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Enhancing An Iris Detection Using Integration of Semantic Segmentation Architecture and Data Augmentation

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ABSTRACT

An iris recognition is a biometric way of identifying people in the ring-shaped portion of the eyeball surrounding the pupil. An iris recognition is used in biometrics because each iris is unique to an individual. Unfortunately, even though researchers have considered various approaches to improve the detection of iris recognition, obtaining higher accuracy remains a challenging task. More specifically, the major drawbacks contributed by the poor quality of images such as blur, lighting infection, and data scarcity. Therefore, in this work, we proposed the utilization of semantic segmentation and data augmentation approach to enhance the iris detection capability in terms of accuracy. The semantic segmentation (SS), a part of Mask R-CNN, is applied to overcome the image quality limitation. This approach partitions an image into multiple image segments known as image regions to differentiate dissimilar objects in an image using pixel level. Subsequently, using the data augmentation (DA) approach, new data is derived artificially from existing data that has been effective in improving the model generalization and precisely solving issues of data scarcity. The proposed model namely SS+DA has been evaluated using benchmark datasets known as CASIA and IITD. The experiment result shows that the proposed method is able to obtain an above 99% accuracy rate for both the CASIA and IITD datasets.

I. INTRODUCTION

Conventional methods of human identification, such as keys, passwords, and access cards, have given a means of identifying biological patterns such as the face, voice, fingerprint, iris, and finger vein. Face, voice, fingerprint, iris, and finger vein patterns are all frequently employed for personal identification. Existing research [1], [2] has demonstrated that, of the aforementioned biological patterns, the iris pattern is the most reliable and secure form of personal identification due to significant advantages such as stability, informativeness, safety, contact lessness, and many more. Considering these benefits, iris recognition has increased in popularity as well, and many studies from diverse researchers continue to focus on iris identification [3], [4].

Deep learning-based algorithms, notably ones based on various Convolutional Neural Network designs, have led to significant improvements in many computer vision applications over the previous decade. It's not unforeseen that, in terms of biometrics technology, iris recognition has seen a surge in the use of solely data-driven approaches at all stages of the recognition pipeline, from preprocessing (such as off-axis gaze correction), segmentation, and encoding to matching. However, the impact of deep learning on different phases of the iris identification pipeline is unequal [5], [6].

Unfortunately, iris recognition is regarded as an impenetrable topic, with most results indicating space for improvement. For many years, this issue has motivated various research

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projects. Despite the clear improvement in the effectiveness of such techniques, they all confront unique challenges when dealing with severely degraded data. Images are commonly blurred in motion, poorly focused, partially obscured, and off-angle. Furthermore, in the case of visible light data, strong reflections from the environments surrounding the people are readily apparent further complicating the segmentation task.

Hence, in this work, we propose modified semantic segmentation and integration of data augmentation to enhance the detection performance of iris recognition in terms of accuracy. Semantic segmentation (SS), an element of Mask R-CNN, is employed to overcome the quality of image constraints. This method divides an image into many picture segments known as image regions to distinguish various items in an image at the pixel level. Following that, new data is produced artificially from existing data using the data augmentation (DA) strategy, which has been effective in increasing model generalization and accurately fixing data scarcity challenges.
The remainder of the part is structured as follows: Section 2 comprises the discussion of the related work in which several similar previous studies have been explored and reviewed. The overall detail of the proposed methods has been briefly explained in Section 3. Section 4 discusses the obtained result via conducted experiments using different benchmark datasets and is followed up by the summary and future work in Section 5.

II. RELATED WORK

Identity authentication has advanced its methods by utilizing iris biometrics [7] rather than fingerprints and other physical identity authentication technologies. Iris biometric authentication [8] gradually increased stability beyond the age of three due to uniqueness, random patterns with higher complexity, a highly protected interior eye, and feature stability. Iris biometric systems extract the iris to obtain ocular information to identify individuals, hence iris localization is critical. These applications in several sectors emphasize the relevance of pupil localization in diagnosing diseases, enforcing safety, and enforcing security, among other things. As a result, eye-tracking installations are required in these circumstances [9].

