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Deep Learning for Robust Iris Recognition: Introducing Synchronized Spatiotemporal Linear Discriminant Model-Iris

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Abstract

A novel Synchronized Spatiotemporal Linear Discriminant Model –Iris (SSLDMNet-Iris,) a deep learning architecture is introduced in this work which is designed to address the challenges associated with iris recognition under varying environments, such as occlusion, variations in eye pupil dilation, and lower image quality. This has been implemented by integrating multi-scale convolutional feature extraction with synchronized temporal modeling through Gated Recurrent Units (GRUs), the proposed SSLDMNet-Iris model effectively can catch both intricate texture details and global spatial patterns related to the iris. Additionally, the model utilizes Fisher's Linear Discriminant (FLD) for features extraction and optimizing the separation between classes while minimizing intra-class variance, thereby raising recognition accuracy. Comprehensive experiments conducted on seven benchmark datasets (i.e., CASIA Iris 1.0, CASIA Iris 2.0, CASIA Iris 3.0, CASIA Iris 4.0, IITD, UBIRIS, MMU), and exhibit a promising accuracy rate where, the SSLDMNet-Iris surpassing traditional models

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like VGG16, AlexNet, and ResNet. Notably, SSLDMNet-Iris attains 100% accuracy on CASIA Iris 1.0, CASIA Iris 2.0, and MMU datasets, while maintaining high computational efficiency with a reduced processing time. These results highlight the robustness and versatility of SSLDMNet-Iris, making it an ideal candidate for real-time iris recognition applications.

Keywords: Artificial intelligence, Deep learning, Iris recognition, SSLDMNet-Iris, Feature extraction.

1. INTRODUCTION

Due to the rapid advancement in Iris recognition technology, there have been a lot of developments in various sectors including the security and surveillance sector, biometric based identification and access control [1]. The initial works for the implementation of iris-based recognition systems are not much more than just the raw feature extraction methods, for instance, the Gabor wavelet-based feature extraction [2], and Daugman's rubber sheet model [3]. With the advancement in artificial intelligence [4], and the emergence of Deep learning the accuracy and the confidence of iris recognition systems have been enhanced especially in low light conditions [5]. These include variation in lighting conditions [6], distortions arising from variation in pupil size [7], and interference from reflection and occlusion [8]. However, some of these challenges and issues have not been fully addressed, hence, in some cases, identity authentication systems are unable to capture a clear iris image due to motion and distance [9]; or the Iris images may be partially obscured by eyelashes, eyelids or even contact lenses which may hinder the system's capability of obtaining reliable information [10]. Another issue which remains a big challenge is how the system will operate where there is variation in lighting conditions, including infrared lighting or visible lighting surrounding the object [11]. Such challenges make it necessary to develop more stable models that would be able to perform well in real-life settings. [12]. In the area of iris recognition, there have been efforts from the researchers to develop recognition systems that are able to counter the challenges that are discussed herein with the aim of realizing reliable performance under various conditions [13]. In the current state of the art, the work in iris recognition has been directed at enhancing the performance of feature extraction process by combining the shallow and deep level image characteristics for effective recognition especially where the irises are partly obscured or under the influence of varying lighting conditions [14]. The integration of these multi-scale features helps the models to capture both the large level features such as the iris texture and furrows hence improving the efficiency of the recognition process [15]. The use of real time applications has been increasing especially in personal devices, embedded systems and security checkpoints [16], hence there is need to produce new ways of improving the computational performance of iris recognition. There is a growing need for models that are able to deliver high levels of accuracy while at the same time minimizing the power consumption [17]. This has led to the creation of lightweight architectures that are able to support real time operation without really affecting recognition performance. The following applications have been made possible by these systems such as remote monitoring, mobile authentication and night vision security where conventional imaging systems produce unreliable results [18]. The utilization of deep learning models, especially Convolutional Neural Networks (CNNs), has transformed the domain of iris recognition [19]. These models have exhibited exceptional proficiency in tackling ongoing challenges, including occlusions, varied environmental conditions, and cross-modality recognition, like the integration of iris recognition with additional biometric methods [20]. Nonetheless, current research persists in investigating methods to augment model robustness, scalability, and adaptability in practical applications, thereby ensuring that iris recognition systems maintain their prominence in biometric technology.

The next parts of this paper are arranged as follows: In Section 2, some related literature of iris recognition using variant deep learning models are presented and discussed. Section 3 presented the suggested methodology phases. The newly developed deep model (SSLDMNet-Iris) is described in Section 4. Section 5 shows the experiments results of the presented system using four datasets. A discussion about the performance of the introduced deep model is illustrated in Section 6. Section 7 provides the conclusion, and the future works intend.

