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Convolutional Neural Network For Iris Recognition

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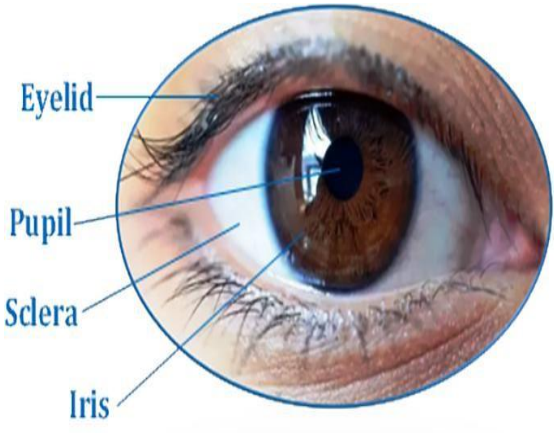
Abstract: *Due to their capacity to overcome a number of significant shortcomings in unimodal biometric approaches, such as noise affectability, populace coverage, intraclass diversity, etc., multimodal biometric methods have been widely adopted by many implementations. Non-universality and spoofing vulnerability Based on the building of a deep learning model for images of a person's (right & left) irises, a multimodal biometric real-time technique is proposed in this study. The features of transfer learning methods and convolution neural network characteristics have been combined to create this system. Through this research, the back-propagation technique was the training system of choice, with Adam's optimization approach being employed to change weights and alter learning rates as the learning process progressed. Two publicly available datasets are gathered to evaluate the system's effectiveness.*

Key words: *Multimodal biometric, Iris recognition, deep learning, Convolutional Neural Network (CNN), Transfer learning*.

1. INTRODUCTION

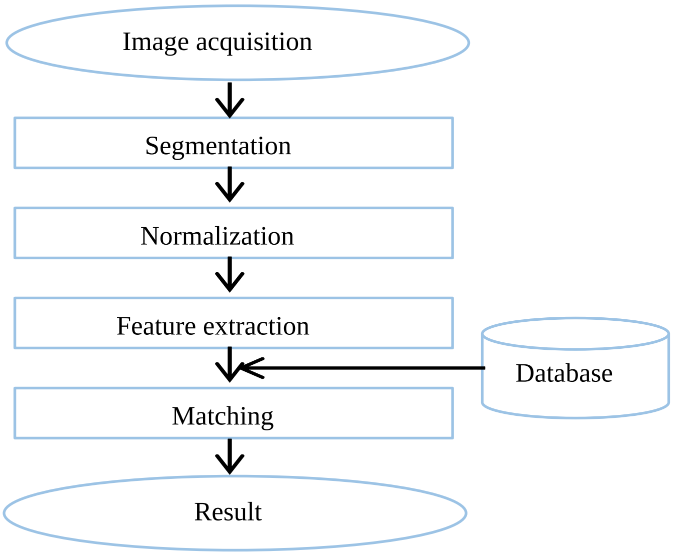
Human identity and biometric authentication are essential and trustworthy ways for establishing goals. Applications for biometric systems are being created that can be used in automated processes to identify people more successfully and uniquely than with traditional approaches. Such as passwords. A physical or behavioral feature is used in biometrics, an automatic method for authenticating a person. Physical characteristics like the face, voice, fingerprints, and even the iris, as well as behavioral characteristics like keystroke dynamics, dynamic signature identification, and speaker identification, are attributes that will be created or acquired. The iris feature is extensively used in high-performance and reliable biometric systems because it has a number of important advantages over other biometric features (such a fingerprint or face). Despite these advantages, the application of the iris identification method is challenging since the iris acquisition procedure may collect unimportant elements such Eyelashes, Eyelids, Pupils, Sclera, Iris which can significantly affect the outcomes of iris segmentation and recognition.



2. RELATED WORK

The authors offered a thorough overview of related research that included several recent Iris Recognition analysis experiments in this section. The linked study that comes after discusses multiple iris recognition methods as a whole system with various classifiers. Some of the datasets and classifiers stated in the linked work are employed in our suggested system. The final image was provided to CNN as an input. Using open datasets including CASIA-Iris-V1, IITD iris databases, CASIA-Iris-Interval, and CASIA-Iris-thousand, the suggested model was tested. The outcomes demonstrated that the accuracy of the proposed system is greater than that of characterizing photographs that have been normalized. Based on the available research, it was obvious that greater attention should be placed on the pre-processing and segmentation stages for an iris-based biometric system to become trustworthy and accurate.

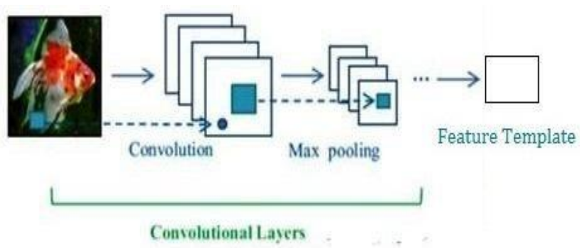
3. METHODOLOGY



4. PROPOSED SYSTEM

This section gives a quick summary of the proposed deep learning approach, which applies two methods of discriminative learning: a transfer-learning CNN.

