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Comparison of Supervised and Unsupervised Learning Methods for Iris Recognition using MATLAB

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***Abstract*—A stable, authentic, and reliable system is necessary to control and secure areas. This biometric recognition system uses Iris Patterns that differ in every individual for identification. The Iris Recognition system consists of Image Acquisition, Segmentation, Normalization, and Identification. Iris images are downloaded from the CASIA Iris V1.0 database. Image Subtraction and Binarization are done to define the Iris and Pupil boundary. To separate the Iris region from the image, Iris Segmentation is performed by applying Canny Edge Detection and Circular Hough Transform. Daughman's Rubber Sheet Model converts normalized images into a rectangular block. Here, an unsupervised and supervised learning approach is used for authentication. The entropy of normalized images is utilized for comparison. For supervised learning, we have used the Support Vector Machine classifier to authenticate the image. A Histogram of Oriented Gradients is used to extract the features from the iris patterns and the input image is compared to get results of authentication.**

***Index Terms*— Iris Recognition, Iris Segmentation, Hough Transform, Canny Edge Detection, Daughman's Rubber Sheet Model, Entropy, Support Vector Machine, Histogram of Oriented Gradients.**

I. INTRODUCTION

Considering the rapid growth in technology, the need to have an efficient and reliable security system is increasing. The traditional approach of security systems can be duplicated, misused and hence are not safe. Different biometric traits include fingerprint, Iris, face, signature, voice etc. The human iris is a sight organ that regulate the amount of light entering the retina. It is the region between the pupil and white sclera of the human eye. The Iris Patterns contains various characteristics like freckles, furrows, crypts etc. Once developed, the iris patterns do not change over an individual's lifetime. To add to this, not only the iris patterns of identical twins differ, but also the left and right irises of the same individual are different. The uniqueness, complexity and stability of the iris patterns in humans makes it a very secure and ideal system for biometric identification. The main aim of this study is to propose a significant and effective approach to segment and classify the clear or noisy iris images. The approach used for the system here consists of four main steps Image Acquisition, Iris Segmentation, Image Normalization and Identification.

This work presents an Iris Recognition System with images from the CASIA database. Machine learning (ML), which is based on pattern recognition and computational learning, allows computers to learn and predict.

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Supervised learning involves using labeled data during training, while unsupervised learning discovers hidden patterns without labels.
We apply both methods for iris region detection and compare their performance. In unsupervised learning, entropy values were obtained from normalized images for classification. The supervised approach used an SVM classifier and HOG for feature extraction. The rest of the paper is organized as follows: Section II discusses related work, Sections III–X describe our method, and Section XI provides findings and conclusions.

Fig 1. Block diagram representation of the Iris Recognition System

II. RELATED WORKS

Here is a survey of some research papers that have implemented iris recognition systems with different feature extraction techniques and classification methods using CASIA database. Szymkowski et al., [6] proposed a Discrete Fast Fourier Transform system for iris-based human identification recognition using principal component analysis technique. Support vector Machine (SVM), K-nearest neighbors (KNN) and Artificial Neural Networks were the three techniques used for categorization. During the testing of experiments for different methods, SVM algorithm gave the most precise results.
Al-Dabbas, Hind & Azeez, Raghad & Ali, Akbas., [7] proposed three algorithms to implement iris image recognition with different feature extraction techniques to examine the classifications in machine learning approaches, The algorithms proposed are OneR, J48 and JRip depending on LDA feature extraction for the iris recognition system. Comparison of algorithm was done by applying Performance Measures that are designed for evaluating systems such as precision, recall to achieve the highest accuracy algorithm.Karthika and Ramkumarb [8] proposed two machine learning algorithms in an uncontrolled environment image dataset. SVM and Convolutional Neural Network(CNN) models were used in this. Mean accuracy of Iris Segmentation of sample images using CNN is 93.9% and by using SVM is 71.6%. Salve and Narote[20] proposed a novel iris recognition system that effectively integrates advanced feature extraction techniques. The study emphasizes on precise segmentation of the iris region. And 1D Log-Gabor filters are used for feature extraction which enhances the spatial and frequency characteristics of iris patterns. The superior performance of SVM with RBF kernel has given out a remarkable accuracy of 95.6% outperforming other methods