2. RELATED LITERATURES

Iris identification has progressed, especially with deep learning, and has been extensively researched to improve its accuracy and efficacy under difficult settings. This section provides a discussion number of noteworthy contributions and their performance outcomes on how deep learning has improved iris identification by addressing reliable feature extraction, data augmentation, and classification.

In [21], A new architecture of deep CNN, so called IrisConvDeeper, has been introduced, to enhance the accuracy under challenging environments of iris recognition. It includes fourteen layers of convolution along with Dense blocks so it can effectively manage the complexities of iris texture. It has been evaluated on two datasets, namely CASIA-Iris-V3 and IITD, and exhibits a recognition accuracy of over 98%.

In [22], the Capsule Neural Network (CapsNet), has been applied to overcome the limitations of CNNs, like high sample requirements and sensitivity to noise. The pre-trained models have been integrated with them (VGG16, InceptionV3, ResNet50) and exhibits an enhancements of around 4-5% in accuracy rate compared to CNNs, especially in different lighting scenarios.

In [23], a deep ResNet combined with a pupil detection method to overcome iris segmentation challenge, especially in low-quality images. The intention was also to identify the ocular area, including located beyond the iris, hence enhancing resilience under difficult acquisition conditions, such as motion blur or opacity. Ninety-six percent to 98% accuracies have been acquired on three variant CASIA databases.

In [24], a Conditional Generative Adversarial Network (cGAN) has been presented and employed for data augmentation to address the scarcity of training data in the iris recognition system. The acquired images using the cGAN highly improved the recognition efficiency, and the accuracy increased by 3-7% using these augmented images.

In [25], introduce a combination of CNN and Resnet to raise the performance of iris recognition in challenging environments. This integration made the model able to catch both localized and global features, in which it shows an error rate equal to 1.01% and 1.12%.

In [26], CNN, infrared (NIR) images have been employed for iris recognition. The mid-level features from convolutional layers have been utilized to increase the accuracy, in which, results exhibit an ERR of less than 1%.

In [27], An iris recognition system has been introduced based on CNN called IRISNet, that extract the features and classify them without domain-specific knowledge.it shows an iris identification rates equal to 97.32% for original images and 96.43% for normalized one using the IITD V1 dataset.

In [28], a comprehensive deep learning approach has been introduced which integrates both segmentation and recognition phases utilizing the Mask R-CNN architecture. The CASIA-Iris Thousand dataset has been used for evaluation and the system achieved 99.14% accuracy rate.

In [29], the network so called YOLOv2-has been employed to perform iris and sclera recognition without the need of segmentation. The features of both sclera and iris regions are combined to be used by the model and show a mean Average Precision (mAP) equal to 99%.

In [30], Presented a new iris identification system using GAN-based image reconstruction to increase accuracy rate in unconstrained environments. Their approach was very proficient at minimizing errors and distortions resulting from motion blur or noise in the iris images. It is evaluated using databases like Noisy Iris Challenge Evaluation II and MICHE and shows a 5-8% increase in identification accuracy.

In [31], presented a CNN model of type 2 dimension for iris recognition which implements augmentation and enhancement methods, to make the training dataset bigger and raise up the accuracy. The presented model shows a training accuracy equal to 95.33%, while the testing accuracy was 100% with efficient consumption time.

In [32], introduces a condensed 2-channel deep CNN model, named (2-ch CNN) to achieve iris recognition in high accuracy. Three variant online augmentation methods have been employed and show high effectiveness with a minimized count of parameters.

In [33], introduces a system that employe a low-level CNN layers without any training for rapid recognition. a pre-trained models has been used for classification and feature extractors and a masking technique has been adopted to reduce the effects of borders. The system shows high accuracy and minimizes the computation times on datasets (CASIA Iris Lamp, CASIA Iris Thousand).

Recent developments in iris recognition have markedly improved performance; nonetheless, substantial limits remain, especially regarding computing complexity, scalability, and generalizability across varied situations. Considering the mentioned limitations in the related literatures, a new iris recognition system is presented using deep learning in this paper with the following contributions:

1. Propose SSLDMNet-Iris, a novel deep learning model to achieve high recognition accuracy with a reduced recognition time for iris recognition in real-world conditions, including occlusions, low-resolution images, and variations in lighting and pupil dilation.
2. Design a lightweight and efficient iris recognition system by integrating Fisher's Linear Discriminant and parallel convolutional branches, which significantly reduces computational complexity while maintaining high accuracy.

3. Evaluate the proposed system using seven benchmark datasets with many variations to demonstrate the high scalability and generalization of the proposed model.