Deep learning has transformed iris identification, a biometric tool utilized to recognize people based on the distinctive patterns found on their iris. Conventional approaches were based on handcrafted features and algorithms, but deep learning techniques, notably convolutional neural networks (CNNs), have significantly increased accuracy and efficiency. Iris detection with deep learning often involves preprocessing the picture of the iris to improve contrast and reduce noise. Next, the model of CNN is used for extracting characteristics from the iris patterns. These attributes are learned via training on a huge dataset of iris images. Throughout the training procedure, CNN is learning to recognize subtle patterns in the iris, including furrows, crypts, and freckles that are distinctive for every person. The algorithm repeatedly adjusts its parameters via backpropagation, reducing the disparity between anticipated and actual iris properties. After training, the deep learning algorithm can correctly recognize humans through comparing current iris scans to previously established patterns. This procedure, known as iris matching, compares the similarities of iris characteristics retrieved from an input image with those preserved in a database. In general, deep learning has considerably increased the accuracy as well as the dependability of iris identification systems, rendering them useful for a variety of purposes particularly identity verification [6], [10].

The segmentation of the iris is a critical stage in iris recognition. Feeding a segmented iris image into a recognition approach often yields better results than utilizing the whole iris image. Traditional manual iris segmentation methods are computationally complex and necessitate substantial specialist knowledge. Numerous investigations have focused on segmenting iris images employing deep learning approaches to accomplish iris segmentation more conveniently and reliably. Unfortunately, the detection of iris is seen as an extremely challenging problem that indirectly has motivated numerous research works for decades in achieving higher performance in iris recognition. Regardless of the clear improvement in the effectiveness of such techniques, they all confront unique challenges when dealing with severely degraded data. Images are regularly blurred by motion, are poorly focused, are partially occluded, and are off angle. Furthermore, harsh reflections from the environs surrounding the people are visible in the context of light-sensitive data, adding to the difficulty of the segmentation process [3], [11], [12]

Recently, consisting of many other computer vision problems, DL-based architectures have been claimed as giving consistent progress above the state-of-the-art for the iris segmentation difficulty, with various models presented. Table 1 provides a unified view of the most essential current DL-based methodologies, with the approaches listed in chronological order.

TABLE 1: Previous Study in Iris Recognition

Author/Year	Methods	Data	Objective	Result
[13]	Deep Semantic Segementation	CASIAv4 IITD	Proposing deep semantic segmentation in improving performance such as accuracy	CASIA (98.51%) IITD (98.4%)
[14]	CNN, VGG16, ResNet, Inception	Custom Dataset	Proposing a reliable method for detecting corneal arcus with high accuracy	ResNet (88%) Inception (77%) VGG16 (72%)
[15]	CNN, VGG19, ResNet	UBIPr Database	Proposing novel method in improving accuracy using periocular territory	VGG19 (96%) ResNet18 (88%)
[16]	CNN, VGG16, ResNet50, Inception, v3	CASIA UBIRISv2	Proposing a DCNN model to identify dissimilar photos that able to improve the accuracy	CASIA (99.64%) UBIRIS (98.76%)
[17]	CNN	CASIA UBIRISv2	Improving segmentation of iris pictures to obtain higher accuracy	CASIA (99.5%) UBIRISv2 (98.92%)
[18]	Deep CNN, DenseNet	ND Database IIITD Database	Proposing a novel DCLNet to obtain higher accuracy	IITTD (99.10%) ND (84.34%)
[19]	DNN	CASIA UBIRISv2	Combine DNN with an augmentation strategy to increase the quality of poor photos	CASIA (99.71%) UBIRISv2 (97.82%)
[20]	CNN Encoder_decoder Network Semantic Segmentation	CASIAv4 IITD UBIRISv2	Proposing fully residual encoder and decoder network for accurate iris segmentation	CASIAv4 (96.59%) IITD (96.82%) UBIRISv2 (94.31%)

Several explorations and experiments have been conducted by the research community to improve iris recognition as illustrated in Table 1. Diverse methods and approaches have been taken into consideration to improve iris recognition via different strategies by employing augmentation, segmentation, CNN, and so forth. For instance, [13] have proposed a dual-path fusion network model by integrating deep semantic segmentation that strengthens the ability to extract significant features in contrast to the conventional approaches. Furthermore, using this method, to enhance the segmentation accuracy, parallel branches are constructed to extract shallow spatial features into the main network and merge shallower spatial information alongside deep semantic information. The proposed methods have been evaluated against well-known CASIA and IITD benchmark datasets and managed to obtain 98.5% and 98.4% accuracy rates respectively.