III. IMAGE ACQUISITION

Image acquisition involves capturing an image using a camera or a scanner, you can also import an existing image, into your computer. The image acquired should have good resolution and clarity for it to work for Iris Recognition system. Images should be free from noise like reflection, low lighting, eyelash eyebrow disturbance etc. In the system curated here, images are downloaded from CASIA V1.0 database to use as input to the system. Next, to align the tilted iris images and to help solve the issue of rotation, scaling etc Image Registration is done. After Registration, the colourful images are converted to greyscale images. Grey scale conversion is done by eliminating the hue and saturation information while retaining luminance.

$$0.299*R+0.587*G+0.114*B \qquad (1)$$

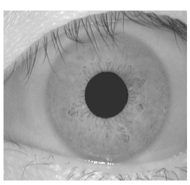

Fig 2. Database image from CASIA dataset

IV. IMAGE SUBTRACTION

Image Subtraction is done on the grayscale image and the image size is brought down to 60 pixels Next, to obtain a defined pupil and iris boundary for easier segmentation of the iris region, Binarization of the image is done by replacing the pixel values with 1 or 0. If the luminance value in the image is greater than the threshold value, then the pixel values are replaced with (white), for luminance value lesser than the threshold value, the pixel values are replaced with 0 (black).

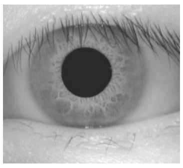

Fig 3. Subtracted Image

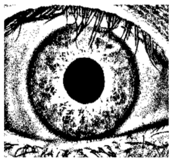

Fig 4. Binarized Image

V. IRIS IMAGE SEGMENTATION

Image segmentation is used to get the Iris and Pupil boundary. Prior to performing Iris Image Segmentation, we need to apply Canny Edge Detection to find the edges in the binarized image. To smoothen the eye image, 2D Gaussian filter is used. Before the Normalization is done, eye image should be pre-processed to localize pupil and to get the iris boundaries.

A. Iris Localization

Canny Edge Detection

Canny Edge Detection method is applied to find the edges in the binarized image(Fig 1.7) It is used for detecting both strong and weak edges. In general, the Iris-Sclera boundary can be considered a weak edge while the Pupil-Iris as the strong edge. An edge map is generated by the detector, which helps define the most change in the grayscale intensity of the edgesInthe image. These areas are founded by determining the gradients of the image. In order to make the circle detection process more efficient and accurate, the edge detected image is transformed to Hough space by applying the Circular Hough transform.

Smooth image with 2D gaussian: $n\sigma * I$(2)

Apply sobel operator: $\nabla n\sigma * I$(3)

Gradient Magnitude:$\|\nabla n\sigma * I\|$ (4)

Laplacian along the direction at each pixel is given by: $\frac{(\nabla n\sigma * I)}{(\|\nabla n\sigma * I\|)}$(5)

Circular Hough Transform

The Hough transform is a standard computer vision algorithm that can be used to determine the parameters of simple geometric objects, such as lines and circles, present in an image. The circular Hough transform can be employed to deduce the radius and center coordinates of the pupil and iris regions. Firstly, an edge map is generated by calculating the first derivatives of intensity values in an eye image and then thresholding the result. From the edge map, votes are cast in Hough space for the parameters of circles passing through it. Votes size and center in a special area for each circle. Many votes for the transformation from image space to parameter space *Image space:* $(x_i - a)^2 + (y_i - b)^2 = r^2$*(6)*

Parameter space: $(a - x_i)^2 + (b - y_i)^2 = r^2$ *(7)*

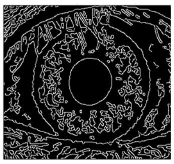

Fig 5. Canny edge detection

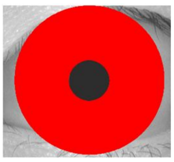

Fig 6. Iris Region detection

VI. IRIS IMAGE NORMALIZATION

The Size of Iris differs from each individual, hence the detected iris region needs to be transformed to fixed dimensions to facilitate proper comparison. Normalization of the segmented image is done by converting the image to rectangular block with constant polar dimensions using Daughman's Rubber Sheet Model. This method maps out every point in the segmented iris region in cartesian coordinates to a point in a rectangular region in polar coordinates. Produces a 2D array with horizontal dimensions of angular resolution and vertical dimensions of radial resolution. In Daughman's Rubber Sheet Model, ϴ is angular resolution, r is radial resolution and cartesian coordinates are represented by (x,y). The remapping of iris region is modelled as

$$I\big(x(r,\theta), y(r,\theta)\big) \rightarrow I(r,\theta) \quad (8)$$
$$x(r,\theta) = (1-r)x_p(\theta) + rx_1(\theta) \quad (9)$$
$$y(r,\theta) = (1-r)y_p(\theta) + ry_1(\theta) \quad (10)$$

