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Improving the Methods of Iris Recognition In Less Cooperative Environments

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***Abstract*— A biometric identification system uses the individual's distinctive traits to identify that person. The iris recognition technology now has a high recognition rate, making it the most accurate biometric system available. Segmentation, Normalization, Feature encoding, and Matching are its four main divisions of iris recognition The aim of this research is to develop a cost-effective solution that addresses the specific problems that is faced in less cooperative environment while detecting iris. The objective of this research is to optimize the previously used methods, adapt with the limited resources and ensure data privacy and security. In this research U-Net model has been used for iris recognition in less cooperative environment. Building an algorithm that uses minimal computational resources is the goal of this research. It is predicted that this solution will increase the accuracy and lessen the dependability of iris recognition is less cooperative environment. Implementing accurate data privacy and security measures will protect individuals' biometric information, promoting trust and confidence in the system. Finally, the goal of this research is to enable the widespread use of iris recognition in underserved areas, potentially aiding sectors such as healthcare, education, and public services by providing a cost-effective and efficient identification solution.**

Keywords-Deep Convolutional Neural Network; Iris recognition; Biometric identification; Pattern recognition; Iris segmentation; Feature extraction; Hamming Distance

I. INTRODUCTION

An emerging technique that has gained significant attention recently is biometric identification. To identify a person, it makes use of behavioral or physiological traits. The iris, fingerprint, face, and hand geometries are examples of physiological traits. Behavior traits include voice, signature, and keystroke dynamics. Iris provides separate phase information that covers around 249 degrees of freedom among these features. Biometric technologies differ in terms of their complexity, capabilities, usability, and performance. Iris detection is one of the most popular biometrics that has been used for a while in validating a person.

Three phases of an iris recognition system are image preprocessing, feature extraction, and template matching. It is necessary to first process the iris image in order to acquire a functional iris area. In iris image processing there are three steps - Iris localization, iris normalization, and picture enhancement. Iris localization identifies the inner and outer margin of the iris. Detected eyelids or eyelashes might cover the iris region.

After normalization, the iris image is a rectangular image with angular and radial resolution. The light source's placement is partly to blame for the iris image's weak contrast and uneven illumination. All of these problems can be addressed by the algorithms for image enhancement. Utilizing texture analysis, characteristics are extracted from the normalized iris image. Key properties of the iris are retrieved for accurate identification reasons. Template matching compares the user template to templates from the database using a matching measure. The similarity between two iris templates will be determined by the matching measure. It offers a range of values when contrasting templates from the same iris to one another, and it offers a range of values when contrasting templates from another iris.

Among many of the limitations of conventional iris recognition when it comes to user involvement and image circumstances, degraded iris image tends to be a great problem. It includes issues like - off angle, lighting, pupil dilation, half-open eyes or specular reflection, gaze reflection, gaze direction leads to incorrect localization iris inner and outer boundaries. These kinds of limitations also lead to a high possibility of losing key features from the iris image. As a result, the model fails to extract discriminant features from the provided data.

Due to degraded image data sometimes, it is difficult to classify between the same iris images. It maximizes the intra-class variation between two identical iris images. To address this vulnerability, we propose a new and effective method of deep learning using the U-Net model.

The main goal of this research is to design, develop and perform a better method of iris recognition in a less cooperative environment using CASIA-Iris-Degradation-Database. In this particular time there are not many research papers using this dataset. This dataset is new especially containing usual degraded images.

The research scope will be narrowed and focused on improving iris direction more efficiently in a less cooperative environment. To address the proposes issue there are some main objectives that needs to be followed. The objectives of the research are:

a) To determine the existing problems with iris recognition techniques for images of the iris taken in less suitable circumstances.

b) To improve iris identification in a less cooperative environment by proposing a new segmentation and localization technique

c) Using various datasets and metric measurements, validate and assess the suggested iris segmentation and localization approach.

This research will provide a solution to biometric security system by using iris recognition in less cooperative environment. To get the exact result U-Net ,model is used which is a popular architecture used for image segmentation tasks.