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Furthermore, [14] created a dependable approach and technology for detecting the presence of Corneal Arcus (CA). The approach can automatically detect the existence of CA in patients with undiagnosed Familial Hypercholesterolemia (FH), which was previously hard to determine. The authors stated that utilizing CNN, VGG16, Resnet, and Inception algorithms resulted in high accuracy scores and a great association with expert decisions.

[15] attempted to tackle the iris recognition systems that were presented with non-ideal photos that caused poor performance. To address the problem, the authors evaluate the usability of the periocular region, a new feature-rich biometric trait, in two non-ideal scenarios: picture matching with different position variations and image matching on different sides of the periocular. The authors claimed that VGG19 has 94% and 96% accuracy for photos with 30 and -30 degree posture variation, respectively, and Resnet18 has around 88% for matching images on the same side.

Additionally, a study by [16] em
ployed pre-trained DCNN models to connect images from the same subject and detect dissimilar shots from different subjects to explore more distinguishing traits from the periocular region or iris. The authors solved the problem of images suffering from various noise artifacts such as shadows, specular reflections, occlusion by the eyelid, eyelashes, hair, off-angle, motion-blur, and rotational as a result of carrying imaging conditions, resulting in data inadequacy and complicating the recognition task by using VGG16, Resnet50, and Inception-v3.

In addition, [17] aim to improve the segmentation of off-axis iris images taken by a user-facing camera in uncontrolled settings on a wearable AR/VR device. Frontal iris region segmentation is compared to state-of-the-art algorithms with substantially higher complexity to achieve excellent levels of performance. The authors tackled the problem of near-eye iris segmentation, a new challenge brought on by the emergence of growing AR/VR headset technology. Although the dataset of iris samples captured from a user-facing camera on AR/VR devices is a significant barrier, the authors stated that the results show promising levels of off-axis segmentation accuracy, and the resulting trained neural network significantly outperforms state-of-the-art frontal iris segmentation.

[18] also claimed that, despite significant improvements in iris identification, contact lenses might be considerably deceiving as the contact lens folds all around the iris region difficult to be collected. Consequently, the authors present a novel Densely Connected Contact Lens Detection Network (DCLNet), known to be a deep convolutional network with dense connections between layers. DCLNet was constructed by modifying DenseNet121 and then adding a Support Vector Machine (SVM) classifier.

However, in an effort to address the issue where acquisition becomes less constrained and the quality of images is frequently worse than concentrated iris acquisition methods, [19] also make an effort at introducing an end-to-end deep neural network model with an augmentation strategy that significantly enhances the quality of iris segmentation on less high-quality photos. The authors use Fully Convolutional Deep Neural Network (FCDNN) and Semi Parallel Deep Neural Network (SPDNN) to tackle the difficulties.

On the other hand, non-ideal conditions caused by external light and sound, along with user non-cooperation, that affect iris performance, are resolved by [20] utilizing Semantic Segmentation, CNN, and Encoder-Decoder Network. The exploratory outcomes showed that the suggested approach functioned as best it could, according to the authors. While this was going on,

Based on prior research in similar disciplines, gaps in poor-quality photos, such as blur and poor illumination, caused the method to fail to recognize iris images more correctly. Therefore, the detection precision of the method is low, and the images contain numerous noise artifacts such as shadows, reflections, occlusion by the eyelashes and eyelids, or off-angle, which hinder the recognition process owing to diverse imaging conditions. Therefore, an innovative approach is necessary to bridge the aforementioned gaps, which have become a difficult task to complete nowadays. Consequently, the objective of this research has focused on proposing the enhancement of semantic segmentation and data augmentation to improve detection performance in terms of accuracy, specifically for blur and poor lighting-infected images.

III. PROPOSED SOLUTION

The proposed solution includes a modified Semantic Segmentation structure which is adopted with a Data Augmentation module. Figure 1 illustrates the architecture of the proposed solution namely MSSDA (Modified Semantic Segmentation Data Augmentation) which enables iris recognition more accurately.