Convolutional neural network: Deep learning network design known as Convolutional Neural Networks (CNN) is capable of autonomously learning representations of picture information. It performed better than other conventional handcrafted technical characteristics as well. An input layer, a convolutional layer, a pooling layer, a fully connected layer, and a Soft Max layer make up the Convolutional Neural Network (CNN) architecture in general. Alternating layers of locally connected convolutional layers make up a CNN. The same number of filters are included on each layer. A classifier is created using down sampling layers and fully connected layers. Every neuron accepts input from a small piece of the layer above thanks to the local receptive field. The convolution filter is the same size as well. Convolutional and down-sampling layers both employ local receptive fields. The convolutional layer is subjected to weight sharing in order to regulate capacity and reduce model complexity. Last but not least, nonlinear down sampling was utilized in the down sampling layers to reduce both the number of free parameters in the model and the spatial size of the image. CNN excels at teaching and is incredibly productive. In addition, the layers of the convolutional neural network are as follows: **The Convolutional Layer, The Pooling Layer.**

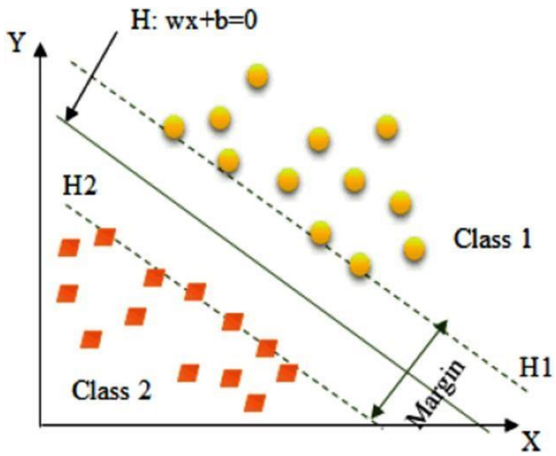


5. ALGORITHM

while current epoch< specified epoch **do**
while t<N/ mini batch size **do**
Forward prop. with mini batches of training data
Compute the error function
Weight update with gradient descent
Backprop. of the gradient to previous layers
endwhile
endwhile

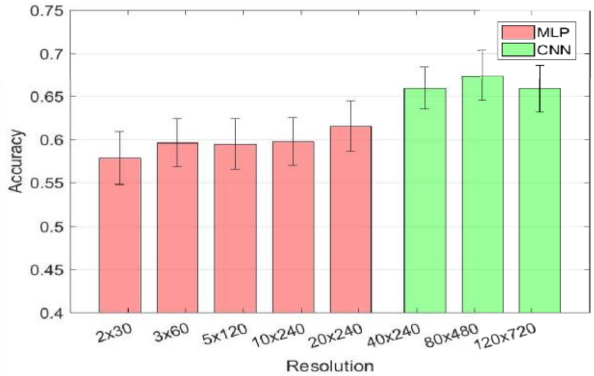
6. CLASSIFICATION

Support Vector Machine: Support vector machines (SVM), which operate under the structural risk minimization principle, do pattern recognition. SVM is viewed as a binary classifier that efficiently distinguishes between the two classes of data. Finding the ideal hyperplane between two different classes of data and turning a non-linearly separable classification problem into a linearly separable problem are the two main components of building an SVM classifier



7. FEATURES

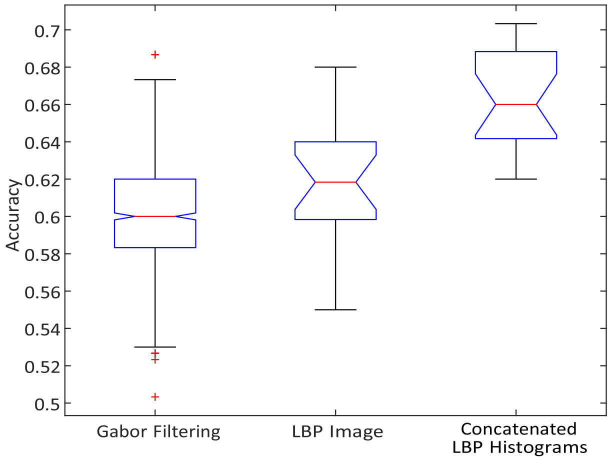
Data- Driven Features: Hand-crafted techniques (such Gabor filtering, LBP, etc.) and data-driven techniques, in which the raw pixel intensity is fed into neural networks that may "learn" characteristics, are both investigated as ways to extract discriminative features from the normalized iris images.



Hand-Crafted Features: Popular examples of tailored feature extraction methods include Gabor filtering and LBP. Gabor filtering is carried out as part of the typical procedure for developing the "iris code". Each row of the normalized iris was subjected to 1-Dimensional Gabor filtering in the studies presented here. We decided to investigate a set of wavelengths that are comparable to those used for iris identification. Previous research on gender-from-iris employed LBP. These parameters might not be the best for gender classification since the fundamental goal of iris recognition is to maximize the differentiation between individual subjects and attenuate any non-person-specific traits (such as gender, race, eye colour, etc.).

