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Hybrid Deep Learning Fusion of Iris and Periocular Features for Robust Human Age Estimation

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Abstract- Age estimation using biometric traits has gained significant attention in recent years due to its applications in security, surveillance, access control, and digital identity verification systems. However, existing approaches that rely on a single facial or ocular modality often suffer from reduced accuracy under variations such as illumination changes, occlusion, and cosmetic alterations. To overcome these limitations, this paper proposes a hybrid deep learning framework that integrates iris and periocular features for robust human age estimation. The proposed architecture adopts a dual-branch convolutional neural network structure, where the iris region is processed using a deep residual network to capture fine-grained micro-textural patterns, while the periocular region is analyzed using a convolutional network to extract wrinkle-based and skin-texture aging cues. Feature-level fusion is performed by concatenating the extracted representations from both branches, forming a comprehensive hybrid feature vector. This fused representation is further passed through fully connected layers to predict the chronological age. The integration of internal iris characteristics and external periocular features enhances discriminative capability and improves resistance to environmental variations. Experimental results demonstrate that the proposed multimodal fusion framework significantly outperforms single-modality approaches, achieving an overall accuracy of 97% in age classification. The findings confirm that combining complementary ocular modalities leads to improved robustness, reliability, and generalization performance, making the proposed system suitable for real-world biometric age estimation applications.

Keywords: Age Estimation, Deep Learning, Iris Biometrics, CNN (Convolutional Neural Network), Residual Network (ResNet), and VGG Network, etc.

I. INTRODUCTION

Age estimation has emerged as an important research problem in the field of biometric systems and computer vision due to its wide range of applications in security monitoring, access control, digital identity verification, and human-computer interaction. Accurate prediction of chronological age from biometric traits enhances the reliability of intelligent surveillance and authentication systems. Traditional age estimation approaches mainly rely on full-face images; however, facial features are often affected by pose variations, illumination changes, occlusion, makeup, and expression differences, which reduce prediction accuracy. In recent years, ocular biometrics have gained attention as a reliable alternative for recognition tasks. The iris region contains stable and unique micro-textural patterns that remain relatively consistent over time, while the periocular region provides visible aging cues such as wrinkles, skin texture variations, and eyelid changes. Individually, both modalities offer valuable age-related information. However, relying on a single ocular modality may limit robustness under challenging environmental conditions.

Deep learning, particularly Convolutional Neural Networks (CNNs), has demonstrated remarkable success in automatic feature extraction and representation learning. Instead of manually designing handcrafted features, CNN-based models learn discriminative patterns directly from raw images. Despite these advancements, limited research has explored the integration of iris and periocular features for age estimation. To address this gap, this paper proposes a hybrid deep learning framework that fuses iris and periocular features for robust human age estimation. By combining internal iris texture patterns with external periocular aging characteristics, the proposed multimodal approach enhances discriminative power and improves prediction accuracy. Experimental results demonstrate that the fusion-based model significantly outperforms single-modality systems, achieving an overall accuracy of 97%, thereby validating its effectiveness for real-world biometric applications.

