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RESEARCH ARTICLE

Secure Biometric Identification Using Orca Predators Algorithm With Deep Learning: Retinal Iris Image Analysis

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ABSTRACT Biometric recognition using retinal and iris images is a refined and extremely safe technology in the biometrics field. The retina and iris are exclusive and constant functional features of the human eye that can be employed for individual identification. Retinal and iris detection systems are highly well-known for their high exactness and safety. The individuality and constancy of these features make them challenging in order to spoof or replicate. Biometric detection utilizing retinal and iris images improved by deep learning (DL) models has accompanied a novel period of highly exact and effective identity verification. DL models namely convolutional neural networks (CNN) and recurrent neural networks (RNN) employed for feature removal as well as matching, permitting complex and individual patterns of retina and iris to be taken with notable precision. This technique provides enlarged security and reliability. It is precious in numerous applications like access control, border control, healthcare, and mobile device verification while addressing the challenges of flexible lighting situations and accommodating users with eye conditions. This article presents an effective secure biometric retinal iris identification using an orca predator's algorithm with deep learning (SBRIC-OPADL) technique. The main aim of the SBRIC-OPADL technique is to accomplish biometric security using retinal iris images. Primarily, the SBRIC-OPADL technique exploits the Wiener filtering (WF) approach for the removal of noise that exists in the input iris images. Besides, the SBRIC-OPADL technique exploits the EfficientNet model for the extraction of feature vectors. Moreover, the hyperparameter tuning process of the EfficientNet model takes place using OPA. Furthermore, the biometric identification process can be performed by the use of a convolutional autoencoder (CAE). To validate the enhanced biometric detection results of the SBRIC-OPADL technique is tested using the biometric iris dataset. The extensive results highlighted that the SBRIC-OPADL technique reaches better performance over other models.

INDEX TERMS Biometric detection, iris image, deep learning, machine learning, orca predators algorithm.

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I. INTRODUCTION

In everyday life, security has been enlarged due to digitalization because it encouraged the improvement of trustworthy as well as smart biometric-based individual recognition methods [1]. Evaluating and statistical study of the populace's exclusive physical, as well as behavioral features is called biometrics. Highly advanced knowledge is mainly utilized to identify and access the control. Customary classifying models generally employ passwords or else cards [2]. These kinds of techniques are injured by losing or theft of cards or else forgetting PINs. For this reason, biometric recognition techniques help to recognize people without trusting what they have or remember are ample essential [3]. In the current scenario, Iris recognition (IR) has gained more interest due to its high exactness. This biometric IR model has come with numerous benefits such as uniqueness and durability over time [4]. IR methods excellently distinguish persons by analyzing difficult patterns within the iris. Overall it is highly appropriate for many security uses.

Iris biometric systems have gained high attention in recent years due to their uniqueness and significance as a biometric verification process [5]. Employing pattern detection and digital image processing models, this method differentiates people depending on the consistency of their Iris. It is an outside noticeable interior tissue that is secure by cornea [6]. According to a study, the iris of a human rests stable during his or her lifetime but has some slight alterations throughout childhood. IR is one of the effective techniques that are extremely popular in classifying persons even when their looks or other identification procedures may change [7]. This highly advanced technology is utilized for discovering terrorist activities at borders and offering access to vastly protected areas like airports and financial industries. In order to improve IR, this research mainly concentrates on directing a relative study of machine learning (ML) techniques for determining the most effective system for biometric IR [8].

Even though there are high developments in IR technology there are quiet challenges that want to be addressed. The main challenge is that effectual ML models are needed to develop the performance of IR systems. In the literature, numerous ML techniques have been examined namely support vector machines (SVM) and CNN. However, there has been restricted relative examination and estimation of these techniques from the perspective of IR [9]. It is highly notable to evaluate their accuracy, performance as well and efficiency for classifying the most useful model. Deep learning (DL) based technique offers an endways learning structure that can equally absorb feature illustration while execution of regression [10]. This is mainly attained via a multi-layer neural network that is also termed a Deep Neural Network (DNN) in order to learn manifold levels of representations that agree to diverse levels of concept, which is well-suitable to find original patterns of data.

This article presents an effective secure biometric retinal iris identification using an orca predators algorithm with deep learning (SBRIC-OPADL) technique. The objective of the SBRIC-OPADL technique is to accomplish biometric security using retinal iris images. Primarily, the SBRIC-OPADL technique exploits the Wiener filtering (WF) approach for the removal of noise that exists in the input iris images. Besides, the SBRIC-OPADL technique exploits the EfficientNet model for the extraction of feature vectors. Moreover, the hyperparameter tuning process of the EfficientNet model takes place using OPA. Furthermore, the biometric identification process can be performed by the use of a convolutional autoencoder (CAE). To validate the enhanced biometric detection results of the SBRIC-OPADL technique is tested using the biometric iris dataset.

II. LITERATURE WORKS

Abdel-Latif and El-Sayed [11] main goal is to project an effectual multimodal biometric method that depends upon iris and retinal structures in order to pledge precise human detection and enhance the exactness of recognition utilizing DL models. The Iris area was divided from the image employing the traditional Mask R-CNN technique and single blood vessels were divided from retinal images of similar individuals by utilizing a major bend. Mazumdar and Nirmala [12] report a healthy retina identification method with decent usage of CNN for programmed feature removal. Colour retina image is openly served into CNN technique for removing features that are constant in dissimilar geometric scales and for radiance alterations and extreme images. The method is trained by employing an optimized technique and then executed verification utilizing a function of softmax in the last level of the CNN technique.

