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Research Article

Identification of Human Being using Periocular Biometrics with Multi-Layered Network

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Abstract: The coronavirus disease 2019 (Covid-19) pandemic has significantly reduced people's life expectancy and conveyed fears to people around the world. These requirements raise concerns about the long-term impact of wearing face masks and social marginalisation. This highlights the need for contactless biometry to check. Eye biometrics are the best option. Biometric characteristics-based personal identification systems are generally recommended for verifying the identity of people in public locations such as ATMs, banks, school visit systems, and airport immigration clearance systems. Compare it with other networks such as Face Net, Alexnet, DeepiristNet-A, DeepiristNet-B. recognition. The error rate is 3.39 times lower than the other errors.

Keywords: Periocular Biometrics, Human Identification, Covid-19, Security, Multi-layered Networks.

1. Introduction

Periophthalmic detection is progressing so far as to be used for individual identification in no particular restrictions. It can be combined or used independently with other modalities such as Face and Iris. There are several advantages, the first of which is that problematic areas can simply be filled from previously recorded viewing views.[1] Second, taking images of the iris requires less surgical intervention. [2] [3] This was the case when detections related to other modality were used. [4]

This facial feature is especially appealing as it is simply about taking photos from many perspectives, and is a great incentive to use surveillance cameras. Periocular characteristics are one of the most promising biometric properties for people's detection. [5] It affects skin texture, eye contour, eyelids, eyelashes, eyebrows, and folding around the eyes. [6]

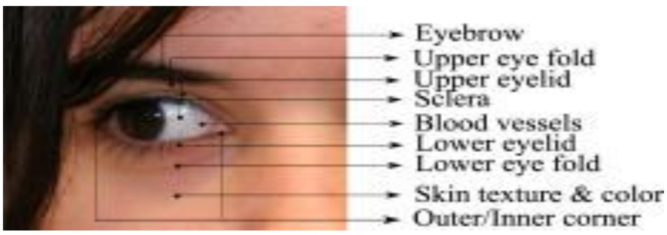

Figure 1-Anterior Area

A review of various aspects of eye biometrics shows: (b) Various developed property extraction and matching techniques. (c) Detection via different spectra. (d) Fusion with other biometric modalities (face or iris). (e) Mobile device recognition. (f) Applicability in other contexts. (g) Peripheral data set. (h) A competition organized to assess the effectiveness of this biometric modality. [7]

2. Materials and review:

Multi-Layered Network 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.

3. Technique

Images as compared to the authentic UBIRIS.v2 records, photographs in the UBIPr variant present day the UBIRIS.v2 set have been cropping collection compared to the unique UBIRIS.v2 statistics, photographs inside the UBIPr variant brand new the UBIRIS.v2 set were cropped to encompass a wider location ultra-modern the ocular area.[45] it is in particular suitable for studies on Periocular popularity. The applied dataset become the pre- current UBIPr dataset. The ocular, or eye, place is depicted in images from this series. it's far cutting-edge the periocular location. The dataset includes 11,000 publicly to be had snap shots which have passed through noise discount to improve their practical look. The innovative Commons Attribution-Non-commercial-percentage A like four.0 worldwide license governs the usage of the dataset. The dataset includes photographs brand new shifting human beings, which contributes to some blurriness. the eye positions also are changed, and every player has had their eyes photographed at the least ten instances, with 521 specific participants and 11,000 photos. This indicates that a complete modern-day approximately 21 snap shots, including photographs trendy both eyes, are available to every person or participant. numerous angles and eye motions are employed to create visuals for all and sundry modern`s eye. all the pictures have been resized to 224 by using 224 pixels.[46]

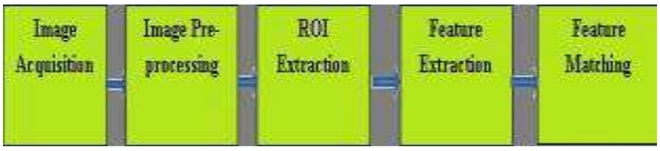

Fig 2. Block Diagram

The lighting, stand modern day off distance, gaze, and posture ultra-modern the UBIPr pix captured with the visible mild (VL) sensor in discern (three) aren't the equal. The photographs modern the location variation, which include each side and the front perspectives, are displayed in determine three. The stand today off distance degrees from eight meters to 4 meters with various resolutions: 7 meters with 561 by using 541 pixels, 6 meters with 651 pixels, 5 meters with 801 by using 651 pixels, and four meters with 1001 by using 801 pixels.

