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A Robust Convolutional Neural Network for Iris Recognition System

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***Abstract*— Iris recognition, a biometric modality, has grown significantly in recent years. Traditional techniques relied on feature extraction methods and classical machine learning classifiers. However, deep learning models, particularly Convolutional Neural Networks (CNNs), have exhibited remarkable performance in learning discriminative features from iris images, making them robust to variations in imaging conditions and achieving state-of-the-art recognition accuracy. Nonetheless, injuries or occlusions affecting the iris can lead to increased error rates due to missing information. This study presents and evaluates CNN-based models for iris recognition. Various CNN architectures were employed for feature extraction, and the best-performing model was selected. Features from the left and right iris (one instance) were fused to create a multiple-instance system, enhancing recognition performance. The proposed approach was tested using the SDUMLA-HMT iris dataset. The results demonstrate that our system achieves an accuracy of 100%. Comparative analysis with existing methods indicates that our system outperforms the current state-of-the-art techniques for iris recognition.**

Keywords— One instance, Multiple instances, Recognition system, Convolution Neural Network, Iris.

I. Introduction

Biometric systems for identification are becoming more and more common. They identify a person based on their behavior or physical traits [1]. Iris recognition comes as one of the most secure [2]. The iris's unique patterns, which can even distinguish between identical twins, are largely responsible for its efficacy. In previous times, traditional machine learning methods and manually created features were used for iris detection. On the other hand, performance has significantly improved due to recent advances in deep learning, namely with Convolutional Neural Networks (CNNs) [3]. CNNs are exceptionally good at extracting discriminating features from iris images, which helps them to be robust over changes in imaging settings and obtain state-of-the-art accuracy in recognition tasks [4].

Despite these advancements, iris recognition systems face challenges when the iris is partially occluded or injured, leading to increased error rates due to missing information. To address this issue, we propose a multiple-instance system for iris recognition. Our approach aims to improve recognition performance in scenarios where partial iris information is available.

This study explores the application of deep learning techniques, specifically CNNs, to iris recognition. Our research aims to achieve robust and stable recognition performance even in challenging conditions. To validate the effectiveness of our proposed CNN architecture, we conducted experiments on the SDUMLA-HMT Iris dataset.

The rest of this paper is structured as follows: A summary of relevant iris recognition research is provided in Section 2. The CNN models used in this research are described in Section 3. Using the suggested methods, Section 4 describes in detail the experimental setup and outcomes. Finally, Section 5 presents the conclusion.

II. Related Works

Iris recognition has attracted a lot of attention from researchers due to its exceptional dependability compared to other biometric modalities.

Khorimah and Juniati [5] utilized the rubber sheet model for normalization and the Hough transformation to identify the iris region. The authors extract characteristics using the box-counting method. The k-nearest-neighbor (knn) algorithm is also used in the classification stage. After identifying the iris region using the circular Hough transform, Dua et al. [6] generate rectangular iris images by utilizing the rubber sheet model. The authors coded the rectangular iris image using the Log-Gabor filter, and a neural network was utilized for the classification phase. Discrete Wavelet Transform (DWT) and DCT have been combined by Abdalla et al. [7] and used to extract features from normalized iris images. The suggested feature extraction method produced good results when used to the multi-class SVM classifier. Two modified Self Organizing Maps (SOM) were introduced by Winston and Hemanth [8] and are used for iris recognition. According to the IITD database, the suggested maps have an accuracy percentage of 98.4%. A novel method for iris detection based on the Fuzzy Local Binary Pattern (FLBP) [9] was presented by Abdo et al. [10]. The FLBP technique was tested by several classifiers on various datasets of iris images, and it performed well with the SVM classifier.

III. Proposed System

The proposed transfer learning-based model for recognizing and classifying iris images is illustrated in Fig. 1. Our approach begins by separating our datasets into left and right iris images, followed by the utilization of three pre-trained CNN architectures for feature extraction. In this section, we will provide a detailed description of our proposed model.

A. Features extraction using CNN models

In computer vision, the use of transfer learning with pre-trained models is a common practice. The following subsections will offer a brief overview of the pre-trained models used in this study.

convolutional layers and 3 fully connected layers (144 million parameters).