Arora et al. [13] suggest a new DL technique for combining features removed from a person's face and iris to obtain further protected biometric authentication methods. Primarily, the author removes facial and iris features distinctly by employing many CNN approaches. Malik et al. [14] main goal of this paper is to deliver an effective process to identify somebody dependent on exclusive retina features. A developed model relies on retinal blood vessel design by employing random forest (Bagging tree) and multi-scale local binary pattern (MSLBP) as feature removal and organization. MSLBP is a useful technique to remove features at 6 scales per-pixel stage. The previous work found absence depends on humble dual design with attention to trivial regions and per-pixel level in surroundings. Tobji et al. [15] intend a procedure "FMnet" for iris detection utilizing Fully Convolutional Networks (FCNs) and Multi-scale Convolutional Neural Networks (MCNNs). By enchanting into thoughts, CNN is to absorb an effort at dissimilar purposes. The developed iris detection technique overpowers current problems in traditional models that only make use of handcrafted feature removal by executing extraction and grouping structures. Conti et al. [16] present a new multimodal biometric procedure that relies on a combination of iris as well as retina in a spatial area.

The developed solution monitors position and detection methods that are generally assumed in computational linguistics and bioinformatics. Particularly, features are removed distinctly for the retina and iris, and then merging is acquired depending upon contrast score through Levenshtein distance.

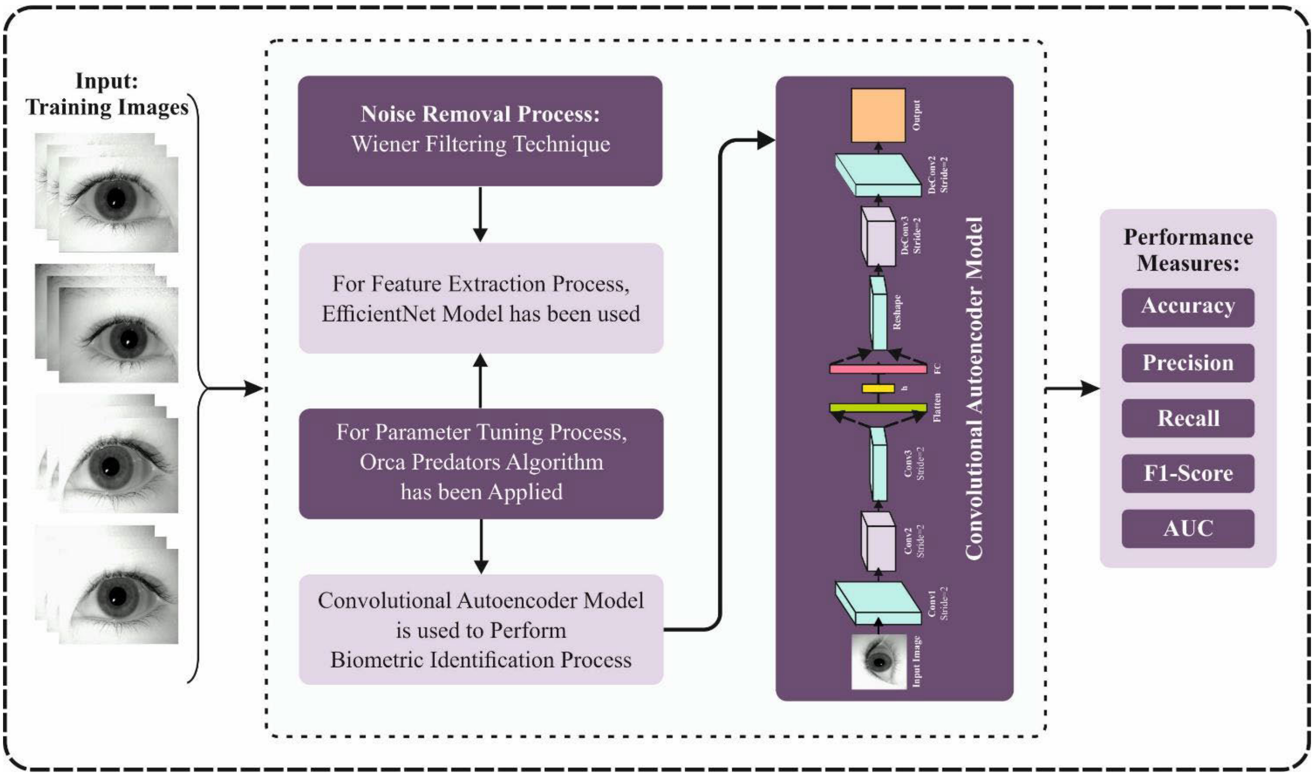


FIGURE 1. Workflow of SBRIC-OPADL algorithm.

Gona and Subramoniam [17] mainly concentrated on the execution of a multimodal biometric reorganization system (MBRS) employing DLCNN detection. At an early stage, images from fingerprint, face, and iris datasets are useful to Gaussian filters that pre-process them and remove dissimilar kinds of sounds. In the second stage, the GLCM is employed in order to abstract multimodal features. Next, Principal Component Analysis (PCA) is utilized for decreasing features that pick optimal features from accessible sets. At last, the DLCNN classification algorithm is mainly employed to execute the biometric restructuring process from a dataset of tests employing trained features. The authors [18] propose a verification and classification model using iris recognition. MobileNet employed in developed technique to remove features from iris pictures. In the next phase, the feature vector gained from an image is equated with kept feature vectors in the database.

III. THE PROPOSED METHOD

In this article, we present an effective SBRIC-OPADL technique. The goal of the SBRIC-OPADL technique is to accomplish biometric security using retinal iris images. It contains three major processes namely WF-based preprocessing, EfficientNet-based feature extraction, OPA-based parameter tuning, and CAE-based detection. Fig. 1 describes the entire workflow of the SBRIC-OPADL technique. The SBRIC-OPADL approach for secure biometric retinal iris detection takes place in a systematic working procedure to accomplish superior accuracy and security. Primarily, the WF can be executed to the input iris images to eliminate noise, enhancing overall image quality. Afterward, the EfficientNet approach can be deployed for feature extraction, capturing vital forms in the retinal and iris images. The OPA method adjusts the hyperparameters of the EfficientNet approach and optimizes its solution. The extraction features are then provided to a CAE for biometric detection, facilitating the reconstruction of intricate patterns and allowing accurate individual detection.

