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Studying the Generalization Capability of the ResNet-50 model in Independent Iris Classification Tasks

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ABSTRACT

This study evaluate a deep learning and transfer learning framework based on the ResNet-50 architecture to support iris biometric systems through multiple classification tasks.. In this paper, we propose training several distinct and independent models for three non-sequential classification tasks: image authenticity verification (fake/real), gender classification (male/female), and iris orientation determination (right/left). This design aims to evaluate the effectiveness of employing a unified backbone architecture for multiple classification tasks, enabling efficient handling of various classification challenges while maintaining system flexibility. Furthermore, this approach establishes a foundation for the future integration of individual models into a unified framework capable of simultaneously classifying multiple attributes. The experimental results demonstrated that the proposed models achieved promising classification performance across different tasks. The Real/Fake classification model obtained the highest accuracy, achieving approximately 99–100% validation accuracy, indicating strong generalization capability. In contrast, the Gender and Iris Orientation classification models showed relatively lower performance due to the higher variability in iris image characteristics, achieving validation accuracies of approximately 86% and 80%, respectively. Demonstrating the proposed framework's flexibility and strong generalization capability, thus increasing its potential for adoption and use in security and intelligent biometric systems.

دراسة قدرة التعميم لنموذج ResNet-50 في مهام تصنيف القزحية المستقلة

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الكلمات المفتاحية:
الشبكات العصبية الالتفافية
شبكة ResNet-50
تصنيف الصورة
القزحية
الأنظمة الحيوية
التعلم بالنقل

الملخص

هذه الدراسة تقيم إطارًا قائمًا على التعلم العميق والتعلم بالنقل باستخدام معمارية ResNet-50 لدعم أنظمة القياسات الحيوية المعتمدة على قزحية العين من خلال تنفيذ مهام تصنيف متعددة.. في هذا البحث، نقترح تدريب عدة نماذج مستقلة ومنفصلة لتنفيذ ثلاث مهام تصنيف غير متسلسلة، وهي: التحقق من أصالة الصورة (حقيقية/مزيفة)، وتصنيف الجنس (ذكر/أنثى)، وتحديد اتجاه القزحية (يمين/يسار). يهدف هذا التصميم إلى تقييم فعالية استخدام بنية أساسية موحدة لتنفيذ مهام تصنيف متعددة، بما يضمن التعامل بكفاءة مع تحديات التصنيف المختلفة مع الحفاظ على مرونة النظام. كما يرئ هذا النهج اساسا لإمكانية دمج النماذج مستقبلًا في إطار موحد قادر على تصنيف عدة خصائص في الوقت نفسه. أظهرت النتائج التجريبية أن النماذج المقترحة حققت أداءً واعدا عبر مختلف المهام. وقد حقق نموذج تصنيف الحقيقي/المزيف أعلى دقة، حيث بلغت دقة التحقق حوالي 99–100%، مما يشير إلى قدرة قوية على التعميم. في المقابل، أظهرت نماذج تصنيف الجنس وتحديد اتجاه القزحية أداءً أقل نسبيًا بسبب التباين الأكبر في خصائص صور القزحية، حيث بلغت دقة التحقق حوالي 86% و80% على التوالي. وتُبرز هذه النتائج مرونة الإطار المقترح وقدرته العالية على التعميم، مما يزيد من إمكانياته للتبني والاستخدام في أنظمة الأمن والأنظمة الذكية للقياسات الحيوية.

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1. Introduction

Image classification represents a foundational subfield of computer vision that processes image pixels numerically to extract patterns, subsequently assigning a predefined "class" or "label" to the visual content [1][2][3]. Previously, most researchers relied on handcrafted features to describe images, which presented significant challenges when dealing with massive amounts of data, as feature extraction became increasingly complex [4]. These difficulties prompted the development of deep neural network models. With the ever-increasing reliance of the computer vision community on deep learning systems, convolutional neural networks (CNNs) have evolved into essential solutions for visual classification problems. While traditional methods relied on manual feature extraction techniques requiring precise preprocessing and often failing to generalize [4][5], CNNs have demonstrated high efficiency and a superior ability to automatically learn features without human intervention. Iris recognition is a vital element in modern security fields, as traditional protection methods have proven inadequate and unreliable due to their susceptibility to theft, forgery, or being forgotten. Conversely, biometric technologies—such as facial recognition, fingerprinting, and iris recognition—offer more secure and reliable means of identity verification [5]. Presentation Attack Detection (PAD) is an essential component of modern biometric systems, aiming to identify and prevent attempts to deceive the system using artificial artifacts or manipulated biometric samples. In iris recognition, PAD techniques enhance system reliability by distinguishing genuine iris images from presentation attack samples, thereby improving the security and robustness of biometric authentication systems. With the availability of diverse iris image databases containing both genuine and fake data, and covering variations in sex, orientation, and multiple imaging conditions, it has become possible to conduct a comprehensive evaluation of the models' generalizability. Therefore, iris image classification has emerged as a significant research topic in this field.

