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PERFORMANCE ANALYSIS OF DEEP LEARNING MODELS FOR IRIS RECOGNITION

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Abstract—Security and authentication of an individual today is vital to many applications that are ranging from the banking sector to the cyber forensic field. Biometrics which are based on "what an individual is" rather than "what an individual possesses" has proved to be the best individual authentication system. The iris biometric being universal, unique, permanent, collectible and reliable than other existing biometric systems is the best security solution for various online and offline applications. The existing iris recognition methods which are segmentation/normalize based, confront many problems when the representation of data attenuates the differences due to heavy occlusion of eyelashes, translation, scale, rotations, motion blurs, pupillary dilation, and non-regular reflections around the eyes in a user non-cooperation environment. Deep-learning classification models are capable of accurately identifying the genuine and imposter comparisons by analyzing the displacements between the corresponding patches in pairs of iris images even in severely noisy environments. The iris texture of an individual differs between the left and right eye and varying even between the eyes of the twins makes it a more secure way of authentication when compared with other biometric recognition systems. We have conducted experimentation on four well-known data sets (CASIA, Polaris IITD, Ubiris, and MMU), concluding positively about the effectiveness of the proposed CNN-based deep learning algorithms.
Keywords— Convolutional Neural Network, Deep Learning, (CNN), Iris Recognition, Biometric.

I. INTRODUCTION

Biometrics are highly dependable systems up to this date for ensuring individuals' secure and authentic transactions. Among the behavioral and biological biometric systems, iris is the well-accepted biometric for majority of the applications. It is a visible highly protected internal organ with an extremely data-rich physical structure, high reliability, high security, and a high degree of randomness and variability stands prominent, irrespective of age, twins, expressions, pose, and makeup [1,2]. Most of the iris systems are designed in a highly controlled cooperative environment, which is the major reason for failure in non-cooperative environments, i.e., noisy, off-axis rotations, motion blur and partially open eyes. Iris recognition system, despite achieving a high accuracy rate lags due to the time-consuming preprocessing and normalization process. Extracting effective features, even in intense environments is the major important stage in a lot of object recognition and computer vision tasks. In this paper, we evaluate the recently developed deep-learning based approaches for iris recognition. Their suitability is analyzed experimentally on standard iris datasets which will help the research community/industry personnel for designing the authentication system based on iris biometric. We experiment with an iris recognition system where the features are extracted from the Image Net dataset. The features learned from these deep architectures can be transferred to analyze the performance of the related tasks with or without adaptation to the new task using the transfer learning technique. The reduction in training time and increased performance with fewer data to train are the major benefits of the transfer learning technique. The experimental study is tested on four public datasets namely Polaris IITD iris database, CASIA-Iris-V1, Ubiris, and MMU.

II. LITERATURE SURVEY

In [3], airis system based on semantic segmentation structures with high-proficiency deep learning-based iris segmentation approach was introduced. This proposed method was considered as a foresee of precise and unique iris system using numerous past CNN-based iris segmentation strategies. The proposed methodology accomplished best-in-class execution on different benchmarks. Further, as an overall drop-in substitution, iris segmentation strategy would altogether improve the exhibition of non-helpful iris acknowledgment.

In [4], a Self-Learning computational intelligence system was proposed. The Gabor channels generated the highlight vector from iris highlights. The neural net was introduced including vectors, and afterward, directed for iris recognition. The Hough change from the edge picture was obtained using a dim scale iris image. The iris ring from the picture is extracted by eliminating the pointless parts and translated into a square shape picture of 64x512 pixels. A low-pass Gaussian channel is applied to eliminate disorders and to obtain a normalized picture having a high concentration of recurrence. It is then converted to a 1-D cluster of 160x1 as an element vector from AAD esteems.This one-dimensional cluster is applied as a contribution to the refined neural organization for verifying a certified client. The proposed method separated comprehensive and restricted information about the iris. The execution showed results that this calculation can successfully confirm individuals by recognizing their irises.

