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An Improved Method for Human Identification Based on Iris Recognition Using Hybrid Convolutional Neural Networks and Grey Wolf Optimization

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Abstract—**Identifying a person through the iris is important in the security and medical fields. Biometric engineering image processing has a crucial application in iris facial recognition. This paper proposes the suggested Grey Wolf Optimizer-Convolutional Neural Networks (GWO-CNN) technique. The SVM algorithm was used for selecting the best GWO features. The proposed algorithm was performed on several standard datasets. The proposed GS-CNN technique demonstrates the performance of experimental evaluation on the CASIA database. The results show that the proposed GS-CNN technique outperforms other classifiers, achieving the highest accuracy of 98% on the CASIA-V1 dataset and 96% on the CASIA-Iris-Interval dataset. This highlights the effectiveness of the GS-CNN approach in iris recognition tasks.**

Key Words: CNN algorithms, *GWO technique*, feature selection, CASIA.

1. INTRODUCTION

With the rapid technological changes, the security factor of individuals and organizations has also decreased. Therefore, in proportion to the rapid development of computer networks and communications, the need for reliable methods of verifying individuals is even more felt. The common methods to identify people are based on two things: the things you own, such as your house key and credit card, which, if lost, can be used by others, or the things you know, such as your name. Users and passwords are easy to get by guessing or trying if they are very simple and difficult to remember. If they are too complicated, we will have to write them down somewhere. In this case, they can be lost or stolen. A strong instrument for accurate human identification is the iris. It can confidently determine people's identities. The most critical step in the iris detection system is the extraction of desirable features. The iris detection method has historically been implemented using a variety of features. The majority of them rely on custom features created by biometricians. Therefore, when high-dimensional datasets comprise redundant and unrelated characteristics, selection is crucial in machine feature learning.

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A variety of optimization techniques are utilized to overcome this issue. Various optimization problems have been solved using different metaheuristics in the past few years. Nature has been a major source of inspiration for the development of metaheuristics, which are considered to be highly effective problem-solving tools. Many algorithms have been introduced that draw inspiration from nature and its processes. The GWO algorithm is widely recognized for its ability to solve various optimization problems by drawing inspiration from nature. Its performance is considered satisfactory in this regard [1]. The algorithm known as GWO imitates the hunting mechanism and hierarchical structure of grey wolves found in nature. To simulate this hierarchy, four types of grey wolves - alpha, beta, delta, and omega - are utilized [2]. The application of Grey Wolf Optimizer has proven to be successful in solving a range of problems such as economic dispatch, optimal design of double-layer grids, feature subset selection, time forecasting, and more [3].

The main contribution of this research is listed below:

- The GWO algorithm is utilized to extract the most optimal features.
- Utilizing SVM for feature selection to determine the optimal GWO features.
- Feeding GWO-SVM features to the Convolutional Neural Network (CNN) to detect the iris of the eye.

In this paper, a new technique based on a combination of GWO and Convolutional CNN SVM is presented to improve iris recognition. Section 2 provides a comprehensive review of previous work in the field of iris recognition, focusing on traditional methods and their challenges. In Section 3, the proposed methodology is explained in detail, including the roles of GWO, CNN, and SVM in the process. Section 4 presents the experimental results obtained using the CASIA dataset, comparing the performance of the proposed technique with other methods. Section 5 discusses Challenges and Practical Applications .Finally, Section 6 discusses the main conclusions of the study.

II. Literature Review

Zhao and Kumar [4] developed a revolutionary deep learning-based iris highlight representation that may provide widespread coordination with accuracy and speculative capacity for iris recognition. To explore the spatially comparing features for further precise iris recognition, this effort should focus on learning more robust iris mask info using deep networks.

Arsalan, Hong [5] suggested a two-stage strategy to find the real iris limit in an unfavorable environment. Through altered roundabout HT, a hard iris limit was discovered in the main stage, characterizing the ROI by the somewhat increased iris range. The information obtained from the return on investment was applied via VGG-face calibrating to CNN in the following stage. Two yield highlights are provided by the CNN yield layer. Karakaya [6] used deep learning approaches to enhance off-target iris identification. The effectiveness of the off-target iris recognition frameworks was improved by using convolutional neural networks. Zanlorensi, Luz [7] offered VGG and ResNet-50 networks for iris recognition. Designers proposed a specific information increase strategy for iris photos and used interchange gaining from the face space.

Varkarakis, Bazrafkan [8] considered the challenges of individual confirmation on emerging wearable AR/VR show glasses. A further expansion measure was performed to a choice of the mutilated iris pictures, summing contrast, obscurity, or the picture's shadows to reflect the variation in image quality performed in reality. Iris detection has been achieved by combining edge-based and learning-based methods [9]. A meticulous plan was devised for creating a six-layer Faster R-CNN that would be used to find and collect the eyes. The pupillary region was arranged by utilizing a

Gaussian mixing structure in conjunction with the bouncing box found by Faster R-CNN. Khalifa, Taha [10] proposed deep convolutional neural nets-based identifiable evidence based on iris gender. The mechanism of this method uses the diagram cut segmentation strategy to chop apart the iris from an original image. The expansion tactics used in this exploration keep the preparatory information while overcoming the trailing case and making the original construction tougher as well safer.