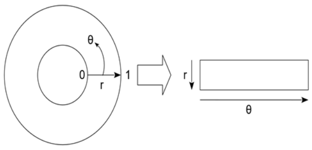

Fig 7. Daughman’s Rubber Sheet Model

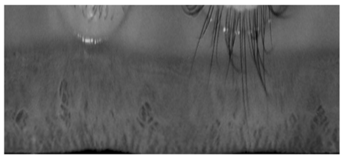

Fig 8. Normalized Image

VII. Feature Extraction Using Entropy

Entropy quantifies the randomness in an image, expressing its texture and information content. Entropy also quantifies how many bits it would take to represent image information. The greater the entropy, the more detailed the image. Low entropy represents uniformity. In data classification, entropy can be used to choose the most informative features but may be susceptible to noise and model instability.
We calculated entropy values for every normalized database image and saved them. This information was associated with MATLAB, which compares the entropy of new images with the database. A match identifies the image as genuine; otherwise, it is fake. An Arduino Uno with red and green LEDs shows the result—green for genuine and red for false alarm.

$$H(x) = -\sum\big(p(x) * log_2\, p(x)\big) \qquad (11)$$

p(x) is the probability of the pixel value x appearing in the image

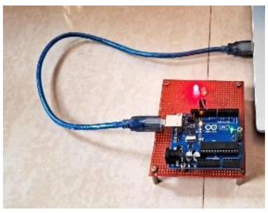

Fig 9. Detection of non-authentic image

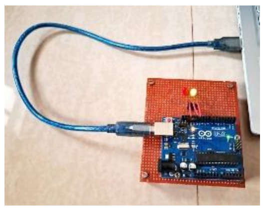

Fig 10. Detection of authentic image

VIII. Classification using Support Vector Machine

Support Vector Machine (SVM) is a classification and regression tool which uses machine learning theory to maximize predictive accuracy while reducing the over fit of the data. When working with huge datasets, support vector machines are
particularly useful in machine learning and pattern recognition for classification. Applying appropriate data transformations
that create boundaries between data points based on predetermined classes, labels, or outputs, resolves difficult problems. The SVM algorithm aims to locate a hyperplane that properly divides the data points into separate classes.SVM tries to maximize the distance between the two vectors, more the distance efficient is the classification. The hyperplane equation dividing the points is written as,

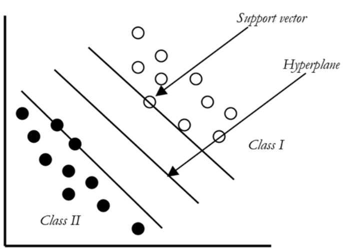

Fig 11. SVM Classifier

$$w^T + b = 0 \quad (12)$$

Where b is intercept and bias term which indicates the position of hyperplane, and w is weight term which is perpendicular to hyperplane, and the orientation of hyperplane is given by w.

IX. Feature Extraction using Histogram Oriented Gradients

To determine the shape and pattern of an object, Histogram of Oriented Gradients, a feature descriptor technique is used in computer vision and image processing it examines the distribution of edge orientations inside it. Using this technique an image is first divided into tiny pixel and then the gradient and magnitude and orientation of each pixel are then obtained. It is often used to extract features from image data. This is done by extracting the gradient and orientation of the edges, these orientations are calculated in localized portions. To determine the gradients in x and y direction we need to subtract the pixel value on the left of the selected pixel from the value on the right. This process isrepeated for all the pixels in the image. Total gradient magnitude of the pixel is given by,

$$x = \sqrt{G_x^2 + G_y^2} \quad (13)$$

Where, Gx is change of gradient in x direction

Gy is the change of gradient in y direction

To calculate the orientation of the pixel, the angle would be

$$\phi = \text{atan}\left(\frac{G_y}{G_x}\right) \quad (14)$$

Histogram, a plot to show the frequency distribution of the set of continuous data is generated using the obtained gradients and orientation. Thus, resulting in extraction of HOG features from it.

