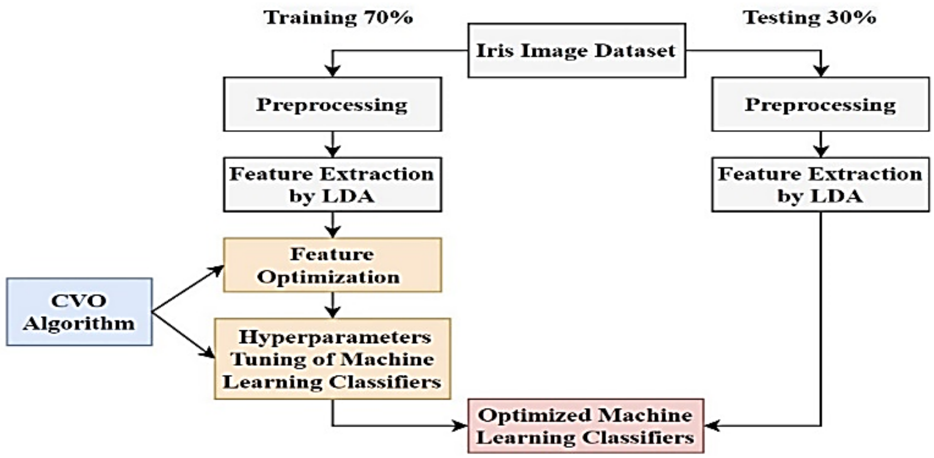


Figure 1: An overall diagram of the proposed iris recognition model.

get an unambiguous and unique set of characteristics that may be applied to the identification and optimization method. When scaling images, interpolation techniques are frequently used to add extra pixels when the image is enlarged or remove excess pixels when it is decreased [36]. The recommended solution is built on the bilinear interpolation resizing technique.

3.2.2 Extraction of features using Fisher's Linear Discriminant (FLD)

This is a technique used to extract relevant shape information from a pattern provided in an attempt to simplify the formal procedure of pattern classification. Fisher discriminant analysis or Fisher's linear discriminant (FLD) is a widely used technique for feature extraction and dimensionality reduction [36]. This is used in supervised classification to find out linear combinations of features that are most useful in distinguishing between different classes or categories. This feature extraction method is implemented in the proposed system for a multi-class domain. Two metrics, between class dispersion matrix F_B and within class dispersion matrix F_W were developed [37]. As illustrated in Eq. (4), the numerical objective function O(w) is obtained by increasing the ratio between with and within-class spreading. Eigenvectors are used to construct the projection matrix Θ*. The effectiveness of this method is widely recognized, resulting in minimizing the needed time and raising the system performance [38, 39].

$$F_B = \sum_{\tau=1}^{\chi} \Gamma_\tau \, (\beta_\tau - l)\,(\beta_\tau - \eta)^T \tag{1}$$

$$F_W = \sum_{t=1}^{c} \sum_{x_k \in x_i} G_i (b_k - h)(b_k - h)^T \tag{2}$$

$$y = \Theta^T X \tag{3}$$

$$O\,(W) = \frac{\Theta^T F_B \Theta}{\Theta^T F_W \Theta} \tag{4}$$

The vector h represents the average of the samples in class t, while bi denotes a collection of samples from class t. Additionally, b_k refer the images' count of that class, b represent the segregated classes count, and finally G_i exhibits the quantity of training samples within class t

3.2.3 Corona virus optimization algorithm- based feature optimization

The extracted features from the iris images will be improved and enhanced by the application of the CVOA method in conjunction with the FLD approach. The objective of this technique is to offer a top-notch collection of features that precisely depict the essential information of the iris images in different perspectives and scenarios. TABLE 1 displays the main parameter employed in the CVOA technique for optimizing features.

Table 1: The CVOA algorithm-related parameters utilized in the feature optimization phase.

Name	**Description**
Lower bound "LB"	Smallest number of features
Upper bound "UB"	Highest number of features
Iteration	The total number of iterations is one thousand.
Initial Population	There are one thousand features in the original set considered as Initial Population
New Population	Improved features with every new iteration.
Evaluation function	Function for evaluating the fitness of a sphere.

