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Iris Recognition Using Ensemble Learning with perspective of Deep Learning

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Abstract: ***Identity recognition through human iris organ is claimed as one of the famous biometrictechniques due to its reliability promising higher accurate return as compared to other traits.Because of itshigh acceptance, immutability, and uniqueness, iris recognition is the most well-known and widely utilised biometric technique. Daugman's patented techniques are used in iris recognition systems, and these algorithms are capable of producing flawless recognition rates. The work presented in this project involves developing Daugman's algorithms for segmentation and normalisation of human iris images for use in an iris recognition system. These algorithms use a Gaussian blur filter for iris image segmentation and Daugman's Rubber Sheet Model for image normalisation, as well as a Convolutional Neural Network (CNN) for feature extraction. Finally, support vector machine is used to classify the features (SVM). The classification method is carried out utilising RF and KNN. An output is formed by combining the ensemble models of all three models. The MATLAB tool is used to assess the experimental results. Here, we got accuracy of ensemble model is about to 99.5% with FAR is about to 0.1%.***

Key Terms: ***Deep Learning, Convolutional Neural Network, Iris Recognition.***

I. INTRODUCTION

Biometric technology is concerned with determining an individual's identification based on their distinct physical or behavioural features. Physical traits like fingerprints, palm prints, hand geometry, and iris patterns, as well as behavioural characteristics like typing pattern and handwritten signature, provide unique information about a person and may be utilised in authentication applications. Iris recognition is a relatively recent term for the automated technique of recognising individuals based on their iris patterns. The performance of an iris recognition system's subsystems determines its overall performance. The system's performance is defined by the quality of picture capture, segmentation, normalisation, and feature extraction. IRIS recognition is the automated technique of identifying people based on their iris patterns. In big databases, iris recognition algorithms have achieved very low false match rates and very high matching efficiency. This is not totally surprising considering (a) the iris stroma's complex textural pattern, which varies greatly between people, (b) the apparent permanence of its distinctive characteristics, and (c) its low genetic penetrance [1]-[5]. The National Institute of Science and Technology (NIST) conducted a large-scale study that demonstrated the excellent detection accuracy of iris recognition in operational circumstances [6], [7].
According to a 2014 [8] research, over one billion people throughout the world have their iris scans electronically enrolled in various databases around the world. This includes around 1 billion persons in the Unique Identification Authority of India (UIDAI) programme, 160 million in the Indonesian national ID scheme, and 10 million in the US Department of Defense programme. As a result, the iris is expected to play an important part in next-generation large-scale identification systems.Aside from its appealing physical properties, the success of iris identification is anchored in the creation of efficient feature descriptors, particularly the Gabor phase-quadrant feature descriptor established in Daugman's pioneering work [3], [5], [9]. This Gabor phase quadrant feature descriptor (also known as the iriscode) has dominated the area of iris identification, demonstrating exceptionally low false match rates and great matching efficiency. Other iris descriptors proposed by researchers include Discrete Cosine Transforms (DCT) [10], Discrete Fourier Transforms (DFT) [11], ordinal measures [12], class specific weight maps [13], compressive sensing and sparse coding [14], hierarchical visual code-books [15], multi-scale Taylor expansion [16], [17], and others.Readers are directed to [18]-[21] for a comprehensive list of methods suited for iris recognition.
Given the widespread use of classical texture descriptors for iris recognition, such as the Gabor phase-quadrant feature descriptor, it is instructive to take a step back and answer the following question: how do we know that these hand-crafted feature descriptors proposed in the literature are actually the best representations for the iris? Furthermore, can we improve performance (in comparison to the Gabor-based technique) by developing a unique feature representation scheme that might perhaps meet the upper bound on iris identification accuracy with minimal computing complexity?One possible answer is to use current breakthroughs in Deep Learning to discover a data-driven feature representation method. An ideal representation technique for the iris identification job might theoretically be inferred by autonomously learning the feature representation from the iris data. Deep learning