A. PREPROCESSING

Primarily, the SBRIC-OPADL technique exploits the WF approach for the removal of noise that exists in the input iris images. WF is one of the useful models that is used to diminish the effect of sound in input iris images, providing a dual-fold benefit in the field of biometric recognition [19]. By connecting a statistical technique that takes power spectral density of noise as well as spectral features of iris pattern, WF efficiently differentiates genuine iris features from annoying sound. One of the main advantages of the WF model is its flexibility to dissimilar noise profiles and can decrease image degradation while conserving serious iris data. This model contributes significantly to the trustworthiness and accuracy of biometric verification, eventually strengthening the security and efficacy of such uses.

B. EFFICIENTNET MODEL

For the feature extraction process, the EfficientNet model is utilized. The efficientNet model is an advanced technique

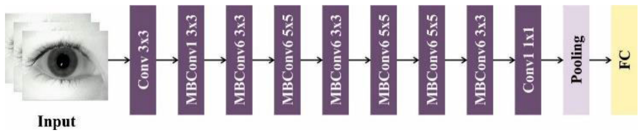


FIGURE 2. Architecture of the EfficientNet model.

because it attains 84.4% exactness with 66M parameters in the ImageNet detection issue, which can be measured as a cluster of CNN approaches [20]. EfficientNet contains 8 methods among BO and B7, and as the method number grows, the quantity of designed constraints does not grow much, but accuracy rises remarkably. When compared to other CNN techniques, EfficientNet employs a novel activation function known as Swish instead of the ReLU activation function. An objective of the DL framework is to expose more effectual techniques with smaller models. This technique attains efficient outcomes by regularly ascending depth, width, and resolution while scaling down the method. In the compound scaling model, the 1st stage is to hunt for a network to discover associations amid dissimilar scaling sizes of a base system below stable resource restraint. In this method, an appropriate scaling influence for depth, width, and resolution sizes is defined. Then, these constants function to measure the base system in a preferred target network. The chief goal of the DL framework is to expose more effectual techniques with smaller models. EfficientNet achieves effective effects by reliably scaling depth, width, and resolution while scaling down the method when evaluated with other methods.

Fig. 2 illuminates the framework of the EfficientNet technique. The chief structure block for EfficientNet was overturned bottleneck MBConv which was primarily introduced in MobileNetV2, due to the enlarged FLOPS budget, it employed somewhat more MobileNetV2. In MBConv, blocks contain a level that primarily enlarges and then compresses networks, therefore direct links are utilized among bottlenecks that join fewer networks than development layers. In complex scaling, the compound coefficient φ employed with values that are expressed in Eq. (1) to consistently measure depth, width, and resolution.

$$\begin{aligned} depth&: d = \alpha^{\varphi} \\ width&: w = \beta^{\varphi} \\ resolution&: r = \gamma^{\varphi} \\ &\alpha \geq 1, \beta \geq 1, \gamma \geq 1 \end{aligned} \tag{1}$$

whereas α, β, γ are coefficients that are defined by grid search. φ is a user-defined constant that controls how many assets are accessible for perfect measuring, while α, β, γ define how these extra resources are allocated to system width, depth, and resolution, correspondingly. In a regular convolution procedure, FLOPS are relative to d, w^2, r^2. The scaling convolution system is given in Eq. (1) that raises FLOPS of the system by almost $(\alpha, \beta^2, \gamma^2)^{\varphi}$ in total.

Starting from Baseline EfcientNet-BO, the compound scaling technique measures this method in dual phases which are mentioned below:

Assume that there are double as numerous resources accessible, grid search is executed with $\varphi = 1$, and optimal values are originated for α, β, γ.

Attained α, β, γ values are defined as endless and base system mounted up to attain EfcientNet-B1 to B7 utilizing Eq. (1) by dissimilar φ values.

C. HYPERPARAMETER TUNING USING OPA MODEL

At this stage, the hyperparameter tuning process of the EfficientNet model takes place using the OPA model. A pod of orcas collected of N individuals well-known in OPA [21]. The orca is proficient in swimming in any size such as 1, 2, 3, and in extra-dimensional space. These main to the subsequent creation of measured techniques for groups of orca:

$$P = [p_1 \ p_2 \ \cdots \ p_N] = \begin{bmatrix} p_{1,1} & p_{1,2} & \cdots & p_{1,D} \\ p_{2,1} & p_{2,2} & \cdots & p_{2,D} \\ \vdots & \vdots & \ddots & \vdots \\ p_{N,1} & p_{N,2} & \cdots & p_{N,D} \end{bmatrix} \tag{2}$$

whereas, symbol P symbolizes the populace dimension of orcas that looks like a cluster of realistic results of optimization issues. The sign p_N shows the place of *the* Nth orca member, where N signifies the amount of accidental values supposed for every parameter of the developed organizer. These parameters contain t_a, Ki_a, Kd_a, n, Kp_b, Ki_b, Kd_b, Kab, μ, N_1, N_2, and N_3. In addition, $p_{N,D}$ denotes a place of Dth size of N th orca, whereas D matches amount of controller increases requisite to be enhanced, which in occasion of 12 parameters.