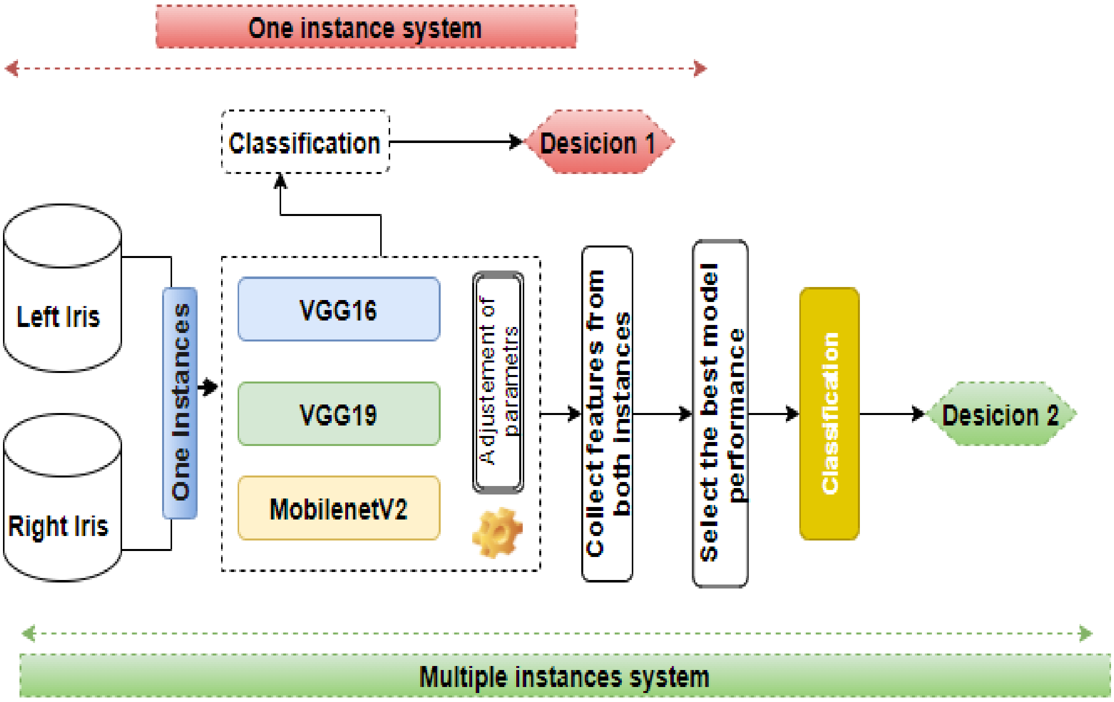

Fig1. The proposed system

– **MobileNetV2**

Using the inverted residuals and linear bottlenecks concept, Sandler et al. [11] introduced the CNN MobileNetV2 model, The Inverted Residuals block with Linear Bottleneck has 3 layers, according to its structure: layer one is a pointwise convolution with a size of 1 × 1, which enlarges the dimensions. A pointwise convolution with a size of 1× 1 works as a dimension reduction after the second layer, which is a separable depth-wise convolution with a size of 3 × 3. The ReLU activation function is carried out by the first and second convolutions of the block. As shown in Fig. 3, the MobileNetV2 design starts with a typical convolution layer and advances to 17 levels of residual bottleneck blocks, 1 pointwise layer convolution, and only a fully linked layer.

— **VGG16 and VGG19**

In 2014, Simonyan et al. [12] proposed deep convolutional neural networks called VGG (Visual Geometry Group), notably VGG16 and VGG19, which extend the AlexNet architecture by adding more convolutional layers. The numbers 16 and 19 refer to the total weight layers in each network. VGG's most distinctive feature is its use of simpler, uniform architecture with fewer hyperparameters than usual. They focus on convolutional layers with 3x3 filters and a stride of 1, using the same padding, and max pooling layers with 2x2 filters and a stride of 2. This pattern is repeated throughout the architecture, gradually increasing network depth. Both VGG16 and VGG19 end with 2 fully connected layers of 4096 units each, followed by a final dense layer with 1000 units and a softmax activation for output classification. While VGG16 has 13 convolutional layers and 3 fully connected layers (138 million parameters), VGG19 has 16

IV. EXPERIMENTAL RESULTS AND DISCUSSION

In this section, we describe the metrics used for evaluating the proposed system performance. Additionally, we compared the suggested system with various currently used techniques.

A. *Evaluation Metrics*

The suggested system is examined utilizing precision, recall, accuracy, and F1-score as indicated in Equations 1, 2, and 3. The number of right negative sample predictions was designated by TN and the number total of accurate positive sample predictions by TP, the number total of incorrect positive sample predictions by FN, and the number of incorrect negative sample predictions by FP. we also plot the Cumulative Match Characteristics (CMC) curves to provide a summary of how each model performed at various ranks.[13]

