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Enhanced honey badger algorithm and random forest-based mechanism for iris detection in authenticate users in information systems

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Abstract

Iris recognition became the important element in new authentication systems because of its high accuracy and robustness. In this paper, we present the developed Honey Badger Algorithm (HBA) combined with classification algorithm based on Random Forest for iris diagnosis in info systems. Presented development defines Levy Flight algorithm for developing global search abilities, adaptive inertia weight to balance local and global searches, active weighting to set exploration and exploitation trade-off in runtime. The generally accessible iris set of data is used for validating presented technique. Developed HBA performance is compared to traditional HBA and other state-of-the-art optimization methods. Assessment is performed using several metrics, such as accuracy and Error Rate. Experimental outcomes illustrate that presented developed HBA considerably develops classification accuracy and feature selection efficiency, making it satisfactory strategy for safe and reliable user authentication in info systems. Additionally, the proposed algorithm is compared with other methods, showing that the proposed method has higher classification accuracy (97.44%) and lower Classification Error Rate (2.56%).

Keywords: Iris Recognition, Honey Badger Algorithm, Random Forest, Feature Selection, Levy Flight, Adaptive Inertia, Dynamic Weighting, Authentication Systems.

1. Introduction

Nowadays, sensitive data protection and info security are significant [1]. One of the main issues in info systems refers to users' identification and authentication for avoiding unauthorized access. Biometric techniques have appeared as one of the most efficient solutions for considering such concern and are quickly obtaining popularity. In this case, iris recognition has proven to be a highly safe and appropriate technique for user authentication [2]. Although, some issues stay in iris recognition process in real-life areas like various capturing scenarios, variations in lighting conditions, image quality. Human iris is a sight organ which, through changing pupil size, monitors light reaching the retina volume. Iris texture is completely improved before birth, the minutiae do not rely on genotype, that relatively remains fixed over lifetime (except for disease- and normal aging-based biological shifts), this might be applied shortly for forensic identification after subject's death [3].

In biometric authentication domain, iris recognition has appeared as one of the most reliable and safe techniques for user identification. Unique human eye iris models present high accuracy and robustness in confirming ID of an individual, making it optimum solution to secure sensitive info and systems [4]. Although, in spite of its potential, iris recognition yet meets some issues, particularly while developed in real-life areas. Such issues contain variations in image quality, shifts in computational complexity, lighting conditions, occlusions in processing massive iris images' datasets [5].

The issue mentioned here refers to requirement for developing iris recognition systems efficiency and accuracy through considering present techniques' restrictions. Traditional mechanisms sometimes tackle with choosing related features from iris images, causing decreased performance in noisy/unideal situations [6]. Also, a lot of global feature selection algorithms' optimization abilities are sometimes not enough, restricting their capability to efficiently explore and exploit space of solution.

Present study motivation stems from increasing requirement for more appropriate and effective biometric authentication systems which could act in broad real-life conditions' range. Through integrating Developed HBA [7] with RF, presented technique targets at developing the two process of feature selection and classification accuracy. HBA is developed with a Levy Flight algorithm [8] for developing its global search abilities, adaptive inertia is applied for balancing local and global search, guaranteeing better exploration and exploitation in optimization process. Present study aim is providing new algorithm for iris recognition and user authentication given the developed HBA and RF combination. Present technique targets at developing identification accuracy and feature selection using HBA to choose related features, pursued by RF app to group user's identity. Also, for developing global search HBA ability, algorithm of Levy Flight is incorporated. Adaptive inertia is applied for balancing local and global search abilities, active weights are used via runtime for regulating exploration and exploitation. Present study has 4 contributions as:

- Levy Flight algorithm incorporation for developing global search abilities and avoiding local optima.
- Adaptive inertia weight introduction, actively setting balance among exploration and exploitation to for optimizing search process.
- Dynamic weighting implementation that fine-tunes the trade-off among exploration and exploitation in runtime for better feature selection.
- Leveraging feature selection through developed HBA, decreasing computational complexity when keeping high classification performance.

Research structure is organized as: Section 2 presents general literature review and background on developed mechanisms and feature selection methods related to iris recognition. Section 3 organizes method, detailing process of feature selection and strategy of iris recognition which uses developed HBA in relation with RF. Section 4 provides experimental outcomes and analysis, assessing presented technique performance of applying different metrics. At last, Section 5 concludes study and proposes recommendations for future research to later increase systems of iris recognition.