During the chasing phase, when orcas originate based on a cluster of fish, they do not ring to follow. Alternatively, they employ sonar to interconnect as well as form their struggles. When a pod of orcas breaks down, they will throw, transporting a crowd of fish to the water surface and driving into a hut. The surveillance chief classifies orcas' pursuit phase of hunting into dual dissimilar kinds such as prey of driving and encircling. An extra parameter $z1$ developed to control the probability that the orca will execute every action individually. $z1$ will often be a constant value between [0, 1] and an extra amount among zero and unity also generated randomly. When a number is more than $z1$, the driving phase is performed or else the surrounding phase is proficient.

Orcas are capable of defining the place of their prey quickly and appropriately when a school of orcas pursuing is very tiny, space needed to dip is lesser or land is simple to direct so that chasing is easy. If the public of orcas is massive, swimming space is excessive, or hunting land is difficult, orcas' swimming will be simply isolated, building it incredible to precisely achieve objective location. Similarly, it is critical to manage the vital place of the orca gang so preserve it close to prey while preventing the orca band from travelling gone from its place. This is finished so that pod of orcas will not convert unfocussed from its job. The size of the orca populace proposes a dual possible plan for the orca hunt. The primary plan is applied if the orca cluster is big (*rand* larger than u), whereas 2nd plan is applied whenever the orca cluster is small (*rand* is less or equal *to* u).

A design of the orca's speed and its post-measure place is mentioned below:

$$v^t_{chase,1,i} = g \cdot \left(m \cdot p^t_{best} - F \cdot \left(h{\cdot}M^t + l \cdot p^t_i\right)\right) \tag{3}$$

$$v^t_{chase,2,i} = e{\times}p^t_{best} - p^t_i \tag{4}$$

$$M = \frac{\sum_{i=1}^{N} p^t_i}{N} \tag{5}$$

$$l = 1 - h \tag{6}$$

$$\begin{cases} p^t_{chase,1,i} = p^t_i + v^t_{chase,1,i} & if\ rand > u \\ p^t_{chase,2,i} = p^t_i + v^t_{chase,2,i} & if\ rand \leq u \end{cases} > u \tag{7}$$

where t signifies cycles' number, $v^t_{chase,1,i}$ is the rapidity of racing ith orca at time t rely on 1st chasing method that is Eq. (3)), $v^t_{chase,2,i}$ is the rapidity of racing of *ith* orca at time t depends on 2nd racing method (i.e., Eq. (4), M stands for a normal place of orca pod, $p^t_{chase,1,i}$ signifies the position of an ith orca at time t relying on the initial racing model, $p^t_{chase,2,i}$ signifies the position of ith orca at time t depending on second chasing model, g, h, l, and m random values among 0 and unity, e signifies arbitrary amount amid zero and dual, F is set to 2, and u symbolizes a quantity inside array of [0, 1], that defines prospect of selecting an exact chasing model. The optimum value for u is similar to 0.9 because OPA has the optimal act at this value.

Once the school of fish is determined to surface then orcas should encircle them into a ball below their controller. At the time of hold, orcas employ sonar to exchange data as well as plan their subsequent move depending on the location of other orcas in the region. In this situation, let's assume that orcas take their locations according to places of 3 other orcas that were selected randomly.

$$p^t_{chase,3,i,k} = p^t_{j1,k} + y\times\left(p^t_{J2,k} - p^t_{j3,k}\right) \tag{8}$$

$$y = 2 \times (rand{-}0.5) \times \frac{M\_it - t}{M\_it} \tag{9}$$

where M_it stands for iterations' maximum number, $j1$,$j2$,$j3$ signify 3 randomly selected orcas from N orcas, and $j1 \neq j2 \neq j3$,$p^t_{chase,3,i,k}$ denotes place of *ith* orca depending on 3rd chasing model at time t.

Through the usage of sonar, orcas are capable of defining the position of their prey and adjusting their places correctly. If orcas cannot sense the proceeding of fish at the time of pursuing operation, then they will endure at the primary place. If orcas see fish receiving earlier though they are following it, it is modify their hunt to track novel places. The subsequent calculation is employed to make essential changes to their locations:

$$\begin{cases} p^t_{chase,i} = p^t_{chase,i} & if\ \mathrm{fit}\left(p^t_{chase,i}\right) < fit\left(p^t_i\right) \\ p^t_{chase,t} = p^t_i & if\ \mathrm{fit}\left(p^t_{chase,i}\right) \geq fit\left(p^t_i\right) \end{cases} \tag{10}$$

where fit ($p^t_{chase,i}$) is the significance of fitness function (FF) linked to $p^t_{chase,i}$, and fit $\left(p^t_i\right)$ is the value of FF associated with p^t_i. To resolve the last issue, the FF index value must be as low as feasible. A related location is enhanced as an outcome.

Once orcas enclosed their objective, separate orcas turned by arriving surrounding region to attack prey, smashing their ends against the circle as well as terminating disconcerted fish. Four orcas are referred to describe 4 optimal places for prominent in a circle. Other orcas enter encircled space by subsequent path outlined by 4 that is previously exclusive. Later concluding their food, if orcas select to arrive enclosure to be swapped by other orcas, the way of travel changes conferring to place of arbitrarily particular orcas. You may estimate the orca's attack speed as well as location employing the following formulas:

$$v^t_{\mathrm{attack},1,i} = \frac{\left(p^t_{1st} + p^t_{2nd} + p^t_{3rd} + p^t_{4th}\right)}{4} - p^t_{chase,i} \tag{11}$$

$$v^t_{attack,2,i} = \frac{\left(p^t_{chase,j1} + p^t_{chase,j2} + p^t_{chase,j3}\right)}{3} - p^t_i \tag{12}$$

$$p^t_{attack,i} = p^t_{chase,i} + c1{\cdot}v^t_{attack,1,i} + c2{\cdot}v^t_{attack,2,i} \tag{13}$$

where $v^t_{attack,1,i}$ signifies ith orca's speed vector to hunt prey at time t, $v^t_{attack,2,i}$ represents ith orca's speed vector to grasp inclusion at time t, $p^t_{1st}, p^t_{2nd}, p^t_{3rd}, p^t_{4th}$ stand for 4orcas in optimal place in turn, $j1$, $j2$, $j3$ represent 3 arbitrary preferred orcas from N orcas in racing stage and $j1 \neq j2 \neq j3$,$p^t_{attack,i}$ shows position of *ith* orca at time t after attacking stage, $c1$ denotes a random value among zero and two, and $c2$ symbolizes random value in ranges of $[-2.5, 2.5]$. Orcas use sonar in a way equivalent to the procedure of hunting their prey to locate it and modify their locations consequently. By employing subsequent pseudocode, one can define where the orca's place links to the least boundary value (*lb*) of probable limits issue.

