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DETERMINING AN APPROACH TO IRIS RECOGNITION DEPENDING ON SHOOTING CONDITIONS

Olesia Barkovska
Corresponding author
PhD, Associate Professor*
E-mail: olesia.barkovska@nure.ua
Igor Ruban
Doctor of Technical Sciences,
First Vice-Rector**
Yuri Romanenkov
Doctor of Technical Sciences,
Vice-Rector for Scientific Work**
Pavlo Botnar
PhD Student*
Anton Havrashenko
PhD Student*
*Department of Electronic Computers**
**Kharkiv National University of Radio Electronics
Nauky ave., 14, Kharkiv, Ukraine, 61166

The object of this study is the development and evaluation of image processing and analysis methods for iris recognition, which can be integrated into human-machine interaction (HMI) systems based on biometric data or other contactless interaction approaches.

Enabling high accuracy and reliability of biometric iris recognition systems under variable imaging conditions remains an open scientific challenge. One of the primary difficulties is the impact of changing lighting conditions, head tilt, and partial eye openness on identification results.

This study assesses the effect of preprocessing methods (Equalization Histogram, CLAHE) on iris image quality and compares the algorithmic method (Hamming Distance) with neural network models (CNN, DenseNet) based on key metrics, including accuracy, False Match Rate, False Non-Match Rate, and Equal Error Rate. Additionally, the influence of training dataset structure and neural network hyperparameters on classification performance was analyzed.

The results demonstrate that the Hamming Distance method (HD = 0.35) achieves 95.5 % accuracy, making it a competitive alternative to neural networks. It was established that combining CLAHE and Equalization Histogram effectively reduces noise and enhances segmentation accuracy. Furthermore, it was determined that the DenseNet-201 neural network achieves an accuracy of 99.93 % when using an optimal dataset split (70 %:15 %:15 %). The study confirms that preprocessing techniques such as normalization and adaptive contrast enhancement significantly reduce recognition errors under varying lighting conditions.

The proposed solution holds significant potential for assistive technologies for individuals with visual impairments, the automotive industry, as well as security systems

Keywords: iris recognition, Hamming Distance, HMI systems, DenseNet, CLAHE, Equalization Histogram

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1. Introduction

For an effective human-machine interface (HMI), it is important to combine the analysis of visual and audio information, creating multimodal interaction. For example, a smart home can use voice commands for basic actions, and gestures for precise control in a noisy environment. This improves the convenience, speed, and reliability of the system.

However, the demand and prevalence of HMI systems go far beyond voice or gesture control systems for smart home elements. Human-machine interaction based on the analysis of user actions, which can be assessed visually, is widely used in various industries. In particular, such technologies are actively implemented in the automotive industry, robotics, medicine, and rehabilitation, where they help improve safety, automate processes, and expand user capabilities. These methods are also used in the military and aerospace sectors, education, scientific research, and smart homes, providing new levels of comfort and efficiency. In addition, visual analysis technologies play an important role in virtual and augmented reality, the entertainment industry, telecommunications, as well as Internet services, which contributes to the creation of a more interactive and personalized user experience (Fig. 1) [1].

A generalized analysis of the ways of human-machine interaction based on the analysis of visual information (Fig. 1) reveals that the main sources of data for the analysis of visual information are:

– hand gestures (multimedia control, calls, car navigation, contactless control of robots and elements of a smart home, for patients with limited mobility, control of applications without physical contact) [2];

– analysis of gaze and pupil state is used in various areas, in particular to improve road safety in ADAS systems that determine driver fatigue. This technology also provides communication opportunities for people with paralysis, allowing them to interact with digital devices using eye movements. In addition, gaze analysis is used for navigation and target selection on work monitors or head-mounted displays, as well as for studying the level of attention of students during the educational process. In the field of virtual reality (VR) and the gaming industry, this technology is used for object selection, scenario adaptation, as well as web interface personalization [3];

– head and body movements (activation of functions such as lane changing, HUD control, immersion in a virtual environment) [4].

The accumulated scientific achievements are implemented in existing software (OpenFace, GazeFlow, EyeRecToo, DeepGaze), hardware (Tobii Eye Tracker, Pupil Labs, SR Research EyeLink, Gazepoint GP3 Eye Tracker), mobile and web solutions (GazeCloud, iMotions, Eyeware Beam), and medical devices (EyeLink Portable Duo, Noldus FaceReader).

It is difficult to achieve consistently high performance of these systems since in real life it is impossible to provide controlled conditions. External factors such as changing lighting, head movement, partial eye closure, can significantly affect the accuracy of gaze analysis. In addition, changes in the physiological characteristics of the user or variations in image quality can also lead to errors in iris recognition. Therefore, it is important to identify the main factors that cause a decrease in the accuracy of gaze analysis and biometric identification under real conditions [5]. Such factors include:

– changing lighting;
– head movements;
– the presence of a dynamic background;
– individual physiological characteristics of a person.

Despite significant advances in iris-based biometric identification, most current recognition systems are optimized for controlled environments, such as stationary devices with high image quality and uniform lighting. However, a promising direction is the integration of iris recognition technologies into interactive HMI (Human-Machine Interfaces) systems that allow access and control without physical interaction. The use of such systems is relevant for people with disabilities who may have difficulty using conventional authentication techniques (e.g., fingerprints or voice recognition). The use of the iris as a key biometric parameter under conditions of dynamic lighting, unstable head position, or partial eye closure remains a challenge that requires further research and optimization of existing methods.

In addition, gaze analysis is used to assess the level of concentration of drivers and operators, which contributes to increased safety in the automotive and industrial sectors. This technology is also widely used in VR/AR systems for selecting objects by eye, improving the convenience and naturalness of interaction with the virtual environment (Fig. 2).