2. Related work

The landscape of iris diagnosis has been broadly mapped in recent years. Present section studies work in iris diagnosis. Naseem Ahmad et al [9] presented the combined strategy for iris diagnosis and tracking applying Tiny-YOLOv3 for eye diagnosis, Seg-Net for iris segmentation, KLT for tracking. Such technique decreases computational complexity through preventing repeated segmentation in every frame and outperforms well on several benchmark sets of data. The benefits contain developed accuracy and robustness in contrary to occlusions and reflections, when restrictions include high computational needs and potential tracking errors in occluded frames.

Safeer et al [10] presented iris liveness diagnosis technique for differentiating genuine irises from spoof attempts applying transfer learning with MobileNets framework. Present strategy fine-tunes a pre-trained CNN to adapt to biometric features in spite of restricted dataset concern. Benefits contain developed accuracy in presentation attack detection (PAD) and developed security for biometric systems. Although, restrictions include reliance on pre-trained models and potential performance drops with highly diverse spoofing methods.

Haq and Saqlain [11] presented ML-driven iris diagnosis system for automatic e-attendance in educational areas, considering COVID-19 SOP limitations. Their technique includes 4 steps: attendance tracking during exams, defaulter list maintenance, iris registration, identity verification. Benefits contain developed accuracy, real-life diagnosis, contactless authentication through desktop app. Although, potential privacy issues, issues might rise in scalability, environmental lighting conditions. Chen et al [12] presented DL-driven U-Net model to automate iris segmentation in pre-operative ptosis surgery evaluations. The model extracts iris edge, fits a circle, computes Margin Reflex Distance 1 (MRD1) for scaling eyelid condition. The stable reference marker changes pixel scales to millimeters. Benefits contain consistency, automation, decreased dependence on manual scales. Although, restrictions might include accuracy variations because of model generalizability, lighting, image quality over various patient sets of data.

Jayanthi et al [13] presented DL-driven combined model for recognition, iris diagnosis, segmentation. The strategy includes preprocessing (applying Gamma Correction, Black Hat filtering, Median filtering), segmentation/recognition, iris localization with Hough Circle Transform applying R-CNN with Inception v2. The model was confirmed on CASIA-Iris Thousand dataset, obtaining 99.14% accuracy, performing better techniques such as ResNet, AlexNet, VGGNet. Benefits contain high accuracy and robustness when restrictions might include computational complexity and requirement for high-quality images for optimum performance.

Jung Soo Kim [14] presented local area-driven fake-iris diagnosis network (LRFID-Net) for diagnosing spoofed iris images, especially those made applying CycleGAN. Against the last techniques which concentrated on artificial eyes, printed images, video replays, present strategy segments the iris into 3 areas for developed diagnosis accuracy. The model was tested on Warsaw LiveDet-Iris-2017 and Notre Dame Contact Lens Detection LiveDet-Iris-2017 datasets, obtaining low classification error rates of 0.03% and 0.11%, in turn. Strengths contain greater accuracy and robustness in contrary to AI-made attacks, when restrictions might include computational complexity and dependency on high-quality sets of data. Mahmood and Ahmed [15] conducted a review of recent Contact Lens Iris Detection (CLID) mechanisms, concentrating on hand-crafted features. They grouped such techniques into spatial field features and transform them that are applied for diagnosing counterfeit iris images made by textured contact lenses. The research bolds shortage of specialized surveys in the last 5 years and compares different traditional CLID methods' performance. Strengths contain presenting general analysis of present techniques, when restrictions might include absence of assessment on DL-driven strategies and real-life sets of data.

Liu et al [16] provides a technique for real-life iris image acquisition and diagnosis applying CNN and light domain concentration mechanism. The system incorporates Radial Basis Function (RBF)-Support Vector Machines (SVM) for classification and is given the FPGA for processing and display. Presented strategy considerably increases accuracy of recognition, with close 100% accuracy and medium assessment time of below 0.05 seconds per frame. Technique performs better present mechanisms such as VDSR and DRCN, obtaining lower error rates as well as higher classification accuracy (96.38%). Although, dependence on complicated hardware such as FPGA can raise complexity and cost of system.