algorithms frequently employ hierarchical multi-layer networks to generate feature maps that improve performance on training data [22]. These networks enable the feature representation method to be immediately learnt and found from data, avoiding some of the problems associated with constructing handmade features. Many computer vision jobs have been substantially revolutionised by deep learning [23], [24]. As a result, we suggest that deep learning approaches, such as Convolutional Neural Networks (CNNs), can be utilised to build new feature descriptors for the iris recognition issue. The limited applicability of deep learning approaches to the problem of iris recognition is owing to the fact that deep learning needs a massive quantity of training data, which most iris researchers do not have at present time. Furthermore, deep learning is computationally costly and necessitates the use of numerous Graphical Processing Units (GPUs).

This discourages the practical deployment of deep learning techniques. Most importantly, there has been no understanding of why deep learning should work for iris recognition, and no systematic analysis has been conducted to determine how best to capitalise on modern deep approaches to design an optimal architecture of deep networks to achieve high accuracy while minimising computational complexity. Simply stacking several layers to create a CNN for iris identification without intuitive insights would be infeasible (because to a lack of large-scale iris datasets in the public domain), non-optimal (due to ad hoc CNN architecture, number of levels, layer configuration...), and wasteful (due to redundant layers). We claim that rather than creating and training new CNNs for iris detection, employing CNNs with established architectures in large-scale computer vision tasks should produce satisfactory results without the time-consuming architecture design phase. The ImageNet Large Scale Visual Recognition Challenge (ILSVRC) [27] is a key source of cutting-edge CNNs. It is held yearly to assess cutting-edge methods for large-scale object recognition and picture categorization.For extracting deep features from pictures, the networks constructed as part of this challenge are typically made accessible in the public domain. Researchers have demonstrated that these off-the-shelf CNN features are extremely effective for a wide range of computer vision tasks, including facial expression classification, action recognition, and visual instance retrieval, and are not limited to the object detection and image classification tasks for which they were originally designed [28]. We will look at the performance of CNNs that have won the ILSVRC challenge since 2012. (before 2012, the winners were non-CNN methods that did not perform as well as CNN-based approaches).

II. LITRATURE REVIEW

A. CNNs - Convolutional Neural Networks

Deep learning approaches, particularly convolutional neural networks (CNNs), have lately led to advancements in a variety of computer vision applications, including object identification and recognition, picture segmentation, and captioning [22–24]. Deep learning has been found to be particularly successful in automating the process of learning feature representation schemes from training data by attempting to emulate the structure and activity of neurons in the human visual cortex through the use of hierarchical multi-layer networks. CNNs are a type of deep learning approach that is used to process photos and videos. CNNs have not only been able to automatically learn image feature representations by utilising repeating blocks of neurons in the form of a convolution layer that is applied hierarchically across pictures, but they have also outperformed several standard hand-crafted feature approaches [29].

Hubel and Wiesel discovered in the 1960s that cells in the animal visual cortex were responsible for detecting light in receptive fields and generating a picture [30]. They also demonstrated how to use a topographic map to illustrate this visual area. Later, Fukushima presented the NeoCognitron, which might be considered the CNN's forerunner [31]. Yan Lecun et al. established the fundamental contemporary CNN architecture, LeNet, in the 1990s for Handwritten Digit Recognition [32]. Many elements of current deep networks are developed from the LeNet, which added convolutional connections and employed a backpropagation mechanism to train the network. When Krizhesky et al. released a CNN named AlexNet in 2012, it greatly outperformed earlier approaches on the ImageNet Large-Scale Visual Recognition Challenge (ILSVRC) [33]. The AlexNet is essentially a bigger version of the LeNet with a more complex structure that is trained on a much larger dataset (ImageNet with 14 million photos) using a considerably more powerful computing resource (GPUs). Many unique designs and efficient learning approaches have been devised since then to make CNNs deeper and more powerful [34-37], delivering breakthrough performance in a wide variety of computer vision applications.With the participation of technological behemoths such as Google, Microsoft, and Facebook, the annual ILSVRC event has become a major arena for recognising the performance of innovative CNN architectures. The "winning" CNNs' depth has gradually grown from 8 layers in 2012 to 152 layers in 2015, while the recognition error rate has decreased dramatically from 16.4% in 2012 to 3.57% in 2015. Figure 1 depicts this incredible growth. Pre-trained CNNs have been open-sourced and widely utilised in various applications, and their performance has been highly promising [28].