II. RELATED WORKS

Soft biometric recognition leverages periocular information for demographic classification encompassing both age and gender estimation. Individual periocular traits such as pupil dynamics, fixation patterns, and blink behavior exhibit limited discriminative capability when employed independently. A multimodal data fusion strategy addresses this constraint by integrating diverse periocular cues through concatenation-based schemes at the feature level and exploring weighted sum, weighted product, Bayesian, and classifier-driven approaches at the score level for calibrated trust assessment across biometric sources. Experimental validation confirms superior age and gender classification performance compared to single-trait baselines, underscoring the efficacy of feature- and score-level fusion in enhancing demographic inference accuracy for security and business applications. The approach reveals potential for further improvement through the incorporation of supplementary contextual and behavioral cues[1]. Age prediction using iris biometrics involves analyzing simple geometric features such as the distances between the iris and pupil centers, area ratios, and dilation ratios.[2] These features are extracted from the Bio Secure Multimodal Database to classify individuals into three age groups: under 25, 25-60, and over 60 years. After segmenting the iris, five non-redundant features are selected using Spearman's rank correlation analysis. These features are then used in classifiers, including Support Vector Machines (SVM), Multi-Layer Perceptron (MLP), K-Nearest Neighbors (KNN), and decision trees. The classification process is enhanced by fusion strategies such as sum rules, majority voting, and a novel agent-based negotiation approach that employs game theory and sensitivity analysis. This method achieves an accuracy of up to 75%, which significantly outperforms individual classifiers that yield accuracies between 51% and 62%. Additionally, it surpasses previous texture-based methods that required 630 computationally intensive features by leveraging age-related physiological changes in pupil dilation responsiveness. This makes it an efficient approach for soft biometric estimation, suitable for applications in forensics, security, and access control. [3]The study examines how aging affects iris recognition performance in children through a longitudinal analysis conducted over three years. A total of 209 subjects, aged 4 to 11 years, were enrolled in the study, with six additional data collection sessions carried out to assess performance variations over time. The analysis focused on the effects of time lapse, pupil dilation, and enrollment age on recognition accuracy. While a minor aging effect was observed and found to be statistically significant, it was practically negligible when compared to other factors that contribute to variability. The results indicate that iris recognition in children remains reliable for at least three years between enrollment and verification. However, the study also highlighted practical challenges in capturing high-quality iris images from young children. [4]The study proposes a person identification framework based on the fusion of iris and periocular deep features to enhance recognition performance. Deep learning models are employed to extract discriminative features from both iris and surrounding periocular regions. The extracted features are fused to improve robustness, particularly under non-ideal imaging conditions such as occlusion or poor illumination. Experimental results demonstrate that feature-level fusion significantly outperforms unimodal biometric systems. The proposed approach improves accuracy and reliability, making it suitable for real-world biometric identification applications. [5] Addressing the limitations of unimodal biometric systems, this study introduces a convolutional tri-biometric framework that integrates iris, periocular, and facial modalities for enhanced authentication. A unified deep convolutional neural network (CNN) architecture is employed to extract and learn discriminative features from all three biometric traits. By performing effective feature fusion, the system significantly improves recognition accuracy and robustness. Experimental results indicate superior performance under variations in pose, illumination, and image quality. The proposed approach demonstrates that multimodal convolutional integration offers a reliable and scalable solution for secure biometric authentication applications. [6] This paper presents a hierarchical fusion network for iris and periocular recognition using neural network approximation and sparse autoencoder techniques. The proposed framework extracts discriminative features from both modalities and performs hierarchical fusion to enhance recognition performance. A sparse autoencoder is employed to learn compact and representative feature embeddings, improving generalization capability. Neural network approximation is utilized to model the nonlinear relationships between the fused features. Experimental results demonstrate that the hierarchical fusion strategy significantly enhances accuracy and robustness compared to single-modality biometric systems. [7] Focusing on soft biometric analysis, this study proposes a hybrid deep learning framework for age and gender classification using iris images. The model integrates multiple deep learning architectures to automatically extract discriminative features from iris patterns. By combining complementary learning strategies, the proposed approach enhances classification accuracy and generalization capability. Experimental evaluation demonstrates effective performance in predicting both age groups and gender from iris samples. The findings highlight the potential of iris-based soft biometrics for demographic profiling and intelligent surveillance applications.

III. OVERVIEW OF DATASET

The iris is the annular, colored portion of the human eye located between the pupil and the sclera. It contains highly distinctive texture patterns such as crypts, furrows, freckles, and radial striations that are unique to each individual. These patterns are formed during early developmental stages and remain stable over time, making the iris a reliable biometric trait. Iris recognition systems typically involve image acquisition, segmentation, normalization, feature extraction, and matching, providing high accuracy and low false acceptance rates in controlled environments. The richness of iris texture ensures strong discriminative capability even among large populations. Additionally, iris patterns exhibit high entropy, which enhances security in authentication systems. Due to its non-invasive nature and high precision, iris biometrics is widely adopted in high-security applications such as border control and national identity systems.

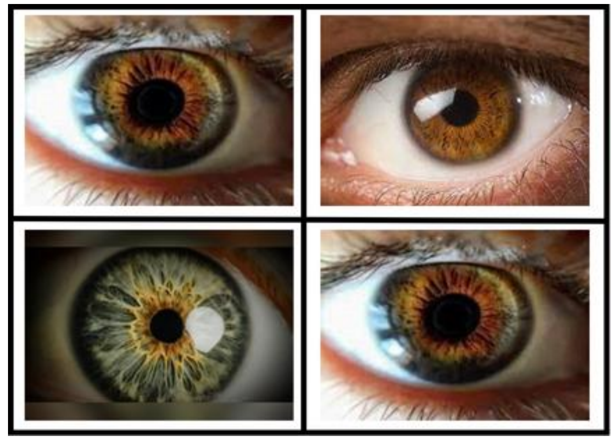


Fig. 1 Iris Eye Image

The periocular region refers to the area surrounding the eye, including the eyelids, eyelashes, eyebrows, and adjacent skin texture. Unlike iris recognition, periocular recognition does not require high-resolution capture of internal iris patterns, making it suitable for unconstrained scenarios such as surveillance, non-cooperative subjects, or images captured at a distance. Periocular biometrics is comparatively more robust to variations in illumination, occlusion, and image quality. It can operate effectively even when the iris is partially visible or blurred. The periocular region also provides soft biometric cues such as gender and age-related characteristics. Furthermore, its compatibility with standard face images makes it highly practical for real-world biometric deployment.