In [5], a variation of UNet based on squeeze modules is proposed to reduce the preparation timefor iris segmentation was proposed. This technique helped in improving the capacity efficiency by minimizing the number of boundaries included. This classification-based method utilized the prospects and the advancements of deep learning techniques. The less unpredictable model discovered prevented over-fitting. The intuitive and robotized age of ground truth reduced the time complexity of specialists in creating a precise segmentation.

In [3], the researchers have presented another methodology for more precise iris acknowledgment. Compulsory student expansion and scale changes during the iris imaging was determined andthe critical hotspot for the oftentimes noticed iris miss happenings wasestablished.The methodology involved fusion of convolutional bit to learn and achieved high iris coordination. Such a methodology additionally improved the engineering of the deep neural organization. The trial results utilizing within database and cross-information base execution assessment, on three diverse public iris picture data sets prove the adequacy of this methodology. Iris pictures innately represent visual data and additionally improve the iris picture coordination with exactness.This methodology utilized the Mask Net which was independently prepared. Improvement of a start-to-finish engineering using Mask Net is deeply attractive and part of additional work in this domain.

In [6], a triple novel, open-sourced irises segmentations apparatuses dependent on traditional inverted neural nets was prepared for iris segmentations task, and not open-sourced beforehand in iris recognition setting.Deep residual networks (He, 2016), CNN joining expanded convolutions and SegNet, where segmentation aftereffects of two model iris pictures showed the strategy of how to apply the subsequent sporadic segmentation covers to a traditional, Gabor wavelet-based iris coordinating, alongside the appraisal of the subsequent iris recognition exactness acquired. Thus, the performance of the CNN was clear in the outcomes of the segmentation of the iris data. in which many iris data have been obtained using various groups and various sensor data including those taken from CASIA Iris and UBIRIS postsMortem Irises v2 posthumous iris pictures.

In [7], an iris segmentation strategy using deep convolutional neural nets was proposed based on the diagram cut. The three convolutional layers out of 16 layers are utilized for extraction having varying convolution window sizes. The expansion strategies overcome the over-fitting issue and make the primary design stronger in retaining the preparedinformation. The proposed method accomplished 98.88% accuracy with a huge improvement in testing stage. The procedure applied new increment strategies to the architecture of confirmed picturesutilizing pre-trained structures decreases the time complexity in the preparation stage and improved the testing accuracy.

In [8], an edge and learning-based hybrid technique was proposed for iris recognition. A well-planned faster R-CNN with six layers was built for finding and grouping the eyes. AGaussian combination model with the bouncing box found by faster R-CNNwas proposed to arrange the pupillary region. The limit of the limbus was constructed utilizing five key limit points.

The iris recognition and filtering were investigated in [9], where a residue convolution neural net, learnt jointly from the features representational and performance recognitions. In this work, an iris recognizing frameworks was built under the concept of transfer learning technique. Previously enrolled convolutional neural network parameter settings were performed using famous IIT Delhi's iris recognition dataset. The iris database had 2240 iris pictures captured from 224 different persons.

In [10], the fundamental focus was to carry out a deep learning procedure for improving segmentation execution on non-decent quality iris pictures. The principal idea is to utilize theinformation for preparing tests to emulate the original pictures acquired from handheld cameras. The network will perform well on the raw data by calculating the cumulative sumfrom the sufficient information made available to the network. It begins with 3x3 portions, with an isolated pooling layer which adds an undesirable noise. The skip associations utilized in the organization improves thesegmentation of unrestricted low-quality photos shot in the outdoors.

The deep learning models considering VGG and ResNet-50 for iris recognition was proposed in [11]. The researchers' utilized exchange gaining from the face space and proposed a particular information increase method for iris pictures. To improve speculation and stay away from over-fitting, two Convolutional Neural Network (CNN) models prepared for face recognition were stored and afterward utilized as iris detection (or highlights). From the correlation of the acquired outcomes, it was observed that the methodologies utilizing just depicted non-standardized and non-fragmented iris picture as a contribution for the organizations producing new best in class results for the authority convention of the NICE.II rivalry.

