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Research Article

The Eye's Signature: Innovative Approaches to Iris Detection

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Abstract:
This research aims to develop and evaluate a deep learning-based iris detection system using a specialized Convolutional Neural Network (CNN) architecture. The research methodology includes data set preprocessing, CNN model design, training using Adam optimization, as well as evaluation using accuracy, precision, recall, and F1 score metrics. The dataset used was obtained from Kaggle and preprocessed before being divided into training, validation, and testing sets. The CNN model consists of three convolutional layers with increasing filter sizes (32, 64, and 128), ReLU activation, batch normalization, and MaxPooling layers for efficient feature extraction, as well as dropout regularization to reduce overfitting. Experimental results show that the proposed model achieves a high classification accuracy of 97.33%, with robust performance against variations and noise in iris images. Comparative analysis with traditional iris recognition methods confirms the superiority of deep learning in handling challenges such as lighting changes and occlusions. Although the results are promising, challenges such as data bias and computational demands are still a concern. Future research will explore more advanced architectures as well as additional pre-processing techniques to improve the generalizability and effectiveness of the system in real-world applications.

Keywords: Biometric Authentication, Convolutional Neural Network (CNN), Deep Learning, Iris Recognition, Secure Identification.

1. INTRODUCTION

In the modern era of security and authentication, biometric identification has gained significant attention due to its high reliability and accuracy. Among various biometric modalities, iris-based recognition is one of the most robust and secure methods (Yuniarti et al., 2024). The human iris possesses intricate and stable patterns that remain unique for each individual, making it an ideal feature for identity verification. Unlike other biometric traits such as fingerprints or facial recognition, the iris is highly resistant to forgery or duplication, which enhances its credibility in high-security applications (Alrawili et al., 2024). Despite its advantages, accurate and efficient iris detection presents several challenges (Qadir & Taujuddin, 2024). Variations in lighting conditions, occlusions caused by eyelids and eyelashes, and the necessity for high-resolution imaging often impact the performance of iris recognition systems (Malgheet et al., 2021). Traditional approaches also struggle with dynamic factors such as eye movement, rotational variations, and noise interference in iris images, which can significantly hinder accurate identification (Nguyen et al., 2024).

To address these challenges, this study proposes a deep learning-based approach utilising a Convolutional Neural Network (CNN) to enhance the accuracy and robustness of iris detection. CNNs have demonstrated exceptional performance in various image recognition tasks, making them suitable for extracting deep iris features (Shalaby et al., 2021). The proposed model incorporates convolutional layers for feature extraction, batch normalisation, dropout, and dense layers to improve classification performance and generalization (Yolcu Oztel, 2024).

The effectiveness of the proposed approach is evaluated using a curated iris image dataset, with data split into training, validation, and test sets to ensure robust model performance (Sumi et al., 2024). By leveraging deep learning techniques, this study aims to provide an improved solution for iris-based biometric identification, overcoming the limitations of traditional methods and advancing the field of secure authentication systems.

2. MATERIAL AND METHOD

This study aims to develop and evaluate a deep learning-based iris detection system by comparing a

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custom Convolutional Neural Network (CNN). The methodology includes dataset preprocessing, model architecture design, training, evaluation, and comparison of performance metrics. TensorFlow and Keras are used for implementation, ensuring scalability and adaptability to real-world applications (Mohammadpour et al., 2022).

Dataset Preparation

The dataset used in this study consists of iris images collected from Kaggle at URL https://www.kaggle.com/datasets/mohmedmokhtar/iris-of-eye-dataset. To ensure robust model evaluation, the dataset is pre-processed and split into training, validation, and test sets using the split folders library (Tran et al., 2022). Image pixel values are normalised to a [0,1] range using the Image Data Generator function with rescaling.