The category of the fitness function for a sphere is utilized, as indicated in TABLE 1. In various optimization and adaptive techniques, this kind of function is commonly used. wherever it is accepted and applied as a benchmark for evaluating optimization techniques' effectiveness. The following Eq (5), represents the primary formula for the sphere fitness function [40]:

$$\mathrm{F(x)} = \sum(\mathrm{x_i^2}) \tag{5}$$

The fitness score of solution x is represented by the function f(x), with x_i showing the i-th of solution matrix x.

3.2.4 Corona virus optimization algorithm- based optimized classifiers

Given their ability to replicate natural behaviors, bio-inspired systems are frequently employed in hybrid approaches to fine-tune machine learning model parameters. Six ML classifiers (i.e., Naïve Bayes (NB) [41], Decision Tree (DT) [42], Random Forest (RF) [43], K-Nearest-Neighbors (K-NN) [44], Support Vector Machine (SVM) [45], Logistic Regression (LR) [46]) have hyper-parameters that need to be optimized to improve the classification performance. and this is the goal of the CVOA , that will modify the most effective hyper-parameters of these ML models to be utilized as optimized classifiers in the final classification phase of the proposed system. TABLE 2 lists the critical variables that will be tuned for every ML model.

In this study, the CVOA method will be used to optimize these hyperparameters. TABLE 3 shows the initial values of these machine learning hyperparameters as well as the values obtained by

Table 2: Hyperparameters of the Implemented Machine Learning Classifiers

Model	Parameter	Demonstration
NB	Var-smoothing	Used to describe the degree of merging that is utilized for the feature variations
LR	C	Sets the level of legalization used to the structure arranged during the train
RF	n-estimators	Controls the number of trees planted during the training stage.
K-NN	n-neighbors	Declare the number of neighbors that the prediction will consider.
SVM	Degree	Utilized to choose the polynomial kernel function's level, which controls the model's adaptability to determine the complexity of the decision boundary.
DT	Max-features	Manages the number of features considered at each node while determining the optimal split.

applying the CVOA method to alter them. The machine learning classifiers in the suggested iris identification system will make use of the acquired hyperparameter values.

Table 3: The optimization of Machine learning models parameters results

Model	Parameters	Initial value	Optimized value
NB	$Var_{Smothing}$	1.00E-09	0.099990407
LR	C	0.166666668	0.098707977
RF	$N_{estimators}$	100	66
K-NN	$N_{\text{Neighbors}}$	5	6
SVM	$Degree$	3	2
DT	$Max_{Features}$	Features' Count	24

4. EXPERIMENTAL RESULTS AND MEASUREMENTS

The efficacy of the new iris recognition system had to be evaluated and validated, and to do this, a comprehensive simulation had to be conducted. To accomplish this, the improved CVOA algorithm machine learning models were used. The targets for the simulation included four different benchmark CASIA iris datasets (i.e. 1.0, 2.0, 3.0, 4.0), It was decided to choose four datasets as it was noted that they presented different challenges in terms of; lighting, locations, occlusion, aging, devices, image qualities, and volumes. Therefore, the effectiveness of the approach was also established, based on the entire evaluation scenario model, for which targets were set for the CVOA algorithm's effect on features and classifiers. As a result, four scenarios evaluated included no CVOA, CVOA with the feature only, then the hyperparameter of the classifiers, and the recommended system on feature, and class genesis together. Several measures were applied to determine how well the system performed to meet the desired result. The measures used in this study are time consuming, F-measure, recall, accuracy, and precision in identification. The belief is that the set model is implemented on a Lenovo laptop with a seventh-generation CORE i7 CPU installed in the 7300HQ variant with a clock speed of 2.5 GHz, NVIDIA GeForce GTX graphics card with 16 GB of RAM, and 6 MB Cachers.