The OPA model develops an FF in order to achieve superior detection performance. It describes a positive integer to signify the improved performance of the candidate solution. In this paper, the minimization of classification error rate is measured as FF which is assumed in Eq. (14).

$$\begin{aligned} fitness\left(x_i\right) &= ClassifierErrorRate\left(x_i\right) \\ &= \frac{No.of\ \ misclassified\ instances}{Total\ no.of\ \ instances} {*}100 \end{aligned} \tag{14}$$

D. CLASSIFICATION USING CAE

Eventually, the biometric identification process can be accomplished by usage of the CAE technique. As a classical unsupervised learning algorithm, CAE is extensively applied in data reconstruction, image denoising, and other domains [22]. It combines the feature extraction process of CNN with the unsupervised feature reconstructed process of AE. Generally, the CAE includes multiple convolutional encoders and deconvolution decoders.

Usually, the convolution encoder has convolution and pooling layers for extracting the features as follows:

$$H = pool\left(\sigma\left(\sum\left(X \odot w^i + b^i\right)\right)\right) \tag{15}$$

In Eq. (15), $pool\,(.)$ indicates the pooling function, the input data is X, $\odot$ indicates the convolution function; the feature attained after encoding is H, the i^{th} convolution kernel in the convolution layer is w^i, b^i is i^{th} bias and σ is the activation function.

Generally, the convolution decoder consists of up-sampling and deconvolution layers that are formulated below:

$$\hat{X} = ups\left(\sigma\left(\sum\left(H \otimes \hat{w} + \hat{b}^i\right)\right)\right) \tag{16}$$

In Eq. (16), the deconvolution function is represented as $\otimes$ the data returned after decoding is $\hat{X}$; i^{th} deconvolution kernel in the deconvolution layer is $\hat{w}$, and $\hat{b}^i$ is i^{th} bias; $ups\,(.)$ shows up-sampling function.

The reconstructed error enhances the network parameter is represented as a Euclidean distance between X and $\hat{X}$ as:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(\hat{X}_i - X_i)^2 \tag{17}$$

In Eq. (17), MSE indicates the reconstructed error, n represents the data number; $\hat{X}_i$ refers to the i^{th} reconstruction data and X_i shows the i^{th} input data.

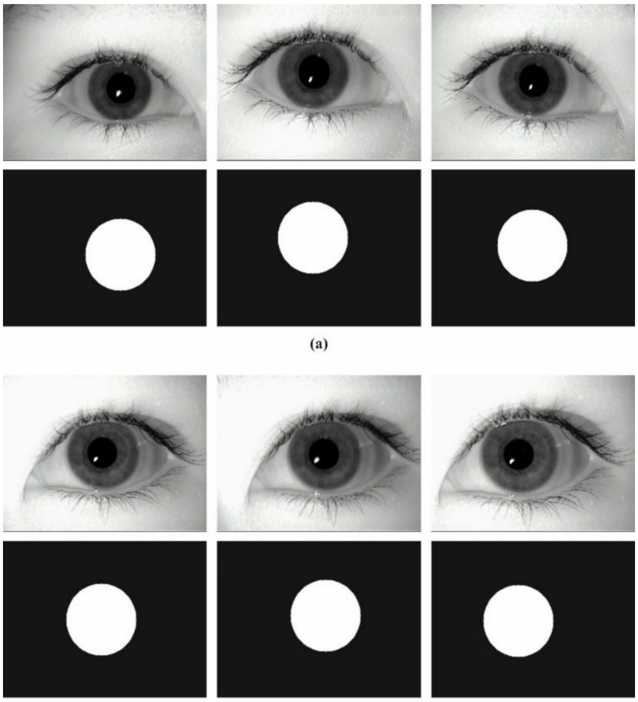
IV. PERFORMANCE VALIDATION

The proposed model is simulated using the Python 3.8.5 tool. The proposed model experiments on PC i5-8600k, GeForce 1050Ti 4GB, 16GB RAM, 250GB SSD, and 1TB HDD. In this study, the biometric identification performance of the SBRIC-OPADL technique can be examined using a set of iris images collected by our own. Fig. 3 demonstrates the sample images.

Table 1 represents the detection results of the SBRIC-OPADL system and EfficientNet-CAE model over five iterations.

In Fig. 4, the detection results of the EfficientNet-CAE model are provided over five iterations in terms of $accu_y$, $prec_n$, and $reca_l$. The results imply that the EfficientNet-CAE model attains five iterations. With iteration-1, the EfficientNet-CAE model offers $accu_y$, $prec_n$, and $reca_l$ of 99.30%, 99.15%, and 99.01%, individually. Simultaneously, based on iteration-2, the EfficientNet-CAE model gives $accu_y$, $prec_n$, and $reca_l$ of 98.96%, 98.96%, and 99.41%, individually. Moreover, with iteration-3, the EfficientNet-CAE system gives $accu_y$, $prec_n$, and $reca_l$ of 99.31%, 99.32%, and 99.19%, respectively.