In [12], the effectiveness of the iris recognition frameworks that are off point were increased convolution neural network [20]. As the deadlock iris recognition frameworks are significantly less compelled than conventional frameworks, the iris improves the exhibition of off-angle iris recognition in customary and untraditional iris recognition systems. As a principal commitment,the utilization of the convolutional neural organizations (CNNs)first included the investigation of the conventional iris recognition structure with segmentation, standardization, and CNN-based encoding and coordination. In nontraditional structures, the creators utilized the iris pictures without segmentation to examine the impact of periocular regions.

In [13], the CNN method is based on adjusted roundabout HT, which characterizes the ROI by the marginally expanded range of the iris. VGG-face calibration was applied to the information obtained from the return for money invested. The CNN layer gives two yield highlights. In this manner, considering these highlights, non-iris focuses are characterized to track down the genuine iris limit. The tests with NICE-II and MICHE databases showed that this technique accomplished higher correctness of iris segmentation contrasted with the cutting-edge approaches. Moreover, in that technique, it is important to diminish the handling time for CNN-based characterization with the window covers separated from the principal stage. To take care of these issues, the creators considered semantic segmentation organization (SSN) which can utilize the entire picture as information. This technique with low performance still gave the accurate ID of the genuine limit even in serious situations. The primary phase of this technique included base cap separating, clamor expulsion, canny edge locator, contrast upgrade, and adjusted HT to fix the iris limit. In the subsequent stage, CNN with the picture contribution of 21X 21 pixels was utilized to fit the genuine iris limit. By using the second stage segmentation technique just inside the ROI characterized by the surmised iris limit, a decrease in the handling time and blunder of iris segmentation was observed. At last, to lessen the impact of splendid SR in iris segmentation execution, the SR districts inside the picture contribute to CNN and are standardized by the normal RGB worth of the iris area.

III. METHODOLOGY

Deep Learning is a subset of machine learning focusing on algorithms to model the human brain called artificial neural networks. Deep learning is an excellent solution when the input consists of voluminous data for processing. CNN is a supervised deep learning technique with three components such as convolution, pooling, and fully connected layer. The convolution layer learns the image features by moving the filter around the image with the configured step size called stride. It calculates the inner product between the pixel values and the parameters by moving horizontally and vertically based on the selected stride window on an image, until it covers the whole image. The pooling layer reduces the computational cost, the training time of the network,the number of parameters, and overfitting by learning invariant features and acting as a regularizer. The fully connected layer is a feed-forward neural network that flattens out the last pooling or convolution layer and fully connects the neurons to the output layer. The size of kernels, number of kernels, length of strides, and pooling size, which directly affect the performance and training speed of CNNs.In this paper, an iris recognition based on transfer learning approachfine-tunedon a pre-trained convolutional neural network (trained on ImageNet), on various popular iris recognition datasets is presented. Deep learning using CNN Models such as Mobile Net, Inception, Nasnet, Efficient Net, and VGG 16/19 are applied for Polaris IITD, Ubiris, MMU and Casia iris datasets. Mobile Net convolutional neural based on a streamlined architecture uses depth wise separable convolutions to build light weight deep neural networks with low latency for mobile and embedded devices.A convolutional neural network architecture from the Inception family with 48 Layers improves label smoothing, factorizes 7 x 7 convolutions, and uses an auxiliary classifier to propagate label information lower down the network.

NASNet-Large is a 22 layered convolutional neural network that classifies a wide range of images based on learnt rich feature representations from an image of input size 331-by-331.Efficient Net convolutional neural network architecture uniformly scales all dimensions of depth/width/resolution using a compound coefficient which is a set of fixed scaling coefficients. Efficient net has 8 different models B0 - B7 with a total of 237 and 813 layers respectively. VGG increases the model performance by increasing the depth of CNNs.The performance of the deep learning models is evaluated based on training accuracy, validation accuracy, testing accuracy, F1-score, sensitivity and precision. The performance obtained using the deep learning techniqueisthen compared with the performance of traditional texture-based algorithms like local binary pattern, local ternary pattern, and principal component analysis.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