Liu, Zhou [11] suggested using a Gaussian, triangular fuzzy mean, and triangle fuzzy logic system means smoothing filter to pre-process pictures by fuzzifying the region after the edges for enhancing waveforms to noise ratios. The deep learning method's training phase utilized a changed image with a fuzzy operation, which speeds up convergence and increases recognition accuracy rates. According to the findings from that research, training on fuzzified images generally outperforms training on raw images. The utilized fuzzified picture filters might improve the sensor ratios by a greater margin than conventional data augmentation techniques. After the processing of image features, accuracy has increased and convergence speed has accelerated even further. Lozej, Stepec [12] investigated the Iris recognition and detection framework's impact. The iris surface was encoded using the deep neural net model CNN, and several experiments were run to assess the methodology's impact on the iris recognition system. The developers avoided the iris-expanded progress outward against out and showed which severe exposition might be done with or beyond regularizing the iris covering because deep learning structures might reveal complicated (nonlinear) data alternations. The results of conventional (heuristic) segmentation methods were added for evaluation purposes, followed by iris expanding. Wang, Zhu [13] proposed two elements that make up a novel's multitasking structure. The first section is just a Fully Convolutional Encoder-Decoder Net against examination units, which might additionally highlight the distinction in supplying diverse probability maps. Sardar, Banerjee [14] suggested iris segmentation using an intuitive UNet variant. The preparation time was cut in half by using the Squeeze Expand modules. As a result of reducing the number of included boundaries, capacity efficiency would simultaneously be improved. For datasets lacking sufficient clear instances, the intelligent component assisted in generating the ground truth. Thakkar and Patel [15] used a self-learning computational smart model. In such a study, the researcher created highlight vectors from iris highlights using Gabor channels. Here, a prepared neural network was used for examination.

The suggested approach by [16] improves the accuracy and efficacy of iris detection by combining sophisticated segmentation techniques with fuzzy clustering approaches. Also, the Bald Eagle Search (BES) algorithm was used to locate and isolate the iris region. The outcomes demonstrate the efficacy of the suggested approach using 400 test photos, each representing 40 individuals. A genetic algorithm and wavelet transformation were used to enable a deep learning architecture for iris recognition [17]. The suggested approach works well for iris recognition and applies to many biometric recognition jobs. In [18], an iris recognition technique based on the advanced Enhance Deep Iris model is proposed. This study was performed on the ND-IRIS-0405 and CASIA-Lamp datasets. The results show that the proposed method detects the iris edge accurately.

III. Proposed Methodology

The proposed model utilized for to iris detection technique has been discussed in this section. The suggested Iris detection model is presented in Fig.1. The incoming iris image is preprocessed. The technique of GWO will be utilized to extract additional features from the Iris image. Feature selection is utilized using SVM to select the best GWO features. The classification of the iris data was carried out by employing the CNN method. Fig. 1 displays the block diagram of the proposed method.