In Fig. 5, the detection analysis of the EfficientNet-CAE method is determined with five iterations with respect to F_{score}, and AUC. The obtained outcome denotes that the EfficientNet-CAE system gains 5 iterations. According to iteration-1, the EfficientNet-CAE model offers F_{score}, and



(a)

(b)

FIGURE 3. Sample Images a) Right eye and its ground truth b) Left eye and its ground truth.

TABLE 1. Detection outcome of the proposed model with various measures and iterations.

No. of Iterations	$Accu_y$	$Prec_n$	$Reca_l$	F_{score}	AUC
EfficientNet-CAE					
Iter-1	99.30	99.15	99.01	99.44	99.08
Iter-2	98.96	98.96	99.41	99.52	99.31
Iter-3	99.31	99.32	99.19	99.41	99.44
Iter-4	99.36	99.32	99.43	99.43	99.40
Iter-5	99.14	99.47	99.11	99.40	98.97
SBRIC-OPADL					
Iter-1	98.27	99.36	99.20	99.27	99.64
Iter-2	99.30	99.58	99.37	99.16	99.56
Iter-3	99.70	99.87	99.79	99.61	99.78
Iter-4	99.19	99.49	99.38	99.50	99.34
Iter-5	99.47	99.44	99.55	99.36	99.26

AUC of 99.44%, and 99.08%, respectively. Simultaneously, with iteration-2, the EfficientNet-CAE system gives F_{score}, and AUC of 99.52%, and 99.31%, individually. Also, on iteration-3, the EfficientNet-CAE methodology gives F_{score}, and AUC of 99.41%, and 99.44%, correspondingly.

In Fig. 6, the detection analysis of the SBRIC-OPADL model is described in five iterations in terms of $accu_y$, $prec_n$, and $reca_l$. The achieved outcomes pointed out that the SBRIC-OPADL model attains 5 iterations. According to iteration-1, the SBRIC-OPADL model offers $accu_y$, $prec_n$, and $reca_l$ of 98.27%, 99.36%, and 99.20%, individually.

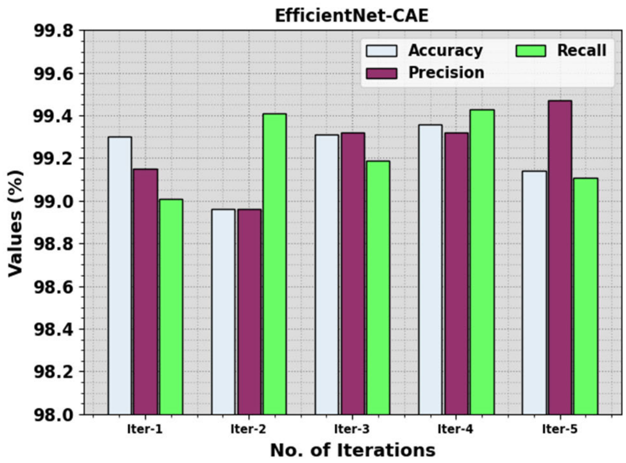


FIGURE 4. ***$Accu_y$*, *$Prec_n$*, and *$Reca_l$* analysis of EfficientNet-CAE system under various.**

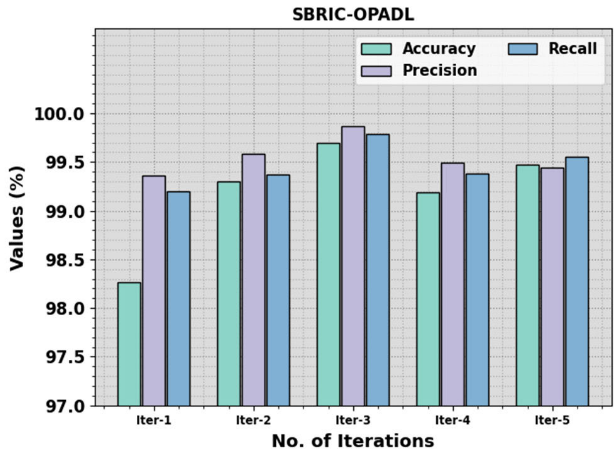


FIGURE 6. ***$Accu_y$*, *$Prec_n$*, and *$Reca_l$* analysis of SBRIC-OPADL system under various iteration.**

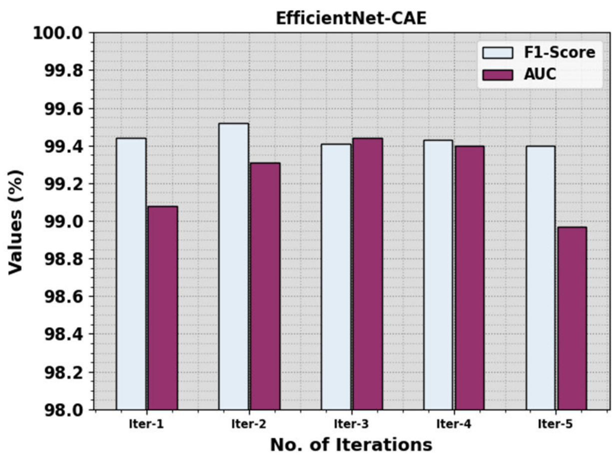


FIGURE 5. ***F_{score}*, and AUC analysis of the EfficientNet-CAE method under various iteration.**