This research aims to develop a unified framework based on a stable architecture to facilitate maintenance and development. This framework involves training multiple, independent models and assessing their generalizability across various classification tasks (such as sex determination, orientation, and forgery detection). This approach is expected to support iris biometric systems by enabling multiple iris image classification tasks.

In this research, generalization refers to the capacity of the same architectural framework to maintain high-performance when deployed across multiple independent classification tasks within the same biometric domain, thereby allowing the same backbone architecture to be adapted for different classification tasks.

The ResNet-50 residual network is a deep residual learning model utilizing a 50-layer architecture optimized for image processing. To mitigate training latency and reduce the computational cost of the model, it is design that enables efficient feature representation while maintaining deep network performance. [6][7].

To address the degradation problem and facilitate the training of very deep neural networks, ResNet introduces residual learning through shortcut connections., ResNet-50 employs a 50-layer residual learning architecture based on specialized bottleneck blocks. Each bottleneck block consists of three convolutional layers arranged as 1×1, 3×3, and 1×1 convolutions. The first 1×1 convolution reduces the number of feature dimensions, while the 3×3 convolution performs feature extraction, and the final 1×1 convolution restores the feature dimensions. This structure reduces computational cost and parameter complexity while preserving strong feature representation capability. Furthermore, the use of shortcut connections enables identity mapping, allowing gradients to propagate more effectively through the network and alleviating the vanishing gradient problem during deep model training [7].The Residual Network ResNet-50 architecture was selected for this work because of its superior capability in extracting deep features and mitigating the vanishing gradient problem through its residual connections, while simultaneously striking an optimal balance between accuracy and computational complexity.

The primary contribution of this work lies in evaluating the reusability of the identical architecture across multiple classification tasks specifically liveness detection (spoofing mitigation), gender classification, and eye side determination (left/right)—utilizing independent models that share the same underlying framework.

2. . Literature review

In the scientific literature, several studies have been proposed for classifying and analyzing iris images using deep learning techniques. One of the most prominent of these pioneering studies was presented in [1], where highly relevant advancements in iris image classification have emerged. A framework for classifying the right and left irises of 46 individuals was developed using a 5-layer CNN, achieving a test accuracy of 93.09%.

In [6], an automated system was developed to classify unknown iris images into right or left categories using CNNs. Utilizing 32×32 pixel images extracted from the NIST ICE, LG, and CASIA PLR datasets—distributed equally between training and testing sets with a 50%-50% split—the system achieved an accuracy ranging from 97% to 100%.

As this research field has developed, the classification of demographic and biological characteristics has become increasingly important. A deep neural network-based classification model (DLNN) was proposed in [8] to classify left and right human iris images using the CASIA-Iris-lamp dataset, which contains 16,163 iris images.

This model achieved an accuracy of 99.57%, outperforming alternative models that did not exceed 93.35%. Similarly, a RAG-Net model based on the ResNet-50 architecture was introduced in [9], incorporating a U-Net model and an attention gate mechanism to improve performance, which yielded an accuracy of 95.05% on the CASIA.v4-distance database. Furthermore, a comprehensive review of the latest relevant research and identified research gaps was conducted in [10], confirming the efficiency of CNNs in classifying the sex from iris images with an accuracy reaching up to 98.88%.

Multi-category classification has also been investigated more recently. A diagnostic system designed to classify iris images into three distinct categories using 1,032 images was developed in [11]. A performance comparison between the Inception V3 and ResNet-50 models revealed that the latter achieved a higher accuracy of 93.81%.

To improve security, biometric spoofing challenges have been addressed through the classification of real and fake facial images. A framework to differentiate between real and fake faces was proposed in [12] using the ResNet-50 model on a dataset consisting of 589 real and 700 fake images; despite employing data augmentation techniques, it achieved a test accuracy of 53%.