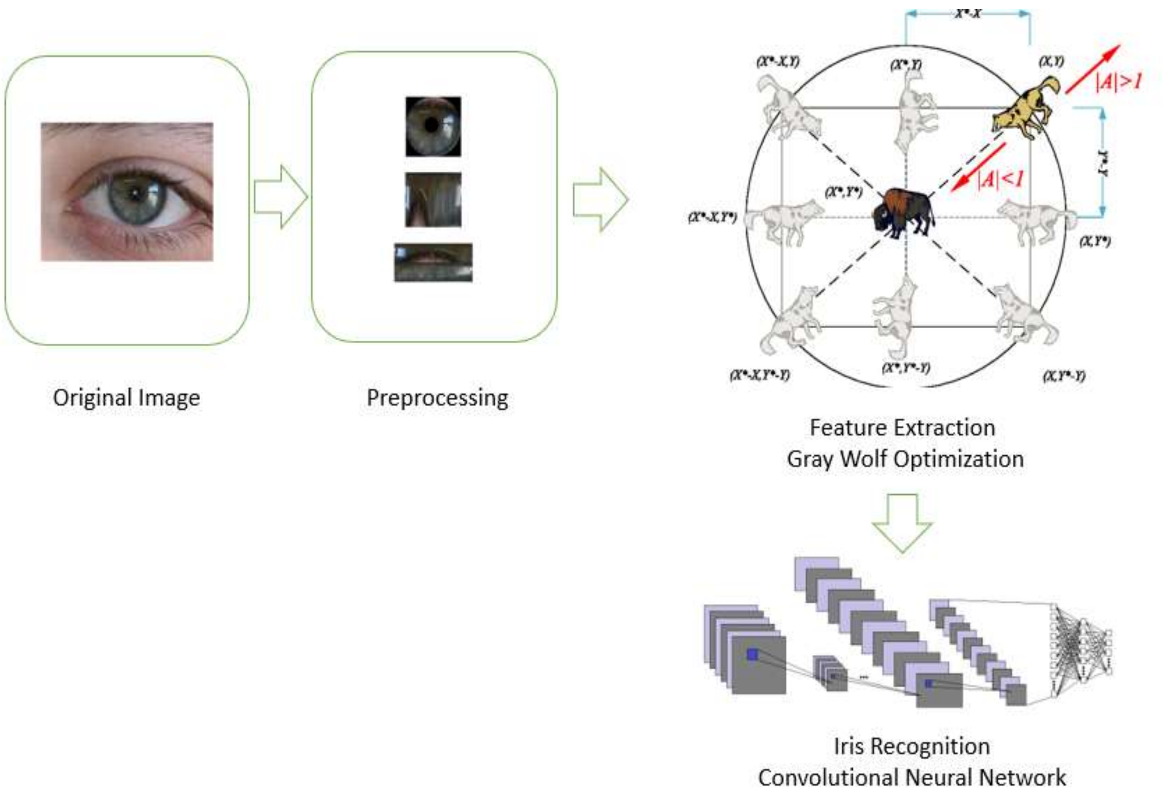


Fig. 1. The block diagram of proposed Iris detection techniques

A. Data set

To diagnose the iris, the initial step involves capturing a series of high-quality images of the iris using sensors and cameras. The global biometrics community has utilized the CASIA Iris Image Database (CASIA-Iris) since 2002. The database has undergone an enhancement from CASIA-IrisV1 to CASIA-IrisV3. The subgroups of CASIA-IrisV3 consist of straightly, CASIA-Iris-Interval, CASIA-Iris-Lamp, and CASIA-Iris-Twins. The 3 modern subgroups are CASIA-Iris-Distance, CASIA-Iris-Thousand, and CASIA-Iris-Syn. The CASIA-IrisV4 contains 54,601 iris images from 1000 virtual subjects and 1800 real subjects. The images were taken under the synthetic or near-infrared and are 8-bit grayscale in JPEG format (see Fig. 2 and 3).

