# Recognition of Human using Periocular Biometrics with Deep Dense Network.

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**Abstract** *–The COVID-19 pandemic has drastically reduced people's life expectancy and instilled fear in people all around the world. Concerns over the long-term effects of wearing a facemask and social alienation are raised by these requirements, which emphasize the necessity for contactless biometrics for verification—of which ocular biometrics is the best alternative. Generally speaking, biometric feature-based person identification systems are preferred for verifying a person's identity in public places such as ATMs, banks, school attendance systems, airport immigration clearance systems, etc. Compared to other networks like face net, Alexnet, deepiristnet-A, and deepiristnet-B, the UBIPr dataset and hybrid optimum dense capsule network combined with the African vulture algorithm provide superior accuracy for human recognition. It has an error rate that is 3.32 times lower than the other.*

**Keywords**-*COVID-19, security, Periocular Biometrics, Deeply Dense Network, Human Identification.*

## I. INTRODUCTION

Periocular recognition has advanced to the point that it can be utilized for personal identification, particularly in situations without restrictions. It can be combined with other modalities like face and iris, or utilized independently. This has been the case whether the recognition is applied in conjunction with the other modalities or as a stand-alone attribute.[1] It has several benefits, the first of which is that the problematic area might be simply cropped from previously captured face images.[2] Secondly, compared to taking a picture of the iris, taking a picture of it requires less surgical intervention.[3][4] This face feature is especially attractive because it's simple to photograph from many perspectives, making it a fantastic subject for security camera use. Periocular features are among the most promising biometric traits for person recognition. [5] It affects the skin's texture, the contour of the eyes, the eyelids, the lashes, the eyebrows, and the wrinkles around the eyes.[6]
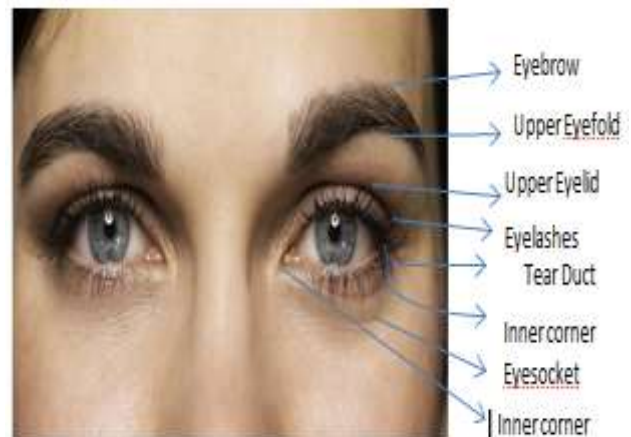


Fig. 1- Periocular Region

Next, a review of the different aspects of ocular biometrics is given, including: (a) the anatomical cues that are present in the ocular region and can be used for recognition; (b) the various feature extraction and matching techniques that have been developed; (c) recognition across different spectra; (d) fusion with other biometric modalities (face or iris); (e) recognition on mobile devices; (f) its applicability in other contexts; (g)

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Periocular datasets; and (h) competitions organized to evaluate the efficacy of this biometric modality.[7]

## II. LITERATURE REVIEW

Park et al. (2009) introduced a novel method for utilizing periocular region-based biometric systems as a supporting biometric feature for other biometric systems or as a stand-alone modality.[8] Furthermore, they proposed the use of the periocular region as a biometric characteristic for identifying individuals. They then grew larger (Park et al. 2011).[9] on their proposed proposal to examine the Periocular region's utility under less-than-ideal scenarios, like shifting locations, concealing significant eye features, and incorporating the eyebrow into the Periocular zone of interest.[10-14]Their research's results provided strong support for the necessity of developing an effective periocular biometric system to be used in circumstances where other biometric traits, such as face and iris biometrics, are not totally dependable.[15]

Since deep learning has proven effective in computer vision and biometrics, periocular recognition has also adopted this technique. In earlier work (Nie et al., 2014), an unsupervised convolutional version of Restricted Boltzmann Machines (CRBM) based on learning approaches was developed for periocular recognition.[16] Raja et al. (Raja et al., 2016b, 2020) extracted features from Deep Sparse Filters and fed them into a dictionary-based classification system using a transfer learning methodology.[17-26] On the other hand, Raghavendra and Busch (2016) extracted texture features using Maximum Response (MR) filters and put those characteristics into deeply linked auto encoders for classification.[27] Further studies that employed transfer learning techniques might be found in (Luz et al., 2018; Silva et al., 2018; Kumari and Seeja, 2020).[28-30] Deep neural networks were employed by Proena and Neves (2018).[31-34]

Because of the training procedure, the network implicitly ignores the iris and sclera area. In Wang and Kumar (2021) as well as Zhao and Kumar (2018),[35] In order to highlight the eyebrow and eye, two significant areas of the periocular image, the authors integrated the attention model with the deep architecture.[36] Some studies used pre-existing off-the-shelf CNN models to extract deep features at various convolution levels (Hernandez-Diaz et al., 2018; Kim et al., 2018; Hwang and Lee, 2020).[37][38] The authors proposed compact

and tailored deep learning models (Zhang et al., 2018). [39] for use with mobile devices. Unsupervised convolutional autoencoders are another method of deep learning (Reddy et al., 2019).,[40]