A Custom CNN Model

A deep learning model was developed based on a traditional CNN architecture optimised for feature extraction and classification of iris images (Liu et al., 2021). The custom CNN model consists of three convolutional layers with increasing filter sizes of 32, 64, and 128, utilising the ReLU activation function to enable hierarchical feature extraction. Batch normalisation is applied after each convolutional layer to stabilise learning and accelerate convergence (Alzubaidi et al., 2021). MaxPooling layers are incorporated to reduce spatial dimensions while preserving essential features, ensuring efficient feature representation (). To mitigate overfitting, dropout regularisation is implemented, with dropout rates ranging from 30% to 50%. Finally, the extracted features are passed through fully connected layers, where the flattened output undergoes further processing before being classified through a softmax activation function, allowing for multi-class classification (Salehin & Kang, 2023).

Training Process

The training phase involves feeding the pre-processed iris images into the custom CNN model. The categorical cross-entropy loss function is the optimisation criterion suitable for multi-class classification problems (Zhang et al., 2020). The Adam Optimiser was chosen for its adaptive learning rate capability, facilitating efficient weight updates and faster convergence. The model is trained for 30 epochs with a batch size 32, ensuring stable learning while balancing computational efficiency.

Validation and Testing

The trained model is validated using the reserved validation dataset. This step ensures the model generalises well to unseen data before final testing (Myllyaho et al., 2021). Hyperparameter tuning is performed based on validation results, refining aspects such as dropout rates, learning rates, and the number of convolutional layers to optimise performance.

The final evaluation is conducted on the independent test set, measuring real-world applicability by assessing accuracy, robustness to variations, and classification consistency. The effectiveness of the proposed approach is then compared against traditional machine learning classifiers or pre-existing iris recognition methods.

3. RESULT AND DISCUSSION

To The proposed CNN model was trained for 30 epochs, achieving a final accuracy of 97.33%. The training process showed a steady decline in loss and increased accuracy, demonstrating effective learning. The accuracy progression across epochs indicated that the model successfully captured the intricate features of iris patterns, leading to high classification performance.

Training accuracy and loss were recorded over 30 epochs to assess the model's learning efficiency. The results indicate that the model experienced a consistent increase in accuracy while the loss gradually decreased, suggesting proper convergence, as shown in Figure 1.