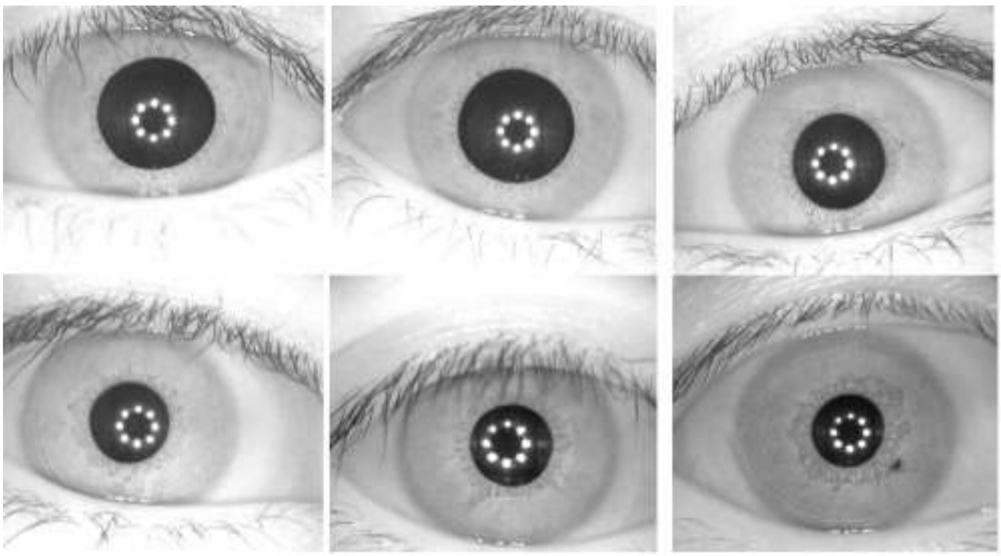


Fig.2. Sampled pictures along the cassia-iris-period

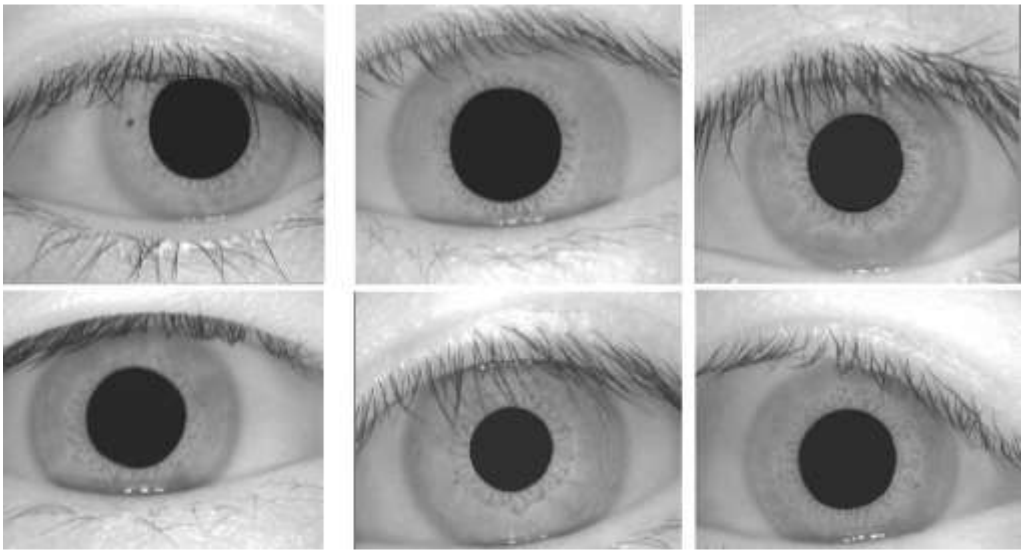


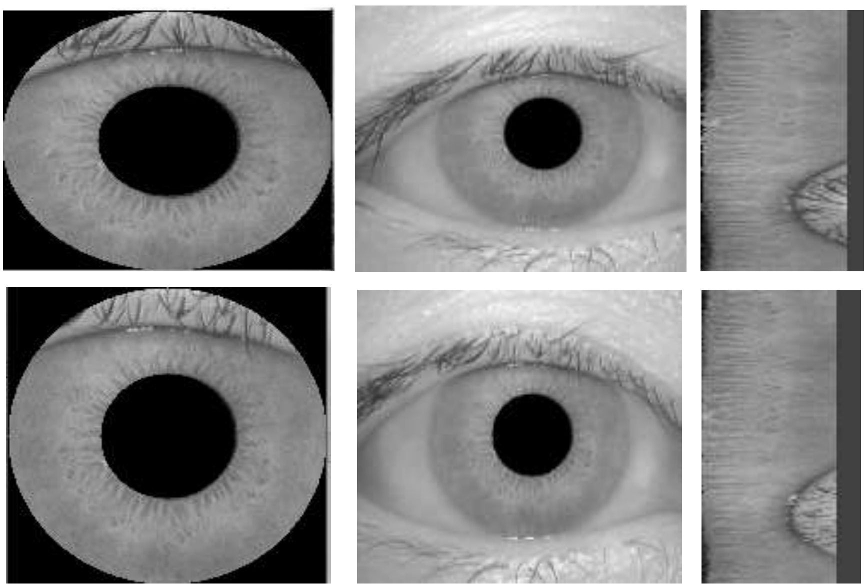
Fig.3. Sample images from the cassia v1

B. Iris Segmentation

In the iris segmentation stage, the digital eye image is isolated into two circles, including the inner circle surrounding the pupil (the inner black circle) and the outer circle for the borders of the iris (the borders of the colored part of the eye). The location of the circular in the iris is determined using the Hough transform.

C. Transformation

The circular shape of the image is transformed into a rectangular shape, resulting in a segmented image. The iris area that has been split is usually mapped onto an area with fixed dimensions. Fig. 4 shows the result of the transformation.



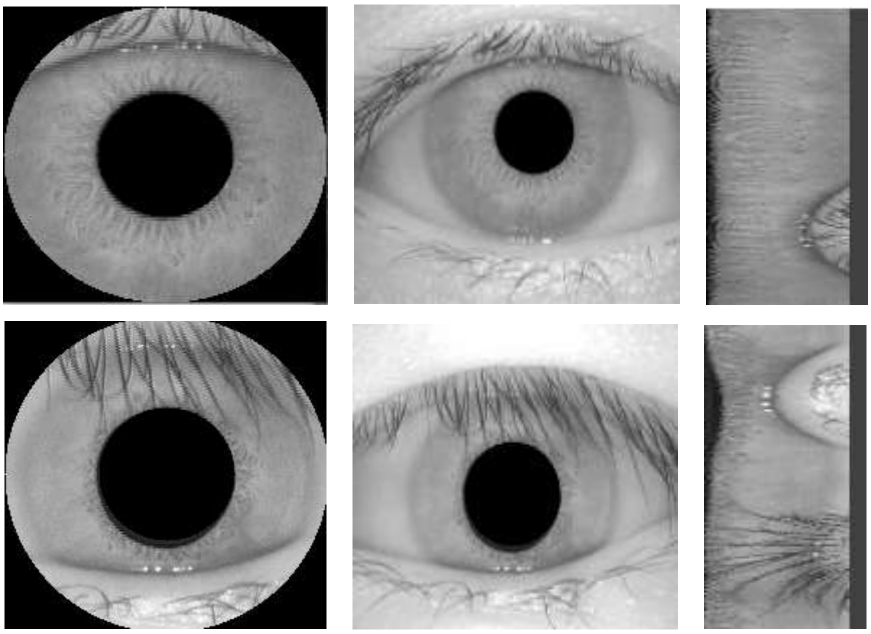


Fig.4. The result of transformation.

D. Histogram of Oriented Gradients (HOG)

A considerable amount of research has been dedicated to enhancing the computation of HOG features to improve their processing speed and decrease power consumption [19]. The authors suggested a technique for locally normalized Histogram of Oriented Gradient (HOG) descriptors. They demonstrated that this approach offers superior performance to other available feature sets, such as wavelets. The approach involves assessing well-normalized local histograms of image gradient orientations in a dense grid. It is often possible to describe the appearance and shape of an object within a local area by analyzing the distribution of local intensity gradients or edge directions without requiring exact knowledge of the location of these gradients or edges. The concept is based on the idea that the distribution of these gradients or edges can provide sufficient information about the object's visual features [20].