Deep embedding that considers heterogeneity (Garg et al., 2018), [41] According to Reddy et al. (2020), a compact convolutional neural network (CNN),[42] Generalized Label Smoothing Regularization (GLSR)-trained networks (Jung et al., 2020) and semantics-assisted CNN (Zhao and Kumar, 2017). [43] Although deep learning methods provide state-of-the-art recognition capabilities, their efficacy is primarily data-dependent. Following the feature extraction phase, several researchers proceeded to alter the feature vector, typically using methods like feature selection, subspace projection, or dimensional reduction (Beom-Seok Oh et al., 2012; Joshi et al., 2014). [44] These solutions aim to reduce processing complexity and boost accuracy by compressing the feature set into a representative feature set.

## III -METHODOLOGY

Collection Compared to the original UBIRIS.v2 data, photos in the UBIPr variation of the UBIRIS.v2 set have been cropped to encompass a wider area of the ocular region.[45] It is particularly suitable for research on Periocular Recognition. The utilized dataset was the pre-existing UBIPr dataset. The ocular, or eye, region is depicted in images from this collection. It is a part of the periocular region. The dataset contains 11,000 publicly available photographs that have undergone noise reduction to improve their realistic appearance. The Creative Commons Attribution-Non-Commercial-Share Alike 4.0 International license governs the use of the dataset. The dataset includes images of moving people, which contributes to some blurriness. The eye positions are also changed, and each participant has had their eyes photographed at least ten times, with 521 unique participants and 11,000 photos. This indicates that a total of about 21 photographs, including pictures of both eyes, are available to each user or participant. Various angles and eye motions are employed to create visuals for each person's eye. All of the photos were resized to 224 by 224 pixels.[46]



Fig 2. System Block Diagram

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The lighting, standoff distance, gaze, and posture of the UBIPr images captured with the visible light (VL) sensor in Figure (3) are not the same. The images of the position variant, which include both side and front views, are displayed in Figure 3. The standoff distance ranges from 8 meters to 4 meters with varying resolutions: 7 meters with 561 by 541 pixels, 6 meters with 651 pixels, 5 meters with 801 by 651 pixels, and 4 meters with 1001 by 801 pixels.



Fig 3. UBIPr Dataset Images

**Image preprocessing and parabolic contrast enhancement**

Spatial domain approaches and frequency domain techniques are the two basic categories of contrast enhancement algorithms. The foundation of image enhancement in spatial domain approaches is the direct manipulation of a picture's pixels. Frequency domain processing techniques work by modifying the Fourier transform of a picture. When frequency domain techniques are applied, the image is first transferred into the frequency domain. This suggests that the Fourier Transform of the image is computed initially. The image is obtained by performing the Inverse Fourier transform after completing all of the boosting processes on the Fourier transform. Principal component analysis (PCA), also known as Karhunen-Loeve expansion, is a conventional dimensionality reduction method for feature extraction. Numerous domains, including signal processing, pattern recognition, data mining, computer vision, and machine learning, have made substantial use of it. Dimensionality reduction and image compression are closely related topics. [47]

While normal PCA operates on one-dimensional vectors, which have inherent problems handling high dimensional vector space data, such as photos, 2DPCA works directly on matrices or uses the PCA algorithm to the original image without turning it into a one-dimensional vector. This 2DPCA capacity outperforms regular PCA when processing big dimensions vector space data. A practical concept for 2DPCA-based color image compression is presented in this study. Several

other 2DPCA variants are also applied, and the proposed method effectively combines several 2DPCA-based approaches. [48]

Deep learning is an end-to-end technique that applies recognition functions layer by layer to extract and abstract visual features. Deep learning was used by Krizhevsky et al. [49] won the competition for ImageNet Computer Vision Champions. Consequently, the representation of deep learning approaches using convolutional neural networks has become a popular research area in pattern recognition. GoogLeNet, ResNet, and DenseNet have all been proposed one after the other. [50] In terms of outcomes, DenseNet has surpassed many other deep learning models because of its unique dense connectivity architecture, which permits interconnection between any layers and skip connection mode, which sends data directly from shallow to deep layers.
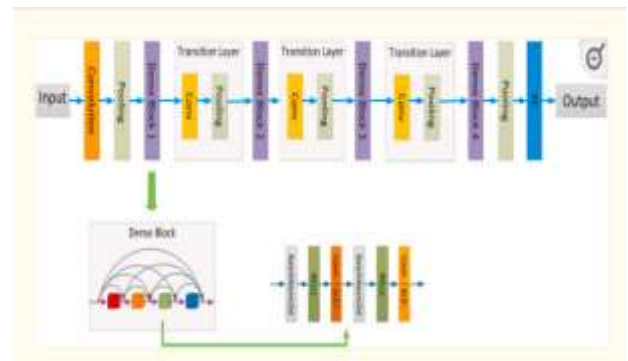