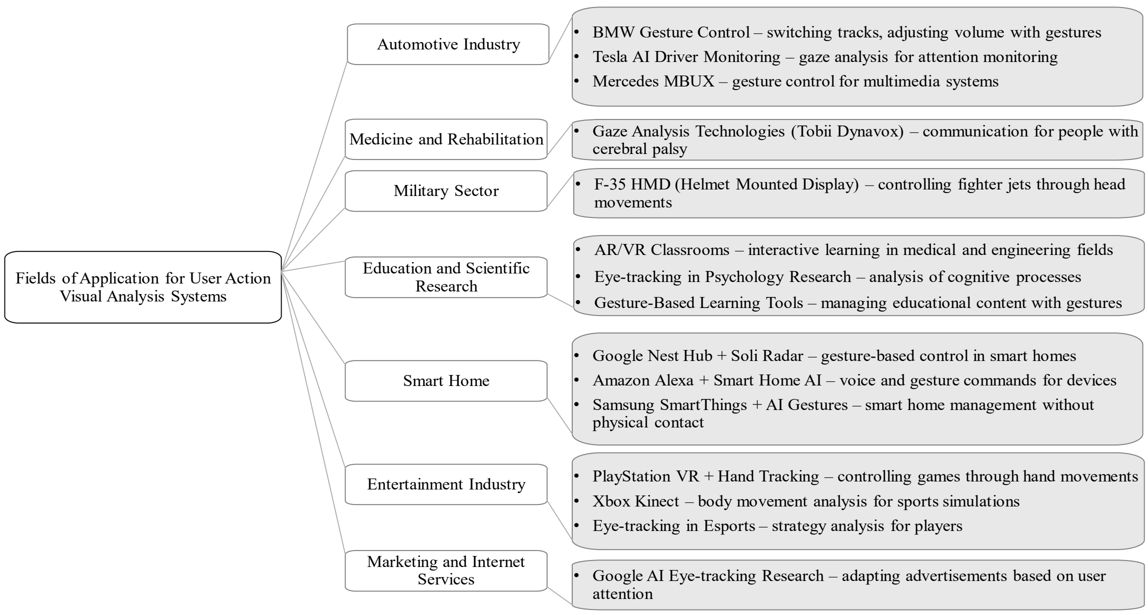

Fig. 1. Domains of human-machine interaction based on user action analysis

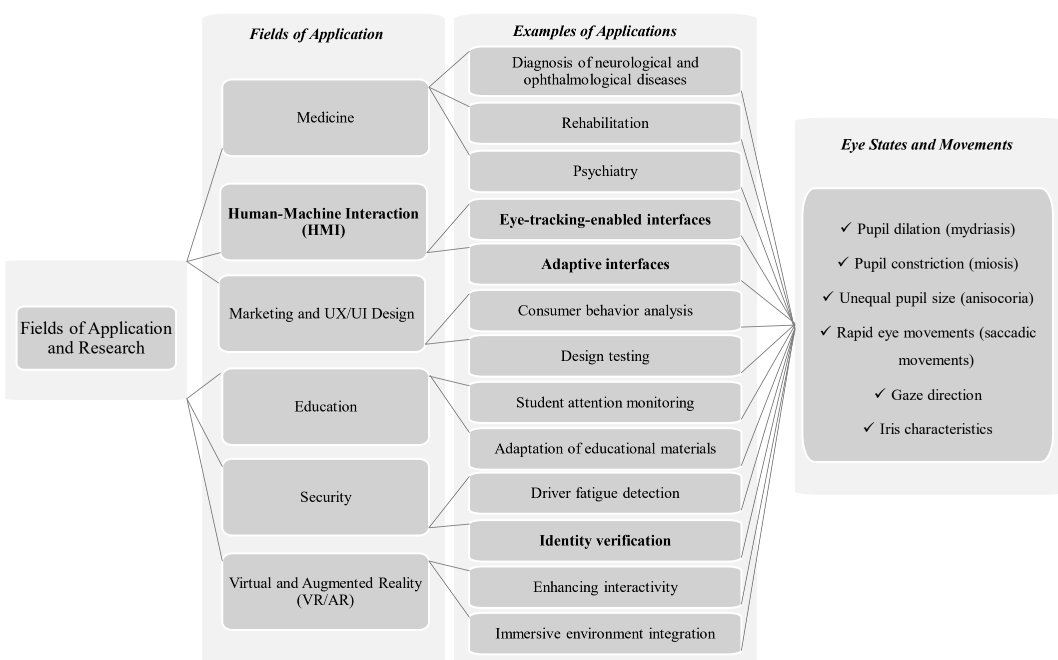

Fig. 2. Overview of problem domain. The relevance of studying the condition of the eye and the direction of gaze

The evolution of iris and gaze direction analysis technologies over the past decade has been driven by the development of deep learning algorithms, the availability of computing power (GPU, TPU), and improvements in the quality of cameras and other sensors [6, 7].

It is assumed that research in this area would have both applied and theoretical benefits.

The theoretical benefit is that analyzing the impact of variable lighting, head tilt, and partial eye closure could expand the scientific understanding of the robustness of biometric algorithms to external factors. Comparison of conventional algorithmic approaches and modern deep neural networks would make it possible to determine the optimal methods for use under uncontrolled conditions.

The applied benefit is that the results obtained would contribute to the development of HMI systems for contactless authentication that could be used in smart homes, mobile devices, as well as specialized devices for people with disabilities. Increasing recognition accuracy under variable conditions would improve the usability of biometric systems, making them more accessible to a wide range of users.

Thus, conducting research aimed at evaluating recognition methods to ensure the stability of biometric systems under uncontrolled conditions will contribute to their widespread use in HMI interfaces for smart devices and inclusive technologies.

2. Literature review and problem statement

In [8], it was proved that for each person there are differences in the patterns and color of the iris, even between the right and left eyes, which remain unchanged over time. Even the iris pattern of identical (monozygotic) twins is different. Thus, recognition techniques developed using iris patterns can be considered the most suitable for identification and authentication. This is especially true in areas such as authentication systems, time and attendance systems, law enforcement systems, banking applications, etc. However, the cited paper does not answer which of the methods for quantitative analysis of scleral pigmentation is the most effective for comparative studies – highest contrast or relative contrast. A likely reason is the lack of a single standard for measuring eye contrast in primates.

In [9], recognition results are reported, obtained on the basis of conventional algorithmic methods (normalization by the Daugman method, circle detection by the Hoag method, PCA method for principal component analysis). The disadvantage of the work is that it does not take into account the behavior of the model under variable shooting conditions. Despite the reasonably high recognition accuracy of 98 %, it cannot be said that the approach would give the same high accuracy when the head is tilted or in poor lighting. This allows us to say that it is advisable to conduct research to improve this approach under variable shooting conditions. This can be ensured by testing the proposed solutions on the CASIA-Iris-Thousand dataset, which is a more complex and representative data set due to the high variability of shooting conditions and the number of images.