3. PROPOSED DEEP SYNCHRONIZED SPATIOTEMPORAL LINEAR DISCRIMINANT MODEL FOR IRIS RECOGNITION (SSLDMNet-Iris)

SSLDMNet -Iris is a novel deep learning architecture designed for sequential data processing, combining multi-scale feature extraction with synchronized temporal modeling. The proposed deep model will be utilized after implementing a series of preprocessing operations on the input iris image and extract a set of features using the Fisher's Linear Discriminant (FLD) method. The proposed deep model has the ability to learn from features at multiple spatial scales while synchronizing this information with temporal dependencies through Gated Recurrent Units (GRUs) and incorporating the features obtained from Fisher's Linear Discriminant (FLD) for enhanced feature separability. The introduced model's architecture effectively captures local and global patterns, analyzes them discriminatively, and integrates them into the temporal dynamics of the data. FIGURE 1 depicts the architecture of the SSLDMNet -Iris model, and the layers of information are described in TABLE 1.

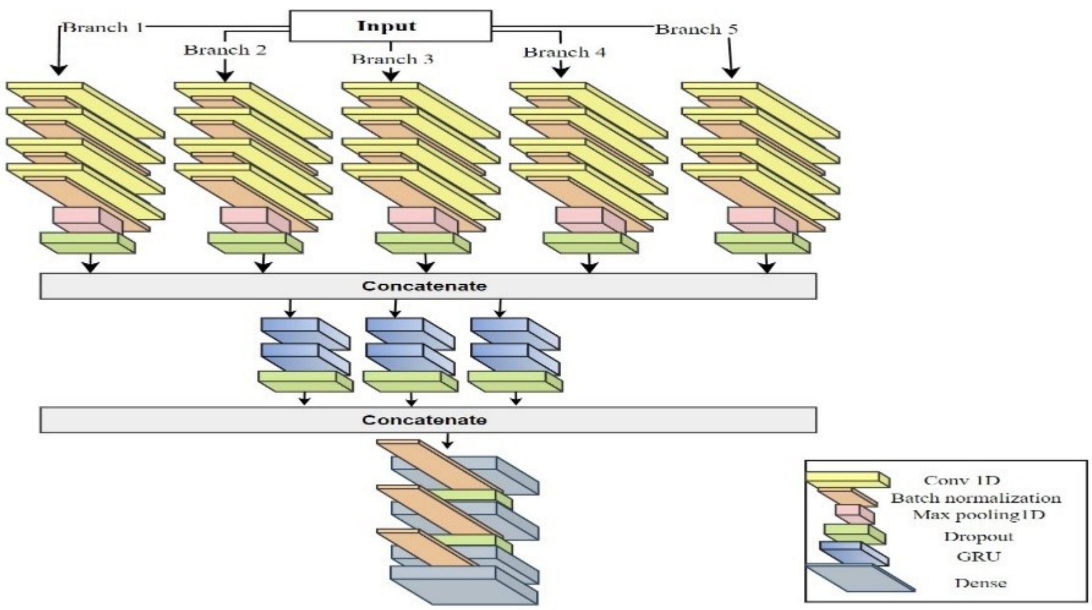

Figure 1: The architecture of the proposed deep SSLDMNet -Iris model.

The SSLDMNet –Iris proposed model presents an innovative framework for iris recognition, utilizing powerful spatiotemporal processing to tackle the specific challenges associated with biometric analysis. several significant advantages are related to the proposed SSLDMNet –Iris including:

1. Multi-Scale Extraction of Features for Iris Texture Assessment: The architecture incorporates several convolutional branches with different kernel sizes for efficiently capturing both very fine and coarse features of the iris texture. The multi-scale tackle allows SSLDMNet -Iris to

accurately identify important biometric features, including crypts, ridges, and furrows related to iris texture, which are vital in successful iris recognition.

2. Temporal Modeling for Variable Data: Real-time working iris recognition systems may suffer from temporal variations in picture quality due to factors such as blinking, variation in pupil diameter or motion. SSLDMNet -Iris utilizes GRUs to model the temporal dependencies in video-based iris detection or in consecutive frames. This ability increases the model's ability to process the variable iris data while ensuring that the data produced is both accurate and consistent.

3. Robust Regularization Versus Noise: Sometimes iris images are corrupted by noise which may be caused by changes in illumination, specular reflections or the detector. Batch normalization and dropout are some strategies that SSLDMNet -Iris uses to prevent over-fitting and enhance the robustness of the model especially when dealing with noisy or low-quality data sets. This makes it even more suitable for application in real life biometric systems.