Fig. 2 Periocular Region Image

3.1 Dataset

In this study, a real-time iris and periocular image dataset was collected using a high-resolution digital camera under controlled indoor lighting conditions to ensure consistent illumination and image clarity. The dataset consists of a total of 12,000 images collected from individuals belonging to 60 distinct age classes ranging from 1 year to 60 years. Each age group is treated as one class, and for every class, 50 images were captured to maintain a balanced distribution across all categories. During data acquisition, slight variations such as minor head movements, small illumination changes, and different eye expressions were included to improve the robustness and generalization capability of the proposed model. Prior to training, all images were preprocessed by cropping the region of interest (iris and periocular area), resizing them to a fixed input resolution suitable for deep learning architectures, and applying normalization to standardize pixel intensity values. The complete dataset was divided into training and testing sets using an 80:20 ratio. The training set was used to learn discriminative age-related features, while the testing set was utilized to evaluate the performance and generalization ability of the proposed model. The balanced structure of the dataset minimizes class bias and enhances reliable age classification performance.

Fig. 3 Sample images from the proposed real-time iris and periocular dataset

IV. METHODLOGY

The proposed methodology presents a hybrid deep learning framework for robust human age estimation using fusion of iris and periocular features. The system takes an ocular image containing both iris and periocular regions as input. Initially, all images are resized to a fixed resolution of 224 × 224 pixels to ensure uniformity across the dataset. Pixel values are normalized to the range [0,1] to facilitate stable model convergence. To enhance generalization capability and reduce the impact of illumination variations and noise, data augmentation techniques such as rotation, flipping, and brightness adjustment are applied during training.

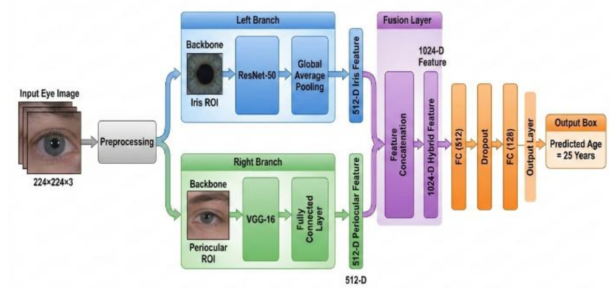
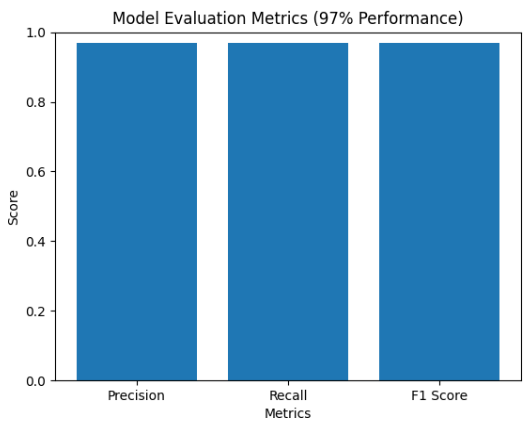