Additionally, the AlexNet architecture was utilized in [13] to construct an efficient iris classification model, which successfully achieved an accuracy of 99.57% on the MMU dataset and a perfect 100% on the AMF dataset.

Through the analysis of these studies, it was observed that they address one independent classification task at a time (sex, gender, or forgery detection). Therefore, this work aims to expand on this concept by evaluating the applicability of a comprehensive and generalized iris classification framework based on ResNet-50 across multiple independent classification tasks. Separate models are trained for liveness detection, gender classification, and eye side determination to assess the effectiveness and reusability of the same architecture for biometric security applications.

3. Material and method

The proposed methodology is defined by designing a set of independent models, each dedicated to a specific task without any sequential dependencies between them. This design aims to explore the generalizability of a unified architectural backbone across multiple classification tasks. This strategy enables effective handling of diverse classification challenges, including image variability and the presence of pseudo-samples, while maintaining system flexibility. Furthermore, this methodology facilitates the potential future integration of individual models into a unified framework capable of co-classifying multiple attributes. As illustrated in figure. 1, the proposed methodology encompasses several sequential phases, spanning from data collection to final model evaluation.

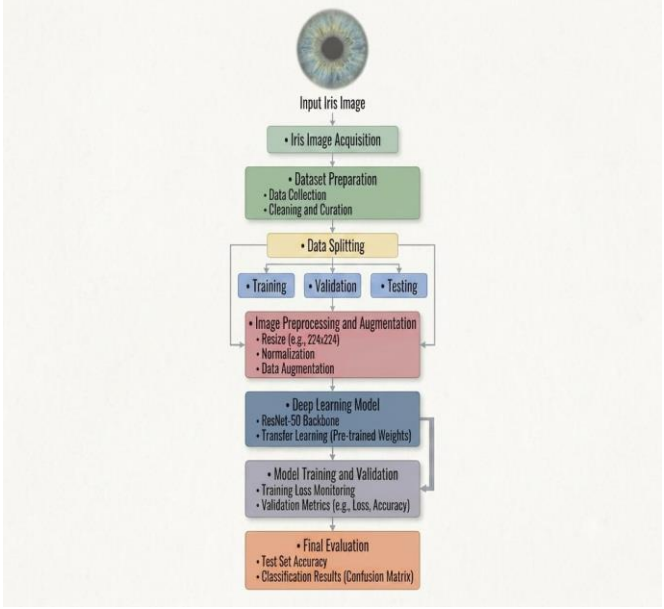


Figure 1:Methodology Steps

A.Datasets

Datasets are a fundamental component in training and evaluating deep learning models. In this study, three independent datasets were used, formatted and compiled to suit the research objectives as follows:

• **Dataset A for Real/Fake Model:** Used to train the first model, which specializes in detecting forgeries and classifying iris images into (real and fake). This is the complete Liveness Detection database, which includes original, synthetic, and pre-printed images. This set contains 8,000 images.

• **Dataset B for Female/Male Model:** Used to train the second model, which specializes in classifying sex (male and female). This set contains 13,000 images, manually compiled and formatted into folders from the MMU2 and UBIPR1 databases.

• **Dataset C for Left/Right Model:** Used to train the third model, which aims to determine iris orientation (right and left). This set includes 6,000 images, manually compiled and formatted into folders from the CASIA-Interval and MMU-LR databases.

The numerical variance across the three independent datasets (A, B, and C) is primarily dictated by the distinct nature of each classification task and the characteristics of their respective source databases. Specifically, sex classification (Dataset B) requires a substantially larger volume of instances (13,000 images) to effectively extract and learn highly intricate and subtle biometric facial/iris features, contrasted with the less complex feature spaces required for spoofing detection or orientation identification. Given that the classification pipelines are structurally decoupled and executed independently at separate intervals, utilizing the maximum available capacity of each distinct dataset was prioritized. This approach optimizes the generalization capability of each individual network architecture, intentionally avoiding under-sampling techniques that risk the omission of critical intra-class feature representations during the optimization phase.

B. Data segmentation

Data Segmentation: A strict and standardized physical segmentation strategy was adopted across all datasets in this study. The images were pre-separated at the filesystem level into three completely independent folders: Training, Validation, and Testing, at ratios of 80%, 10%, and 10%, respectively.