We use Polaris IITD, Ubiris, MMU, and Casiadatabase to carry out the experiments. Polaris IITD iris dataset consists of 2240 iris images with resolutions 224x 64, Ubiris iris dataset consists of 1877 iris images with 200x150 resolutions, MMU consists of 995 iris images with resolution 320×238 and Casia dataset with 756 iris images of resolutions 320x280. We perform our experiments using Tensor Flow 2.x framework with GPUs on Google Collaboratory. We split the dataset into training, validation and testing using a stratified sampling technique. Each convolution layer relates to rectified linear unit (ReLU) activation function with the final extracted features fed to fully connected layer with SoftMax as activation function. The augmentation and the batch normalization technique are also adopted to reduce the internal covariate shift and instability in distributions of layer activations in deeper networks and to avoid the effect of over-fitting in our experiment, we use 60 percent for training, 20 percent for validation and 20 percent for testing. The architecture for our neural network is fine-tuned by evaluating the training and validation losses under different hyper parameter settings. The hyper parameter involves a batch size of 32 layers with 50 epochs, the momentum of 0.9, dropout of 50 percent, label smoothing of 0.1, categorical cross entropy as the loss function, and widely used optimizer Stochastic Gradient Descent (SGD) with a learning rate of 0.01with early stopping technique. The performance of different deep learning model for Polaris IITD, Ubiris, MMU and Cassia dataset are summarized in the graph below.