E. Gray Wolf Optimization (GWO)

The family Canidae includes Canes lupus, commonly known as the grey wolf. Apex predators are how grey wolves are classified, which means they are at the pinnacle of the food chain. Grey wolves tend to reside in packs. Living in a pack is the preferred habitat for grey wolves, with an average group size of 5-12 individuals [2]. The hierarchy of gray wolves is divided into four groups: wolf-alpha, wolf-beta, wolf-delta, and wolf-omega. Alpha is the wolf with the strongest foundation for gathering authority. Beta Wolf is the second member of the wolf gathering's social pecking order. The gray wolf is at its lowest level at omega. The gray wolves' analytical structure concerning the hunting mechanism is provided below:

$$\vec{D}\alpha = \left|\vec{C}_1 . \overrightarrow{X}\alpha(t) - \vec{X}(t)\right| \quad (1)$$

$$\vec{D}\beta = \left|\vec{C}_2 . \vec{X}\beta(t) - \vec{X}(t)\right| \quad (2)$$

$$\vec{D}\delta = \left|\vec{C}_3 . \overrightarrow{X}\delta(t) - \vec{X}(t)\right| \quad (3)$$

where, $\vec{D}$={ $\vec{D}\alpha$, $\vec{D}\beta$, $\vec{D}\delta$} is length vector and $\vec{X} = \{ \vec{X}\alpha , \vec{X}_\beta , \vec{X}_\delta \}$ indicate location vector.

$$\vec{X}_1 = \vec{X}\alpha(t) - \vec{A}_1 . (\vec{D}\alpha) \quad (4)$$

$$\vec{X}_2 = \vec{X}_\beta\ (t) - \vec{A}_2 .(\vec{D}\ \beta) \quad (5)$$

$$\vec{X}_3 = \vec{X}_\delta\ (t) - \vec{A}_3\ (\vec{D}\delta) \quad (6)$$

$$\vec{X}\ (t+1) = \frac{\vec{X}^1 + \vec{X}_2 + \vec{X}_3}{3} \quad (7)$$

The calculation of coefficient vectors for alpha and beta, when dealing with delta wolves, is detailed below:

$$\vec{A}_1 = 2\vec{a}.\vec{r}_{\alpha_1} - \vec{a} \quad (8)$$

$$\vec{C}_1 = 2\vec{r}_{\alpha_2} \quad (9)$$

$$\vec{A}_2 = 2\vec{a}.\vec{r}_{\beta_1} - \vec{a} \quad (10)$$

$$\vec{C}_2 = 2\vec{r}_{\beta_2} \quad (11)$$

$$\vec{A}_3 = 2\vec{a}.\vec{r}_{\delta_1} - \vec{a} \quad (12)$$

$$\vec{C}_3 = 2\vec{r}_{\delta_2} \quad (13)$$

The initial random vector in the interval (0,1) can be represented by $\vec{r}_{\alpha_1}$, $\vec{r}_{\beta_1}$, $\vec{r}_{\delta_1}$, while the second random vector in the same interval can be denoted by $\vec{r}_{\alpha_2}$, $\vec{r}_{\beta_2}$, $\vec{r}_{\delta_2}$.

The gray wolf group members update their positions based on their hierarchy, with alpha, beta, and delta wolves and their prey. The prey is caught by the gray wolves, who then finalize the hunt by launching an attack on it. The calculating $\vec{a}$ vector is given below:

$$\vec{a} = 2 - \frac{2.Iter}{Maxiter} \quad (14)$$

The illustration of the flow chart operation might be described as follows:

1) The population size and maximum number of iterations are used to initialize the parameters of both GWO and CNN algorithms.
2) Next, the initial cost function is defined.
3) The values of alpha, beta, and delta will be calculated using a random initial generation of the population.
4) Applying the average function to update the current wolf position for each wolf action.
5) Calling the CNN algorithm.
6) Applying positions updating.
7) Computing the features using GWO wolf fitness functions.
8) Further updating the alpha, beta, and delta wolf positions.
9) Check to reach maximum iteration; if not, repeat the procedure.
10) If yes, end the program and stop.

F. Convolutional Neural Networks (CNNs)

The classification process is used to determine whether the iris is for a specific person or another by matching the template to other existing templates. CNNs have found a wide scope of interest through utilizing them in various vitality applications. This high interest has been initiated due to the various properties provided by the CNNs, especially in pattern recognition and object identification implementations.

CNN strategy depends on feature selection for the target image properties such as; Features and Classifications. There are several benefits and useful achievements gained via applying such strategies in the suggested model, which might be listed as success:

1) Low dependency upon the preprocessing operation of data.
2) Reducing the demands for human efforts and actions.
3) Simple in implementation.
4) Fast processing.
5) Highest accuracy among all image prediction techniques.

IV. Results

This part contains the findings of the suggested approach. The suggested system's outcomes are compared with those of the most popular supervised machine learning algorithms, RF, KNN, and SVM classifiers. Table 1 shows the GWO parameters for feature extraction and Table 2 displays the parameters and layers details of the CNN algorithm.