4.1 CASIA Iris Dataset Version 1.0 Results

It is a 756 captured image for 108 human eyes in grayscale taken in controlled indoor environments in two sessions with limited scalability; lacks diversity in lighting and environmental conditions using Custom near-infrared (NIR) camera. The images were taken with a single camera for each eye [47]. FIGURE 2 show samples of the dataset, while FIGURE 3, illustrates the feature optimization using the CVOA.

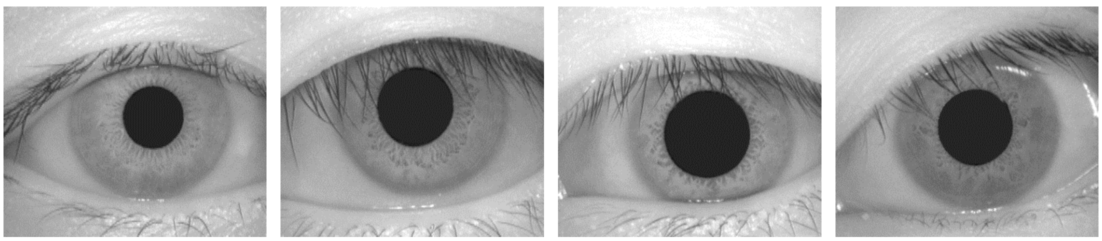


Figure 2: CASIA Iris dataset version 1.0 images samples

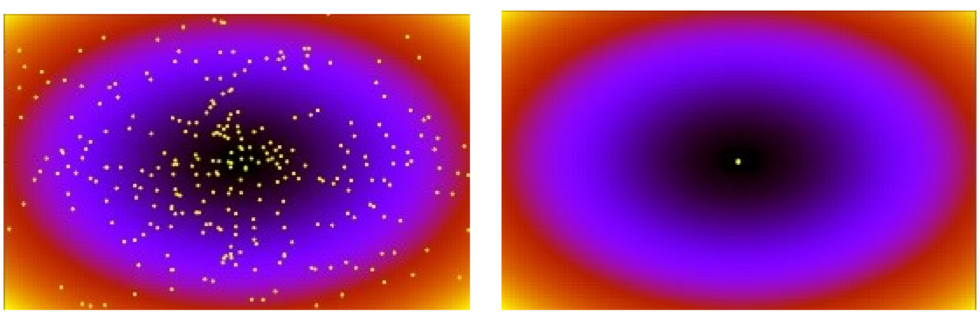


Figure 3: CVOA population on the features of the CASIA Iris dataset version 1.0

It becomes necessary to compare the experimental results of the proposed system concerning the two unique study situations that had been discussed earlier. TABLE 4 explains the obtained experiments outcomes from implementing the proposed system on the CASIA Iris version 1.0 dataset using the two scenarios along with the proposed system.

The recommended approach has achieved the highest possible results for the CASIA Iris dataset version 1.0, as can be shown in the previous results, and the improved NB approach has resulted in 100% accuracy and a reduction in time for all classifiers.

Table 4: Results for CASIA Iris 1.0 dataset

Models	**Acc. %**	**Time (ms)**	**Acc. %**	**Time (ms)**	**Initial Parameters**	**Acc. %**	**Time (ms)**	**Optimized Parameters**
LR	1.00	155.5316	1.00	149.1039	0.166666667	1.00	145.8917	0.098707978
NB	0.76	21.93379	0.97	19.98353	1.00E-09	1.00	15.96999	0.099990408
RF	0.98	1413.355	0.99	1171.756	100	1.00	496.8157	66
DT	0.70	356.1738	0.87	309.1714	No features	0.99	115.8173	24
KNN	0.78	15.01608	0.90	82.98547	5	1.00	47.9809	6
SVM	0.99	110.6508	1.00	94.73085	3	1.00	88.80115	2
	Without CVOA		**CVOA for feature-level optimization**			**CVOA for features and classifier optimization**		

4.2 CASIA Iris Dataset Version 2.0 Results

It composed of 1,200 iris image captured using Advanced NIR iris camera with variations in pupil dilation and ambient lighting, and with variability restricted to controlled lighting conditions also has high variations in pupil dilation and ambient lighting The self-built CASIA-IrisCamV2 device and the OKI-developed Irispass-h were the two devices used to gather this dataset [48]. Datasets samples are shown in FIGURE 4, while FIGURE 5, shows illustrate how the CVOA was used to optimize features for this dataset. The two scenarios of the CVOA method research and the suggested system outcomes on this dataset are explained in TABLE 5.