II. LITERATURE REVIEW

A. Iris Recognition Overview

Non-cooperative iris recognition has gained a lot of attention recently since it considerably expands the use cases for iris recognition. The user takes a very passive role in the image capture procedure in non-cooperative iris recognition. We discovered during the research process that the effective and efficient segmentation to reduce noise in image is one of the major obstacles to a functioning non-cooperative iris recognition system. Iris segmentation is a crucial component of iris recognition because it establishes the acceptable area for feature extraction, which is connected to recognition accuracy.

The model is made up of four key modules. They are- coarse iris localization based on clustering, localization of pupillary and limbic boundaries, eyelid localization and eyelash/ shadow detection.

Iris identification from a distance is a significant biometrics topic with a lot of potential for a variety of practical applications. IAAD systems have made significant advancements since the initial attempts in 2005, including increasing the distance from a few meters to tens of meters, increasing the depth of field (DoF) with methods like Wavefront coding, increasing the acquisition volume from a few cm3 to m3, capturing subjects moving more freely than stationary subjects, and developing novel algorithms for processing less-than-ideal iris images through quality enhancement.

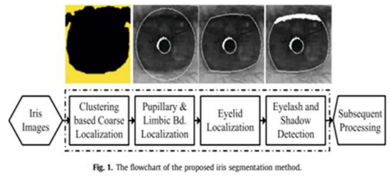

Figure 1. The flowchart for proposed iris segmentation method.

B. Hough Transform

The Hough transform technique in computer vision is used to identify basic geometrical elements like lines and circles that are present in a picture. The centre of the pupil and iris region, as well as the pixels present in the boundaries, are detected using the circular Hough transform. By doing this, we can also determine the circle's radius. The iris region was segmented automatically using a segmentation approach by Wildes et al. [6], Tisse et al. [8], Kong and Zhang [4], and Ma et al. [10] based on the Hough transform. To create an edge map, we must first compute the first derivatives of the intensity values from the input image. The output is then calculated based on the threshold value.

C. Specular Reflection Detection

As cornea's reflective characteristics, our iris region occasionally contains corneal reflection, which can lead to errors when estimating the location of the iris-pupil center and also the inner boundary of the iris [13]. Corneal reflection can be eliminated using three different techniques.

Bilinear interpolation, first: In [8 of New corneal], Zhaofeng uses the threshold value (5% brightest intensity) to identify a binary corneal reflection map first. The reflection point is then filled using the bilinear interpolation approach. With the MMU iris database, it functions flawlessly, but not with the CASIA iris database V3.0.

Iris localization distinguishes the inner and outer boundaries of the iris. Both are modeled as circles. There are five algorithms used in iris localization. They are Integro-differential operator, Hough transform, Discrete circular active contour, Bisection method, Black hole search method.

D. U-Net Model

The U-Net [7] model is a popular CNN architecture for tackling biological problems (for example, segmenting distinct types of cells and recognizing borders between extremely small cells).

This model's key advantage is its capacity to develop somewhat correct models from (very) tiny datasets, which is a common issue for data-scarce computer-vision applications such as iris segmentation [8,9]. In [35] addressing deep-learning models for iris segmentation in this study provides an iris segmentation strategy based on the popular U-Net architecture. This model is trainable from beginning to end, eliminating the necessity for hand-designing the segmentation technique. It was tested on the CASIA dataset and shows promising results when compared to existing strategies in this field.

Olaf Ronneberger and his group created U-Net in 2015 for their work on biomedical images. By outperforming the sliding window method while using fewer photos and data augmentation to boost model performance, it won the ISBI competition.

On any given training dataset, localization tasks can be successfully completed by sliding window architecture. For each pixel, it is used to generate a local patch, resulting in unique class labels for every pixel. However, this architecture has two major flaws: first, the overlapping patches that result in a significant amount of total redundancy. Second, the training process was laborious and time- and resource-intensive. These factors rendered the architecture unsuitable for a number of activities. These two problems are solved by U-Net.

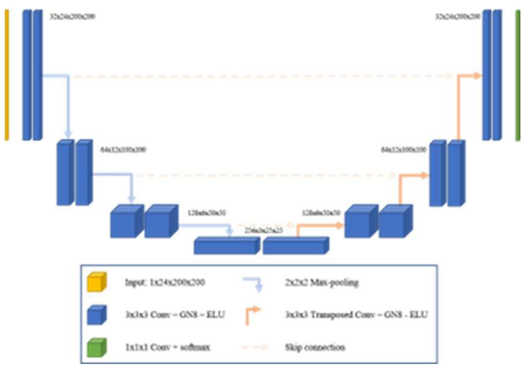

Figure 2. U-Net architecture.