Table 1. GWO Parameters

Parameters	Value
NSA[1]	30
Iteration	20
Dimension	28800
Best score	Alpha score
Best-pos.	0.027
D-alpha	0.744
D-beta	0.78
D-delta	0.88

Table 2. Parameters and layers details of the CNN algorithm

Layer	Output shape	Parma
Conv1D	(None, 98, 256)	50176
Batch normalization	(None, 98, 256)	1024
Conv1D	(None, 96,128)	98432
Batch normalization	(None, 96,128)	512
Dropout	(None, 96,128)	0
Max pooling	(None, 48, 128)	0
Flatten	(None,6144)	0
Dense	(None,1000)	6145000
Batch normalization	(None,1000)	4000
Dropout	(None,1000)	0
Dense	(None,99)	99099

A. Comparison with Machine Learning Algorithms

Two common feature extraction methods were used, including Principal component analysis (PCA) and HOG. The results of the implementation of the machine learning algorithms most commonly used in classification (Multi-Layer Perceptron (MLP), Random Forest (RF), Support Vector Machine (SVM), and K-Nearest Neighbors (KNN) on the data set utilized in our research are shown in this section. The findings are displayed in Table 3. Fig. 5-8 demonstrates the result of MLP, RF, SVM, and KNN algorithms. Fig. 5. On the dataset CASIA-V1, the findings demonstrate that the suggested algorithm GS-CNN works better than any other classifier, attaining the highest values in every metric (precision 0.97, recall 0.95, F1 score 0.96, and total accuracy 0.98; see Figure 5). Other classifiers, particularly PCA+RF, performed worse. Figure 6 With an overall accuracy of 0.96, the results demonstrate GS-CNN's supremacy once more. While HOG+RF performed the worst, the HOG+SVM classifier did rather well.

[1] NSA: Number of search agents

Table 3. The Results of Classification

Classifier	Feature extraction technique	No. of class	Dataset	Precision	Recall	F1-score	Accuracy
MLP	HOG	108	CASIA-V1	0.91	0.90	0.89	0.92
RF		108	CASIA-V1	0.42	0.47	0.41	0.49
SVM		108	CASIA-V1	0.95	0.93	0.93	0.94
KNN		108	CASIA-V1	0.86	0.86	0.85	0.88
MLP	PCA	108	CASIA-V1	0.76	0.77	0.74	0.78
RF		108	CASIA-V1	0.53	0.5	0.50	0.59
SVM		108	CASIA-V1	0.89	0.90	0.89	0.93
KNN		108	CASIA-V1	0.86	0.88	0.86	0.89
Proposed GS-CNN	GWO	108	CASIA-V1	0.97	0.95	0.96	0.98
MLP	HOG	247	CASIA-Iris-Interval	0.86	0.86	0.86	0.94
RF		247	CASIA-Iris-Interval	0.50	0.53	0.48	0.62
SVM		247	CASIA-Iris-Interval	0.72	0.76	0.72	0.84
KNN		247	CASIA-Iris-Interval	0.77	0.79	0.76	0.86
MLP	PCA	247	CASIA-Iris-Interval	0.82	0.84	0.83	0.88
RF		247	CASIA-Iris-Interval	0.65	0.66	0.62	0.71
SVM		247	CASIA-Iris-Interval	0.85	0.86	0.84	0.90
KNN		247	CASIA-Iris-Interval	0.86	0.84	0.83	0.89
Proposed GS-CNN	GWO	247	CASIA-Iris-Interval	0.92	0.94	0.92	0.96

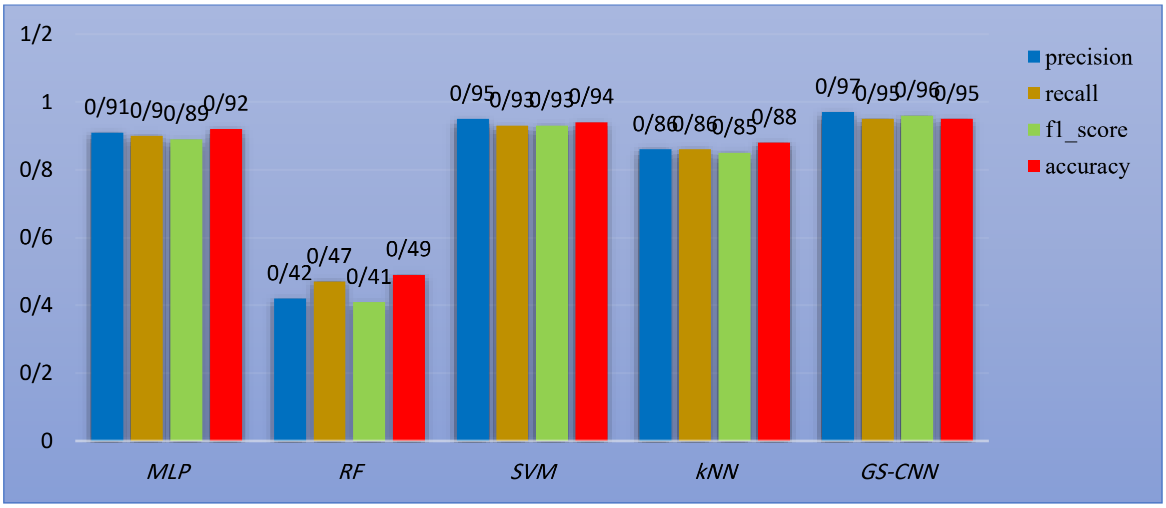


Fig.5: The results of classifier comparisons (CASIA-V1)