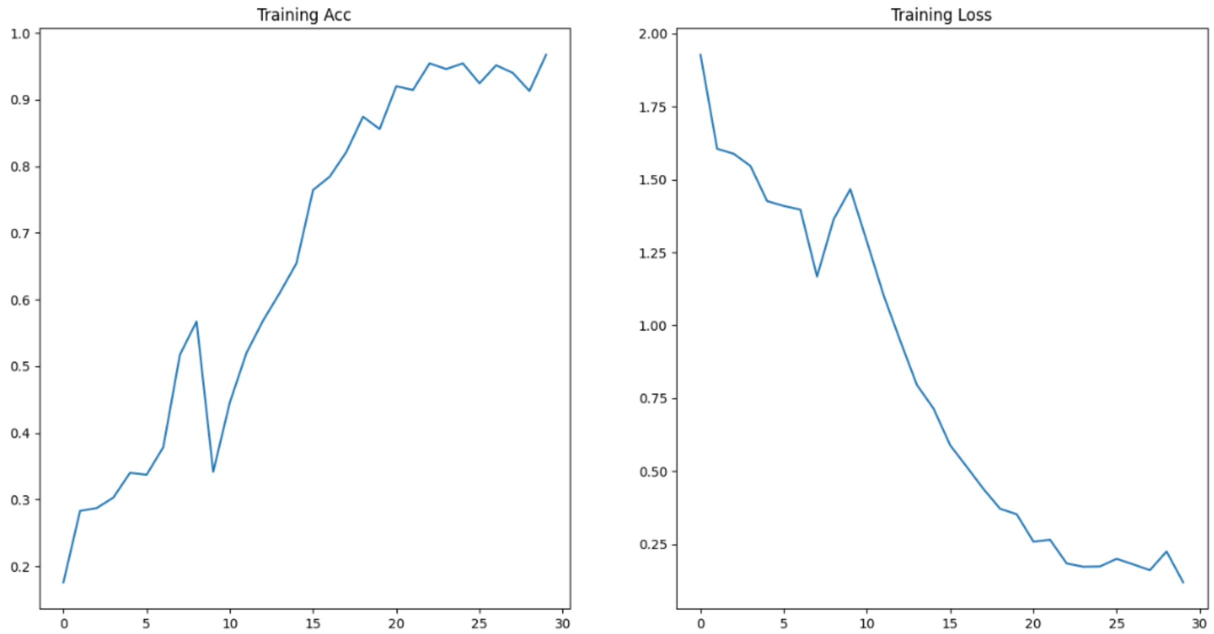

Figure 1. Training accuracy and loss

The model started with a lower accuracy and steadily improved with each epoch, reaching a final training accuracy close to 98%. Initially high, the loss consistently decreased as the model learned to distinguish iris features, demonstrating effective optimisation of network weights.

This trend confirms that the model effectively generalises the training data, reducing overfitting risks while maintaining high performance.

The confusion matrix provides insights into the model's classification accuracy for each class, as shown in Figure 2.

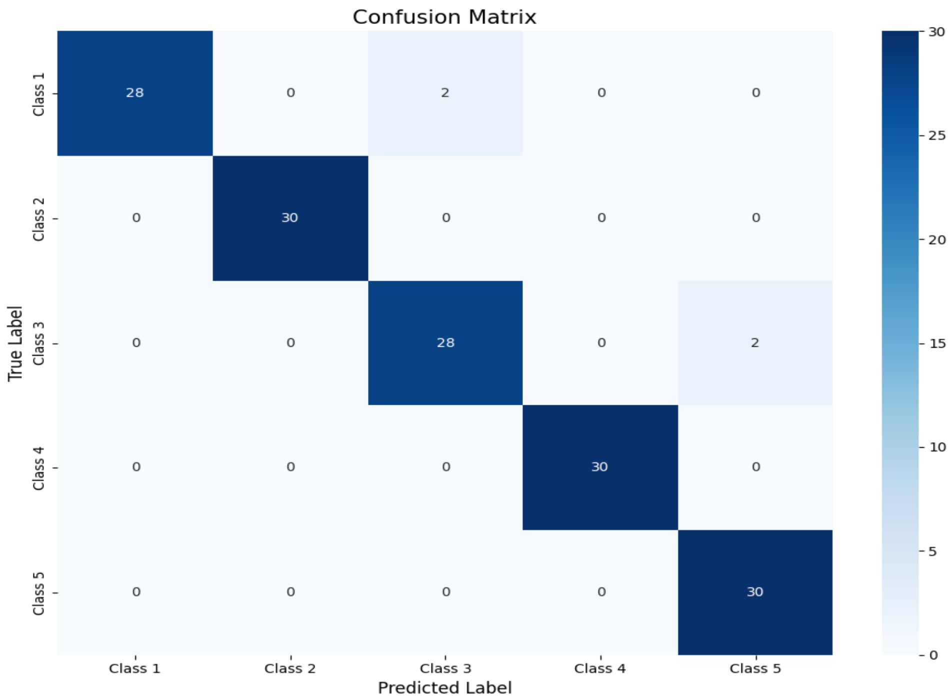

Figure 2. The confusion matrix

The matrix shows that the model correctly classified most samples, with only minor misclassifications in two instances for class 0 and class 2. The high diagonal values indicate strong predictive performance across all classes.

The classification report further quantifies the model's effectiveness with precision, recall, and f1-score metrics, as shown in Table 1.