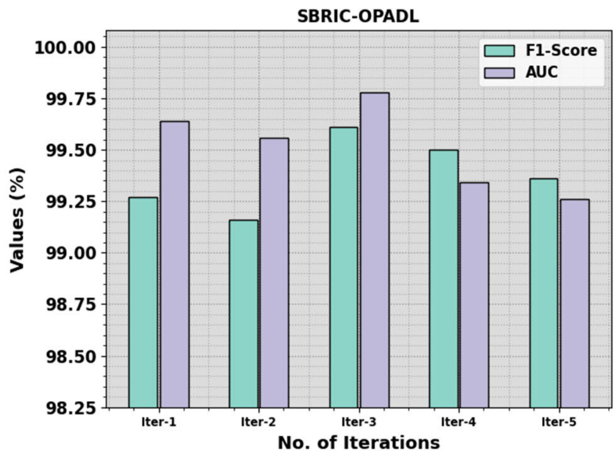


FIGURE 7. ***F_{score}*, and AUC analysis of the SBRIC-OPADL approach under various iteration.**

Concurrently, with iteration-2, the SBRIC-OPADL method provides $accu_y$, $prec_n$, and $reca_l$ of 99.30%, 99.58%, and 99.37%. Besides, with iteration-3, the SBRIC-OPADL method gives $accu_y$, $prec_n$, and $reca_l$ of 99.70%, 99.87%, and 99.79%, respectively.

In Fig. 7, the detection analysis of the SBRIC-OPADL system is evaluated with five iterations with respect to F_{score}, and AUC. The attained outcome shows that the SBRIC-OPADL algorithm gains 5 iterations. Based on iteration-1, the SBRIC-OPADL model offers F_{score}, and AUC of 99.27%, and 99.64%, separately. Further, on iteration-2, the SBRIC-OPADL approach provides *an* F_{score}, and AUC of 99.16%, and 99.56%, individually. Similarly, based on iteration-3, the SBRIC-OPADL technique gives *an* F_{score}, and AUC of 99.61%, and 99.78%, respectively.

To determine the effectiveness of the EfficientNet-CAE system, we can be made $accu_y$ curves in the testing (TS) and training (TR) phases, which are exhibited in Fig. 8. Two curves offer valued insights into the learning evolution and the capability of the model in generalization. Since raising the number of epochs, an obvious enhancement in both TR and TS accuracy curves could be apparent. It has enrichment that indicates the model's abilities to better recognize patterns along with two such as the TR and TS databases.

Fig. 9 also shows an overview of the EfficientNet-CAE loss values in the training method. The lower trend in TR loss over epochs pointed out that the model frequently improves their weights for decreasing predictive errors with the TS and TR databases. The loss curve reflects how the model fits the training databases. Remarkably, the TR and TS loss constantly decrease, displaying the efficiency of learning patterns of models existing in these two databases. Also, this demonstrates the model's variation in lessening discrepancies among original and predicted training labels.

To evaluate the effectiveness of the SBRIC-OPADL model, we have made $accu_y$ curves for the training (TR) and testing (TS) phases, as displayed in Fig. 10. Two curves offer valued insights into the learning evolvement and proficiency of

FIGURE 8. ***Accu$_y$*** **curve analysis of EfficientNet-CAE approach.**

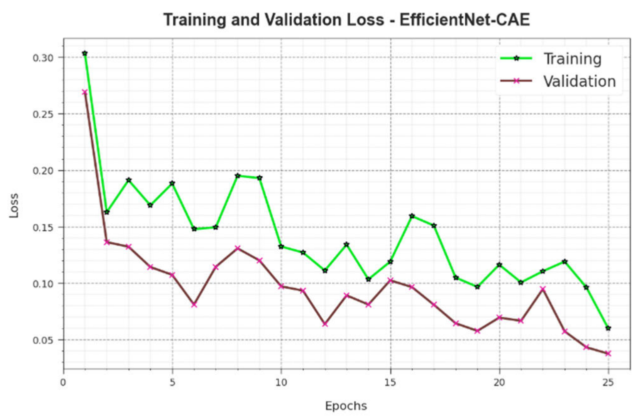


FIGURE 9. **Loss curve analysis of the EfficientNet-CAE approach.**

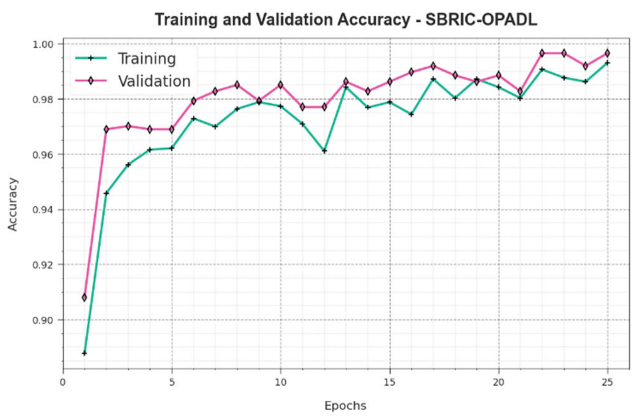


FIGURE 10. ***Accu$_y$*** **curve analysis of SBRIC-OPADL approach.**

the model for generalization. As we improve the number of epochs, a perceptible upgrading in these two TR and TS $accu_y$ curves becomes obvious. This heightening exhibits the ability of greater identification patterns at the TS and TR data.

Fig. 11 exhibits an overview of the SBRIC-OPADL loss values in the training process. The minimizing trend with TR loss over epochs denoted that the model often enhances its weights for reducing predictive errors with the TS and TR databases. The loss curve deliberates how the model fits the