4. Features Fusion Complementary: The parallel convolutional branches of SSLDMNet -Iris help in identifying spatial characteristics which are not extracted by the other branch thus providing a richer and more comprehensive representation of the iris patterns. This integration enhances the models' discriminative power especially in discriminating against irises that have similar patterns or in situations where the iris is partly covered or has reflections.

5. Flexibility in Iris Recognition Situations: The capabilities of SSLDMNIris include the following iris recognition modalities: Image based iris recognition, video-based iris recognition and multi angle iris recognition. Its ability to handle variable sequence length and adapt to different imaging conditions makes it more suitable for application in privacy, authorization and verification of identity.

6. Real Time Computing computation, for this the makes Purpose it of Application: for GRUs SSLDMNet are -Iris more to efficient provide in their required efficiency for real time iris recognition systems. This capacity is essential in cases of airport security checks or mobile identification where processing has to be done in real time.

3.1 Datasets

This research employs seven iris datasets as shown in TABLE 2, to assess the efficacy of the suggested iris recognition system. These datasets are well-established in biometric research and present a range of challenges, including differences in acquisition conditions, equipment specifications, and inherent drawbacks. FIGURE 2 shows samples of the seven utilized datasets.

4. EVALUATION AND MEASUREMENT RESULTS

A thorough study was conducted in order to assess and confirm the effectiveness of the proposed SSLDMNet-Iris model for effective and efficient iris detection, the performance metrics such as precision, recall, F-measure, accuracy and time have been used. The chosen metrics are intended to provide a thorough analysis of the model's performance in the iris recognition task with emphasis

Table 1: Related information on the SSLDMNet -Iris model layers'

Layer	Output Shape	Parameter
Branch 1 (3x3 Convolutional)		
Convolution 1D	(None, 107, 16)	64
Batch_norm	(None, 107, 16)	64
Convolution 1D	(None, 107, 32)	1568
Batch_norm	(None, 107, 32)	128
Convolution 1D	(None, 107, 64)	6208
Batch_norm	(None, 107, 64)	256
Max pooling 1D	(None, 54, 64)	0
Dropout	(None, 54, 64)	0
Branch 2 (5x5 Convolutional)		
Convolution 1D	(None, 107, 16)	96
Batch_norm	(None, 107, 16)	64
Convolution 1D	(None, 107, 32)	2592
Batch_norm	(None, 107, 32)	128
Convolution 1D	(None, 107, 64)	10304
Batch_norm	(None, 107, 64)	256
Max pooling 1D	(None, 54, 64)	0
Dropout	(None, 54, 64)	0
Branch 3 (7x7 Convolutional)		
Convolution 1D	(None, 107, 8)	64
Batch_norm	(None, 107, 8)	32
Convolution 1D	(None, 107, 16)	912
Batch_norm	(None, 107, 16)	64
Convolution 1D	(None, 107, 32)	3616
Batch_norm	(None, 107, 32)	128
Max pooling 1D	(None, 54, 32)	0
Dropout	(None, 54, 32)	0
Branch 4 (2x2 Convolutional)		
Convolution 1D	(None, 107, 32)	96
Batch_norm	(None, 107, 32)	128
Convolution 1D	(None, 107, 64)	4160
Batch_norm	(None, 107, 64)	256
Convolution 1D	(None, 107, 128)	16512
Batch_norm	(None, 107, 128)	512
Max pooling 1D	(None, 54, 128)	0
Dropout	(None, 54, 128)	0

continued..

Table 1: Continued...

Layer	Output Shape	Parameter
Branch 5 (4x4 Convolutional)		
Convolution 1D	(None, 107, 16)	80
Batch_norm	(None, 107, 16)	64
Convolution 1D	(None, 107, 32)	2080
Batch_norm	(None, 107, 32)	128
Convolution 1D	(None, 107, 64)	8256
Batch_norm	(None, 107, 64)	256
Max pooling 1D	(None, 54, 64)	0
Dropout	(None, 54, 64)	0
Concatenate	(None, 54, 352)	0
Branch 1 (Temporal Modeling)		
GRU	(None, 54, 16)	17712
GRU	(None, 8)	600
Dropout	(None, 8)	0
Branch 1 (Temporal Modeling)		
GRU	(None, 54, 16)	17712
GRU	(None, 8)	600
Dropout	(None, 8)	0
Branch 1 (Temporal Modeling)		
GRU	(None, 54, 16)	17712
GRU	(None, 8)	600
Dropout	(None, 8)	0
Concatenate	(None, 24)	0
Fully Connected Layers		
Dense 1D	(None, 128)	3200
Batch_norm	(None, 128)	512
Dropout	(None, 128)	0
Dense 1D	(None, 64)	8256
Batch_norm	(None, 64)	256
Dropout	(None, 64)	0
Dense 1D	(None, 32)	2080
Batch_norm	(None, 32)	128
Dense 1D	(None, 108)	3564
Total parameters: 132,004		

on reliability and precision. The SSLDMNet-Iris model architecture has sixty-one layers in order to offer effective multi-scale feature extraction together with synchronized temporal processing of iris patterns. The model has been developed on a Lenovo laptop with Microsoft Windows 10 64-bit as the operating system, an Intel(R) Core (TM) i7-7700HQ CPU 2.80 GHz and 16.00 GB of