Table 1. The classification report

Class	Precision	Recall	F1-Score
0	1.00	0.93	0.97
1	1.00	1.00	1.00
2	0.93	0.93	0.93
3	1.00	1.00	1.00
4	0.94	1.00	0.97

The model demonstrated exceptional performance with an overall accuracy of 97.33%. Both macro and weighted averages revealed consistent precision, recall, and F1-score of 0.97, indicating robust and balanced classification across different iris species. These high-precision metrics suggest the model's reliable capability to distinguish between iris classes with minimal error rates.

The high accuracy achieved by the model demonstrates its effectiveness in recognising unique iris patterns. The minimal misclassifications suggest that the model can distinguish between different iris classes with high reliability. However, a few misclassified instances indicate potential areas for improvement, such as enhancing feature extraction techniques or incorporating additional training data.

Comparing the CNN approach to traditional iris recognition methods, this deep learning-based model shows superior generalisation capabilities and robustness to variations in iris images. Learning deep hierarchical features allows it to handle challenges like noise and occlusions better than traditional handcrafted feature-based approaches.

Furthermore, analysing the training accuracy and loss provides valuable insights into model behaviour. The smooth convergence of training loss and increasing accuracy over epochs confirm effective learning dynamics. Future work could focus on further optimising hyperparameters, experimenting with deeper architectures, or integrating augmentation techniques to enhance model generalisation.

Overall, the proposed method successfully enhances iris-based biometric identification, offering a promising solution for secure authentication systems. Future improvements could include exploring more advanced architectures, fine-tuning hyperparameters, or integrating additional pre-processing techniques to optimise performance further.

Despite high accuracy, the model faces several critical constraints. Dataset bias poses a significant challenge, as the model's performance heavily relies on training data diversity. Limited variations in iris images could compromise its real-world applicability.

While promising within the current dataset, the model's generalisation may require additional fine-tuning and expanded training data to ensure robust performance on unseen samples. Computational demands present another substantial limitation, with deep learning models necessitating extensive computational resources that might restrict deployment on edge devices.

Lastly, the model's vulnerability to extreme occlusions remains a potential weakness. Although noise is handled effectively, significant interruptions from eyelids, eyelashes, or optical reflections could still compromise classification accuracy, highlighting the need for continued model refinement.

4. CONCLUSION

This study proposed a deep learning-based approach for iris-based biometric identification, leveraging a custom Convolutional Neural Network (CNN) to enhance detection accuracy and robustness. The model demonstrated a high classification accuracy of 97.33%, effectively capturing the intricate features of iris patterns. The results showed consistent performance across various iris classes, with minimal misclassifications, confirming the model's reliability.

The model successfully overcame noise, lighting variations, and occlusions by integrating convolutional layers, batch normalisation, dropout regularisation, and adaptive optimisation techniques. The confusion matrix and classification report highlighted strong predictive performance, emphasising the model’s effectiveness in distinguishing different iris patterns. Compared to traditional methods, the CNN-based approach exhibited superior generalisation, enabling more reliable iris recognition.

Despite these promising results, challenges such as dataset bias, computational resource requirements, and vulnerability to extreme occlusions remain. Addressing these limitations through advanced preprocessing techniques, deeper network architectures, and additional dataset expansion could enhance performance. Future work may explore real-time deployment optimisations and integration with other biometric modalities for improved authentication security.

The proposed deep learning model provides a highly accurate and efficient solution for iris recognition, contributing to the advancement of secure biometric authentication systems. Its potential for real-world applications highlights the importance of continued research in deep learning-driven security technologies.