Image preprocessing methods, such as histogram equalization (HE) or adaptive contrast enhancement (CLAHE), are used to improve the quality of input images before recognition. Studies reported in [10] show that the use of CLAHE could improve recognition accuracy by 1–6 % in combination with neural network methods, which suggests the feasibility of using contrast enhancement and noise reduction methods. In [11, 12], it is shown that all CLAHE, AHE, and HE methods are effective in improving the contrast of iris images in terms of PSNR since their average PSNR exceeds 30 dB. However, the study of the hybrid approach has not been highlighted, which limits the practical value of the highlighted approaches. The hybrid approach could provide local contrast enhancement (CLAHE) with subsequent brightness equalization (HE), which would lead to an increase in recognition accuracy.

In study [13], it is shown that geometric normalization is an important stage of preprocessing of the input image since it provides the possibility of a partially invariant position of the person relative to the recorder. However, the work does not provide a quantitative assessment that proves the benefits of geometric normalization. Thus, the study of the influence of geometric normalization on the accuracy of iris recognition is appropriate. This could make it possible to determine the percentage of compensation for the angle of inclination of the head relative to the recorder, unifying the input data for deep neural network models that are sensitive to positional changes.

A well-known step towards improving the performance of neural network analyzers, such as OOP image classifiers, is to analyze the impact of image preprocessing methods on the accuracy of the classification result. In [14], sufficiently high results of the achieved accuracy of OOP recognition based on DenseNet121 for two datasets were shown; however, the issue of image preprocessing to increase accuracy was not paid attention to. This can be attributed to the shortcomings of the work, which does not allow for the reuse of the obtained results and reproduction of the achieved accuracy. Thus, studying the impact of preprocessing methods (brightness histogram equalization and segmentation) would further increase the recognition accuracy.

A large number of modern studies choose to use classifiers based on machine learning. This is due to the increasing availability of cloud computing resources. In [5, 15], the effectiveness of using neural network methods for iris recognition (convolutional neural networks, including densely connected networks) is shown. However, those papers do not state at what fine-tuning of the neural networks such accuracy was achieved. This limits results implementation and contradicts the principles of open science. A likely reason is the large volume of research when analyzing a large number of neural network models. All this allows us to argue that it is advisable to conduct a study aimed at determining the settings of the neural networks that would provide the highest accuracy, especially on newer datasets than MICHE-I and CASIA v4.0.

Paper [16] reports low test results of the iris recognition accuracy at the level of 0.768. This may be caused by an incorrect image preprocessing pipeline, or insufficient study of the fine settings of the neural network analyzer. Thus, the study of the parameters of the selected analyzer and the assessment of the impact of preprocessing methods on the accuracy of classification could improve the selected approach.

Our review of modern methods of iris recognition revealed a number of local problems that limit the effectiveness of existing solutions. Among such problems are dependence on variable shooting conditions, limited research on hybrid methods, uncertainty of optimal hyperparameters of neural networks, insufficient analysis of image preprocessing in neural network or conventional algorithmic approaches, as well as the lack of a single methodology for conducting and planning research to take into account all the foregoing influences and dependences on the accuracy of analysis.

3. The aim and objectives of the study

The aim of our study is to define an approach to processing iris images under shooting conditions invariant to changes in lighting, head tilt, and eye opening degree. This will make it possible to improve the process of iris analysis for further use for accessing HMI systems in the cases of low quality input images or the presence of noise.

To achieve this goal, the following tasks must be solved:

– to assess the impact of normalization methods and brightness histogram equalization methods on the accuracy of iris image recognition to form an improved algorithmic approach to iris recognition;

– to assess the impact of fine-tuning of the neural network model of iris recognition on the accuracy metric and accuracy loss indicators.

4. The study materials and methods

The object of our research is the methods for processing and analyzing iris images, which can be implemented in human-machine interaction systems based on biometric data or other contactless methods of interaction, including people with disabilities and helping them to interact effectively with technology.

Before starting the research, it was assumed that the iris images would be obtained under standard conditions, i.e., without excessive noise or serious artifacts. It was assumed that the main factors affecting the recognition accuracy are lighting, head tilt, and partial eye opening.

A simplification is that the study uses only static images, without taking into account moving video streams.

The hypothesis of the study assumes that the combination of conventional algorithmic image processing methods (Hamming Distance, CLAHE, Equalization Histogram) with neural network models (CNN, DenseNet-201) could improve the accuracy, speed, and stability of iris recognition systems under conditions of variable lighting, head tilt, and partial eye openness. Confirmation of the hypothesis would ensure high recognition accuracy under real conditions and simplify integration into human-machine interaction (HMI) systems.

Examples of input images with the described defects are shown in Fig. 3.

To find the inner (iris) and outer (sclera) boundaries of the eye, the Daugman's integrated-differential operator method is considered in the work.

When working with the specified operator, the following parameter values were experimentally established, which are adjusted and oriented to physiological measurements of the iris (Table 2):

– minimum radius – 10 mm (the minimum radius of the circle is the contour of the pupillary edge of the iris, which the algorithm will search for in the image and consider as the boundaries of the pupil. This will help avoid false detection of very small circles that are not part of the eye);

– maximum radius – sect *0.8 (determines the upper threshold of the radius of the circle – the ciliary edge of the iris, excluding circles with a larger radius from consideration, as those that do not belong to the iris);

– smooth mask (SM) – 3–7 pixels (applied to Hough space, reducing noise for more accurate circle detection). Increasing the size of the blur mask resulted in loss of detail, which negatively affected the construction of connected circles in Hough space.

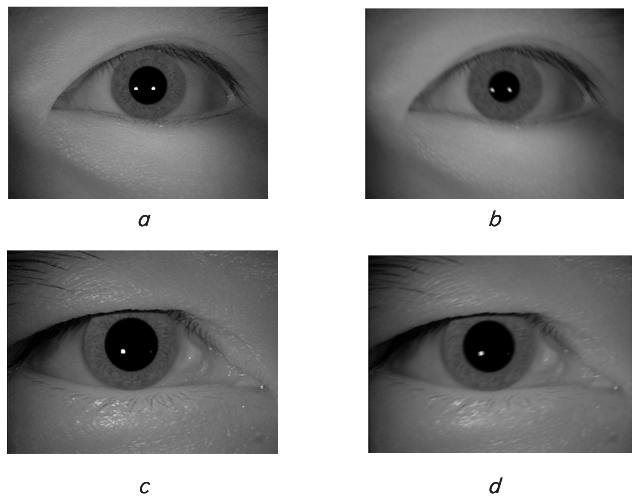

Fig. 3. The studied features and defects of the input images: *a* — noise-free image of the open eye; *b* — noisy image of the open eye; *c* — noise-free image of the covered eye; *d* — noisy image of the covered eye

The minimum and maximum radii for circle search were determined iteratively with a step of 0.1 mm.