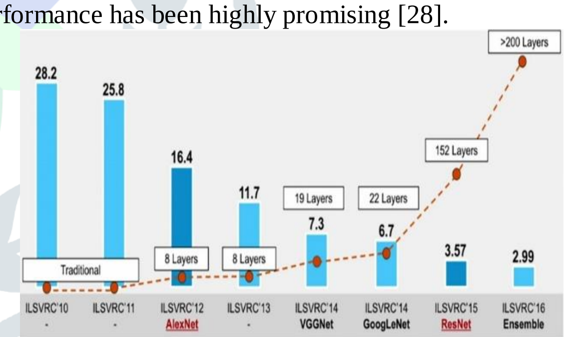

Fig. 1. Recent ConvNets proposed in ILSVRC.

B. In the literature, CNNs for iris recognition

A variety of deep networks have been proposed to improve iris identification performance. DeepIris is a 9-layer network introduced by Liu et al. that consists of one pairwise filter layer, one convolutional layer, two pooling layers, two normalisation layers, two local layers, and one fully-connected layer [38]. On both the Q-FIRE [39] and CASIA [40] datasets, this deep network had a very promising identification rate. Gangwar et al. [25] used more sophisticated layers to build two DeepIrisNets for iris recognition.DeepIrisNet-A has eight convolutional layers (each followed by a batch normalisation layer), four pooling layers, three fully connected layers, and two drop-out layers. DeepIrisNet-B, the second network, adds two inception layers to improve modelling capability. These two networks outperformed the ND-IRIS-0405 [41] and ND-CrossSensor-Iris-2013 [41] datasets. CNNs have also been employed for iris segmentation [42], [43], spoof detection [44], [45], and gender categorization [46] in the iris biometrics field. While self-designed CNNs such as DeepIris [38] and DeepIrisNet [25] have demonstrated promising results, their main limitation is the network architecture, as the number of layers is restricted by the quantity of training data.

The ND-CrossSensor-2013 collection, which comprises just 116,564 iris pictures, is presently the largest public dataset accessible. This figure is far from the millions of parameters that comprise any very deep neural network. Transfer learning can be used to compensate for the lack of a big iris dataset. CNNs trained on other big datasets, such as ImageNet [47], may be used directly to the iris recognition domain. CNN models that have been pre-trained on ImageNet have been effectively ported to a variety of computer vision applications [28]. Minaee et al. demonstrated that, despite being pre-trained on ImageNet to categorise objects from various categories, the VGG model performs relatively well for the task of iris identification [26]. However, several additional sophisticated designs have been presented in the literature since the introduction of the VGG model in 2014. In this study, we will use CNN architectures, especially those that won the ImageNet competition, to do iris identification.

III. PROCESSUNDER RECOGNITION OF PATTERNS

The automatic detection of patterns and regularities in data is known as pattern recognition. It is used in statistics, signal processing, image analysis, information retrieval, bioinformatics, data compression, computer graphics, and machine learning. Iris recognition is one type of biometric technology included in the model. It employs mathematical pattern-recognition algorithms on iris video pictures. At least 1.5 billion people have been recognised using an iris recognition technology throughout the world.