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REFFERENCE

Alrawili, R., AlQahtani, A. A. S., & Khan, M. K. (2024). Comprehensive survey: Biometric user authentication application, evaluation, and discussion. *Computers and Electrical Engineering*, *119*, 1–25. https://doi.org/10.1016/j.compeleceng.2024.109485

Alzubaidi, L., Zhang, J., Humaidi, A. J., Al-Dujaili, A., Duan, Y., Al-Shamma, O., Santamaría, J., Fadhel, M. A., Al-Amidie, M., & Farhan, L. (2021). Review of deep learning: concepts, CNN architectures, challenges, applications, future directions. In *Journal of Big Data* (Vol. 8, Issue 1). Springer International Publishing. https://doi.org/10.1186/s40537-021-00444-8

Liu, G., Zhou, W., Tian, L., Liu, W., Liu, Y., & Xu, H. (2021). An efficient and accurate iris recognition algorithm based on a novel condensed 2-ch deep convolutional neural network. *Sensors*, *21*(11). https://doi.org/10.3390/s21113721

Malgheet, J. R., Manshor, N. B., & Affendey, L. S. (2021). Iris Recognition Development Techniques: A Comprehensive Review. *Complexity*, *2021*. https://doi.org/10.1155/2021/6641247

Mohammadpour, L., Ling, T. C., Liew, C. S., & Aryanfar, A. (2022). A Survey of CNN-Based Network Intrusion Detection. *Applied Sciences (Switzerland)*, *12*(16). https://doi.org/10.3390/app12168162

Myllyaho, L., Raatikainen, M., Männistö, T., Mikkonen, T., & Nurminen, J. K. (2021). Systematic literature review of validation methods for AI systems. *Journal of Systems and Software*, *181*, 111050. https://doi.org/10.1016/j.jss.2021.111050

Nguyen, K., Proença, H., & Alonso-Fernandez, F. (2024). Deep Learning for Iris Recognition: A Survey. *ACM Computing Surveys*, *56*(9). https://doi.org/10.1145/3651306

Qadir, T. O., & Taujuddin, N. S. A. M. (2024). Black hole algorithm along edge detector and circular hough transform based iris projection with biometric identification systems. *International Journal of Electrical and Computer Engineering Systems*, *15*(1), 59–68. https://doi.org/10.32985/ijeces.15.1.6

Salehin, I., & Kang, D. K. (2023). A Review on Dropout Regularization Approaches for Deep Neural Networks within the Scholarly Domain. *Electronics (Switzerland)*, *12*(14). https://doi.org/10.3390/electronics12143106

Shalaby, A. S., Gad, R., Hemdan, E. E. D., & El-Fishawy, N. (2021). An efficient CNN based encrypted Iris recognition approach in cognitive-IoT system. *Multimedia Tools and Applications*, *80*(17), 26273–26296. https://doi.org/10.1007/s11042-021-10932-x

Sumi, M. R., Das, P., Hossain, A., Dey, S., & Schuckers, S. (2024). A Comprehensive Evaluation of Iris Segmentation on Benchmarking Datasets. *Sensors*, *24*(21), 1–19. https://doi.org/10.3390/s24217079

Tran, N., Chen, H., Bhuyan, J., & Ding, J. (2022). Data Curation and Quality Evaluation for Machine Learning-Based Cyber Intrusion Detection. *IEEE Access*, *10*(June), 121900–121923. https://doi.org/10.1109/ACCESS.2022.3211313

Yolcu Oztel, G. (2024). Vision transformer and CNN-based skin lesion analysis: classification of monkeypox. *Multimedia Tools and Applications*, *83*(28), 71909–71923. https://doi.org/10.1007/s11042-024-19757-w

Yuniarti, A. R., Rizal, S., & Lim, K. M. (2024). Single heartbeat ECG authentication: a 1D-CNN framework for robust and efficient human identification. *Frontiers in Bioengineering and Biotechnology*, *12*(July), 1–16. https://doi.org/10.3389/fbioe.2024.1398888

Zhang, J., Lu, C., Wang, J., Yue, X. G., Lim, S. J., Al-makhadmeh, Z., & Tolba, A. (2020). Training convolutional neural networks with multi-size images and triplet loss for remote sensing scene classification. *Sensors (Switzerland)*, *20*(4), 1–21. https://doi.org/10.3390/s20041188