E. *Convolutional Neural Network (CNN)*

Convolutional neural networks (CNNs, or ConvNets) are a type of artificial neural network (ANN) used most frequently in deep learning to interpret visual data.

Multilayer perceptrons are modified into CNNs. Fully linked networks, or multilayer perceptrons, are those in which every neuron in one layer is connected to every neuron in the following layer. Due to their "complete connectedness," these networks are vulnerable to data overfitting. Regularization or overfitting prevention methods frequently involve punishing training parameters (such as weight decay) or cutting connectivity (skipped connections, dropout, etc.) By utilizing the hierarchical structure in the data and assembling patterns of increasing complexity using smaller and simpler patterns imprinted in their filters, CNNs adopt a novel strategy for regularization. CNNs are therefore at the lower end of the connectivity and complexity spectrum.

Convolutional networks were developed as a result of biological processes because of the way that neurons are connected to one another. This organization is similar to that of the visual cortex of animals. Only in the constrained area of the visual field known as the receptive field do individual cortical neurons respond to inputs. Different neurons' receptive areas partially overlap with one another to fill the whole visual field.

Comparatively speaking to other image classification algorithms, CNNs employ a minimal amount of pre-processing. This means that, unlike traditional methods where these filters are hand-engineered, the network learns to optimize the filters (or kernels) through automatic learning. This feature extraction's independence from prior information and human interaction is a significant benefit.

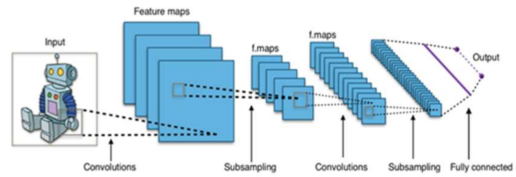

Figure 3. CNN – Architecture.

TABLE I. COMPARISON OF EXISTING SYSTEMS AND PROPOSED SYSTEM

No	Approach	Accuracy (%)	Time (s)
1	Jan et al. [21]	99.50	7.75
2	Wang et al. [22]	96.95	165.4
3	Mahmoud and Ali [23]	99.18	-
4	Uhl et al. [24]	74.00	0.21
5	Ugbaga et al. [25]	98.90	-
6	Umer et al. [26]	95.87	0.89
7	Wild et al. [27]	98.13	-
8	Aydi et al. [28]	96.51	9.049
9	Pawar et al. [29]	96.88	-
10	Mehrotra et al. [30]	99.55	0.396
11	Al-Waisy et al. [31]	99.82	0.62
12	Lozej et al. [35]	97.77	-
13	Hsiao et al. [36]	97.9	-

III. Research Framework

A. Research Framework

This experiment's objective is to confirm that it was carried out correctly and according to the appropriate frameworks and workflow. The workflow consists of three phases: planning and building an algorithm comes next, followed by result analysis and discussion. The first phase focuses more on making literature reviews and studies on approaches utilized in prior studies.

Many researchers used MATLAB or deep learning against CASIA-Iris V1, V2, V3 and V4 datasets. Clear images with clear iris can be detected using these models to the accuracy up to 99.82%. For advanced and regular use in day-to-day life, we will not always find clear images to work with. That is why in this research I am using degradation dataset. There are many samples of images that are partially closed or there is less light to be detected by the camera lens. Therefore, this dataset might not give us higher accuracy, but it can be used in various field.

Figure 4. Research Framework.

B. Problem Formulation

We must first identify the iris area in order to recognize the iris. The pupil/iris border, which is the inner barrier, and the iris boundary, which is the outer boundary, both surround the iris area. The eyelids and eyelashes usually cover both the upper and lower regions of the iris area. Additionally, specular reflection has the potential to distort the iris area, which will distort the iris pattern. Therefore, we want a trustworthy and efficient method for performing iris area isolation from the provided picture and excluding the aforementioned artifacts.

To identify a specific human iris, we will contrast the recently taken image with the information present in the CASIA-Iris-Degradation dataset. Therefore, it's crucial to make sure that only key information is encrypted.