Talab et al [17], a method for low to high resolution face recognition has been proposed, which is called subpixel convolution neural network. It is a convolutional neural network commonly used during image processing to increase the chances of detecting low resolution images. Subpixel convolution neural network is used to convert low resolution images to high resolution format. This conversion is based on the features extracted from the image. Subpixel neural network using several evaluation tools has recorded higher performance based on image resolution compared to the performance of traditional evaluated methods. Evaluations were performed on the Yale face database and the ORL dataset. For the Yale and ORL datasets, the accuracy of the proposed method was 95.3% and 93.5%, respectively, which is higher than other methods.

Kim et al [18], an eye detection method using Zernike torques with SVM is presented. This method uses zimic torques to display eye / non-eye patterns and SVM as a classifier. Due to the invariant features with respect to the rotation of the zimic torques, the proposed method can detect the eye very well, even if the face has been changed. Experimental results confirm that the proposed method presents superior performance compared to the gray values method with SVM. Given the broad review iris diagnosis techniques, this is obvious when present systems have obtained considered developments in accuracy and efficiency, they sometimes meet issues like restricted scalability, high computational requirements, reliance on pre-trained models, difficulties to control different methods of spoofing and real-life conditions. Creating upon such work, our presented technique defines developed HBA combined RF-driven classification algorithm for iris diagnosis in info systems. Development contains Levy Flight algorithm addition developing global search abilities, active weighting, adaptive inertia weight for balancing local and global searches, active for setting exploration and exploitation trade-off.

3. Proposed Method

Presented technique Developed RF and HBA for improving iris recognition accuracy via effective feature selection and classification. Main presented technique elements are as:

3.1 Data Preprocessing

First stage in presented iris recognition technique is data preprocessing that has critical role in developing iris images quality before later analysis. Iris images sometimes suffer from variations in lighting, noise, low contrast that degrade feature extraction and classification mechanisms' performance. For mentioning such concerns, firstly images are normalized for guaranteeing uniformity in size and scale. Noise removal is performed applying techniques such as Gaussian blur/median filtering for decreasing unrelated info effect on subsequent stages. Also, methods of contrast development like histogram equalization are used for improving iris texture clarity. The next preprocessing stage includes iris segmentation, where interest area (the iris) is separated from other eye elements, like sclera and pupil. Segmentation guarantees that only related iris features are extracted, considerably developing feature extraction process accuracy. Fig. 1 displays a gray image with the detected iris.

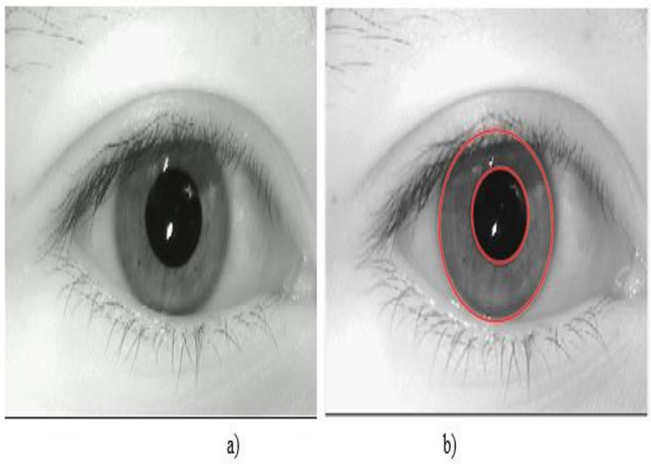

Figure 1- Pre-processing: a) Input image b) diagnosis of the circular circle of the eye iris

3.3 Feature Selection applying Enhanced Honey Badger Algorithm (HBA)

Feature selection is a crucial stage to decrease dataset dimensionality also developing recognition system efficiency. Here, we use Developed Honey Badger Algorithm (HBA) for feature selection. HBA is a nature-inspired optimization mechanism given the honey badgers' foraging manner, this is especially well-suited for global optimization functions. Although, main HBA is developed in present strategy for developing performance for feature selection in iris recognition.

The first development is Levy Flight algorithm introduction that aids mechanism preventing getting stuck in local optima letting this to perform random, long-distance jumps in search process. Such algorithm develops global search mechanism ability, making it able for exploring solution space more efficiently and finding optimum feature set. The second development refers adaptive inertia usage that actively sets balance among exploration and exploitation in optimization process. By adapting inertia weight, mechanism could switch among global search and local search based on present optimization step, developing the two-feature selection speed and accuracy. The third development includes active weights' app that are set in optimization process for regulating trade-off between exploration (discovering new features) and exploitation (refining present solutions). Such developments guarantee that HBA is better equipped to choose the most informative and related features that are critical for the subsequent classification stage.