The dataset partitioning was executed based on subject-independent identities rather than random allocation. This mechanism ensures that no different images of the same person's iris are included in different sets (e.g., one image of the same person in training and another in testing), forcing the model to learn the general texture features and patterns of the iris rather than memorizing individual identities.

The Validation folder was isolated for exclusive use in monitoring the loss function, hyperparameter tuning, and applying early stopping techniques to prevent overfitting. The Testing folder was completely isolated to serve as a final, neutral evaluation tool for measuring the model's ability to generalize when faced with specific challenges. serving as an entirely unseen validation pool.

C. Image Preprocessing and Augmentation

Regarding image preprocessing, a standardized pipeline was implemented to unify data formats and reduce computational complexity. Since the majority of the original images were grayscale, they were converted into a three-channel format (RGB-like) by duplicating the single channel, ensuring compatibility with the input requirements of the pre-trained ResNet-50 architecture on ImageNet. All images were then resized to fixed dimensions of 200 × 56 pixels, a deliberate choice that balances the preservation of fine iris textual structures with the reduction of computational overhead during training.

During the training phase exclusively, online data augmentation [18] techniques were applied to enhance the model's generalization ability. These techniques included random rotations within ±7°, horizontal and vertical translations up to ±7% pixels, and shear transformations within ±7°. These augmentations simulate natural variations in capture angles and eye positioning during acquisition without introducing excessive distortion to the underlying iris texture.

Finally, the images were converted into PyTorch tensors and normalized using the mean and standard deviation derived from the ImageNet dataset, ensuring that the input statistical distribution aligns with the pre-trained network to enhance training stability.

D. Model Architecture

The proposed Architecture illustrated in Figure 2 was implemented using the PyTorch framework, utilizing the ResNet-50 architecture as the core backbone for all classification models due to its high efficiency in extracting deep visual features and its capability to mitigate the vanishing gradient problem through residual connections. To minimize computational complexity, the input dimensions were configured to 200 ×56 pixels, while a batch size of 32 was selected to ensure stable gradient updates within the memory constraints of the Graphics Processing Unit (GPU) .

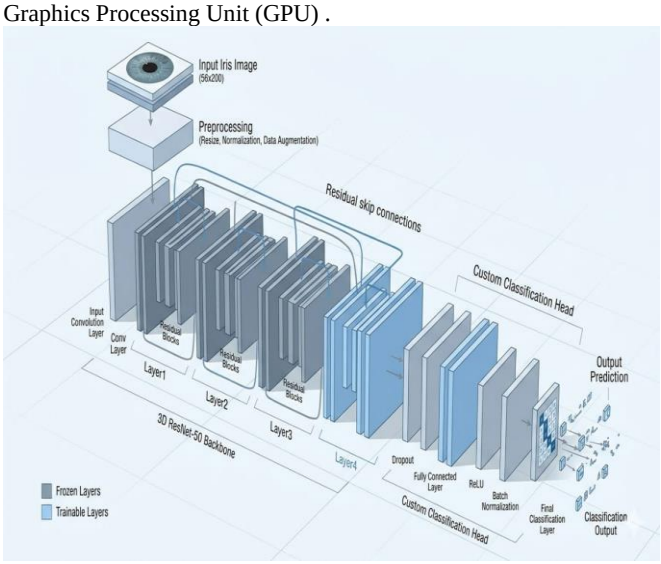


Figure 2:Architecture of proposed Model

The CrossEntropyLoss function was employed as the loss function for all classification tasks. Binary classification tasks were implemented using two output classes, following the same multi-class classification formulation. For optimization, the AdamW optimizer was deployed with a differentiated learning rate strategy. A highly conservative learning rate of 5×10^{-6} was assigned to the trainable parameters within the classification head. Concurrently The early layers of the ResNet-50 backbone were frozen, while the layer4 block was partially fine-tuned along with the newly added fully connected classifier., which were permitted to undergo partial adaptation.

To enhance generalization and prevent overfitting, a robust regularization strategy was implemented, incorporating Batch Normalization, a weight decay of 5×10^{-4} and Dropout layers. Additionally, gradient clipping with a threshold of 1.0 was applied to eliminate gradient instability, alongside a ReduceLROnPlateau scheduler to automatically decay the learning rate when the validation loss plateaued.