The anatomical structure of the eye and iris is shown in Fig. 4. The iris is located on the front of the sclera, has a circular shape, and dimensions on average 12.5 mm horizontally and 12.0 mm vertically; the pupillary edge of the iris varies from 1.1 mm to 8.0 mm [13].

To correct the sensitivity of the iris recognition methods to the shooting conditions, we consider the algorithmic methods of image processing, machine learning, and mathematical filtering, such as [12]:

– contrast and brightness enhancement methods (CLAHE, AHE, HE) are used for working in low light and shadows;

– noise filtering and contour extraction methods (Daugman operator, Hough-line detector) eliminate the influence of eyelashes, eyelids, and light reflections;

– machine learning and deep neural networks (CNNs) are used for processing low-resolution images;

– morphological operations remove glare and artifacts on the surface of the eye.

For conducting research, the selection of an appropriate database plays an important role. It can be found that the most popular datasets for IR spectra are IITD, UBIRIS.v2, ND-IRIS0405, MICHE-I, CASIA-V4-Interval, CASIA-V4-Distance, CASIA-V4-Thousand, CASIA-Iris-

Lamp, Clarkson Dataset, Warsaw Dataset, Notre Dame Dataset, CASIA-Iris-Thousand, and IIITD-WVU Dataset. In our paper, CASIA-Iris-Thousand was selected for conducting research with the following characteristics: it contains a representative sample of 20,000 iris images from 1,000 different individuals (8-bit jpeg files with gray level 640*480) with variable shooting conditions. A feature of the selected dataset is that the data is structured and well-labeled, which makes it possible to test both conventional recognition algorithms (Hough, Daugman) and modern CNN architectures (ResNet, MobileNet, Transformer-based models).

Improvements in methods for processing and analyzing the input image of the eye are aimed at reducing the impact of various types of noise and defects in the input image (Fig. 5).

In conducting the study, the main attention has been paid to the methods of segmentation and histogram equalization of images. These methods have the greatest impact on the quality of feature extraction and the accuracy of subsequent image recognition in the case of a covered eye, which may be accompanied by low contrast and clarity. The experiments performed as part of the study are shown in Fig. 6; they involve studying the impact of the specified methods on the overall accuracy of iris-based recognition.

The research methodology proposed in Fig. 6 generalizes and improves existing methodology through a comprehensive study of the effects of preprocessing (contrast, normalization, segmentation), hybrid feature vector construction, and fine-tuning of neural network classifiers on improving the quality and stability of iris recognition in complex conditions, which is important for practical application in biometric systems, as well as for access to HMI systems, especially for people with disabilities or under variable shooting conditions.

When using neural network technologies, the end result is given in the form of a class number, which indicates the solution to the classification problem. When using non-neural network algorithms at all steps of iris recognition, the result is given in the form of a similarity score. The similarity score is calculated based on the Hamming distance and determines the number of positions in the feature vectors of two binary images that differ. That is, if the formed feature vectors completely coincide, the Hamming distance will be equal to 0.

The OpenCV computer vision and image processing library was used for image processing and data pre-processing; machine learning methods were implemented and tested using the TensorFlow library.

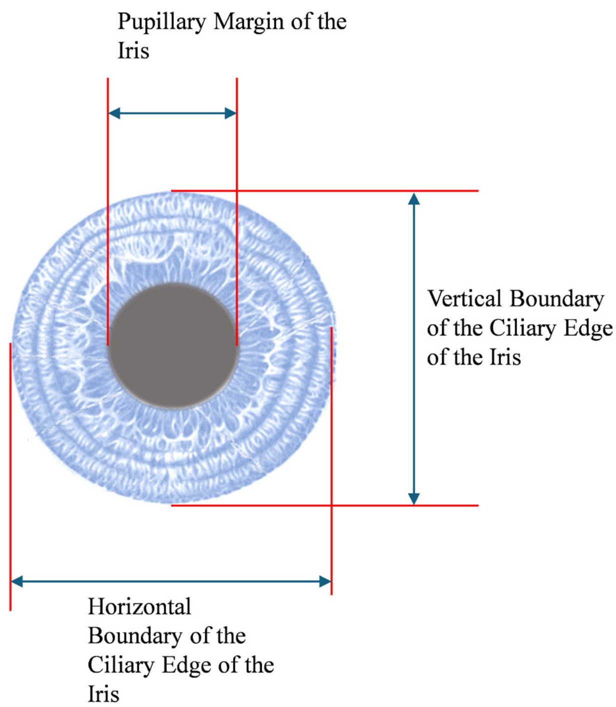

Fig. 4. The structure of the human iris

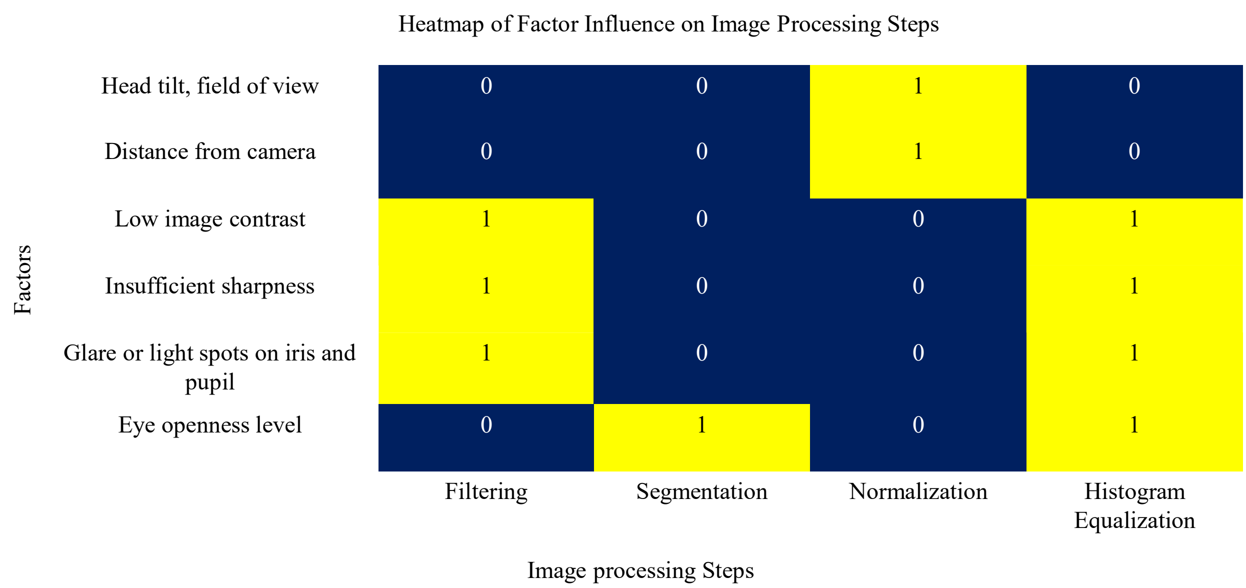

Fig. 5. Heat map explaining the purpose of image preparation methods to reduce certain types of defects and reduce the impact of noise