Applying developed HBA, the mechanism chooses the most informative and discriminative features from the extracted set that considerably decreases data dimensionality and increases subsequent classification stage accuracy.

3.4 Feature extraction from Convolutional neural network

This section uses CNN to extract features from images. The images obtained from the iris of the eye from the previous step are given as input to CNN. In the training process, CNN will be configured in 6 layers including convolution, input, activation function, pooling. In the first layer, the input contains images. Image size is 120 * 240. The second layer is convolution having 3 * 3 filter and its number is 96. Padding is also performed. The third layer is the activation function, like the relu function. The activation function is used to minimize error in output. The bias and weight in each layer are updated and the modified parameter is given as input to the next layer. The CNN training algorithm is similar to 2D images. However, in this paper, the proposed training of CNN for one-dimensional convolution is considered for different layers. Fig. 2 shows the padding of CNN architecture. The features extracted from the fc-1 layer of this architecture are given to the general regression neural network in the next step.

```
16×1 Layer array with layers:

 1  'imageinput'    Image Input             120×240×1 images with 'zerocenter' normalization
 2  'conv_1'        Convolution             96 3×3×1 convolutions with stride [1  1] and padding 'same'
 3  'batchnorm_1'   Batch Normalization     Batch normalization with 96 channels
 4  'relu_1'        ReLU                    ReLU
 5  'maxpool_1'     Max Pooling             2×2 max pooling with stride [2  2] and padding [0  0  0  0]
 6  'conv_2'        Convolution             16 3×3×96 convolutions with stride [1  1] and padding 'same'
 7  'batchnorm_2'   Batch Normalization     Batch normalization with 16 channels
 8  'relu_2'        ReLU                    ReLU
 9  'maxpool_2'     Max Pooling             2×2 max pooling with stride [2  2] and padding [0  0  0  0]
10  'conv_3'        Convolution             32 3×3×16 convolutions with stride [1  1] and padding 'same'
11  'batchnorm_3'   Batch Normalization     Batch normalization with 32 channels
12  'relu_3'        ReLU                    ReLU
13  'fc_1'          Fully Connected         32 fully connected layer
14  'fc_2'          Fully Connected         19 fully connected layer
15  'softmax'       Softmax                 softmax
16  'classoutput'   Classification Output   crossentropyex with '1' and 18 other classes
```

Figure 2 -The padding of CNN architecture

3.4 Iris Recognition applying Random Forest (RF)

After choosing the most related features applying developed HBA, and extracting features from images by CNN the next stage is classification. Here, we use RF, the ensemble learning mechanism known for its robustness and high accuracy in controlling complicated and large datasets. RF constructs several decision trees in training step and integrates such trees' outputs for making the last decision. Every tree in the forest is trained on a random data subset that decreases risk of overfitting and develops model's generalization ability.

In presented technique, chosen features from HBA and CNN are fed into RF classifier that learns relations among such features and related user identities. In training process, classifier is presented with labeled iris data (where each image is related to particular user identity), letting it to create a model which could predict identity of unseen and novel images. Once trained, RF model could appropriately group novel iris images given the learned models. This feature selection and classification integration guarantees the system could make reliable decisions in real-life scenarios, where variations in image quality, lighting, noise are usual. The selected features are input into RF classifier that learns models and relations among feature set and related user identities. Classifier is trained applying labeled dataset and tested on separated test set for assessing its performance.

3.6 Post-processing

A post-processing stage is used for later developing system robustness and reliability. Such stage normally includes methods like majority voting/confidence scoring, where system collects predictions from several classifiers/decision trees and chooses the most confident outcome. It aids mitigating errors which might rise because of noisy data/small variations in iris images. Through integrating hybrid predictions, system becomes more resilient to errors and raises total accuracy. Stage of post-processing guarantees that last classification outcome is as reliable as feasible that is especially significant for security-sensitive apps such as iris recognition for authentication.

4. Validation experiment and result analysis

4.1 Dataset

For developing dataset size, valid data from different populations were needed. We achieved images applied here from dataset Iris Challenge Evaluation (ICE) [19]. Images were chosen for assuring front images in concentration with some congestions. Such attempt was important for reducing confounding agents' existence which impact iris recognition, so guaranteeing that monitored matching outcomes were cubic phase component outcome rather than other agents. Forty-six (46) users were chosen, each of them was illustrated with ten (10) various images and 5 images are associated with the left eye of these people and 5 images are associated with the right eye of these people. Fig. 3 illustrates data subset. 460 selected iris images were applied here.