X. Confusion Matrix

To evaluate the performance of a classification model, a table that compares the predicted values of dataset to the actual values is used. It helps visualize the results of classification algorithm. The table consists of different combination of predicted and actual values. We have True Positive(TP), False Negative(FP), True Negative(TN),False Negative(FN). This Table is very useful for measuring accuracy, precision, recall etc. The interpretation of True Positive(TP) is that the prediction made was positive and the result is positive. True Negative indicates the predicted value is Negative but the value turned out to be positive. The confusion matrix shows how many data points are correctly classified and the number of incorrectly classified data points. The diagonal elements display the number of points where the predicted value matches the true label and the non-diagonal shows the incorrectly labelled data points. In that we have obtained the Matrix plot for images with Noise and also for the images with no external Noise.

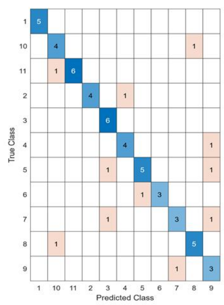

Fig 12. Confusion matrix of test images without noise

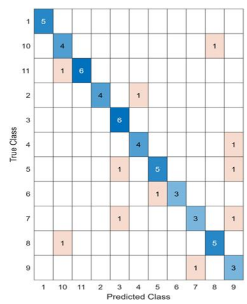

Fig 13. Confusion matrix of the test images with noise

XI. K- fold cross validation

Cross Validation is a resampling technique, that is used to validate machine learning models against a limited sample of data. In the case of K-fold cross-validation, the dataset is divided into a K number of folds and is used to check the model's ability and it's performance when new data is given. Here, K represents the number of groups into which the data sample is divided. We have K sets of data to train and test our model. So the model will get trained and tested K number of times but for every iteration, we will use one fold as test data and rest as training data. We get accuracy score by applying mean for all folds. K-fold Cross validation helps us generalize the machine learning model, which results in better predictions of unknown data. By using this approach, we can achieve a stable and accurate outcome which will help solve the issue related to random precision. This method prevents the overfitting of dataset and it validates the performance of our model.

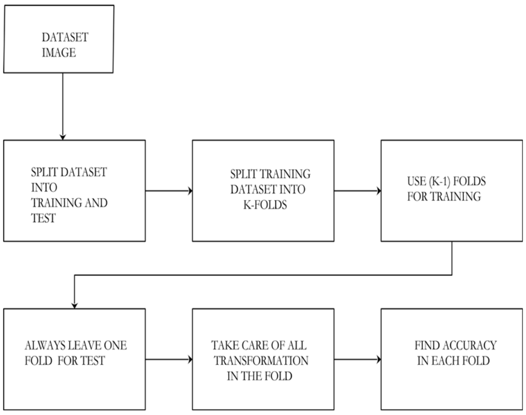

Fig 14. Flow chart of K- Fold Cross Validation

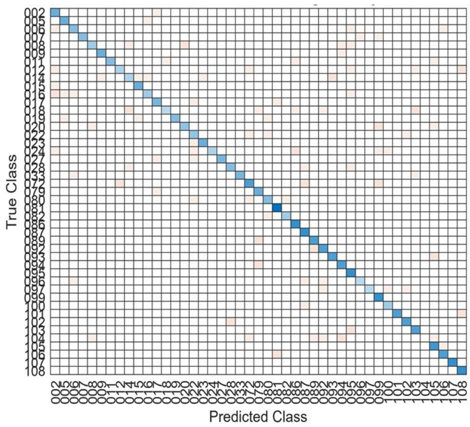

Fig15. Confusion matrix for K- Fold

XII. Wavelet Transform for Denoising Images

Wavelets are small oscillating functions that are localized in both the time and frequency domain. They are used as basic functions to decompose a signal.Wavelet Transform breaks down signal by scaling and translating the wavelet. Scaling means stretching or compressing the wavelet. It adjusts the width of the wavelet to analyze different frequency components. Translating refers to the shifting of the wavelet. It shifts the wavelet to analyze different portions of the signal in time. Wavelet denoising techniques are used to denoise the signal with wavelet transform. They help remove unwanted noise while retaining important data. This denoising approach done on images is of two kinds, one is Soft thresholding and another is Hard thresholding. Here we have used Soft thresholding to denoise our images. Soft thresholding removes the values below the threshold and also reduces the ones above the set threshold value. It is gentler compared to hard thresholding. Here, the values below the threshold are set to zero, while the others are shrunk by subtracting the threshold frequency from them. The advantage of this method is that it gives a smoother result as it reduces the impact of noise without completely cutting the values. Wavelet thresholding-based denoising can be expressed as