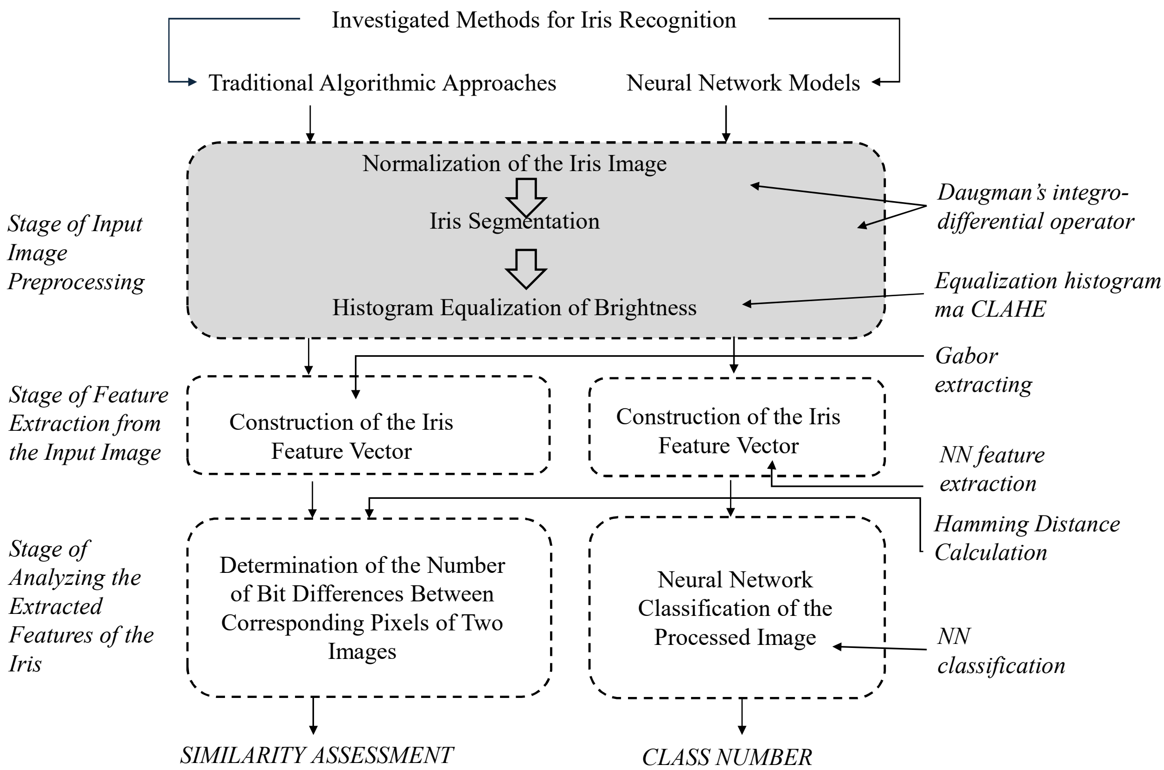

Fig. 6. Generalized research methodology

5. Results of studies of the influence of selected input image processing methods on the indicators of recognition quality assessment metrics

5. 1. Assessment of the influence of normalization methods and brightness histogram equalization methods

The task of the first experiment was to determine the need to perform normalization of input images and the size of the blur mask for accurate segmentation of the input image based on the Daugman method. The experiment was performed in two steps:

– application of Daugman segmentation to the input image, changing the size of the blur mask. Calculation of the Jacquard coefficient for the segmented non-noisy image of the open eye, noisy image of the open eye, non-noisy image of the closed eye, noisy image of the closed eye without prior normalization;

– application of Daugman segmentation to the geometrically normalized preliminary image, changing the size of the blur mask. Calculation of the Jaccard coefficient for a noiseless image of the open eye, a noisy image of the open eye, a noiseless image of the covered eye, a noisy image of the covered eye after preliminary geometric normalization;

By normalization we mean the fight against geometric distortions of the input image – changing the size, pixel coordinates, image rotation in order to unify the dimensions and angles of the image (Table 1).

Analysis of the results in Table 3 revealed that the optimal mask blur size is chosen to be 3 (Sm=3). Further segmentation is performed on contour images prepared taking into account the mask size=3 and after geometric normalization, since the preliminary normalization provides an increase in the coefficient by 8 %.

Table 1

The result of extracting the contours of the pupillary edge of the iris and the ciliary edge of the iris using the Daugman method with and without geometric normalization

Characteristics of the input image	Average estimate of the accuracy of contouring by the Jacquard coefficient		
	Sm=3	Sm=5	Sm=7
No prior geometric normalization			
noise-free image of the open eye	0.93	0.89	0.84
noisy image of the open eye	0.91	0.86	0.82
noise-free image of the closed eye	0.90	0.83	0.81
noisy image of the closed eye	0.89	0.86	0.80
After preliminary geometric normalization			
noise-free image of the open eye	0.989	0.97	0.96
noisy image of the open eye	0.97	0.965	0.94
noise-free image of the closed eye	0.978	0.961	0.939
noisy image of the closed eye	0.971	0.959	0.941

Experiment 2 involved studying the influence of the selected methods of brightness histogram equalization, namely Equalization Histogram and CLAHE, on the accuracy of distinguishing characteristic features of the iris. The accuracy assessment is performed based on the Hamming distance estimate, by analyzing the determined distance for two identical eyes with different shooting conditions and processed by different equalizers. The execution of experiment 2 is as follows (Table 1):

– for the normalized and segmented image, the brightness histogram equalization is performed using the Equalization Histogram method under different shooting conditions. Then, the features are extracted using the Gabor method and the Hamming distance is calculated for two identical eyes with different shooting conditions;

– for the normalized and segmented image, the brightness histogram equalization is performed using the CLAHE method under different shooting conditions. Then, the features are extracted using the Gabor method and the Hamming distance is calculated for two identical eyes with different shooting conditions;

– for the normalized and segmented image, the brightness histogram equalization is performed using the CLAHE and Equalization Histogram methods under different shooting conditions. Then, the features are extracted using the Gabor method and the Hamming distance is calculated for two identical eyes with different shooting conditions.