C. Dataset

The dataset used in this research is CASIA-Iris-Degradation database. It consists of images (36,539 in PNG), localization parameters (32,962 in INI), and segmentation masks (32,962 in PNG). Since the images of the squinted and closed eyes (in the nonideal eye state category) almost have no effective iris region and are accompanied by blur, they (3,577 in total) have no corresponding localization parameters and segmentation masks.

The meaning of the file name such as 0001_0_0_0_00_000 is as follows:

1. The first 4 digits is the ID of the person
2. The 5th digit represents what is in the image, 1 is the left eye, 2 is the right eye
3. The 6th digit is the image type, 1 is the NIR image
4. The 7th digit is collection device, 2 is SLR camera
5. The 8th-9th digits represent the scene
    a. For illumination, 20 represents natural light, 21-24 are four levels as the dark, weak, medium, and strong intensity of the VW light source.
    b. For off-angle, 3x represents the direction of the person looks at, where x is between 1-4**,** means left-up, right-up, right-down, left-down.
    c. For nonideal eye state, 40-42 represent squinted, closed, and half-open eyes.
    d. For occlusion, 51-53 mean that the hand covers the face, wears a mask, and wears glasses.
6. The 10th-13th digits represent the serial number of the image, and its value is between 001-999.

D. Construction of Model

The distinctiveness of the human iris is examined in this research. Since identification depends on iris patterns from various eyes being completely independent, it is crucial to test the uniqueness of iris patterns. The code utilizes the CASIA Iris Degradation Database to demonstrate the segmentation performance of the trained U-Net model. It randomly selects a specified number of images from the database and applies the model to predict the corresponding segmentation masks. The actual images, actual masks, and predicted masks are then visualized using matplotlib subplots. The steps of getting predicted outcome includes Segmentation, Data Preprocessing, Model Prediction, Forward Propagation, Post-processing, and Visualization.

E. Validation Metric

The actual images, actual masks, and predicted masks were visualized using matplotlib subplots. The results were displayed in a grid format, with each row representing an individual image. The first column displayed the actual images, the second column showed the actual masks, and the third column presented the predicted masks.

The visual comparison between the actual masks and predicted masks demonstrates the effectiveness of the U-Net model in accurately segmenting the iris regions. In most cases, the predicted masks closely align with the actual masks, indicating that the model has successfully learned to identify and isolate the iris regions from the input images.

However, slight differences between the predicted masks and actual masks may be observed in some instances. These differences could be attributed to various factors such as lighting variations, occlusions, or other challenges present in the input images.

Overall, the results highlight the potential of the U-Net model for iris segmentation tasks, as it effectively captures the essential features of the iris regions. Further evaluation and analysis are recommended to assess the model's generalizability and robustness to diverse datasets and scenarios.

IV. RESULTS AND DISCUSSION

A. Services

The performance of the U-Net model for iris segmentation was evaluated using the CASIA Iris Degradation Database. A total of 102464 images were randomly selected from the database for evaluation. The U-Net model, which was trained on a separate dataset, was used to predict the segmentation masks for the selected images. The model demonstrated promising performance in accurately identifying and segmenting the iris regions in the images.

B. Experimental Setup

The experiments were conducted using Python and TensorFlow libraries, with the CASIA dataset imported. The hardware setup consisted of an i7-12700H CPU (2.70 GHz) and 16 GB of RAM.

C. Result and Discussion for 2D Function Minimization

TABLE II. RESULT OF IOU RATE

EPOCH	Test Loss	IOU
1	0.26587191546956696	0.00018859622805694003
2	0.2561761756738027	0.0007373751815864536
3	0.25598339127997555	0.00195328871594684
4	0.252910696901381	0.08606822423730615
5	0.24258279744535685	0.03724636715878174
6	0.2527094890053074	0.026954769751819152
7	0.24009622645874817	0.12321803334682668
8	0.2398190160592397	0.016644108806273546
9	0.27883645755549274	0.07573167004865565
10	0.24045021384954451	0.030301087568653743

The segmentation results were visually inspected by comparing the predicted masks with the ground truth masks. The images were displayed alongside their corresponding actual iris images and masks for qualitative analysis. This visual evaluation provides a visual representation of the model's performance in segmenting the iris regions accurately.