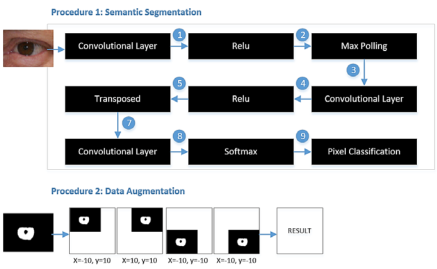

Fig. 1. The overall architecture of the proposed MSSDA

The employed Semantic Segmentation is a part of Mask R-CNN that can generate the mask and pixel label. Furthermore, object detection is distinct from Semantic segmentation, yet it constructs the mask for the considered object. Semantic segmentation took on the task of separating pixels and determining which pixels belong to which object or class. Referring to Figure 1, the overall MSSDA comprises several sequential layers i.e. Input, Convolutional, Max Pooling, RELU, Transposed, Softmax, and Pixel Classification. In particular, two strategies will be used in the implementation procedure: semantic segmentation and data augmentation. The main aim of utilizing semantic segmentation is to produce mask and pixel labels for image classification that can facilitate object detection more accurately.

Semantic segmentation will divide a picture into several segments, or regions, every single one which is associated with a particular class or category. In addition, this semantic segmentation provides a comprehensive comprehension of an image's information by assigning an identity to each pixel, in contrast to simple object recognition, which aims to identify and locate things within an image. Convolutional layers are the first layer we utilized since they are important for extracting characteristics from input images, which the created network uses to classify every pixel into meaningful segments. To enable the network to identify specific characteristics from the input image, such as edges, corners, object classes, categories, and so on, the extracted hierarchical features will be in various levels of abstraction. Max pooling layers are taken into consideration when the non-linear activation function known as RELU (Rectified Linear Unit) is used to lower the special dimensions of the feature map, translation invariance, and computational effectiveness. More specifically, the RELU activation function is utilized to add non-linearity to the formed network for a deep understanding of the complex relationship between input features and output labels. More specifically, for deep networks, this straightforward technique helps the network understand more quickly and avoids the issue of vanishing gradients, which can arise during training if the gradient gets smaller than necessary.

Subsequently, the generated feature maps' spatial dimension was reduced progressively using the max polling function, which indirectly improved the effectiveness of the semantic segmentation model. Moreover, by expanding the network's receptive field, max pooling enables neurons in lower layers to gather data from a larger region of the supplied image. For precise semantic segmentation, this helps the network understand deeper features and context.

Transposed convolution layers are included inside the network to improve the feature maps' spatial resolution. By first executing a convolution process using learnable parameters, and then expanding the zeros using a stride-based method, the implemented transposed convolution efficiently "upsamples" the feature maps, producing an expanded feature map. This has facilitated the precise and more accurate pixel-wise segmentation masks with fine details.

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The softmax function is employed before the final phase of the network in semantic segmentation to generate pixel-wise class probabilities for every pixel in the image being analyzed. The resultant feature map is subjected to the softmax function, which transforms the raw scores into probabilities for each of the pixels that add up to one for all classes. Each pixel's expected probability distribution for each class is represented by the softmax function's output. During inference, the class with the highest probability is often selected as the predicted class for each pixel. Finally, in this procedure, the pixel classification assigned class labels for the entire processed images individually with the aim of the detailed information about the context of the images can be obtained.

On the other side, later the augmentation approach is considered to reduce the overfitting within images, as the performance of the accuracy has tendencies for improvement. Upon receiving the output from prior procedure, the pixel data and image data combined respectively to facilitate training time to obtained desired accuracy. The translation approach has been applied in which each iris image is shifted horizontally and vertically to simulate changes in position of -10 or +10 randomly at x-axis and y-axis within its bounding box. This modification represents alterations to the orientation of the iris around the eye, making the model more reliable in real-world circumstances. By performing translation modification to iris photos, the augmented dataset becomes greater in variety, accounting for differences in iris orientation that could happen in real-world circumstances. This improves the resilience and generalizability of the proposed model for iris detection, resulting in greater performance in real applications.

IV. EXPERIMENTS & RESULT

Dataset

The CASIA v4 Interval and IITD benchmark datasets have been utilized for assessing the suggested method. CASIA Iris Image Database (CASIA-Iris) was created by the Center for Biometrics and Security Research (CBSR) research team and is now available to the international biometrics community. CASIAv4 Interval, in particular, offers a collection of images captured using their close-up iris camera. The most enticing aspect of the iris camera is the circular NIR LED array with appropriate luminous flux for the iris. CASIAv4 Interval is perfect for studying iris image fine texture properties. The IITD collection known as the IIT Delhi Iris Database, on the other hand, principally consists of iris photographs taken from IIT Delhi students and staff. It is accessible for free upon request, and the photographs are saved in bitmap format. The subjects in the database range in age from 14 to 55, with 176 men and 48 women. In this research, the CASIAv4 Interval database comprises 2446 samples from 142 subjects, whereas the IITD database contains 2240 picture samples from 224 subjects. The whole set of iris images from the right eye was used as a training set, whereas the first five photographs from the left eye were used as a test set. As a result, the test set contains 2240 authentic pairs and 624,400 counterfeit pairs.