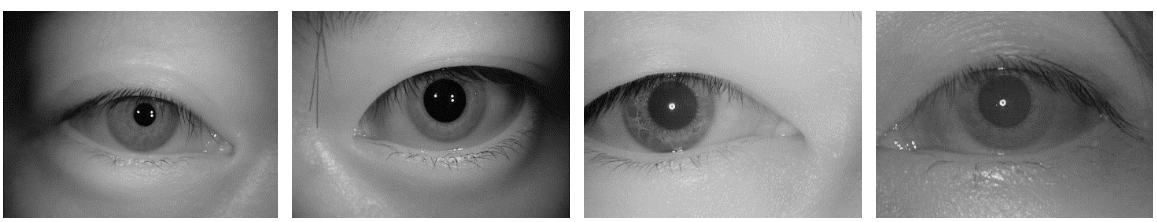
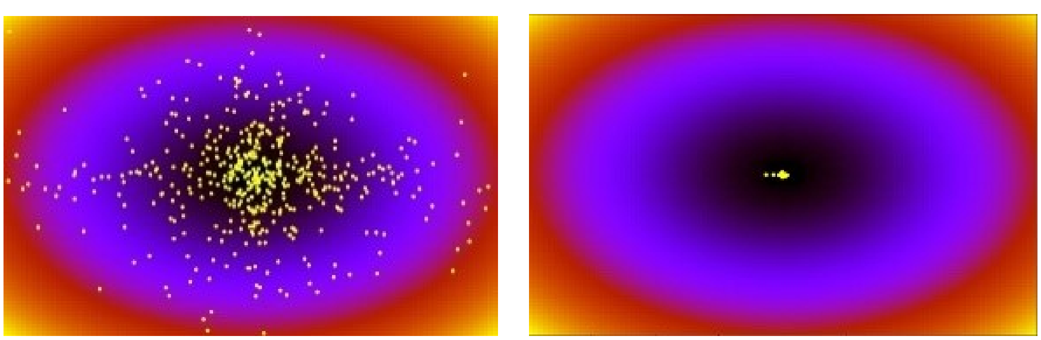


Figure 4: Samples of CASIA Iris dataset version 2.0



Start End

Figure 5: CVOA population on the features of the CASIA Iris dataset version 2.0

Table 5: Results of CASIA Iris dataset version 2.0

Models	Acc. %	Time (ms)	Acc. %	Time (ms)	Initial Parameters	Acc. %	Time (ms)	Optimized Parameters
LR	0.98	304.1989803	0.98	306.5388203	0.166666667	1.00	178.2920361	0.098707978
NB	0.98	20.88308334	0.99	19.94514465	1.00E-09	1.00	13.97132874	0.099990408
RF	0.96	1322.684765	0.99	1296.740055	100	1.00	954.4138908	66
DT	0.60	135.6368065	0.88	134.6545219	No features	0.95	131.6468716	24
KNN	0.98	57.8622818	0.98	51.81622505	5	0.99	38.89536858	6
SVM	0.98	479.7840118	0.99	448.7998486	3	1.00	264.2784119	2
	Without CVOA			**CVOA for feature-level optimization**			**CVOA for features and classifier optimization**	

4.3 CASIA Iris Dataset Version 3.0 Results

The total count of this dataset is 22,051 image captured with High-resolution NIR imaging devices This dataset consists of three distinct subsets: CASIA-Iris-Interval, harvested utilizing a close-up iris camera that was developed in-house; CASIA-Iris-Lamp, harvested using a handheld iris sensor that was produced by OKI; and CASIA-Iris-Twins, harvested using OKI's IRISPASS-h camera during the Beijing Annual Twins Festival. More than seven hundred people contributed 22,034 iris photos to this collection. Near-infrared light [49] was used to take these images. While FIGURE 6, shows the result of applying the CVOA method to optimize the characteristics of the dataset, FIGURE 7, shows samples from the dataset. TABLE 6 exhibits the results from this dataset.