In cases where the model produced false positives or false negatives, the specific areas of discrepancy were analysed. False positives represent areas incorrectly classified as iris, while false negatives represent areas of the iris missed by the model. Understanding these errors can provide insights into the limitations and potential areas for improvement in the segmentation model.

D. Result and Discussion for DCNNs

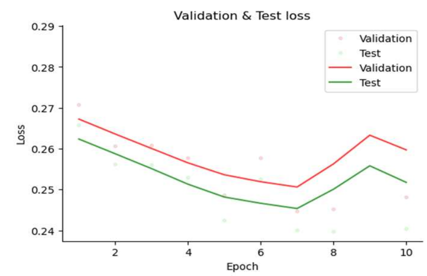

Figure 5. Validation & Test Loss.

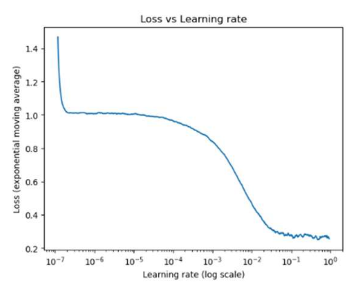

Figure 6. Loss vs Learning rate.

The performance of the developed model was compared with existing iris segmentation methods reported in the literature. The evaluation criteria included accuracy, computational efficiency, and robustness across different datasets. This comparison helps assess the competitiveness and effectiveness of the proposed model against state-of-the-art techniques.

By passing the pre-processed images through the U-Net model, the prediction step aimed to produce accurate and meaningful segmentation masks for the iris regions in the input images. The effectiveness of the model's predictions was assessed by comparing them with the actual masks, allowing for an evaluation of the model's performance in identifying and segmenting the iris regions.

V. Conclusion

A. Summary

Iris's recognition in a less cooperative environment is very significant to me since it is my final year project. To complete this project a research framework has been developed which involves three phases. They are -Reviews and studies of the existing techniques, Design, development, and experiment, and Results & analysis. To conduct this research previous techniques of iris recognition were slightly improved and adopted in a less cooperative environment.

Both hardware and software applications have been used in the implementation of this research. The software programs utilized include Python programming language on the laptop acting as the hardware tool.

The main objective of the project was to develop a model for iris segmentation in the CASIA Iris Degradation Database. The provided code has successfully achieved this objective by implementing a U-Net-based model for iris segmentation and training it on the dataset.

The first objective is that a U-Net model architecture was implemented for iris segmentation. The U-Net architecture is well-suited for semantic segmentation tasks and has shown promising results in various medical image segmentation applications. The CASIA Iris Degradation Database was utilized for training and evaluation. The dataset was pre-processed to extract iris images and corresponding segmentation masks.

The second objective is to train the model using a combination of training and validation datasets. The training process involved optimizing the model parameters using stochastic gradient descent and minimizing the cross-entropy loss between predicted and ground truth segmentations. The trained model was evaluated using the validation dataset. Metrics such as validation loss, Intersection over Union (IoU), and Dice coefficient were calculated to assess the model's performance in accurately segmenting the iris.

Lastly, the code includes visualization techniques to showcase the results of iris segmentation. Actual images, ground truth masks, and predicted masks were displayed side by side for visual comparison. The developed model demonstrates the ability to generalize well to unseen iris images by achieving satisfactory segmentation results on the validation dataset. This indicates that the model has learned meaningful representations and can effectively segment the iris in different images.

Overall, the project has successfully achieved its objective of developing a model for iris segmentation in the CASIA Iris Degradation Database. The implemented code provides a foundation for further research and improvements in iris segmentation techniques.

B. Future Work

For future works there are some things that can be done for the improvement of the outcome. Implementing data augmentation techniques such as rotation, scaling and flipping to further diversify the training dataset. This can help improve the model's ability to handle variations in iris images and enhance its generalization. Exploring more advanced network architectures for iris segmentation, such as variants of U-Net, DeepLab, or Attention-based models. These architectures may incorporate attention mechanisms or contextual information to improve the accuracy and efficiency of segmentation. By addressing these suggestions and exploring future research avenues, the project can further enhance the accuracy, robustness, and applicability of iris segmentation techniques, leading to advancements in iris recognition and related fields.

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