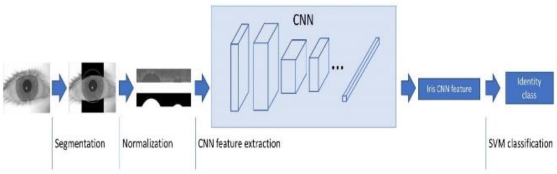

Fig. 2. Off-the-shelf CNNs and categorised using an SVM.

DenseNet-201: Huang et al. from Facebook presented DenseNet in 2016 [37], which connects each layer of a CNN to every other layer in a feed-forward method. According to the authors, using densely linked topologies has various advantages, including "alleviating the vanishing-gradient problem, boosting feature propagation, increasing feature reuse, and significantly lowering the number of parameters." The Appendix contains the detailed architecture of DenseNet-201. In this research, we use the outputs of a predetermined number of dense layers (15) to create CNN Features for the iris identification challenge. It is worth mentioning that various additional strong CNN designs are available in the literature [29], [51].However, we just picked the aforementioned architectures to demonstrate the performance of pre-trained CNNs on the iris identification problem. B. CNN-based iris recognition framework Figure 2 summarises the approach we use to examine the performance of off-the-shelf CNN Features for iris recognition.

Segmentation: Initially, the iris is localised by extracting two circular contours corresponding to the inner and outer iris edges. The integra-differential operator, which can be expressed mathematically as, is one of the most used circle detectors as,

$$max_{r,x_0,y_0}\left|G_\sigma(r) * \frac{\partial}{\partial r}\oint_{r,x_0,y_0}\frac{I(x,y)}{2\pi r}ds\right|, \qquad (1)$$

where I(x,y) denote the input picture and Gα denotes a Gaussian blurring filter. The symbol symbolises a convolution operation, and r is the radius of the circular arc ds that is centred at the point (x_0,y_0). The procedure presented here discovers circular edges by iteratively seeking the greatest responses of a contour given by the parameters (x_0, y_0, r). The iris area is usually hidden by the upper and lower eyelids and eyelashes. The eyelids in such pictures can be localised using the aforementioned operator, but with the contour integration route modified from a circle to an arc. In a given picture, noise masks identify iris pixels from non-iris pixels (e.g., eyelashes, eyelids, etc.).During the segmentation stage, such noise masks are constructed for each input picture and used in the succeeding phases.

Normalization: Due to pupil dilatation and contraction, the area contained by the inner and outer edges of an iris might fluctuate. Before comparing distinct iris photos, the influence of such variances must be reduced. To that aim, the segmented iris area is often mapped to a fixed dimension region. Daugman proposed using a rubber-sheet approach to convert a segmented iris into a fixed rectangular area. This is accomplished by re-mapping the iris area, I(x, y), from raw Cartesian coordinates (x, y) to dimensionless polar coordinates (r, θ), which may be stated mathematically as,

$$I(x(r,\theta), y(r,\theta)) \rightarrow I(r,\theta), \qquad (2)$$

where r is in the unit interval [0,1] and is an angle between [0,2π]. x(r, θ) and y(r, θ) are defined as the linear combination of pupillary $(x_p(\theta), y_p(\theta))$ and limbic boundary points $(x_s(\theta), ys(\theta))$, respectively.

$$x(r,\theta) = (1-r)x_p(\theta) + rx_s(\theta), \qquad (3)$$

$$y(r,\theta) = (1-r)y_p(\theta) + ry_s(\theta). \qquad (4)$$

Another advantage of normalising is that rotations of the eye (due to head movement, for example) are reduced to simple translations during matching.

Fig. 3. Images from the CASIA-Iris-Thousand dataset.