The models were trained for 50 epochs across most tasks; however, the training duration was extended to 100 epochs specifically for the

gender classification task. This extension was necessitated by the pronounced intra-class variability and high visual similarity inherent in gender-related iris features, which demand prolonged training to achieve optimal convergence and precise discriminative boundaries. Throughout the training phase, periodic evaluation was performed on the validation set to monitor performance, with the optimal model checkpoints retained based on the minimum validation loss .

4. Experimental Results

The proposed model was evaluated to measure its ability to classify images across several independent tasks. The research involved three independent models: the first was used to classify images as real or fake, the second to determine the gender of the person in the image (male/female), and the third to determine the orientation of the iris (right/left).

Each image was passed to all three models independently and in parallel, so that each model produced its own evaluation without relying on the results of the others. The three models were evaluated separately using the independent test set, focusing on classification accuracy, generalizability, and computational efficiency.

In addition to accuracy and loss metrics, the biometric performance of the proposed model was further evaluated using the False Acceptance Rate (FAR) and False Rejection Rate (FRR). FAR measures the rate at which fake samples are incorrectly accepted as genuine, while FRR measures the rate at which genuine samples are incorrectly rejected. These metrics provide a more comprehensive assessment of the model's reliability and security performance in biometric authentication scenarios.

The FAR and FRR metrics were applied only to the real/fake classification model because this task is directly related to biometric security and Presentation Attack Detection (PAD). These metrics provide a more suitable evaluation of the model's ability to distinguish between genuine and fake samples. In contrast, the gender and iris-side classification tasks were evaluated using conventional classification metrics, which are more appropriate for attribute-based classification.

A. Results of Real/Fake Model

The model demonstrated high convergence stability and achieved very high accuracy without overfitting or underfitting, as shown in figure 3.

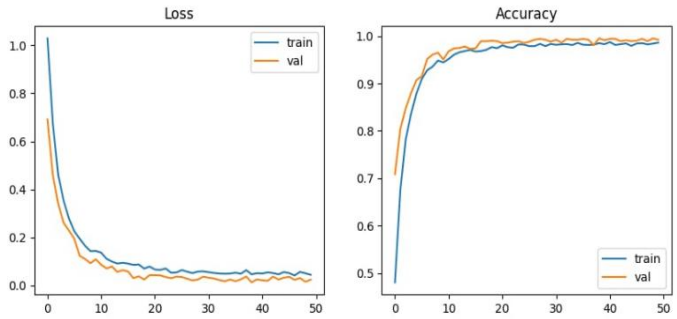


Figure 3: Training and validation loss and accuracy curves for the real/fake classification model.

The loss value for both training and validation drops sharply and rapidly during the first 10 cycles (epochs), then continues to decrease gradually until it stabilizes.

The fact that the validation curve does not rebound upwards until cycle 50 indicates that no obvious signs of overfitting were observed. Training and validation accuracy rise very quickly in the initial stages and then stabilizes at very high levels. Training accuracy stabilizes at around 98% to 99%, while validation accuracy fluctuates and stabilizes between 99% and 100%.

B. Results of Model (Female/Male)

As we can see from figure 4, the training loss and verification loss decrease sharply and in parallel. This is an indication that the model learns correctly and quickly at the beginning.

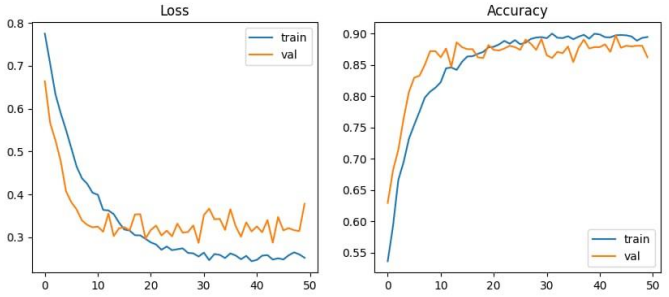


Figure 4: Training and validation loss and accuracy curves for the Female/Male classification model.

In the loss curve (epochs 30-50), a clear divergence emerges. As the training loss approaches its lowest value, the validation loss begins to gradually increase and becomes noisy, culminating in a sharp jump at epoch 49. This indicates that the model has started "memorizing" the training data instead of understanding general patterns.