The sequential application of CLAHE for adaptive contrast improvement in local image regions and EqualizeHist for further global image contrast improvement with a limited maximum contrast value and local area size yields the results given in Tables 2, 3. One can see that the results of the sequential application of the CLAHE and Equalization Histogram methods provide the greatest similarity between the original and input images, therefore, for further research, the pipeline shown in Fig. 7 is considered.

Table 2

Assessing the impact of the Equalization Histogram, CLAHE, and sequential application of the CLAHE and Equalization Histogram methods on the accuracy of iris feature extraction for the open eye

Reference image (no noise) for the open eye	Input image (with noise) under different shooting conditions for the open eye	Average Hamming distance for two identical eyes with different shooting conditions
Evaluation of the impact of the Equalization Histogram method		0.347337
Evaluation of the impact of the CLAHE method		0.29162
Estimation of the impact of sequential using the CLAHE and Equalization Histogram methods		0.125033

Hamming distance (HD) is taken as the main metric for assessing the accuracy of iris classification based on algorithmic conventional methods. In the evaluation, the threshold value of HD is set at 0.35 (this means that if HD is less than this threshold, the patterns belong to the same person) (Table 4).

Table 3

Assessing the impact of the Equalization Histogram, CLAHE, and sequential application of the CLAHE and Equalization Histogram methods on the accuracy of iris feature extraction for a partially occluded eye

Reference image (no noise) for a partially covered eye	Input image (with noise) under different shooting conditions for partially covered eye	Average Hamming distance for two identical eyes with different shooting conditions
Evaluation of the impact of the Equalization Histogram method		0.2849569
Evaluation of the impact of the CLAHE method		0.2669
Estimation of the impact of sequential using the CLAHE and Equalization Histogram methods		0.1217115

Table 4

Estimating the accuracy of iris image recognition based on the probability of correct recognition, false positives, and similarity of biometric templates

HD threshold	False match rate (FMR) – false match frequency (%)	False Non-match rate (FNMR) – false bounce rate (%)	Equal error rate (EER, %)	Recognition accuracy (%)
0.33	0.5 %	9.5 %	5.2 %	95.0 %
0.35	1.2 %	7.8 %	4.5 %	95.5 %
0.40	3.0 %	6.5 %	5.1 %	95.2 %

The analog of the iris recognition accuracy of neural network systems for conventional algorithmic solutions is Recognition Accuracy (RA). The formula used for calculation is as follows:

$$RA = 1 - \frac{FMR + FNMR}{2}.$$

Analysis of the results given in Table 4 reveals that the best balance between accuracy and errors is achieved at HD=0.35. The accuracy of the algorithm ranges from 95.0–95.5 %, which is a high indicator and makes this approach competitive.

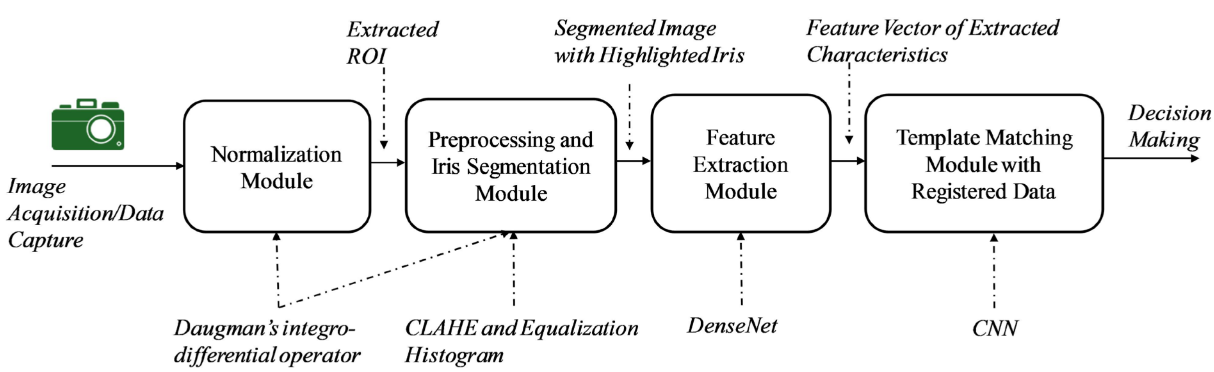

Fig. 7. Iris recognition pipeline without using neural network methods

5. 2. Evaluating the impact of fine-tuning the neural network model

The third experiment involves using the normalization method, image segmentation by the Daugman method, and a neural network implementation of the feature extraction method (DenseNet 201) instead of the Gabor method. Feature comparison is assigned to a convolutional neural network instead of determining the Hamming distance.

Thus, the goal of this experiment is to show the effectiveness of a pipeline in which the tasks of feature extraction and classification are assigned to artificial neural networks (Fig. 8). The experiments are conducted on balanced and unbalanced samples. By imbalance, we mean that a different number of training images is given for representatives of the original classes in the test sample.

The deep learning neural network Densely Connected Convolutional Network was chosen because of its inherent features – each layer in this type of network is connected to every other layer in a denser network. This distinguishes it from conventional convolutional networks (CNNs), in which each layer only passes the output to the next layer forward. The increased connectivity between layers allows for a reduction in the number of parameters that need to be trained, which is more computationally efficient and important under conditions of limited computing resources.

The results of Experiment 3 are shown in Fig. 9.

The fourth experiment involves the use of a neural network pipeline for all stages of processing and analyzing the input image, except for segmentation (Daugman normalization is not used). A convolutional neural network is used as a classifier, the study of whose architecture is the main goal of this experiment.

Before conducting the experiment, the dataset was divided into training, validation, and test sets. The training set is used to train the model, the validation set is used to adjust hyperparameters and evaluate the performance of the model during training, and the test set is used to evaluate the final accuracy of the model. The division was performed as follows:

– training:validation:test sets=70 %:15 %:15 %;
– training:validation:test sets=70 %:5 %:25 %;
– training:validation:test sets=50 %:25 %:25 %.

The next steps are to vary the number of layers and training epochs to achieve the highest classification accuracy and loss function for three different approaches to dataset decomposition. The results are given in Table 5.