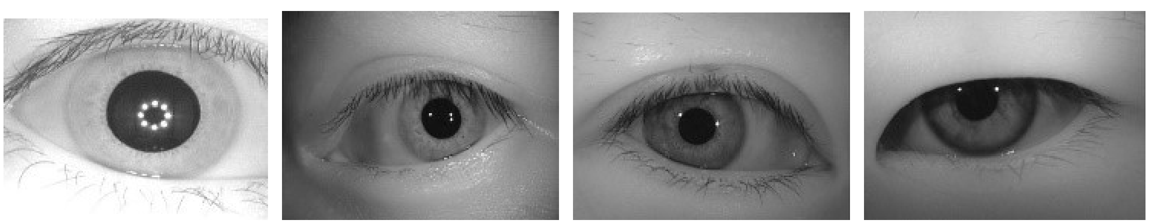
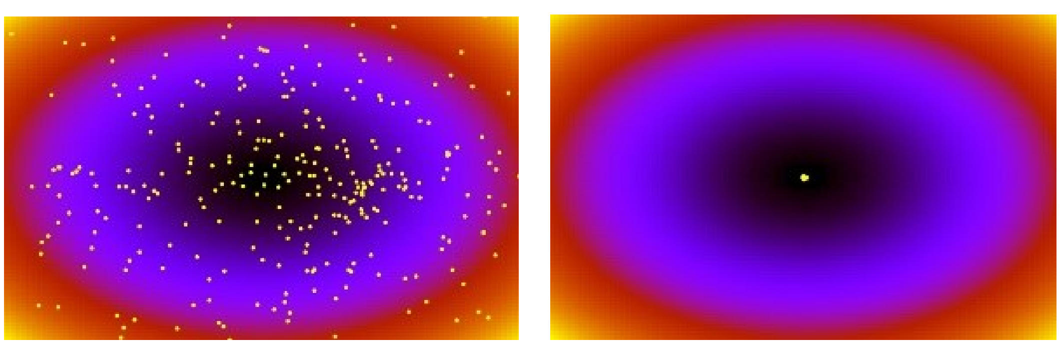


Figure 6: Samples of CASIA Iris dataset version 3.0



Start End

Figure 7: CVOA population on the features of the CASIA Iris dataset version 3.0.

Table 6: Results for CASIA Iris dataset version 3.0

Models	Acc. %	Time (ms)	Acc. %	Time (ms)	Initial Parameters	Acc. %	Time (ms)	Optimized Parameters
LR	0.84	2584.266424	0.93	1577.548981	0.166666667	0.99	1564.161062	0.098707978
NB	0.81	721.1275101	0.93	690.29212	1.00E-09	0.96	400.9160995	0.099990408
RF	0.94	1474.261648	0.94	1229.685001	100	0.99	893.9840794	66
DT	0.94	3149.097681	0.98	1653.732777	No. features	1.00	1298.2010841	24
KNN	0.87	968.81570816	0.91	866.81451607	5	0.98	649.518628	6
SVM	0.93	1820.477962	0.99	1456.861258	3	1.00	1166.485548	2
Without CVOA			**CVOA for feature-level optimization**			**CVOA for features and classifier optimization**		