Fig 4. DensNet 121 Architecture

Every convolution layer receives the output from the layer before it and creates an output feature map, which is then sent to the convolution layer after it, with the exception of the first convolution layer, which receives the input picture. Every L layer has L direct connections, and each layer and the layer above it have one each. The layers of DenseNet-121 are as follows: Seven 7x7 convolution, fifty-eight 3x3 convolution, sixty-one 1x1 convolution, four average pools, and one fully connected layer. In summary, DenseNet-121 comprises 120 convolutions and 4 average pools. Since these layers generate a lot of redundant information, the layers in the second and third dense blocks assign the lowest weights to the output of the transition layers.[51]

### IV-WDS (WEIGHTED DISTANCE SIMILARITY) MATCHING

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The primary objective of weighted distance similarity is to provide query images with highly preferred versions that are more comparable than the raw input photographs.

The class probability of the query photographs sets a bound on the distance between the raw input and query photos.

When query image Q is directed over recommended procedures, probability p for each class is produced. This is utilized to estimate the R raw input weight in the input data. [52]

The goal of the feature-matching module is to match the gallery sample and the probing sample in order to get matching scores. Its simplicity makes it the most widely utilized. The following are this metric's main benefits: comparatively insensitive to small perturbations (deformation); simple to calculate and incorporate into most powerful image recognition algorithms with ease.

Given two M by N pictures, x and y, with x = (x1, x2, xMN) and y = (y1, y2., yMN ) and xkN +l, ykN +l representing the grey levels at (k,l), the Euclidean distance dE (x, y) may be found using the formula d = $\sqrt{[(x2 - x1)2 + (y2 - y1)2]}$. [53]A minor image distance created by a minor distortion is one of the features of the suggested technique. The distortion increases with increasing distance. In addition, the distance is continuous up to the point of deformation. Two images have the same distance if we apply the same translation, rotation, and reflection to them. The metric can be used to images of any size and resolution. The similarity metric quantifies how similar two data objects are to one another. [53]

## V-RESULT & DISCUSSION

**Assessment of performance on UBIPr:**

The efficiency of utilizing periocular images as input for the UBIPr dataset in person identification is contrasted with other existing techniques, such as FaceNet and dual-stream CNN. The proposed model's MAP for the UBIPr dataset is 99.09%.which is greater as compared with the other existing techniques like AlexNet,Deepirisnet-A,DeepIrisNet-B,FaceNet,LCNN29,Multifusion CNN ,VGG-16 and dual-stream CNN [47]

Table 1. Accuracy and equal error rate of UBIPr

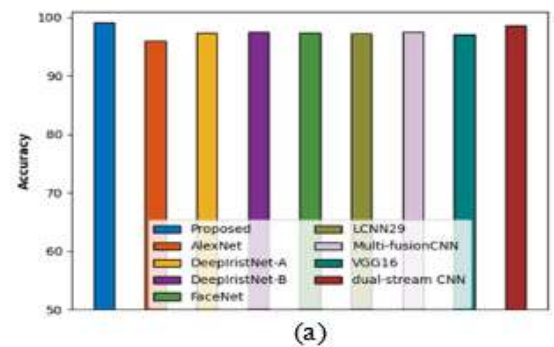| Methods | Results of performance for the UBIPr dataset (%) | |
|---|---|---|
| | Accuracy | EER |
| AlexNet | 96.01 | 7.11 |
| DeepIristNet-A | 97.41 | 5.07 |
| DeepIristNet-B | 97.43 | 4.29 |
| FaceNet | 97.36 | 5.46 |
| Proposed | 99.12 | 3.32 |



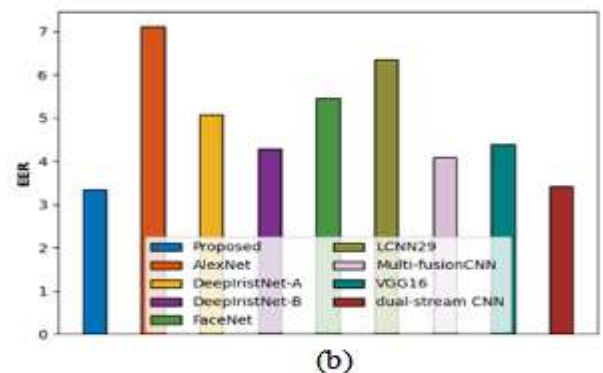**Fig 5(a)Accuracy of dataset UBIPr**



**Fig 5(b) EER of dataset UBIPr**

## VI- CONCLUSION

When low-quality iris images are obtained due to partially occluded, secularly reflective, off-axis gazing, motion and spatial blur, non-linear deformations, contrast changes, and illumination artifacts, the suggested method, which combines a deep dense network with the UBIPr database, improves performance. Expanding the application of deep learning-based methods in ocular biometrics leads to a new avenue: elucidating these deep learning models' capabilities.

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