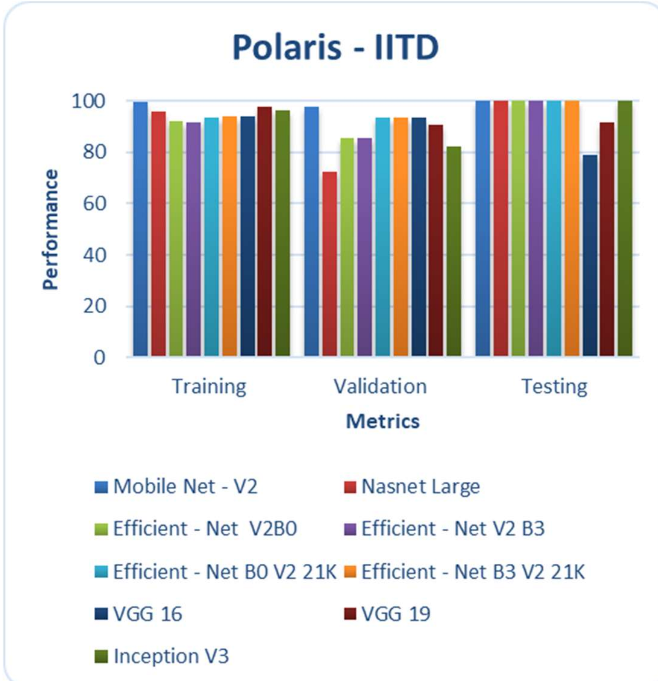

Fig 1: Performance analysis with Polaris Dataset

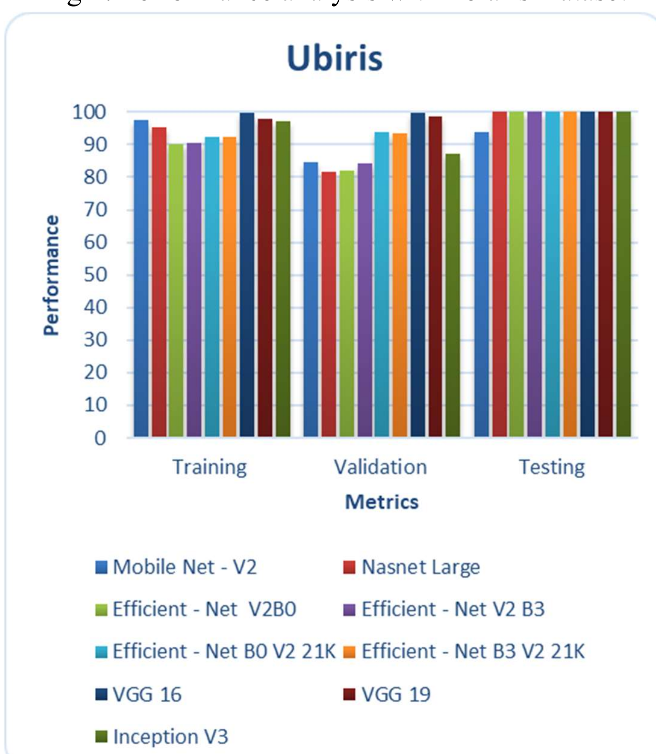

Fig 2: Performance analysis with Ubiris Dataset

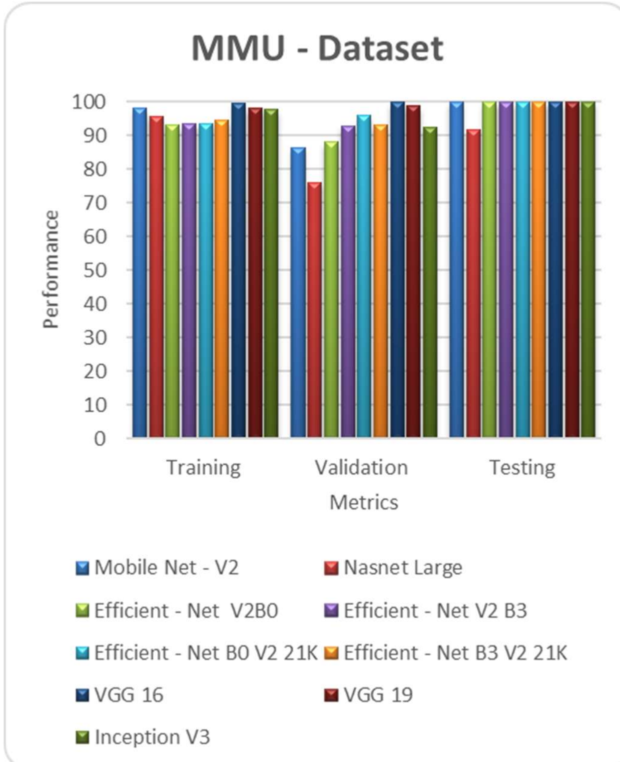

Fig 3: Performance analysis with MMUDataset

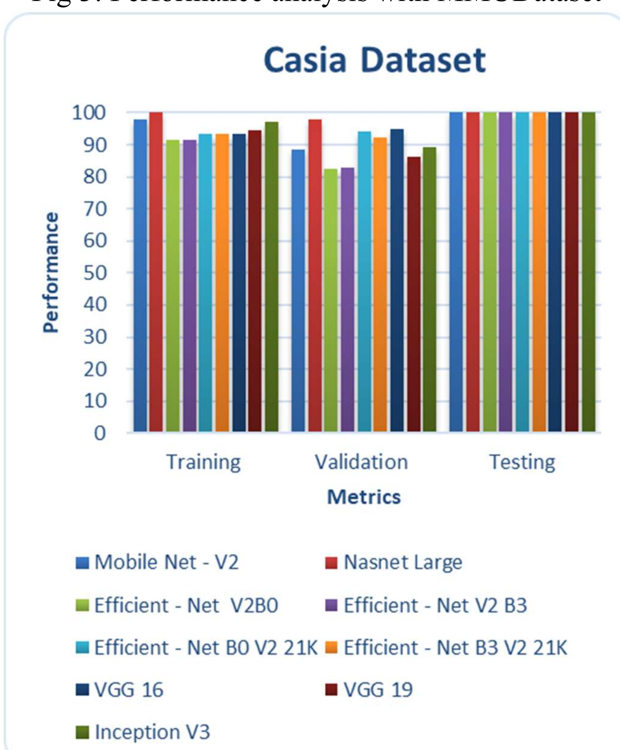

Fig 4: Performance analysis with Casia Dataset

The performance of deep learning algorithms is alsocompared with the accuracy obtained from traditional texture-based algorithms such as local binary pattern, robust local binary pattern, principal component analysis and local ternary pattern. Nasnet model gives the best recognition accuracy compared to all the other models used for iris recognition. Local Binary Pattern (LBP) is an efficient texture based operator used to labeling the pixels of an image by thresholding technique.The thresholding is applied on the neighborhood of each pixel and considers the result as a binary number. The center pixel is considered as the thresholding value in a NXN image. If neighbor pixel has higher gray value than the threshold value then one is assigned to that pixel, otherwise it gets zero value. The resultant matrix contains only ones and zeroes. The obtained binary values from the matrix is then concatenated to obtain a binary code. The binary code calculated is converted to corresponding decimal value and then replaced with the center pixel as shown in figure 5.