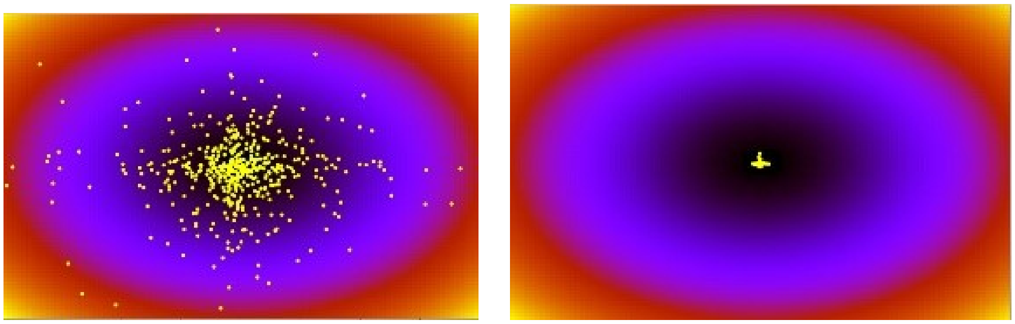
The recommended approach has achieved the best results for the CASIA Iris Image Database 3.0, as can be shown in the previous table. Using the improved NB approach has resulted in 100% accuracy and a reduction in processing time for all classifiers. When the CVOA method is used, the results are noticeably different from what would be achieved if it were not applied. The improvements become more noticeable when the CVOA approach is used for feature selection and categorization.

4.4 CASIA Iris Dataset Version 4.0 Results

This version of CASI Iris Dataset is composed of 54,601 images taken using State-of-the-art operational NIR device [50]. There is artificial variability in this dataset due to intra-class variations like distortion, blurring, and rotation. Consequently, the matching and identification of an iris characteristic had been hindered. While the library contained around 1,800 genuine topics and approximately 1,000 virtual characteristics. Here, samples of the dataset are shown in FIGURE 8, while the scheme of the characteristic optimization technique with CVOA adopted on this database displayed in FIGURE 9.The two scenarios of the CVOA method research and the suggested system outcomes on this dataset are explained in TABLE 7

Figure 8: Samples of CASIA Iris dataset version 4.0

From the table above, it is clear that the recommended strategy led to the best outcomes in CASIA Iris Image Database 4.0. All classifiers have shown a drop-in time and an improvement in accuracy to 100% when utilizing the enhanced NB technique.



Start End

Figure 9: CVOA population on the features of the CASIA Iris dataset version 4.0.

Table 7: Results of CASIA Iris dataset version 4.0

Models	Acc. %	Time (ms)	Acc. %	Time (ms)	Initial Parameters	Acc. %	Time (ms)	Optimized Parameters
LR	0.98	1303.592	0.98	1228.585	0.166666667	1.00	758.6849	0.098707978
NB	0.86	285.311	0.90	241.5376	1.00E-09	0.96	60.87804	0.099990408
RF	0.94	4828.547	0.96	3376.957	100	0.99	1254.928	66
DT	0.73	1089.744	0.87	880.672	No features	0.94	386.9686	24
KNN	0.94	466.79296	0.99	408.8429	5	1.00	251.8606	6
SVM	0.96	1060.235	0.99	1023.532	3	1.00	820.7769	2
	Without CVOA		**CVOA for feature-level optimization**			**CVOA for features and classifier optimization**		

5. DISCUSSION

The experimental results revealed that the proposed approach improved recognition accuracy and reduced efficiency on four open databases. These are the CASIA Iris Image Databases 1.0, 2.0, 3.0, and 4.0. When the iris recognition system was installed with and without the CVOA, the results were hugely different. The results of the second case study show that the CVOA method was first found to be successful when it was limited to feature optimization. Additionally, the outcomes of the recommended system demonstrated how beneficial it is to use the CVOA approach to fine-tune the features and hyperparameters of the machine learning models. The CVOA technique has demonstrated excellent efficacy in collaboration with six machine learning classifiers in the preceding two case studies, spanning four. distinct dataset types with substantial differentiation in iris image properties and scenarios. Furthermore, the excellent results achieved by the suggested method, which uses adjusted classic machine learning models, negate the need for deep learning approaches, which are difficult and demand a great deal of work. Comparison research has been carried out to illustrate the advantages of the presented iris identification technique. TABLE 8–TABLE 11 for the datasets that were utilized in this research provide a summary of the comparison with previous systems that were provided. The proposed has the highest detection rate of 100% and the shortest time of 13.97 ms compared to the existing systems.

Table 8: Analyzing the suggested system against the current methods using the dataset of CASIA version 1.0.