Based on these results, we can conclude that the optimal distribution of the dataset is training:validation:test sets=70 %:15 %:15 %, which achieves almost 100 % accuracy with a 0.5 % loss function for 1500 epochs (Fig. 10).

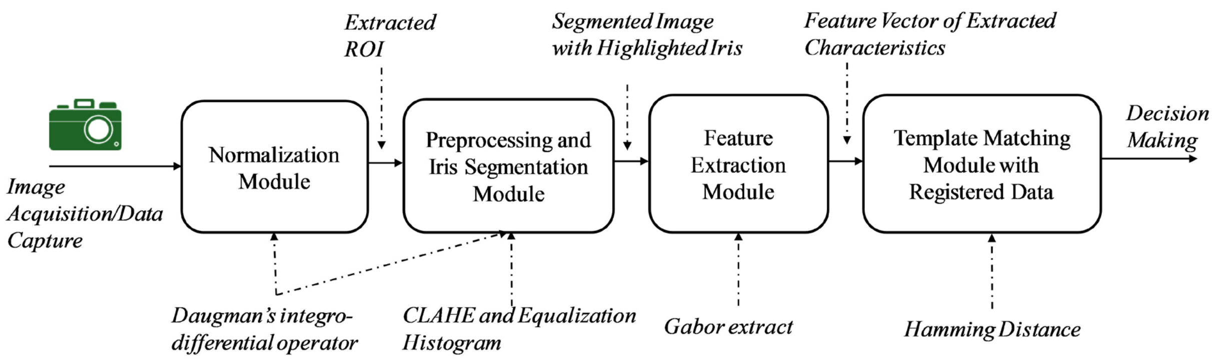

Fig. 8. Sequence of partial neural network iris recognition

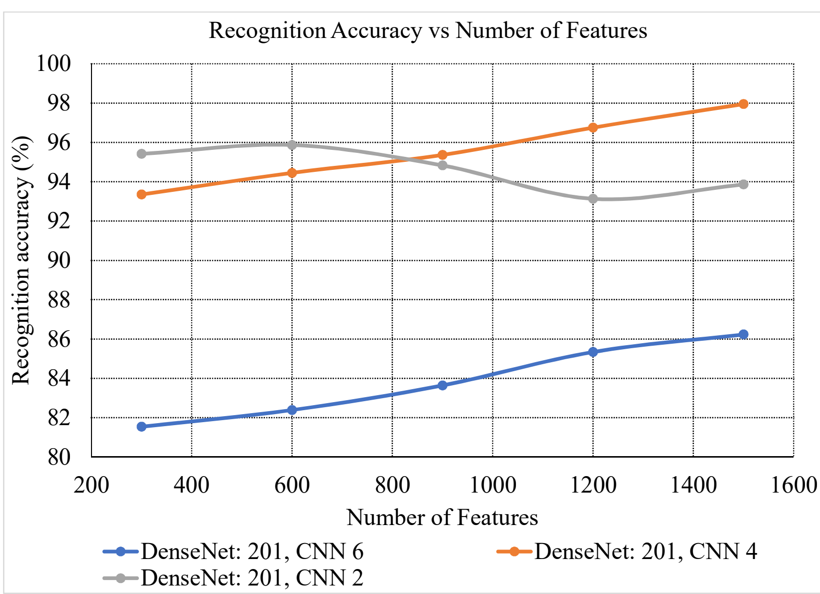

Fig. 9. Line plot showing the dependence of recognition accuracy on the number of epochs for different numbers of layers in DenseNet and CNN

Table 5

Accuracy of neural network iris recognition based on convolutional neural network

Number of CNN layers	Number of epochs of CNN training	Test accuracy of classification in a balanced training sample	Value of loss function
Dataset distribution – training:validation:test sets=70 %:15 %:15 %			
4	200	97.04 %	7.42 %
4	300	97.48 %	6.76 %
4	500	98.41 %	4.61 %
4	800	98.01 %	1.79 %
4	1200	99.43 %	1.28 %
4	1500	99.93 %	0.58 %
Dataset distribution – training:validation:test sets=70 %:5 %:25 %			
4	200	97.17 %	15.42 %
4	300	98.22 %	13.32 %
4	500	97.87 %	10.11 %
4	800	98.88 %	8.87 %
4	1200	98.38 %	8.13 %
4	1500	96.22 %	7.88 %
Dataset distribution – training:validation:test sets=50 %:25 %:25 %			
4	200	95.32 %	22.65 %
4	300	95.82 %	22.05 %
4	500	96.33 %	20.34 %
4	800	96.95 %	18.05 %
4	1200	98.53 %	14.76 %
4	1500	98.14 %	13.76 %

In general, the test accuracy increases with the number of training epochs. Different types of dataset distribution have little effect on the final accuracy, but one can see that the dataset distribution in the ratio of 70 %:15 %:15 % (respectively, training:validation:test sets) shows the best results.

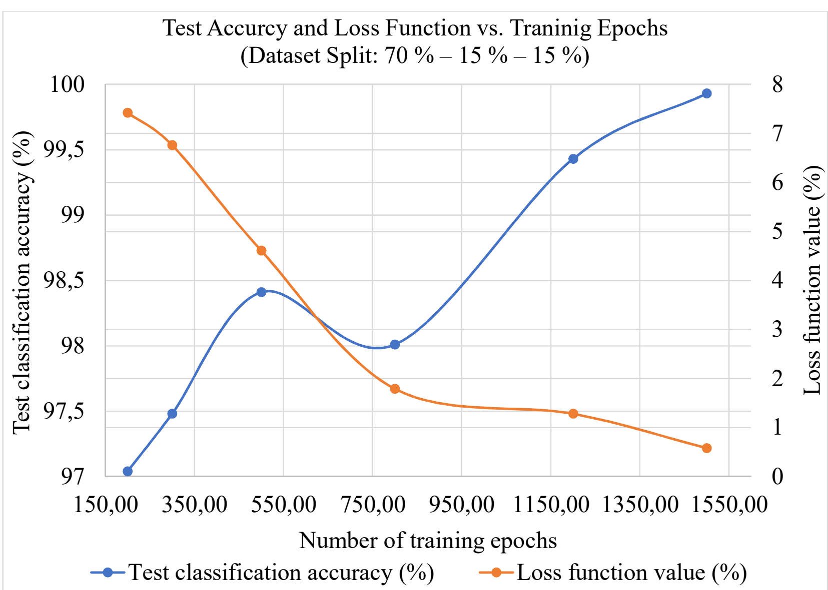

Fig. 10. Accuracy and significance of the loss function of neural network iris recognition based on a convolutional neural network

6. Discussion of results based on determining the methods of iris recognition depending on the shooting conditions

Our results showed that the use of normalization and histogram equalization methods, in particular, makes it possible to significantly improve the accuracy of iris recognition (Tables 2, 3). In particular, the obtained data indicate that such a combination of methods leads to a decrease in the average Hamming distance to 0.1234, which is a significant improvement compared to using only one method. In addition, the balance between accuracy and false positive rate is best achieved at a threshold value of HD=0.35, which provides the algorithm with an accuracy within 95.0–95.5 % (Table 1).