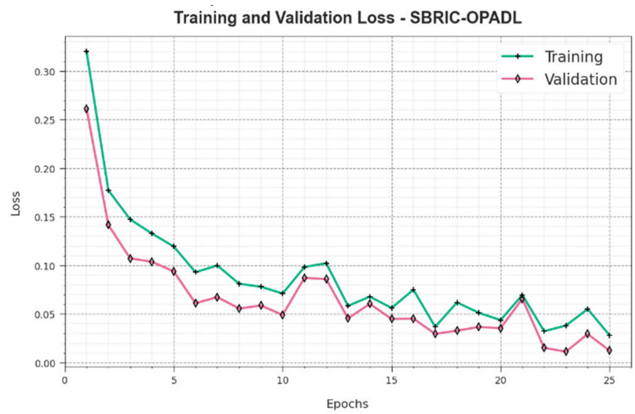


FIGURE 11. **Loss curve analysis of the SBRIC-OPADL approach.**

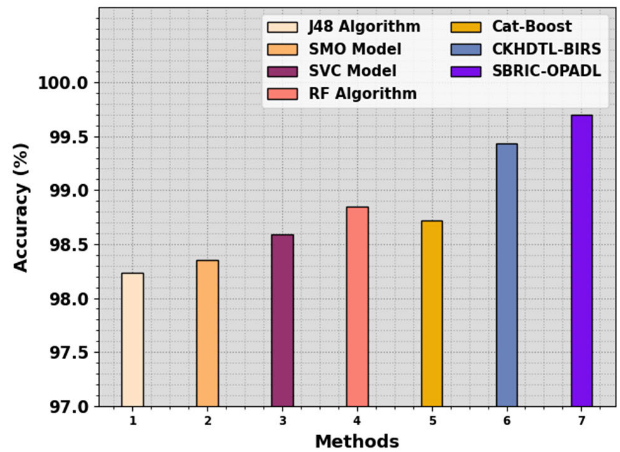


FIGURE 12. ***Accu$_y$*** **analysis of the SBRIC-OPADL model with other existing systems.**

training databases. Mainly, the TR and TS loss constantly diminish, showing the effectiveness of learning patterns of the model presented in these two data. Lastly, this determines the variation of the model for lower discrepancies among original and predicted training labels.

Fig. 12 reveals a comparison result of the SBRIC-OPADL technique [23]. The results imply that the SBRIC-OPADL technique reaches enhanced performance. Based on $accu_y$, the SBRIC-OPADL technique offers to increase $accu_y$ of 99.70% while the J48, SMO, SVC, RF, Cat-Boost, and CKHDTL-BIRS models obtain decreasing $accu_y$ values of 98.23%, 98.35%, 98.59%, 98.85%, 98.72%, and 99.43%, respectively.

Fig. 13 describes a comparison analysis of the SBRIC-OPADL methodology with respect $prec_n$ and $reca_l$. The attained outcome shows that the SBRIC-OPADL technique gets improved performance. Based on $accu_y$, the SBRIC-OPADL model gives a growing $prec_n$ of 99.87% whereas the J48, SMO, SVC, RF, Cat-Boost, and CKHDTL-BIRS models obtain decreasing $prec_n$ values of 98.12%, 98.02%, 96.00%, 98.45%, 98.65%, and 99.60%, correspondingly. Also, with $reca_l$, the SBRIC-OPADL model

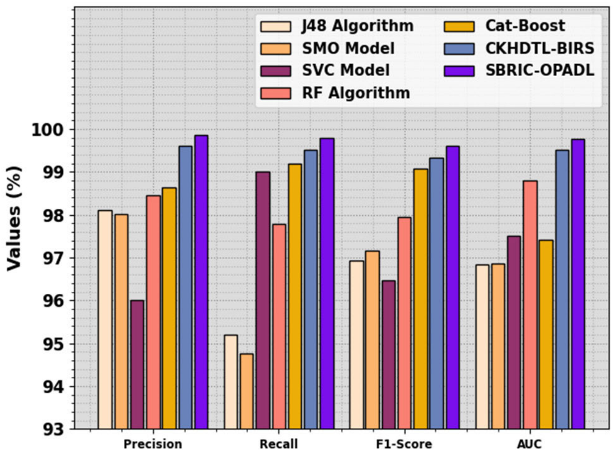


FIGURE 13. **Comparison analysis of the SBRIC-OPADL model with other existing systems.**

gives a growing $reca_l$ of 99.79% but, the J48, SMO, SVC, RF, Cat-Boost, and CKHDTL-BIRS models obtain decreasing $prec_n$ values of 95.19%, 94.76%, 99.00%, 97.78%, 99.19%, and 99.52%, respectively. These achieved outcomes confirmed that the SBRIC-OPADL technique reaches maximum biometric identification performance.

The SBRIC-OPADL approach depicts existing approaches in secure biometric retinal iris detection because of its combined use of advanced technologies and methods. The inclusion of WF at the primary phase significantly improves the input quality of iris images by efficiently eliminating noise. The deployment of the EfficientNet approach for feature extractor strikes a balance among model complexity and computational efficacy, allowing the extraction of discriminative features from retinal and iris images. The unique contribution of the OPA method makes sure that the hyperparameters of the EfficientNet algorithm are heightened, optimizing its solution for the particular task. Additionally, the combination of the CAE in the biometric detection method allows the capturing and reconstruction of intricate patterns from the retinal and iris images. The widespread calculation on a biometric iris dataset depicts that the SBRIC-OPADL approach surpasses other algorithms with respect to accuracy and reliability, demonstrating its efficiency in addressing the challenges of biometric detection but providing finely tuned security and efficiency.

V. CONCLUSION

In this article, we present an effective SBRIC-OPADL technique. The goal of the SBRIC-OPADL technique is to accomplish biometric security using retinal iris images. It contains three major processes namely WF-based preprocessing, EfficientNet-based feature extraction, OPA-based parameter tuning, and CAE-based classification. Besides, the SBRIC-OPADL technique exploits the EfficientNet model for the extraction of feature vectors. Moreover, the hyperparameter tuning process of the EfficientNet model takes place using OPA. Furthermore, the biometric identification process can be performed by the use of CAE. To validate the enhanced biometric detection results of the SBRIC-OPADL technique is tested using the biometric iris dataset. The extensive results highlighted that the SBRIC-OPADL technique reaches better performance over other models.

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