Table 2: Summary of used Iris Datasets

Dataset	Acquisition Device	No. of Images	Key Characteristics	Limitations
CASIA Iris 1.0 [34]	Custom near-infrared (NIR) camera (850 nm)	756	Grayscale images captured in controlled indoor environments	Small dataset size limits scalability; lacks diversity in lighting and environmental conditions
CASIA Iris 2.0 [35]	Advanced NIR iris camera	1,200	Introduces variations in pupil dilation and ambient lighting	Limited scale for deep learning; variability restricted to controlled lighting conditions
CASIA Iris 3.0 [36]	High-resolution NIR imaging devices	22,051	Subsets: Interval, Lamp, Twins, DistanceIncludes lighting and genetic challenges	Motion blur in distance subset; difficulty in distinguishing genetically similar individuals (Twins)
CASIA Iris 4.0 [37]	State-of-the-art operational NIR devices	54,601	High variability: noise, occlusions, off-axis captures; realistic scenarios	Computationally demanding preprocessing: noise complicates segmentation and feature extraction
IITD Iris Dataset [38]	Logitech camera (visible spectrum)	1,120	High-resolution grayscale images from Indian subjects with high intra-class variability	Limited number of subjects; captured in controlled environments with minimal illumination changes
UBIRIS Iris Dataset [39]	Visible spectrum camera (non-NIR)	11,102	Captures iris images under realistic noise conditions, including motion blur, reflections, and off-axis captures	Presence of extreme noise, such as specular reflections and motion blur, poses challenges for segmentation and feature extraction
MMU Iris Dataset [40]	Logitech webcam (NIR)	4,550	NIR-based images captured from multiple sessions, providing variability in pupil dilation and gaze	Small dataset size: limited variability in environmental factors, as images were captured in laboratory conditions

RAM. The language choice for writing and running is Python 3.6.5. The system was trained for one hundred epochs with a batch of sixty-four using a total of 132004 parameters out of which 130324 are trainable and 1680 are untrainable in order to ensure that all the functions are fine-tuned in the training process. A learning rate of 10 e∧(-3) was used in order to guarantee the proper convergence and to avoid overfitting. The SSLDMNet-Iris model was tested on the CASIA Iris 1.0, CASIA Iris 2.0, CASIA Iris 3.0, and CASIA Iris 4.0 datasets. These are well-known and commonly used in iris recognition research as they provide a challenging environment for the model to generalize on various iris patterns and imaging conditions. The model gave very high identification rates with the help of the main performance measures such as accuracy, precision, recall and F-measure. Also, the model had a low Equal Error Rate (EER) which shows that the model is capable of reducing both false positive and false negatives. The findings demonstrate the robustness of SSLDMNet-Iris, which makes it suitable for real-time application in the field of biometrics such as security and

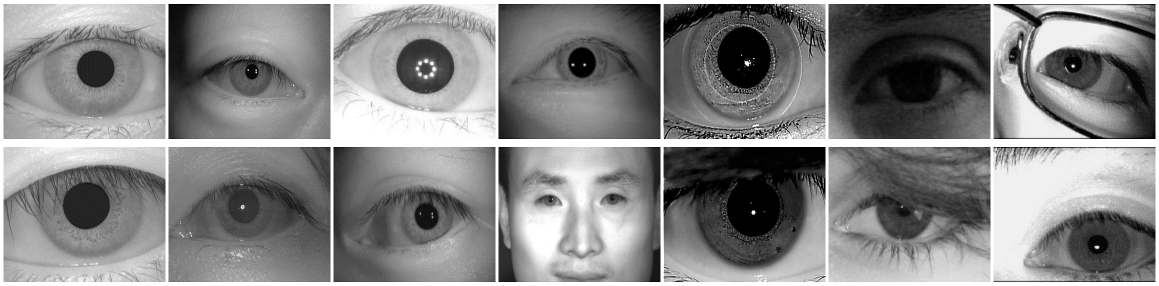

Figure 2: Samples of used Iris Datasets

identification systems. TABLE 3–TABLE 6, presents a detailed comparison of the performance of SSLDMNet-Iris model with other state-of-the-art deep learning models on all seven datasets. This comparison shows that SSLDMNet-Iris is better in terms of accuracy and computational time than other models, thus making it an ideal choice for applications that involve iris recognition. The results show that the proposed model not only gives high identification efficiency but thus also makes it perform well as in suitable terms choice for large scale and real time iris recognition applications.