This is explained by the fact that CLAHE improves the local contrast of images, allowing better detection of iris details, while Equalization Histogram contributes to a uniform distribution of brightness. In addition, the use of a combined approach to processing, which was not used in [10], makes it possible to increase the invariance of the model to changes in illumination and head position.

The foregoing results were achieved by combining image preprocessing using the Daugman algorithm for segmentation, as well as feature analysis using the Gabor method with the CLAHE and Equalization Histogram methods. The recognition accuracy was assessed by calculating the Hamming distance between the reference and noisy images, which allowed us to effectively determine the optimal processing parameters.

One of the identified problems was that the analyzed sources really indicate a positive effect of the CLAHE, AHE, and Equalization Histogram methods on the accuracy of object recognition. However, studies on their joint use, especially under variable shooting conditions, have not been conducted. The results given in Tables 2 and 3 are convincing in that brightness and contrast correction are important stages of pre-processing, which should be performed sequentially. The results in Table 1 prove that geometric normalization provides partial invariance of the model to changes in the position of the head relative to the recorder.

Among the limitations of the proposed solution in terms of assessing the impact of normalization methods and brightness histogram equalization methods on the accuracy of iris image recognition, it should be noted that the CLAHE and Equalization Histogram methods slightly increase the image processing time, which can be critical in real systems with tight time constraints.

For practical application, as well as in further theoretical studies, consideration should be given to testing processing methods on images obtained under different lighting conditions, distances, and recorder positions.

The shortcomings of our study in this part are that the testing did not take into account the requirements for computing systems, which may limit the use of the approach on mobile devices. Therefore, further development of the study in this part involves the integration of hybrid models that combine conventional algorithmic methods with deep neural network approaches to improve the accuracy of iris recognition.

The results of our experiments to assess the impact of fine-tuning the neural network model of iris recognition on the accuracy metrics and accuracy losses showed that the use of a neural network approach using DenseNet and CNN makes it possible to achieve high accuracy of iris recognition. Unlike [13, 14], in which the influence of fine-tuning of neural networks on recognition accuracy was not analyzed, in this work the best results were obtained with a configuration of 201 DenseNet layers and 4 CNN layers, which provides a maximum accuracy of 99.93 % at 1500 training epochs (Fig. 9, Table 5). In addition, the results given in Table 5 prove that fine-tuning cannot be neglected because the increase in test accuracy can be up to 3 %.

This becomes possible due to the fact that the deep architecture of convolutional neural networks allows for more efficient feature extraction, avoiding information loss, and increasing the number of epochs improves the learning of the model. At the same time, the results show that even with a smaller number of layers (2 CNN layers), acceptable accuracy can be achieved, which is important for limited computing resources.

Our results were achieved by using an adaptive approach to neural network tuning, which included changing the number of CNN layers, different dataset distribution configurations, and using deep DenseNet architectures for feature extraction. In addition, experiments showed that the approach without prior normalization, but using EqualizeHist/CLAHE, makes it possible to improve recognition results.

Another identified problem was the lack of demonstration of the influence of fine-tuning of the neural network model on the accuracy of iris recognition. The results given in Table 5 are convincing in that the correct balance between the number of training epochs and the dataset distribution significantly affects the final accuracy of the model.

Among the limitations of the proposed solution in terms of assessing the impact of fine-tuning the neural network model of iris recognition on the accuracy metric and accuracy loss indicators, it should be noted the increased computational complexity for deep models, such as DenseNet 201, as well as the need for a large amount of data to achieve stable results. For practical application, as well as in further theoretical studies, the impact of the dataset distribution should be taken into account.

The disadvantages of our study in this part are the lack of analysis of the model's resistance to the appearance of additional artifacts, such as glasses or contact lenses, or facial hair. Therefore, further development of the study is seen in optimizing the neural network architecture taking into account computational costs and studying the model's resistance to the appearance of additional artifacts on the face or eyes. Also, a promising direction for the development of the study in this part is the introduction of additional adaptation mechanisms, such as transfer learning and the use of neural networks to compensate for changes in the angle of the head.

7. Conclusions

1. The conventional algorithmic approach (Hamming Distance) provides an accuracy of 95.5 % at a threshold HD=0.35, which is competitive compared to modern neural networks. The optimal threshold value of Hamming Distance is 0.35 and provides the best balance between False Match Rate (1.2 %) and False Non-Match Rate (7.8 %). It has been shown that sequential CLAHE and Equalization Histogram significantly improves contrast and reduces errors under variable shooting conditions, namely the average Hamming distance achieved with sequential application of CLAHE and Equalization Histogram is 0.1234 versus 0.3155 when using the Equalization Histogram method alone, and 0.28 using the CLAHE method.

2. Our study of fine-tuning in neural network iris recognition showed higher stability to changes in illumination and head tilt of neural network methods, reaching an accuracy of 99.93 %. This was achieved by training 4 layers of a convolutional neural network for 1500 epochs and distributing the dataset in the ratio training:validation:test sets=70 %:15 %:15 %. The accuracy of the neural network approach based on a convolutional network exceeds by 4.6 % the accuracy of the algorithmic approach without the use of artificial intelligence, as well as by 3 % the partially neural network approach based on normalization and preprocessing by the Daugman, EqualizeHist, and CLAHE methods. Thus, conventional methods (Hamming Distance) are appropriate for systems with low computing resources since they are faster and less demanding on hardware. Neural network models are recommended for scenarios where high accuracy is critical (biometric security systems, banking systems, access to closed facilities).

Conflicts of interest

The authors declare that they have no conflicts of interest in relation to the current study, including financial, personal, authorship, or any other, that could affect the study, as well as the results reported in this paper.

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Data availability

The data will be provided upon reasonable request.

Use of artificial intelligence

The authors used artificial intelligence technologies within acceptable limits to provide their own verified data, which is described in the research methodology section.

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