Features extraction: We utilised CNN Densenet-201 to extract features in this case. A Densenet-201 is a sort of convolutional neural network that employs dense connections between layers using Dense Blocks, which link all layers with matching feature-map sizes directly with one another. Using the composite function operation, an output from the previous layer serves as an input to the second layer. The convolution layer, pooling layer, batch normalisation, and non-linear activation layer are all part of this composite procedure**.**One of the main reasons CNNs perform so well on computer vision tasks is because these deep networks with tens or hundreds of layers and millions of parameters are exceptionally good at collecting and storing complicated picture data, resulting in higher performance. We use the output of each layer as a feature descriptor and provide the associated recognition accuracy to study the representation capabilities of each layer for the iris identification task.SVM classification follows the extraction of the CNN feature vector, which is then supplied into the classification module. Because of its popularity and effectiveness in picture categorization, we adopt a basic multi-class Support Vector Machine (SVM) [52]. The multi-class SVM for N classes is implemented as a one-versus-all method, which is similar to merging N binary SVM classifiers, with each classifier discriminating against all other classes. The test sample is allocated to the class with the greatest margin of error [52].

IV. PROPOSED METHOD

Support Vector Machine as a Classifier:

The Support Vector Machine (SVM) is a novel data categorization technology. Given a training set of instance-label pairs (x_i, y_i), i = 1, 2 . . . , l where $x_i \in Rn$ and $y \in \{1,-1\}$ l The support vector machine (SVM) requires the following optimization issue to be solved.

$$\begin{aligned} \min_{w,b,\xi} \quad & \frac{1}{2}w^T w + C\sum_{i=1}^{l}\xi_i \\ \text{subject to} \quad & y_i(w^T\phi(x_i)+b) \geq 1-\xi_i, \\ & \xi_i \geq 0. \end{aligned}$$

The function here maps the training vectors xi onto a higher (perhaps infinite) dimensional space. Then, in this higher dimensional space, SVM determines a linear separating hyperplane with the greatest margin. The penalty parameter of the error term is C > 0. Furthermore, *K (xi, xj) = φ (xi) Tφ (xj)* is called the *kernel function.* [10] The four primary kernel functions are as follows: Six iris image samples from the CASIA database are utilised to train the support vector machine in this work. Four kernel functions are employed for testing, and the best one is chosen for prediction. The remaining iris samples are utilised for identification.

Random Forest Classifier:

Random Forest is a well-known machine learning algorithm from the supervised learning approach. It may be applied to both classification and regression issues in machine learning. It is built on the notion of ensemble learning, which is a method that involves integrating several classifiers to solve a complicated issue and enhance the model's performance. Random Forest is a classifier that uses a number of decision trees on different subsets of a given dataset and averages them to enhance the predicted accuracy of that dataset.Instead than depending on a single decision tree, the random forest collects the forecasts from each tree and predicts the final output based on the majority vote of predictions. The proposed model flow is depicted in Figure 4.

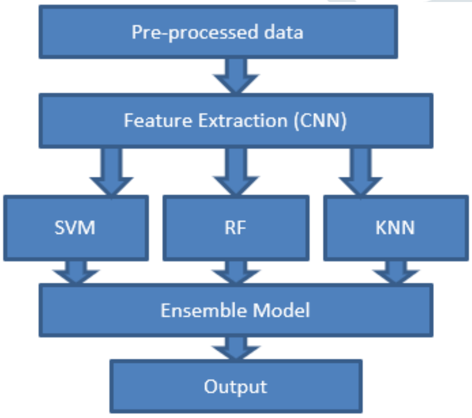

Fig.4. Proposed Ensemble ModelApproach

The Random Forest Algorithm is composed of a number of decision trees, each with a unique set of leaves. It averages the outcomes of many decision trees. Random Forest is a supervised learning system. It is used to solve regression and classification issues. The bagging concept of the ensemble learning RF model will work. All decision and branch nodes are employed in the RF model.

K-Nearest Neighbor:

The k-Nearest Neighbour (k-NN) algorithm is an instance-based supervised learning technique that classifies a new instance by comparing it to previously stored examples in memory that were encountered in training.