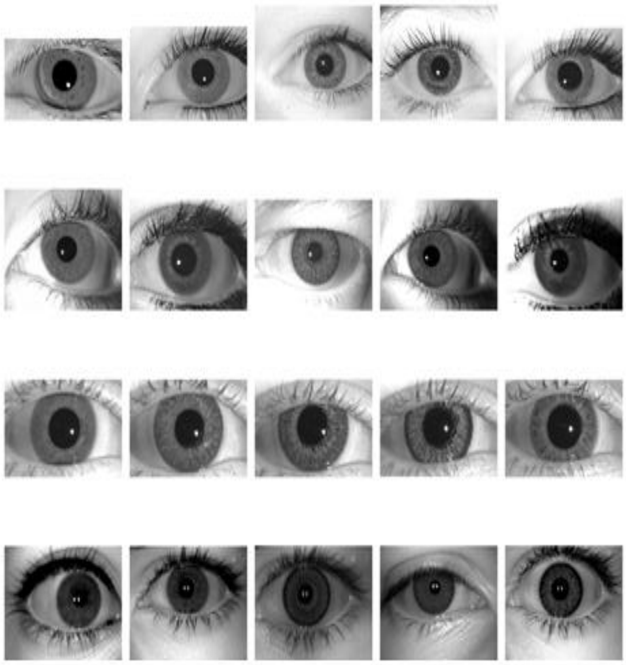

Figure 3- ICE dataset

4.2 Initialization parameters

Table 1 shows the initial parameter values used to train the CNN model. The learning rate is set to 0.001, which determines the step size during weight updates. The activation function is ReLU, which ensures nonlinearity in the model. The network is made up of 16 layers, which allow for deep feature extraction. The input dimensions are 120, 240, 1, and 460, which define the form of the input data. The batch size (32 or 64) determines how many samples are processed every iteration. To avoid overfitting, a dropout rate of 0.2 or 0.5 is used. The model is adjusted with the Adam method, which efficiently adjusts learning rates. The fully connected dense layer has 128 or 256 neurons for classification. The dataset is divided across 80% training and 20% testing, ensuring a fair evaluation. The model is trained for up to 100 epochs, with a mini-batch size of 10 for gradient-based optimization. These parameters are set to improve model performance and generalizability.

Table 1- Initial values for parameters on proposed method

Parameters	Values
Learning rate	0.001
Activity function	relu
Number of layers	16
Dimensions	120,240,1,460
Batch Size	32 or 64
Dropout Rate	0.2 or 0.5
Optimization Algorithm	Adam
Dense Layer Neurons	128 or 256
Train dataset	80%
Test dataset	20%
MaxEpochs	100
MiniBatchSize	10

4.3 The assessment variables

We would apply more appropriate scaling parameters for comparing presented solution with mechanisms. One of the variables applied for showing data classification precision in mechanism is finding accuracy value technique.

Variable selection to assess technique effectiveness relies on issue we are attempting to solve. Assume data samples' number are accessible. Such data are based on model individually and one class is received as output for each. The class predicted by model and certain data class could be shown in a table. Table (2) is known as confusion matrix.

Table 2- Confusion table

<table>
<tr><td rowspan="2"></td><td colspan="3">The label of predicted class</td></tr>
<tr><td>predicted
actual</td><td>healthy</td><td>sick</td></tr>
<tr><td rowspan="2">The label of actual class</td><td>healthy</td><td>True negative (TN)</td><td>False positive (FP)</td></tr>
<tr><td>sick</td><td>False negative (FN)</td><td>True positive (TP)</td></tr>
</table>

True Positive: Samples which have been accurately diagnosed as sick by the test. False Positive: Samples which have been wrongly diagnosed as sick by the test.

True negative: Samples which have been accurately diagnosed as healthy by the test.

False negative: Samples which have been wrongly diagnosed as healthy by the test.