$$X = W^{-1}(T(W_y)) \quad (15)$$

W is the two-dimensional orthogonal wavelet transform(DWT) and W^{-1} is its inverse dimensional orthogonal wavelet transform(IDWT), The hard thresholding function is described as

$$f(x) = x \quad if\ x \geq \lambda (16)$$
$$= 0 \quad otherwise$$

The function chooses all the wavelet coefficients that are greater than the given threshold λ and others to zero
And for soft thresholding,

$$f(x) = x - \lambda \qquad if\ x \geq \ \lambda (17)$$
$$= 0 \qquad if\ x < \lambda$$
$$= x + \lambda \qquad if\ x \leq -\lambda$$

XIII. Results

All experiments were conducted using MATLAB R2023a. Iris segmentation, a crucial step in recognition, relies on Canny edge detection and the Circular Hough Transform for localization. The CASIA v1 database, with iris radii of 90–150 pixels and pupil radii of 28–75 pixels, was used for testing.In the unsupervised approach, entropy values (5–7) were computed for the normalized iris region, with authentication based on database matching. The supervised method employed an SVM classifier with HOG features, outperforming the entropy method, especially in noisy conditions. A confusion matrix highlighted higher misclassification in noisy images, while noise-free images showed better classification accuracy. K-fold cross-validation ensured robustness by averaging accuracy across multiple folds. Incorporating Wavelet Transform-based denoising improved accuracy from 80.84% (73.58%–90.57% per fold) to 82.90% (75.47%–92.45%), demonstrating its effectiveness in noise reduction. Expanding the dataset would further enhance precision and robustness. Results confirm that supervised learning with SVM and HOG is superior to entropy-based unsupervised methods, with denoising playing a key role in improving recognition accuracy.

TABLE I: KFOLD CROSS VALIDATION RESULTS FOR DATASET IMAGES WITH NOISE

Fold No.	Result for 10 Fold cross validation	
	Incorrect Recognized Sample	Accuracy(%)
1	13	75.47
2	11	79.25
3	10	81.48
4	9	83.33
5	5	90.57
6	4	92.45
7	8	84.91
8	12	77.36
9	13	75.47
10	6	88.68

TABLE II: KFOLD CROSS VALIDATION RESULTS FOR DATASET IMAGES WITH NOISE

Fold No.	Result for 10 Fold cross validation	
	Incorrect Recognized Sample	Accuracy(%)
1	9	83.02
2	8	84.91
3	14	74.07
4	11	79.25
5	14	73.58
6	9	83.33
7	11	79.25
8	5	90.57
9	10	81.13
10	11	79.25

XIV. CONCLUSION

The system integrates both unsupervised and supervised learning for efficient iris recognition. Segmentation errors caused by eye movements, occlusions, and reflections effects accuracy. Iris localization has been carried out using Canny edge detection along with circular Hough transform. Iris and pupil radius ranges based on the CASIA V1 database were predetermined. Using Daugman's Rubber Sheet model iris images were normalized to a constant polar coordinate space.

In the unsupervised method, entropy measures (5 to 7) of normalized iris patterns were utilized for verification but performance reduced with noisy images. The supervised method, employing SVM and HOG, was more accurate but did not perform well with noise, highlighting the importance of sophisticated denoising technique. Comparison demonstrated that supervised learning, specifically the use of SVM and HOG, surpassed its performance under noisy conditions. Unsupervised learning based on entropy can have identified patterns in iris data, but was not reliable.

Supervised learning, based on the labeled data and feature extraction, was more robust and accurate and hence the most appropriate for iris identification. Despite limitations, the system demonstrates the potential for accurate human identification when implemented with precision.

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