Figure 3: Images from the Preparing images UBIPr Dataset

The UBIPr Dataset is preparing images and enhancing parabolic contrast The two fundamental types of contrast enhancement algorithms are spatial domain methods and frequency domain methods. The direct manipulation of an image's pixels forms the basis of spatial domain approaches to image enhancement. Techniques for frequency domain processing alter an image's Fourier transform. The image is initially moved into the frequency domain when using frequency domain techniques. This implies that the image's Fourier Transform is calculated first. Once all of the boosting operations on the Fourier transform are finished, the image is produced by executing the Inverse Fourier transform. One common dimensionality reduction technique for feature extraction is principal component analysis (PCA), sometimes referred to as Karhunen-Loeve expansion.

It has been widely used in many fields, including as computer vision, machine learning, pattern recognition, data mining, and signal processing. Image compression and dimensionality reduction are closely related subjects. [47] 2DPCA works directly on matrices or applies the PCA technique to the original image without converting it into a one-dimensional vector, whereas standard PCA works on one-dimensional vectors, which have inherent issues handling high dimensional vector space data, like images. When processing large-scale vector space data, our 2DPCA capability performs better than standard PCA. This paper presents a workable idea for color image compression based on 2DPCA.

The suggested strategy successfully blends multiple 2DPCA-based techniques, and further 2DPCA variations are also used. [48] Deep learning is a comprehensive method that extracts and abstracts visual characteristics by applying recognition functions layer by layer. Krizhevsky et al. [49] used deep learning to win the ImageNet Computer Vision Champions competition. As a result, a major area of pattern recognition research is the representation of deep learning techniques utilizing convolutional neural networks. One after the other, GoogLeNet, ResNet, and DenseNet have all been proposed. [50] Because of its distinctive dense connectivity architecture, which allows for interconnection between any layers and skip connection mode, which transmits data straight from shallow to deep layers Dense Net has outperformed many other deep learning models in terms of results.

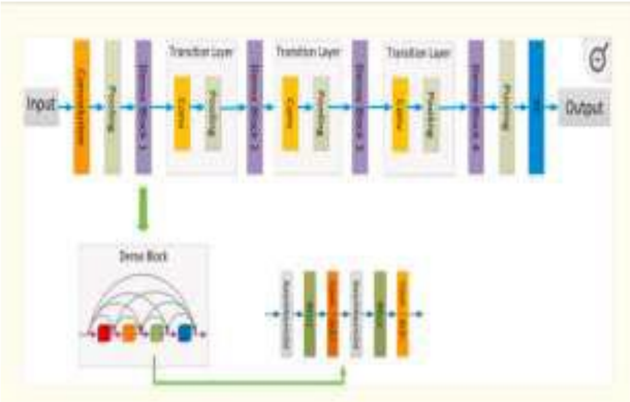

Figure 4: Architecture of Dens Net 121

Except for the first convolution layer, which receives the input picture, each convolution layer takes the output from the layer before it and produces an output feature map, which is then transmitted to the convolution layer after it. Each layer has one direct link, and each L layer has L direct connections, as does the layer above it. DenseNet-121's layers are as follows: Four average pools, one completely linked layer, fifty-eight 3x3 convolutions, sixty-one 1x1 convolutions, and seven 7x7 convolutions. In conclusion, DenseNet-121 has four average pools and 120 convolutions. The layers in the second and third thick levels provide a lot of redundant information The output of the transition layers is given the lowest weights by the layers in the second and third dense blocks.[51]

4.Weighted Distance Similarity, Matching

The primary objective of weighted distance similarity is to provide query photographs with highly preferred versions that are more comparable than the raw input photos. The class probability of the query photographs constrains the distance between the query photos and the raw input. When query image Q is directed over recommended procedures, probability p is produced for every class. This approach estimates the R raw input weight in the input data. [52] The feature-matching module seeks to match the gallery sample with the probing sample to get matching scores. Its simplicity makes it the most widely utilized. The following are this statistic's main benefits: comparatively resilient to small perturbations (deformation); simple to calculate and incorporate into the most powerful image recognition algorithms. The feature-matching module seeks to match the gallery sample with the probing sample to get matching scores. Its simplicity makes it the most widely utilized. The following are this statistic's main benefits: comparatively resilient to small perturbations (deformation); simple to calculate and incorporate into the most powerful image recognition algorithms.