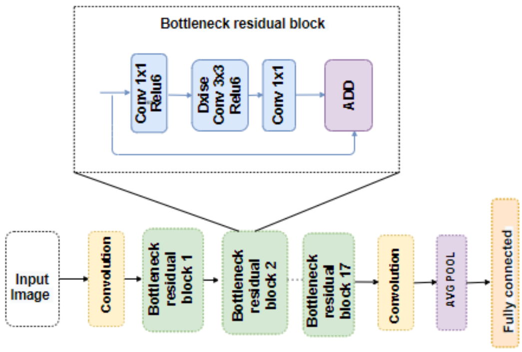

Fig.2.The architecture of MobileNetV2

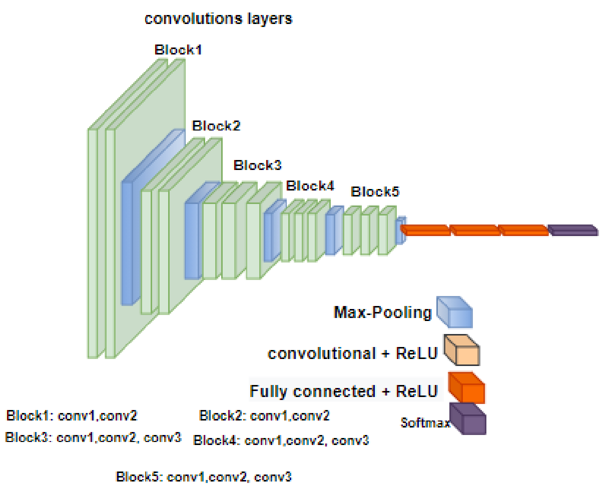

Fig.3.The architecture of VGG

- The Rank one recognition rate is the proportion of probe iris images for which the proper identification is returned as the top match from a gallery.
- The Rank five recognition rate is the proportion of probe Iris images for which the proper identity is returned among the first 5 matches from a gallery.

$$Precision = \frac{TP}{TP+FP} \quad (1)$$

$$Recall = \frac{TP}{TP+FN} \quad (2)$$

$$F1score = 2 * \frac{Precision*Recall}{Precision + Recall} \quad (3)$$

B. Results

In our study, we utilized the SDUMLA Dataset, a publicly available database [14], which comprises six images of both left and right irises from 106 participants, totaling 1278 iris images. We evaluated our model's performance using two experimental scenarios. In the single instance scenario, we split the dataset for each iris (left and right) separately, using 447 images (70%) for training and 192 images (30%) for testing. For the multiple-instance scenario, we combined features from both irises, maintaining the same 70/30 split for training and testing. Across all experiments, we employed pre-trained CNN models with batch sizes of 16, 32, 64, and 128, running for more than 50 epochs. We used RMSprop and Adam optimizers with learning rates varying between 0.x and 0.000x, and x ranges between 1 and 7. These parameters were consistently applied across all recognition experiments to evaluate our model's performance.

In Tables I, II, and III, we present our results in terms of precision, recall, accuracy, and F1 score across the three different models.

C. DISCUSSION

Based on the results from the previous section, we implemented our proposed methods by first selecting the most effective models in terms of precision and computational efficiency. We then separated the left and right iris data and conducted our experiments in single-instance and multiple-instance iris images. For both parts, we tested three CNN models - VGG16, VGG19, and MobileNetV2 using the train-and-error method. Tables I and II present the results for left and right single instances, respectively. VGG16, VGG19, and MobileNetV2 achieved Rank1 accuracies of 93.49%, 94.42%, and 98.60% for the left iris, and 90.70%, 93.95%, and 99.53% for the right iris. The corresponding CMC curves are illustrated in Figures 4 and 5. For the multiple instance method, Table III shows that our three models achieved Rank1 accuracies of 97.64%, 98.11%, and 100%. These results demonstrate that the proposed MobileNetV2 strategy yielded excellent performance, we also plotted the CMC curve along with accuracy and loss curves, as shown in Figure 6. These findings highlight the effectiveness of our approach, particularly with the MobileNetV2 model using multiple instances system.

TABLE I. EXPERIMENTAL RESULTS FOR THE LEFT INSTANCE

Left Iris						
Models	Optim	Prec	Rc	F1	R1	R5
VGG16	RMS	95	93	93	93.49	98.14
VGG19		95	94	94	94.42	98
MobilenetV2		99	99	98	98.60	100
VGG16	Adam	93	93	92	92.56	98.14
VGG19		95	93	92	93.02	95
MobilenetV2		97	97	96	96.74	99

TABLE II. EXPERIMENTAL RESULTS FOR THE RIGHT INSTANCE

Right Iris						
Models	Optim	Prec	Rc	F1	R1	R5
VGG16	RMS	92	91	90	90.70	98.60
VGG19		95	94	93	93.95	98.14
MobilenetV2		100	100	100	99.53	100
VGG16	Adam	91	90	89	90	96
VGG19		93	92	91	92.09	96.28
MobilenetV2		99	99	99	99.07	100

TABLE III. EXPERIMENTAL RESULTS FOR MULTIPLE INSTANCES

Multiple instances						
Models	Optim	Prec	Rc	F1	R1	R5
VGG16	RMS	97	98	97	97.64	99
VGG19		98	98	98	98.11	99
MobilenetV2		100	100	100	100	100
VGG16	Adam	99	99	99	99.06	100
VGG19		97	97	97	97.17	99
MobilenetV2		96	97	96	96.70	98

D. comparison with the state of the art

In Table IV, the proposed approach is compared with earlier deep-learning-based iris techniques. The effectiveness of the proposed and existing deep learning-based algorithms for identifying iris is evaluated using the SDUMLA dataset.