Table 3: Comparison of SSLDMNet-Iris model for CASIA Iris 1.0 and CASIA Iris 2.0 datasets against many types of deep learning models

Model	CASIA Iris 1.0					CASIA Iris 2.0				
	Acc. (%)	**Prs. (%)**	**Rec. (%)**	**F-meas. (%)**	**Time (ms)**	**Acc. (%)**	**Prs. (%)**	**Rec. (%)**	**F-meas. (%)**	**Time (ms)**
VGG16	97	96.8	96.6	96.7	2193	95	94.8	94.5	94.6	4250
EfficientNet	94.8	94.7	94.5	94.6	4468	91.2	91	90.8	90.9	7523
DenseNet	96.2	96	95.9	96	1342	92.8	92.5	92.2	92.4	3405
AlexNet	94.5	94.3	94	94.2	4279	89.5	89.3	89	89.2	7350
ResNet	95.7	95.6	95.3	95.4	3116	93.4	93.2	93	93.1	8208
Xception	97.5	97.3	97	97.1	3690	96.5	96.2	96	96.1	5756
Inception	94.2	94.5	94.3	94.4	2942	92	91.8	91.5	91.6	6003
MobileNet	96.8	96.7	96.5	96.6	1518	94.3	94.1	93.8	93.9	4602
SSLDMNet-Iris	**100**	**100**	**100**	**100**	**1021**	**100**	**100**	**100**	**100**	**3050**

As noticed in the previous illustrated outcomes, the presented system has achieved the greatest results for the CASIA Iris 1.0, CASIA Iris 2.0 and MMU datasets in which the accuracy increased reaching 100 % using the SSLDMNet-Iris architecture . This demonstrates the SSLDMNet-Iris exceptional capability in extracting and analyzing complex iris patterns leveraging multi-scale spatial feature extraction and synchronized spatiotemporal modeling. The system sets a benchmark for state-of-the-art performance in Iris recognition, highlighting its robustness, efficiency, and suitability for critical biometric applications. Applying the SSLDMNet-Iris model on the CASIA Iris 3.0 dataset yielded excellent results with 99.5% accuracy.as shown in TABLE 4. On the other hand, the CASIA Iris 4.0 dataset is one of the largest and most unstructured datasets which present a vast

Table 4: Comparison of SSLDMNet-Iris model for CASIA Iris 3.0 and CASIA Iris 3.0 datasets against many types of deep learning models

Model	CASIA Iris 3.0					CASIA Iris 4.0				
	Acc. (%)	Prs. (%)	Rec. (%)	F-meas. (%)	Time (ms)	Acc. (%)	Prs. (%)	Rec. (%)	F-meas. (%)	Time (ms)
VGG16	97.5	97.2	96.8	97	23200	88	87.8	87.5	87.6	73630
EfficientNet	88.9	88.5	88	88.2	17104	95.4	95	94.5	94.7	45229
DenseNet	95.3	95	94.5	94.8	22400	92.6	92.3	92	92.2	72712
AlexNet	83.4	83	82.5	82.7	36192	89.5	89	88.7	88.8	37813
ResNet	88.2	88	87.8	87.9	54051	85.7	85.4	85	85.2	84315
Xception	92.1	91.8	91.5	91.6	14429	91	90.8	90.5	90.6	55257
Inception	90.7	90.5	90	90.2	23804	92.3	92	91.5	91.7	84160
MobileNet	95.6	95.3	95	95.2	21989	87.8	87.5	87.2	87.3	43381
SSLDMNet-Iris	**99.5**	**99.5**	**99.1**	**99.3**	**10950**	**99.6**	**99.5**	**99.3**	**99.4**	**22876**

Table 5: Comparison of SSLDMNet-Iris model for IITD and UBIRIS datasets against many types of deep learning models