Given two M by N photos, x and y, The Euclidean distance dE (x, y) can be determined using the formula d = √[(x2 – x1)2 + (y2 – y1)2 for two M by N pictures, x and y, where x = (x1, x2, xMN) and y = (y1, y2., yMN) and xkN +l, ykN +l denote the grey levels at (k,l). [53]One of the characteristics of the proposed method is a small picture distance caused by a small distortion. As the distance rises, so does the distortion. Furthermore, up until the point of deformation, the distance is continuous. If we apply the same translation, rotation, and reflection to two images, their distances are equal. Any size and resolution of image can be utilized with this metric. The degree of resemblance between two data objects is measured by the similarity metric. [53]

5. Result and discussion

Evaluation of UBIPr performance: In comparison to other current methods like FaceNet and dual-stream CNN, the effectiveness of using periocular pictures as input for the UBIPr dataset in person identification is evaluated. For the UBIPr dataset, the MAP of the suggested model is 99.09%.which is higher than the other methods now in use, such as AlexNet, DeepIrisNet-A, DeepIrisNet-B, FaceNet, LCN29, Multifusion CNN, VGG-16, and dual-stream CNN. [47]

Table 1. UBIPr's accuracy and equal error rate

Methods	**Results of performance for the UBIPr dataset (%)**	
	Accuracy	**EER**
FaceNet	98.41	5.78
DeepIristNet-A	98.045	5.90
DeepIristNet-B	98.44	4.56
AlexNet	97.05	7.89
Proposed	99.24	3.94

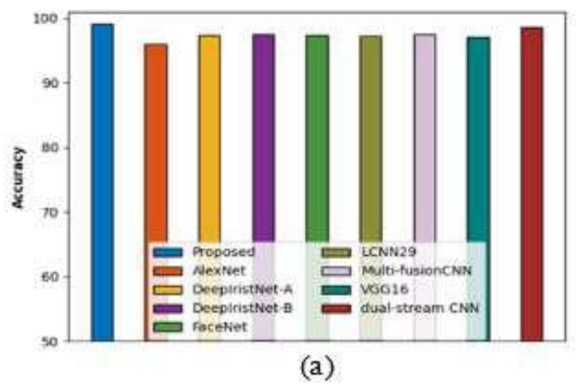

Fig. 5(a): UBIPr dataset accuracy

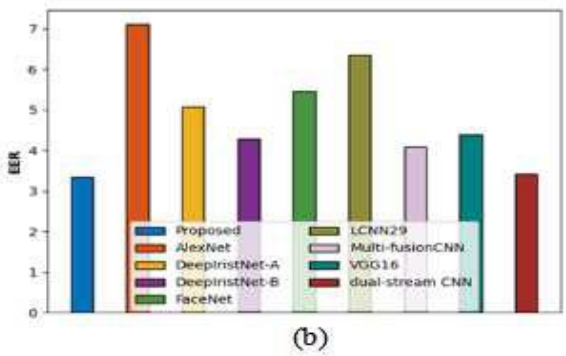

Fig. 5(b): EER of the UBIPr VI dataset:

6. Conclusion and Future Scope

The proposed approach, which combines a deep dense network with the UBIPr database, improves performance when low-quality iris images are obtained because of partially occluded, secularly reflective, off-axis gazing, motion and spatial blur, non-linear deformations, contrast changes, and illumination artifacts. Clarifying the capabilities of these deep learning models is a new path that arises from expanding the use of deep learning-based techniques in ocular biometrics.

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Author brief Introduction

Dr. Nirgish Kumar is pursuing M.Tech Degree, From Faculty of Engineering, Rama University, Kanpur. His research interest fields include Biometric, Machine leaning, computational Intelligence, segmentation techniques, and Data mining. He has published more than 06 papers in various International Journals and Conferences. Presently he is working HBTU Kanpur. He is member of IEEE and paper Reviewers.