The following steps are used to determine the class of an unknown instance:

1. The unknown instance's distance from all other training instances is calculated.
2. The k closest neighbours are determined.
3. Using approaches such as majority voting, the class labels of the k nearest neighbours are utilised to identify the class label of the unknown instance.

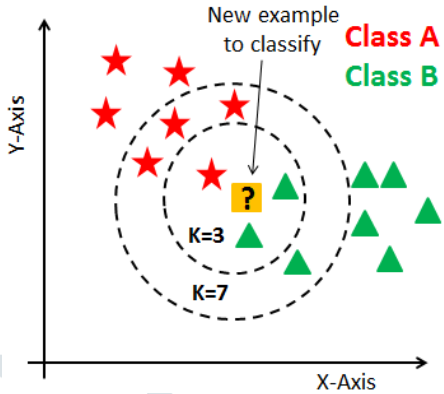

Fig. 5. Sample KNN (K- nearest Neighbor)

KNN is a supervised learning algorithm and one of the most significant non-parameter algorithms in the field of pattern recognition [12]. Without any extra data, the training samples construct the categorization rules. The KNN classification method predicts the category of the test sample based on the K training samples that are the test sample's nearest neighbours, and judges it to the category with the highest category probability.

Boosting Ensemble Modelling:

Ensemble learning is a generic meta-machine learning technique that tries to improve predictive performance by mixing predictions from many models. Although you may create an apparently infinite number of ensembles for any predictive modelling challenge, three strategies dominate the field of ensemble learning. So much so that, rather than being algorithms in and of itself, each is a topic of study that has generated a plethora of more specialised ways. Bagging, stacking, and boosting are the three primary types of ensemble learning methods. Boosting is an ensemble strategy that attempts to alter the training data in order to focus attention on cases that prior fit models on the training dataset have incorrectly identified.The concept of correcting prediction mistakes is essential to boosting ensembles. The models are fit and introduced to the ensemble in a sequential manner, with the second model attempting to correct the first model's predictions, the third correcting the second model, and so on. This often entails the use of relatively basic decision trees that only make one or a few decisions, referred to as weak learners in boosting. The predictions of the weak learners are pooled by simple voting or averaging, with contributions weighted proportionally to their performance or competence.The goal is to create a "strong-learner" out of a slew of purpose-built "weak-learners." The training dataset is often kept intact, while the learning algorithm is adjusted to pay more or less attention to individual examples (rows of data) based on whether they were predicted correctly or poorly by previously recruited ensemble members. For example, the rows of data can be weighted to indicate how much attention a learning algorithm must devote to learning the model.

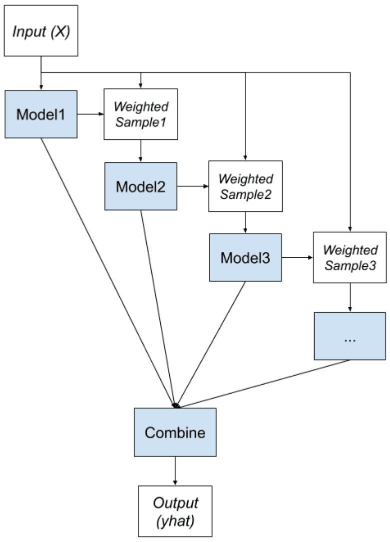

Fig. 6. Bosting Ensemble Model

V. EXPERIMENTAL RESULTS

A. Datasets

Our investigations were carried out on two huge iris datasets: CASIA-Iris-Thousand: This collection comprises 20,000 iris photos from 1,000 participants obtained with the Iris King IKEMB-100 camera [40]. Figure 3 shows some representative photos from the two datasets.

B. Performance metric of Existing Model

We use the Recognition Rate to report performance. The fraction of successfully identified samples at a predetermined False Acceptance Rate is computed as the Recognition Rate (FAR). We choose to publish the Recognition Rate at FAR = 0.1% in this experiment. The Gabor phase-quadrant feature [3] served as the baseline feature description for comparison.