Model	IITD					UBIRIS				
	Acc. (%)	Prs. (%)	Rec. (%)	F-meas. (%)	Time (ms)	Acc. (%)	Prs. (%)	Rec. (%)	F-meas. (%)	Time (ms)
VGG16	94	94	94	94	43700	93.2	93.7	90.1	91.86	20512
EfficientNet	89	90	88	88.98	23820	93.1	94	92	92.98	29683
DenseNet	93.5	94	92	92.98	54600	92	92.7	92.2	92.44	28041
AlexNet	91.8	92	91	91.4	32530	96.5	97.	95	95.98	20108
ResNet	92	92	92	92	84315	97	97	97	97	12673
Xception	95.7	96	95	95.49	55257	95	95.2	93.8	94.49	12957
Inception	91	91	91	91	84160	89.2	89.2	89.2	89.2	20914
MobileNet	96.1	96.5	94.2	95.33	43381	81.7	81.7	81.7	81.7	12093
SSLDMNet-Iris	**99.9**	**99.9**	**99.9**	**99.9**	**22417**	**99.97**	**99.97**	**99.97**	**99.97**	**10628**

variety in the quality of images which make the Iris identification process difficult. However, the proposed approach achieved a very high accuracy of 99.6%. which demonstrates that the system is able to deal with complex and challenging data sets effectively thus making it highly reliable and efficient to use in challenging real-life conditions. The obtained outcomes from IITD Iris and MMU datasets prove the efficiency of the proposed system in obtaining high performance using a little amount of data, while the challenges of noisy data in the UBIRIS datasets demonstrate the high ability of the proposed system in handling many variations and subjects exists in the data, and this is what makes it suitable for real world application.

In this study, we evaluated the execution time (in milliseconds) of several deep learning models—VGG16, EfficientNet, DenseNet, AlexNet, ResNet, Xception, Inception, MobileNet against our proposed SSLDMNet-Iris—across the seven datasets. Execution time was measured as the total

Table 6: Results of comparing SSLDMNet-Iris model for MMU dataset with different types of popular deep learning techniques.

Model	Acc. (%)	Prs. (%)	Rec. (%)	F-meas. (%)	Time (ms)
VGG16	95.7	96	95	95.49	520
EfficientNet	96.1	96.5	94.2	95.33	483
DenseNet	94.9	95.1	95	95.05	490
AlexNet	97.3	97.6	95.5	96.53	418
ResNet	93.1	93.7	90.1	91.86	134
Xception	93.8	94	92	92.98	139
Inception	92.5	92.7	92.2	92.44	134
MobileNet	98	98.4	98.2	98.29	128
SSLDMNet-Iris	**100**	**100**	**100**	**100**	**70**

time taken for model inference on a standard benchmark test. The results indicate that the proposed SSLDMNet-Iris model consistently outperformed the other models in terms of execution time. This substantial reduction in time highlights the efficiency of the proposed model, making it well-suited for real-time applications where fast response times are critical.

5. DISCUSSION

This paper introduced SSLDMNet-Iris, a novel iris recognition model that sets a new benchmark in performance across several challenging datasets with high recognition accuracy. The model achieved 100% accuracy on three datasets (i.e., CASIA Iris 1.0 CASIA Iris 2.0. MMU), along with accuracy ranging from 99.5% to 99.9% for the other four datasets, which significantly surpass existing approaches in both recognition accuracy and computational efficiency.

The robustness of SSLDMNet-Iris lies in its ability to address real-world complexities such as occlusion, pose variations, and low-resolution images due to it being composed of a multi-branch CNN architecture that employs kernels of varying sizes to extract both fine-grained and global features from iris images. This multi-scale approach is novel in its ability to capture intricate iris textures and structural patterns effectively. Moreover, the utilized Gated Recurrent Units (GRUs) is very beneficial in synchronized temporal modelling, which ensures that the two types of information are captured well, (i.e. local, global) iris features thus enhancing the accuracy of the system even under harsh conditions. in addition, the utilization of FLD for dimensionality reduction and feature separability, optimizes the class distinction and minimizing intra-class variance, which enhances recognition accuracy and computational efficiency.

The rapid recognition of the proposed SSLDMNet-Iris model is extremely efficient and ranging from 22876 millisecond for the CASIA Iris 4.0 down to 70 milliseconds for the MMU iris dataset, which make it suitable in real world applications since it has a lightweight architecture with reduced computational complexity compared to state-of-the-art models like VGG16 and ResNet. in which the total number of parameters is equal to 132,004, leading to reduced memory usage compared to larger models with millions of parameters. As a result, it achieves superior accuracy with fewer trainable parameters and faster execution times, enabling its use in resource-constrained environments (e.g., mobile devices and embedded systems). TABLE 7 exhibits a measurement of the complexity related to the proposed deep model.