4.3.1 Accuracy criterion

Accuracy is known as test capability for appropriately differentiating among sick and healthy cases from other cases. For computing test accuracy, total true positive and negative samples rate number tested items should be achieved. Mathematically, such rate could be stated as:

$$Accuracy=(TP+TN)/(TP+FP+FN+TN) \qquad (1)$$

4-4- The results' evaluation

The implementation process is executed by MATLAB 2020b on a 2.1 GHz seven-core Pentium with 12 GB of RAM. This section discusses the evaluation of proposed algorithm using computing experiments. Experiments are performed using a standard dataset. In order to evaluate the efficiency, the proposed method is compared with the method of the article [18], [17], and [16]. Fig. 4 shows the process of improving neural network training with 10 iterations.

The graph below illustrates the model's accuracy over ten training sessions. The model's accuracy fluctuates at the start of the training phase, reflecting the steady change of weights and feature learning. As the training goes, the model gradually improves its accuracy, and after about five sessions, it reaches a value close to 100% and follows a rather consistent trajectory. As the training goes, the model gradually improves its accuracy, and after about five sessions, it reaches a value close to 100% and follows a rather consistent trajectory. This implies that the model effectively learned the data features and achieved convergence. The light and dark spots in the background represent the split of training sessions, allowing us to observe the progressive improvement trend. Also, the presence of two curves in the graph most likely represents the accuracy of the training and validation data, with the wider curve representing average accuracy and the thinner curve reflecting slight variations. The lack of a dramatic decline in accuracy after attaining a high number shows that the model is most likely not overfitting.

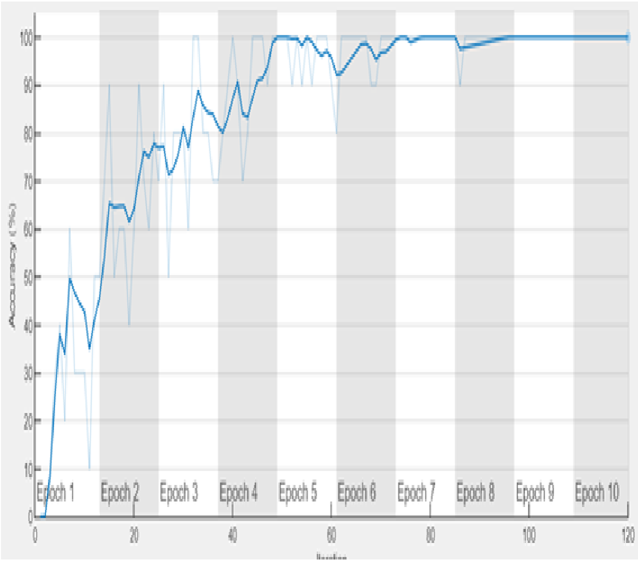

Figure 4- The process of improving neural network training

Based on the confusion matrix, various parameters such as accuracy are calculated. Each eye accuracy is calculated and the mean is considered as the last accuracy. The last calculated accuracy and the error rate parameter that can be calculated depends on the correct and incorrect predictions. Table 3 shows the results comparing the proposed paper method and articles [18], [17], and [16]. As you can see, the proposed method has better performance. In Paper [16], the error rate is 3.62%, resulting in an accuracy of 96.38%, which is slightly lower than the proposed method. Paper [17] has a higher error rate of 6.5%, which results in an accuracy of 93.5%, indicating that the strategy utilized in this study is less effective than the recommended one. Finally, Paper [18] performs the worst, with an error rate of 21% and an accuracy of 79%, suggesting a significant difference in efficacy compared to the other methods. The results show that the proposed method surpasses prior approaches with the lowest error rate and maximum accuracy, indicating its robustness and efficiency in the particular work.

Table 1- Comparison of Iris diagnosis results for images

Paper [18]		Paper [17]		Paper [16]		Proposed method	
Accuracy	Error rate	Accuracy	Error rate	Accuracy	Error rate	Accuracy	Error rate
79%	21 %	93.5 %	6.5 %	96.38%	3.62%	97.44%	2.56%

5. conclusion

In conclusion, the proposed enhanced Honey Badger Algorithm (HBA) integrated with a Random Forest-based classification mechanism offers a significant advancement in iris detection for secure user authentication in information systems. By incorporating the Levy Flight mechanism, adaptive inertia weight, and dynamic weighting, the algorithm effectively improves both the global search capabilities and the trade-off between exploration and exploitation. The experimental results demonstrate superior feature selection efficiency and classification accuracy compared to traditional methods, making the proposed approach a promising solution for enhancing security and reliability in iris-based biometric systems. Future work can explore further optimizations and real-world implementations to refine its applicability in diverse environments.

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