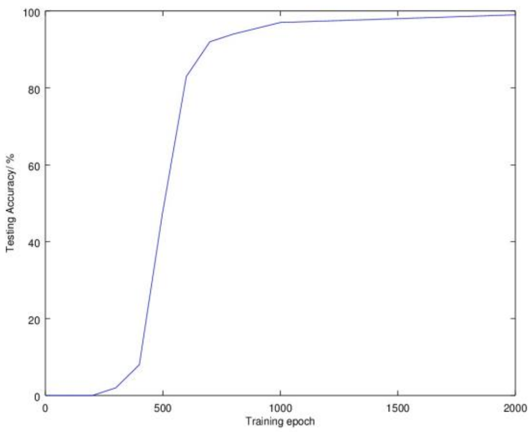
TABLE 1. The Prediction Accuracy Corresponding To Different Number of Training Epoch

Epoch	**10**	**50**	**100**	**200**	**300**	**400**
Accuracy/ %	0	0	0	0	2	8
Epoch	**500**	**600**	**700**	**800**	**1000**	**2000**
Accuracy/ %	48	83	92	94	97	99

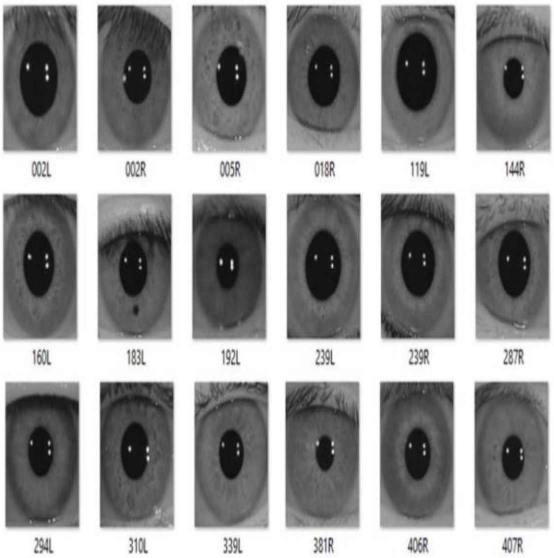


8. ANALYSIS

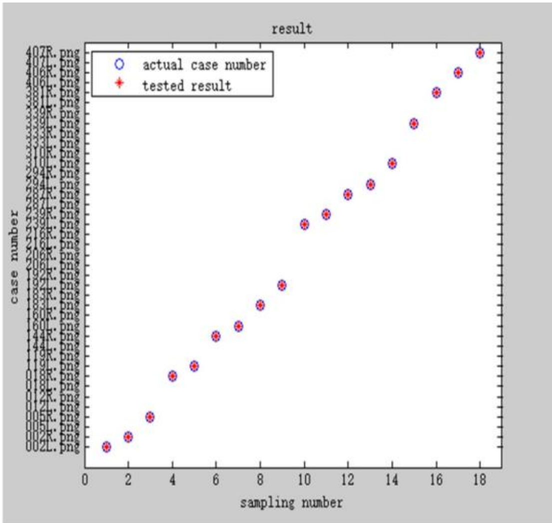
Testing: The dataset is divided into a training set and a testing set. The training set is used to train the model with a predetermined number of training epochs, and the testing set is used to assess the model's performance. To establish a benchmark for the impact of the number of training epochs on the testing accuracy, we began the model's training with 100 training epochs. The model had an accuracy of 0% after only 100 training iterations and was unable to identify any iris images in the testing set. We ran the training data through the model several times because the prediction performance of the model is strongly correlated with the number of training epochs before over-fitting takes place.The prediction results for different number of training epoch: **a. 10, b. 500, c. 1000, d. 2000**



Real- Time Recognition: There are two cases that are absent from the testing set as a result of the training and testing sets' random division (Case 119L, 310L). Hence, we ran a real-time recognition test after the model had been trained with 2000 training epochs. It also seeks to confirm how well the trained model performs in terms of recognition. The photos for 119L and 310L were explicitly added to the real-time recognition testing collection, which also includes other randomly chosen images.



Iris samples used in real-time recognition



Prediction result of real-time recognition

9. CONCLUSION

A promising area of security concern is iris recognition, which uses a person's iris to identify them. Calculating the iris characteristic makes it possible to identify every person in a population. Iris features cannot be lost or forgotten, they are difficult to reproduce, share, or distribute, and they require the individual to be present at the time of verification, which makes iris identification a desirable field. Nonetheless, feature extraction and classification algorithms play a major role in the improvement of accuracy. This study emphasizes feature extraction and categorization as a result. For feature extraction and classification, two relatively new and effective machine learning techniques are CNN and SVM. We selected these techniques, and our experimental findings have shown that.

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