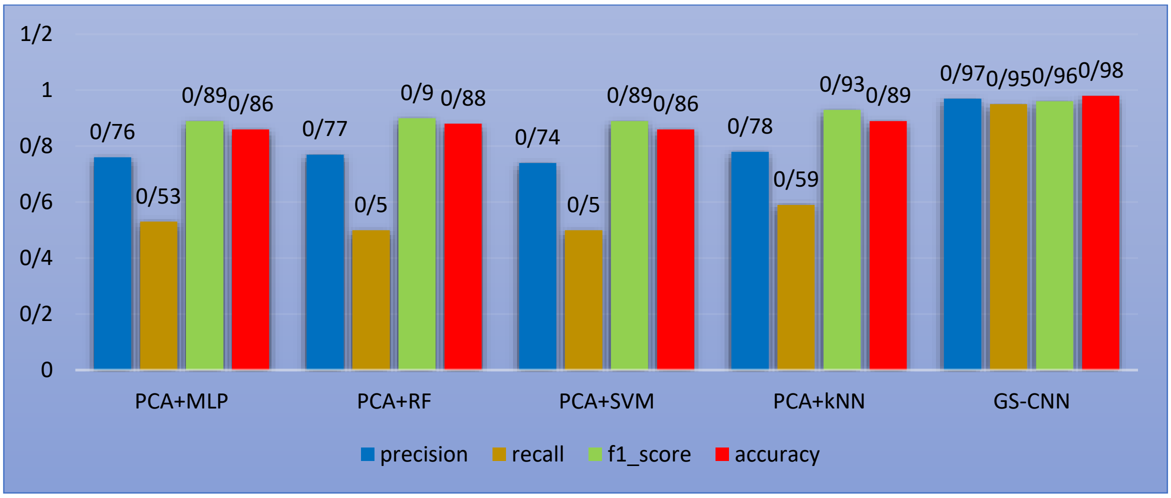


Fig.6: The results of classifier comparisons using PC A(CASIA-V1)

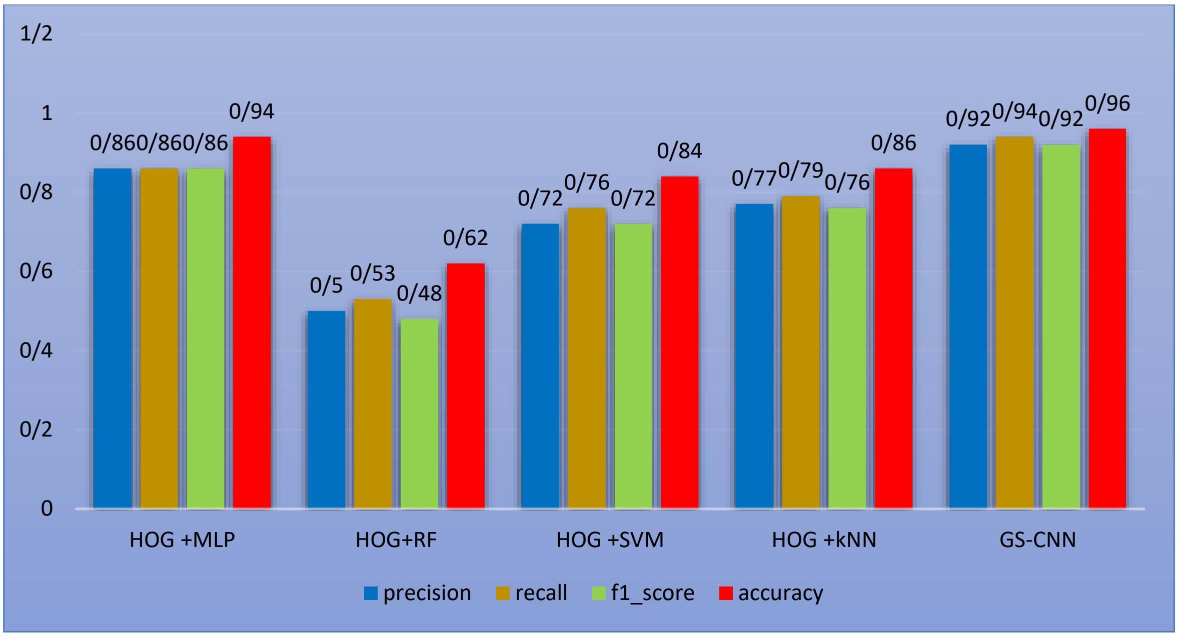


Fig. 7. The classifiers' comparing outcomes using HOG (CASIA-Iris-Interval)