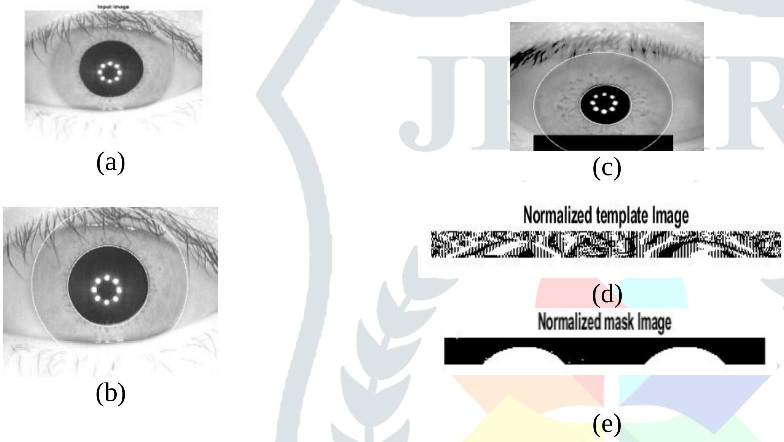

Fig. 7. (a), (b), (c), (d) and (e) are the results obtained to SVM classifiers.

The Hamming distance [3] is a common matching operation using this descriptor. On theAccuracy of iris recognition by using DenseNet-201CASIA-Iris-Thousand datasets, this baseline obtained recognition accuracies of accuracies of SVM 98.3%.respectively.

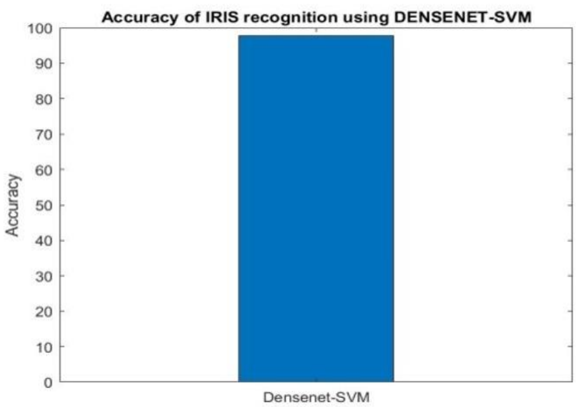

Fig. 8. Accuracy of iris recognition by using DenseNet-201

C. Experimental setup

Every subject's left and right iris pictures are regarded as distinct classes. Thus, the the CASIA-Iris-Thousand dataset has 2,000 classes. We chose 70% of the data for each class at random for training and 30% for testing. It should be emphasised that the training pictures were only utilised to train the multi-class SVMs; the pre-trained CNNs were not altered in any way utilising the training data. This is one of the primary advantages of adopting pre-trained CNNs. For iris segmentation and normalisation, we utilised USIT v2.2 from the University of Salzburg [53]. This software takes each iris picture as an input, segments it using inner and outer circles, then normalises the segmented region. Each iris picture is sent into this software, which then segments it using inner and outer circles and normalises the segmented region into a rectangle of size 64 256 pixels. We used MATLAB [54] to develop our technique for CNN feature extraction. MATLAB is a freshly released deep learning framework from Facebook that combines the benefits of MATLAB. The dynamic graph computation and imperative programming characteristics of this framework are the most sophisticated, making deep network coding more versatile and powerful [54].In terms of our trials, MATLAB provides a large choice of pre-trained off-the-shelf CNNs DenseNet-201, making our feature extraction process considerably easier. We utilised theSVM [55] for classification, with a MATLAB wrapper written in the library [56] for simplicity of interaction with the feature extraction process.