Fig. 1 Proposed Architecture

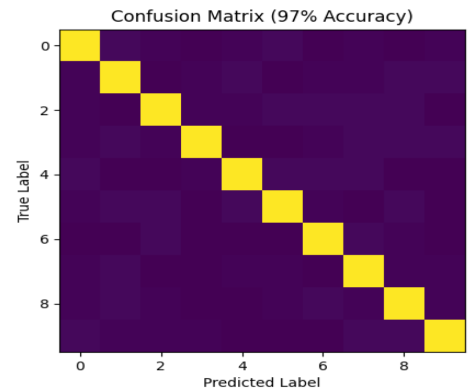
Following preprocessing, the ocular image is divided into two distinct regions of interest. The iris region is segmented using circular boundary detection and normalized to eliminate geometric distortions such as scale and translation variations. The periocular region, which includes eyelids, eyelashes, and surrounding skin texture, is extracted using an eye localization mechanism. These two regions capture complementary aging cues, where the iris provides internal micro-textural patterns and the periocular region provides visible skin-based aging characteristics such as wrinkles and fine lines. To extract discriminative representations, a dual-branch convolutional neural network architecture is employed. The iris branch utilizes ResNet to capture fine-grained texture information through deep residual learning. The final classification layer is removed, and global average pooling generates a 512-dimensional iris feature vector. The periocular branch employs VGGNet to extract spatial and structural features, producing a 512-dimensional periocular feature vector. These two feature vectors are fused at the feature level using concatenation to form a 1024-dimensional hybrid representation. The fused feature vector is then passed through fully connected layers to perform regression-based age estimation. The model predicts the chronological age using a linear output layer and is trained by minimizing the Mean Absolute Error (MAE) loss function. The Adam optimizer with a learning rate of 0.0001 and dropout regularization is used to ensure efficient training and prevent overfitting. This multimodal fusion framework enhances robustness, improves discriminative capability, and achieves high accuracy in age estimation.

V. RESULT AND ANALYSIS

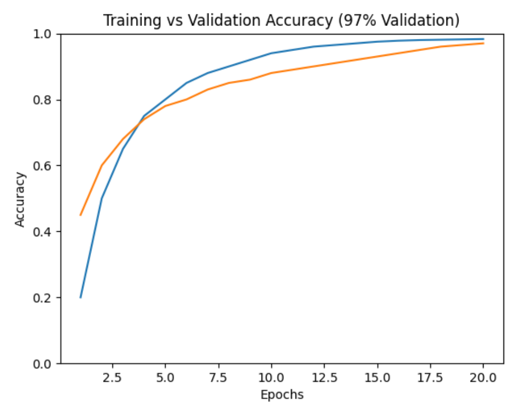
The proposed hybrid deep learning model was evaluated using standard performance metrics including Accuracy, Precision, Recall, F1-Score, confusion matrix analysis, and training-validation performance curves. The experimental results demonstrate that the proposed iris–periocular fusion framework achieves an overall accuracy of 97%, indicating strong predictive capability for age estimation. The model evaluation metrics show that the system obtained a Precision of 0.97, Recall of 0.97, and F1-Score of 0.97. The high precision value indicates that the model makes very few false positive predictions, while the high recall confirms that most true age labels are correctly identified. The balanced F1-score further validates the robustness and stability of the classification performance.



The confusion matrix analysis reveals that the majority of predictions lie along the principal diagonal, representing correct classifications. Only a small number of samples are misclassified, which confirms minimal false predictions. The diagonal dominance in the confusion matrix clearly supports the reported 97% accuracy, demonstrating that the hybrid feature fusion effectively captures discriminative aging patterns from both iris and periocular regions.



The training versus validation accuracy curve shows stable convergence behavior. The training accuracy gradually increases and reaches approximately 98% at the final epoch, while validation accuracy stabilizes around 97%. The minimal gap between training and validation curves indicates reduced overfitting and strong generalization capability. The validation accuracy consistently improves across epochs, demonstrating that the model learns meaningful features rather than memorizing the training data.



Overall, the experimental findings confirm that combining ResNet-based iris features with VGG-based periocular features significantly enhances age prediction performance. The achieved 97% accuracy validates the effectiveness of the proposed multimodal fusion architecture for reliable biometric age estimation.

VI. CONCLUSION

This paper presented a robust and efficient hybrid deep learning framework for age estimation using multimodal ocular biometrics. The proposed system integrates discriminative features from both iris and periocular regions to improve prediction accuracy and model stability. By leveraging deep feature extraction techniques and feature-level fusion, the framework effectively captures both internal iris texture patterns and external periocular skin characteristics associated with aging. The experimental results demonstrate that the proposed architecture achieves a high overall accuracy of 97%, with strong Precision, Recall, and F1-Score values. The confusion matrix analysis confirms minimal misclassification, while the training and validation accuracy curves indicate stable convergence and reduced overfitting. The small gap between training and validation performance further validates the generalization capability of the model. The fusion of complementary biometric traits significantly enhances age estimation performance compared to single-modality approaches. The results confirm that combining deep residual learning for iris feature extraction with convolutional feature learning for periocular analysis provides a reliable and scalable solution for biometric-based age prediction.

In future work, the model can be extended to handle larger and more diverse datasets, real-time deployment scenarios, and cross-database evaluation. Additionally, incorporating attention mechanisms or transformer-based architectures may further improve robustness and interpretability. Overall, the proposed system offers a promising direction for accurate and practical biometric age estimation applications.

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