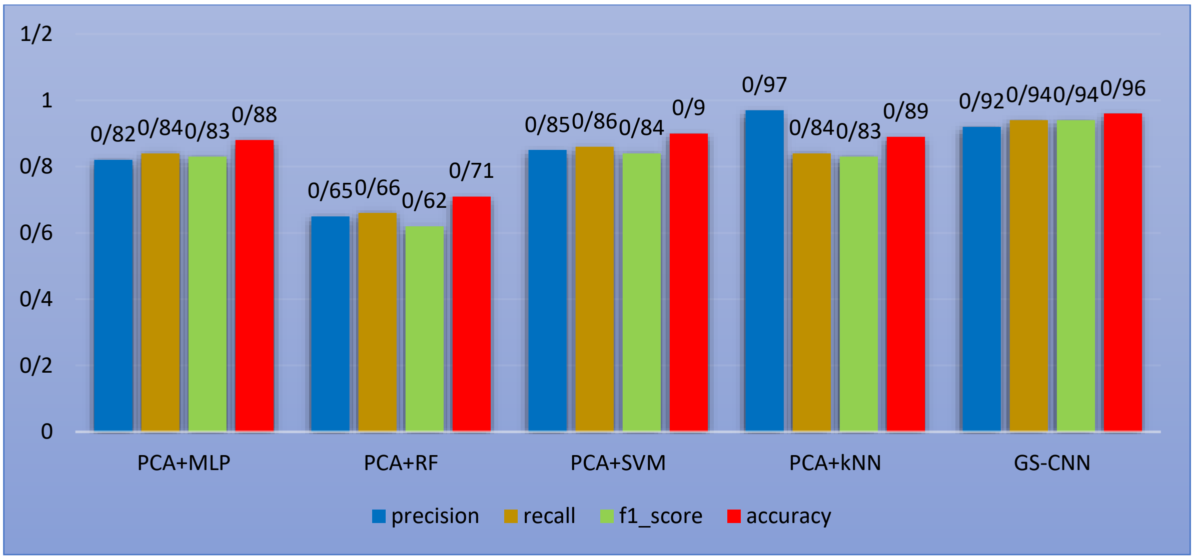


Fig. 8. The results of classifier comparisons using PCA (CASIA-Iris-Interval)

Figure 7. The findings indicate that, when compared to other classifiers, GS-CNN performed the best (accuracy 0.96), while PCA+RF performed poorly on the CASIA-Iris-Interval dataset. As can be seen in Figure 8, GS-CNN performs better than the others, attaining the highest values across all measures (accuracy 0.98). However, out of all the classifiers, RF did the worst.

The proposed model for this study is compared with the experiments of other methods and techniques in recent scientific articles.

V. Discussion

A. Limitations and Challenges

Dataset Dependency: The suggested approach was tested on well-curated standard datasets like CASIA-V1 and CASIA-Iris-Interval, which might not accurately capture the noise and variability found in real-world settings. The system's performance may be impacted by elements like dim lighting, occlusions (such eyelashes or spectacles), and motion blur in real-world situations.

Computational Complexity: The hybrid method that combines CNN for classification and GWO for feature selection requires a lot of processing power. In situations with limited processing power and memory, such mobile devices or embedded systems, this could present deployment issues.

Scalability to Large Datasets: Although the approach demonstrated good performance on datasets with 108 and 247 classes, it has not yet been examined for scalability to larger datasets with thousands of classes or more diverse populations. Larger datasets may necessitate more algorithm optimization due to their increasing complexity.

B. Scalability and Real-World Applications

The suggested GS-CNN approach offers a lot of potential for practical uses, especially in the domains of security and medicine. Nevertheless, there are special opportunities and challenges associated with its application in real-world situations.

***Border Control and Surveillance*:** The technique might be applied to iris recognition in real time at border crossings or airports. However, enhancing the system's computing efficiency would be necessary to achieve real-time performance.

Access Control Systems: The suggested approach's high precision qualifies it for safe access control in delicate establishments, including government buildings or research laboratories.

Applications in Medicine: The technique could be applied in the medical field to precisely identify patients, guaranteeing appropriate maintenance of medical information and lowering errors. Nonetheless, the system would have to manage a variety of demographics and take into consideration possible iris pattern alterations brought on by illnesses.

VI. Conclusion

The use of iris recognition to identify individuals is a significant application. The current paper presents a hybrid approach for iris detection that utilizes GWO for feature extraction and CNN for Iris detection. The results were compared with two-dimensionality reduction methods and four classifiers. The proposed method has achieved the highest accuracy, which can be considered a reliable system to identify or authenticate the person. Specifically, the proposed GS-CNN method outperformed all other classifiers, achieving an accuracy of 98% on the CASIA-V1 dataset and 96% on the CASIA-Iris-Interval dataset.

Statements & Declarations

The authors declare that no funds, grants, or other support were received during the preparation of this manuscript.

Competing Interests

The authors have no relevant financial or non-financial interests to disclose.

Author Contributions

All authors contributed to the study's conception and design.

Data Availability

The datasets generated during and/or analyzed during the current study are available.

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