Evaluation Measurement

The proposed method's performance was evaluated by calculating the accuracy. These metrics are commonly used to assess the performance of some recognition systems (Prathaban, B.P., and Balasubramanian, R. (2020, December 24). The employed formula is as follows:

$$Accuracy = (TP + TN) / (TP + FP + TN + FN)$$

FP = False Positive number of imposter acceptance.
TN = True Negative number of imposter rejection
FN = False Negative number of genuine rejection
TP = True Positive number of genuine acceptance.

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Experimental Result

A set of experiments were carried out to assess the effectiveness of the proposed method. Initially, the labeled data (specifically, pixel label data) will be blended with the image or original data during the semantic segmentation phase. This is due to the data augmentation phases being processed utilizing a variety of epochs such as 10, 20, and 30. Table 2 represents the output from the training stages for two different datasets.

TABLE 2: Training Result

Dataset	Epoch	Accuracy (%)
CASIAv4	10	96.01
	20	99.41
	30	99.99
IITD	10	99.18
	20	99.9
	30	99.94

Based on the obtained results in Table 2, epochs influence determining the success of the suggested strategy during the training stage. The greater the number of epochs, the greater the accuracy. This is because when the epochs increase, the image is divided into a small partition, making it clearer and, as a result, increasing the accuracy of the suggested method. For instance, the obtained result via CASIAv4 and IITD dataset of epochs 30 are slightly higher in terms of accuracy at 99.9% as compared to other epochs.

TABLE 3: Previous State-of-the-art Methods Vs Proposed Method

Dataset	Author	Approach Used	Accuracy
CASIAv4	[21]	Iris Segmentation	91.86%
	[20]	CNN, Semantic and Segmentation	96.59%
	[22]	CNN	99.24%
	[13]	Deep Semantic Segmentation	98.51%
	The Proposed Method	*Semantic Segmentation + Data Augmentation*	*99.9%*
IITD	[23]	Mask R-CNN	96%
	[20]	CNN, Semantic and Segmentation	96.82%
	[24]	Deep CNN, Semantic and Segmentation	94.08%
	[13]	Deep Semantic Segmentation	98.40%
	The Proposed Method	*Semantic Segmentation + Data Augmentation*	*99.94%*

Furthermore, as shown in Table 3, previous work that employed deep learning as a foundation, similar techniques, and well-known datasets such as CASIAv4 and IITD have been compared to the proposed method. The proposed method has outperformed the entire previous work in terms of accuracy. Referring to Table 3, the proposed method has achieved a 99.9% accuracy rate for both CASIAv4 and IITD datasets. The work proposed by Shalaby et al (2021) gained 99.24% via the CASIAv4 dataset and via the TTDI dataset and it is the closest state-of-the-artwork that is slightly gained near to the proposed method. Additional analysis is being performed of the results collected to discover potential improvements. A brief tracing is carried out utilizing the model's output for detection and the label of the data. Unfortunately, because of the image not being

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appropriately labeled, the identical generated pattern makes recognizing the other region difficult. As a result, even though the image is quite clear, the pixel labels could not be made precisely. To achieve a better result, an improved approach to image enhancement should be implemented. However, a concentrated examination of image tagging on unconstrained images is required.

V. CONCLUSION AND FUTURE WORK

The proposed method comprises an integrated component of Semantic Segmentation and Data Augmentation, namely SSDA. This method breaks an image into numerous picture portions known as image regions to distinguish between dissimilar objects from an image at the pixel levels. Furthermore, using the data augmentation (DA) strategy, novel information is artificially produced from current data, which has proven useful in increasing model generalization and accurately resolving data scarcity issues. The suggested model, SS+DA, has been tested on benchmark datasets known as CASIA and IITD. The experiment results reveal that the proposed strategy achieves an accuracy rate of more than 99% for both the CASIA and IITD datasets. For future work, the research under iris recognition could be suggested to incorporate data augmentation methods with dissimilar approaches and validate using real-time data.

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