Ref.	Model	Acc.%	Pre.%	Rec.%	F1.%	Time in Second
[51]	WTZ	0.93	-	-	-	-
[16]	PSO + NN	0.99	-	-	-	-
[17]	BPSO + SVR	0.99	-	-	-	-
[18]	TLBO	1.00	-	-	-	-
[21]	FOA+ NN	0.97	-	-	-	-
[52]	GOA + TST	0.99	-	-	-	-
Proposed	CVOA+ NB	1.00	1.00	1.00	1.00	0.01597

Table 9: Analyzing the suggested method against the current methods using the dataset of CASIA version 2.0.

Ref.	Model	Acc.%	Pre.%	Rec.%	F1.%	Time in Second
[53]	2D GF + KNN	0.95	-	-	-	-
[54]	CNN + ResNet	0.97	0.99	0.92	0.97	-
[55]	VAMRFUS	0.85	-	-	-	-
Proposed	CVOA+NB	1.00	1.00	1.00	1.00	0.01397

Table 10: Analyzing the suggested system against the current methods using the dataset of CASIA version 3.0.

Ref.	Model	Acc.%	Pre.%	Rec.%	F1.%	Time in Second
[21]	GSA + FFNN	1.00	-	-	-	2169
[22]	GLCM+ FLC- PSO.	1.00	-	-	-	9.650
[23]	MLPNN–PSO	0.95	-	-	-	-
[56]	CHT +CNN	0.99	-	-	-	-
[57]	connect extend smooth + Hamming	0.95	-	-	-	-
[58]	TL + GoogleNet	0.99	-	-	-	-
Proposed	CVOA+ DT	1.00	1.00	1.00	1.00	1.298

6. CONCLUSION

The presented iris recognition technique in this paper is based on a unique bio-inspired CVOA algorithm and ML algorithms. With regard to iris image recognition under various environmental circumstances, the primary goal of the suggested system is to solve the issues of time and complexity. The characteristics are acquired by the FLD approach following the completion of image preprocessing. The next step is to find the best or almost optimal set of characteristics using the CVOA , which was motivated by the spread of Corona Virus disease. Based on the optimally

Table 11: Analyzing the suggested system against the current methods using the dataset of CASIA version 4.0.

Ref.	Model	Acc.%	Pre.%	Rec.%	F1.%	Time in Second
[59]	HT + CNN +SVM	0.96	-	-	-	-
[60]	FCO +U-Net	0.98	-	-	-	-
[61]	CNN +GF + ANN	0.98	-	-	-	-
[26]	VLBHO	0.99	-	-	-	-
[62]	PSO+CDT	0.99	-	-	-	-
[63]	Attention +TL	1.00	-	-	-	-
Proposed	CVOA + KNN	1.00	1.00	1.00	1.00	0.252

adjusted hyperparameters obtained by the CVOA, six machine-learning classifiers have also been created. Using four different public datasets, the system has been tested and has produced better results faster than expected from many types of the built classifiers. On the CASIA Iris dataset version 1.0, the developed NB classifier was executed with a recognition precision of 0.01597 seconds. On the other hand, using the CASIA Iris dataset version 2.0, the system shows some very encouraging findings when compared to other techniques that were presently in use. 100% precision was attained by the improved LR, NB, RF, and SVM classifiers in 0.954 seconds, with the NB classifier outperforming the others at 0.01397 seconds. With DT and SVM classifiers, the CASIA Iris dataset version 3.0 results show the best performance, reaching a maximum accuracy of 100%. Moreover, it took 1.298 seconds for the SVM classifier to achieve 100% accuracy as well, the built-in KNN classifier had the fastest recognition time (0.252 seconds), whilst the LR, KNN, and SVM classifiers in the CASIA Iris dataset version 4.0 show a result with high as 100%. The outcomes demonstrate how well the suggested system performs iris identification on datasets with a wide range of changes and a sizable number of samples, all while requiring the least amount of time and effort. Subsequent efforts will concentrate on applying the previously described technology to identify other forms of personal biometrics, such as fingerprints, veins on the fingers, and facial characteristics. Moreover, it uses a CVOA algorithm to generate many categorization methods, such as deep learning.

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