D. Performance analysis of Proposed Model

As previously established, multiple layers encode varying amounts of visual material. We measure the recognition accuracy after utilising the output from each layer as a feature vector to represent the iris to analyse the performance related to each layer. Figure 4 depicts the recognition accuracies for the two datasets: LG2200 and CASIA-Iris-Thousand. Surprisingly, for all CNNs, recognition accuracy peaks in certain middle layers. Layer

10 for VGG, layer 10 for Inception, layer 11 for CNN, and layer 6 for DenseNet-201 on the CASIA-Iris-Thousand.DenseNet-201 on the CASIA-Iris-Thousand dataset. The features of each CNN can explain the variation in "peak layers." Because Inception employs sophisticated inception layers (each layer is a network within a bigger network), it converges to the peak faster than others KNN, RF, SVM, on the other hand, is particularly good at enabling the gradient to flow through the network.

Fig. 9. On thedataset CASIA-Iris-Thousand, the recognition accuracy of different layers in CNNs was tested.

causing the network to function effectively at greater depth, resulting in a later peak in iris recognition accuracy DenseNet's-201 extensive connections let neurons to easily interact, resulting in the greatest detection accuracy among all CNNs for the iris recognition challenge.

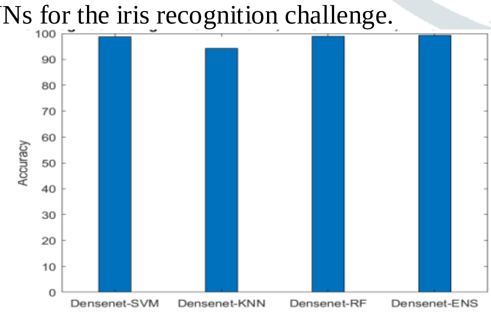

Fig. 10. Accuracy of Iris Recognition Using SVM, RF, KNN, Ensemble learning

As can be observed, peak results do not exist in the CNNs' subsequent layers. This is due to the fact that the normalised iris picture is not as complicated as the images in the ImageNet dataset, which contain huge structural changes in a wide variety of items. As a result, a huge number of layers are not required to encode the normalised iris. As a result, maximal accuracy is reached in the intermediate layers. DenseNet-ENS gets the greatest peak recognition accuracy of all four CNNs models, with 98.3% and 94.6%. accuracies of SVM 98.3%, KNN is 94.6%, RF is 98.4%,on the CASIA-Iris-Thousand dataset. RF and KNN exhibit equal peak recognition accuracies of 98.0% and 98.2% on the CASIA-Iris-Thousand dataset at layers 11 and 10, respectively, and 98.3% and 99.3% on the CASIA-Iris-Thousand dataset at levels 12 and 10, CASIA-Iris-Thousand datasets, respectively. KNN ever-increasing identification accuracy suggests that the number of layers examined in its design may not capture all of the discriminative visual information in iris pictures.

VI. CONCLUSION

We tackled the challenge of iris identification from a deep learning perspective in this study. Our findings indicate that off-the-shelf pre-trained CNN features, albeit originally learned for object identification, may be adapted to the iris recognition challenge. We obtain state-of-the-art recognition accuracy in large iris dataset CASIA-Iris-Thousand, by harnessing state-of-the-art CNNs from the ILSVRC challenge and applying them to the iris identification problem.These first results demonstrate that off-the-shelf Ensemble Learning features may be successfully translated to the iris identification issue, efficiently extracting discriminative visual features in iris pictures and removing the time-consuming feature-engineering work. CNNs' use in automated feature engineering is crucial for learning novel iris encoding strategies that can help large-scale applications. Daugman's IDO method is used for picture segmentation. Daugman's Rubber Sheet Method is used for normalisation. CNN Dense Net-201 is used to extract features. SVM-based classification process Using the CNN technique to train an RF classifier. Using the CNN technique to train a KNN classifier. Increasing accuracy with ENSEMBLE LEARNING of the SVM,RF, and KNN algorithms.Output of the model accuracies of SVM 98.7%, KNN is 94.6%, RF is 99.2%, Ensemble is 99.5%.

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