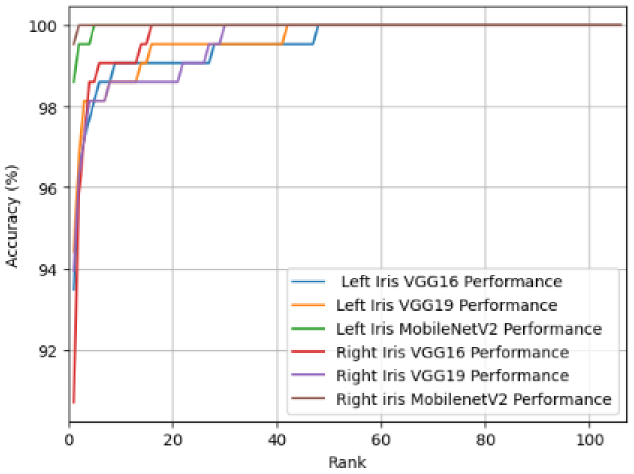

Fig4. The CMC Curves use left and right iris with the RMS optimizer.

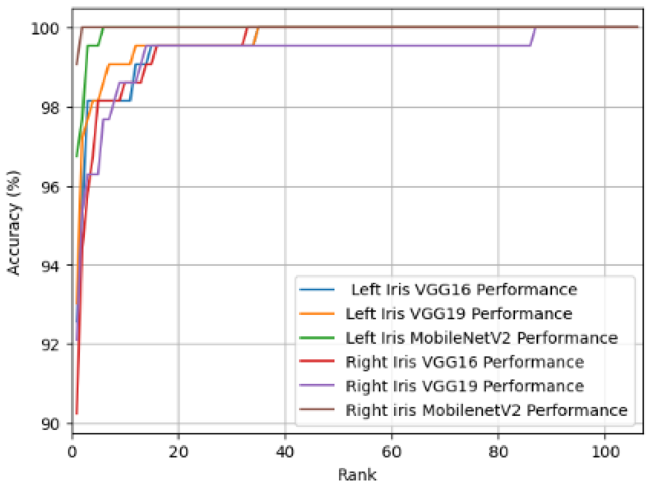

Fig5. The CMC Curves use left and right iris and Adam optimizer.

TABLE IV. COMPARATIVE STUDY

Ref	Year	Method	Accuracy (%)
[15]	2018	CNN (IrisConvNet)	96.99
[16]	2018	CHT+ Rubber Sheet Model	95.75
[17]	2021	PNN	98.68
-	**Our**	**Mobile Netv2**	**100**

V. CONCLUSION AND FUTURE WORKS

This study proposes three CNN models, with experiments indicating that MobileNetV2, when used in a multiple-instance system, is the most accurate and efficient for iris biometric recognition. The effectiveness of this approach was assessed using the SDUMLA dataset, and the experimental results show that it outperforms other similar methods currently in use. Future work will focus on developing a more reliable, secure, and accurate person recognition system by incorporating block attention maps and visual transformers, as well as integrating a fusion model that combines features from multiple modalities to enhance both accuracy and system security.

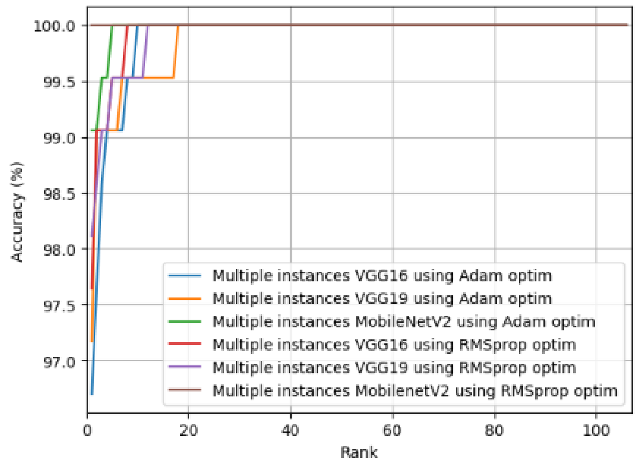

Fig6. The CMC Curves use multiple instances with Adam and RMS optimizers.

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