Table 7: The complexity analysis of the proposed deep model for iris recognition

Component	Type	Complexity	Impact
Convolutional Layers	Computational	$O(n \cdot k^2 \cdot\ d^2)$	Low (multi-scale branches)
GRU Layers	Computational	$O(3 \cdot h^2 + 3 \cdot h \cdot d)$	Medium (3 GRU branches)
Fully Connected Layers	Computational	$O(m \cdot n)$	Medium
Parameter Storage	Memory	132,004 total, 130,324 trainable	Low
Activation Storage	Memory	$O(b \cdot m \cdot d^2 \cdot 4)$	Medium
Training Time	Time	Dependent on small epochs, small batch size, lightweight layers	Low
Inference Time	Time	Seventy MS (MMU) to 22,876 ms (CASIA 4.0)	Medium to Low

The high generalization and scalability of the proposed system has been demonstrated since it has been evaluated on seven iris datasets having many variations and challenges with different counts of samples, and the system shows a high recognition performance across all these datasets. While other studies focus on either improving accuracy or computational efficiency, SSLDMNet-Iris successfully achieves both, marking a significant step forward in practical and scalable iris recognition systems. These results show that the model can perform real time iris detection and identification hence suitable for applications that require fast response time. TABLE 8 presents a detailed comparison between SSLDMNet-Iris against other techniques applied to the seven datasets. These comparisons show that SSLDMNet-Iris is able to provide state-of-the-art identification rates with the added benefit of efficient computation, thus it can be viewed as a game changer in iris recognition.

6. CONCLUSIONS AND FUTURE WORK

This paper proposes SSLDMNet-Iris, an improved iris recognition model which has been developed to address significant challenges such as pupil dilation, occlusions, aging that effect recognition of individuals iris. It exhibited remarkable robustness and computational efficiency, particularly through the implementation of (GRUs) for multi-scale Linear Discriminant feature extraction and temporal modeling, rendering it highly suitable for real-time applications. The evaluation of the proposed iris recognition model using seven datasets with many variations has demonstrated the high generalization of the proposed model. where it achieves a remarkable recognition accuracy equal to 100 % using three bunch mark datasets. The proposed SSLDMNet-Iris is considered to be light weight model with a reduced number of parameters what makes it well suited for real world application. Moreover, the required recognition time for iris is less than one minute in all the seven datasets and this makes it an ideal solution for the iris recognition in very challenging environment

Table 8: Iris Image datasets result comparison.

Study	Dataset	Acc. (%)	Prs. (%)	Rec. (%)	F-meas. (%)	Time (ms)
[41]		99	-	-	-	-
[42]	CASIA Iris 1.0	97	-	-	-	-
proposed		**100**	**100**	**100**	**100**	**1021**
[43]		95	-	-	-	-
[44]	CASIA Iris 2.0	97	97	97	97	-
proposed		**100**	**100**	**100**	**100**	**3050**
[45]		97.8	97.8	97.8	97.8	-
[46]		96.5	96.2	96.0	96.1	-
[47]	CASIA Iris 3.0	99	-	-	-	-
[48]		95.3	95.0	94.7	94.8	-
proposed		**99.5**	**99.5**	**99.1**	**99.3**	**10950**
[49]		96	-	-	-	-
[50]		98	-	-	-	-
[51]	CASIA Iris 4.0	98.5	98.5	98.5	98.5	-
[52]		96.8	96.3	96.0	96.1	-
proposed		**99.6**	**99.5**	**99.3**	**99.4**	**22876**
[53]		98.1	-	-	-	-
[54]		86.8	-	-	-	-
[55]		99.3	-	-	-	-
[56]	IITD	97.24	-	-	-	-
[57]		99.06	-	-	-	-
proposed		**99.9**	**99.9**	**99.9**	**99.9**	**22417**
[58]		98.8	-	-	-	-
[59]		96.12	-	-	-	-
[60]	UBIRIS	94.81	-	-	-	-
[61]		97.9	-	-	-	-
proposed		**99.97**	**99.97**	**99.97**	**99.97**	**10628**
[62]		99.99	-	-	-	-
[63]		-	-	-	-	93
[64]		99.7	-	-	-	-
[65]	MMU	98.01	-	-	-	-
[66]		99.88	99.8	-	-	-
[67]		95.9	-	-	-	-
proposed		**100**	**100**	**100**	**100**	**70**

conditions. Future work should focus on expanding its scope to include applications like 3D iris recognition and multi-modal biometric systems.

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Not Applicable

8. DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

9. ETHICAL APPROVAL

Not Applicable.

10. CONSENT TO PARTICIPATE

The authors provide the appropriate consent to participate.

11. CONSENT FOR PUBLICATION

The authors provide the consent to publish the images in the manuscript. The data used in the publication is publicly available. We provide respective citations for each of the data sources.

12. Code Availability:

The code developed and utilized in this study is publicly accessible at the DOI: https://doi.org/10.5281/zenodo.14166010

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