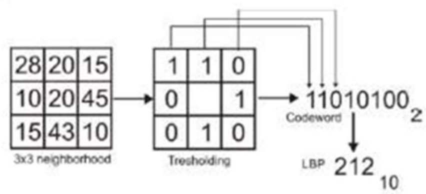

Fig 5: Local Binary Pattern

RLBP minimizes the intra-class variance by complimenting the maximum code obtained from LBP making it more robust to noise and fluctuations.

The threshold pixel has three values (-1,0,1) in LTP and is more robust to noise than LBP. The PCA identifies patterns in data by detecting the correlation between variables to reduce the dimensionality.

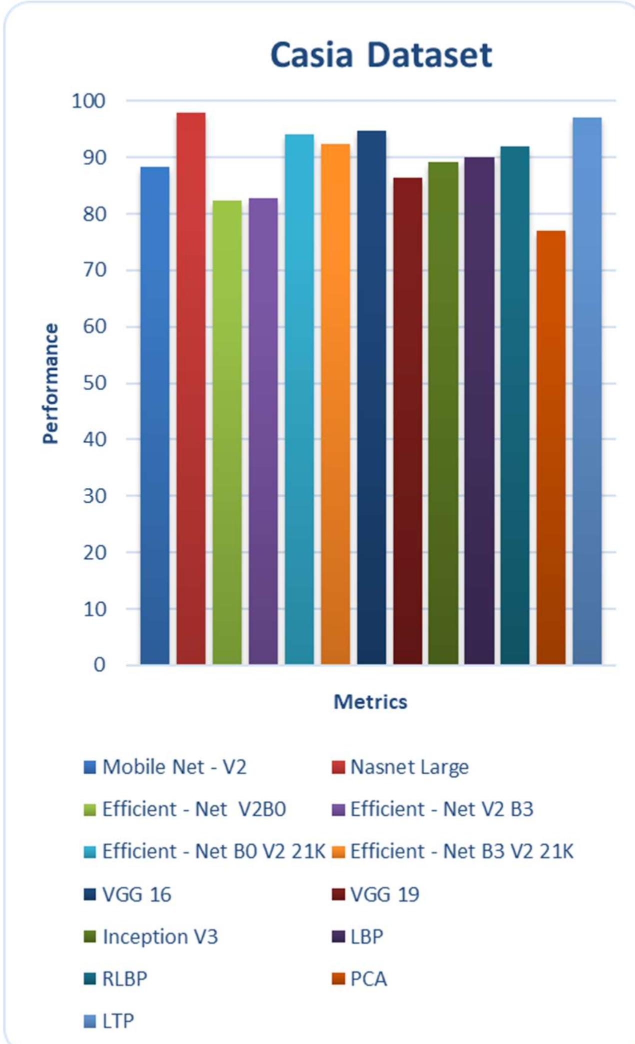

Fig 6: Comparison of DL algorithms with LBP and its variants

V. CONCLUSION AND FUTURE SCOPE

In this work, we provided a performance analysis of the recently developed deep learning-based models for iris biometric recognition. From the above analysis, Mobile net model has better performance on Polaris IITD dataset, VGG16 outperforms other deep learning models on Ubir is and MMU dataset and Nasnet large model performs well on Casia dataset. Deep neural models have shown promising improvement over classical models. Some biometrics such as face, fingerprint have attracted a lot more attention due to their large-scale industrial applications, and availability of variety of datasets. Although deep learning research in biometrics has achieved promising results, still there is a great room for performance enhancements in different directions, such as ensembling deep learning algorithms, creating larger and more challenging datasets, addressing model interpretation, fusing multiple biometrics, and addressing security and privacy issues.

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