Meanwhile, in the accuracy curve (epochs 0–15), validation accuracy initially increases faster than training accuracy. This behavior can occur when regularization techniques such as Dropout are applied, as Dropout is active during training and disabled during validation. However, after the initial improvement, the validation accuracy starts to decline and fluctuate, reaching approximately 86% at epoch 50, while training accuracy continues to improve, indicating signs of overfitting.

D. Results of (Left/Right)Model

As we observe in figure 5 of the period (Epoch) 0 to 20 (the actual learning phase), the model's performance improves in both training and validation; the loss decreases and the accuracy of the two curves increases consistently. This indicates that the model is successfully learning the basic patterns.

The relatively lower performance of the gender classification model cannot be attributed solely to overfitting, as several factors may have contributed to this result. One of the main challenges is the limited discriminative differences in iris texture between males and females, which makes gender classification a more complex task. In addition, variations in image quality, illumination conditions, pupil dilation, and partial occlusion caused by eyelids or eyelashes may affect the extracted features. Furthermore, intra-class variability and limited training data may reduce the model's generalization capability, resulting in lower validation accuracy and increased loss values.

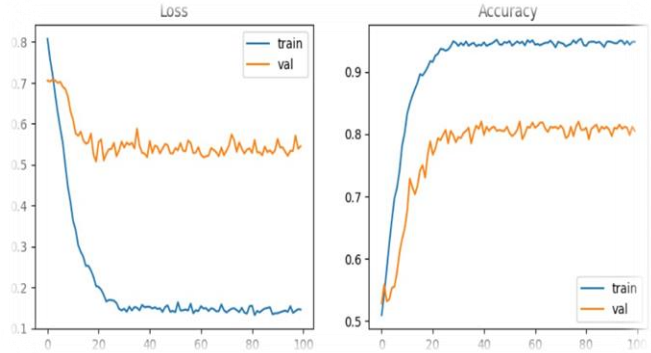


Figure 5: Training and validation loss and accuracy curves for the Left/Right classification model.

The training curves continue to improve until accuracy reaches approximately 95% and loss drops to 0.15. In contrast, the validation curves plateau at a fixed ceiling; accuracy stabilizes at around 80%, and loss begins to fluctuate randomly around 0.52.

The widening gap between training performance (95%) and validation performance (80%) means that after cycle 20, the model stops understanding the general rules and begins to memorize only the finer details and noise of the training data, rendering it unable to generalize effectively to new data. The following table 1 illustrates the model measurement criteria.

Table 1: Performance Evaluation Metrics of the Proposed Models

Model	Precision	Recall	F1-score support	Test Accuracy	FRR	FAR
Real/Fake Model	89.28%	88.58%	87.87%	88.58%	20%	8%

Model	Precision	Recall	F1-score support	Test Accuracy	FRR	FAR
Female/Male Model	90.15%	90%	89.99%	90%	-	-
Left/Right Model	81.22%	80.67%	80.58%	80.68%	-	-

5. Discussion of Results

The empirical results demonstrate the efficacy of the three proposed deep learning classification models across presentation attack detection (liveness detection), gender classification, and iris orientation determination, achieving a commendable peak accuracy of approximately 99% in specific tasks.

Liveness Detection and Feature Overlap: While the liveness detection model exhibits robust classification performance regarding the "Print" category, a pronounced performance degradation is observed in the "Pattern" class. This limitation is primarily attributed to acute feature overlap and underlying class imbalance within the dataset, which impeded the network's ability to extract highly discriminative representations for this specific variant.

Gender Classification and Generalization: The gender classification framework attained a promising accuracy of 90%. However, the training trajectories indicate the onset of overfitting, coupled with a performance disparity between the two cohorts. This variance is likely driven by the intrinsic heterogeneity of visual features distinctive to each gender category.

Orientation Determination and Overfitting: Regarding the iris orientation determination model, explicit overfitting manifests post-epoch 20, characterized by a diverging generalization gap between the training and validation loss trajectories, while the test accuracy plateaus at approximately 80%.

Mitigation Strategies and Data Quality: To mitigate these generalization errors and suppress performance oscillations, integrating regularization techniques—such as Early Stopping, Class Weights, and Data Augmentation—is imperative. Furthermore, these findings underscore that data quality and class equilibrium are paramount factors dictating model stability across all evaluated tasks.

6. Conclusions

In this study, we evaluated a proposed deep learning architecture capable of processing and classifying images across multiple independent tasks ,including liveness detection, sex identification, and eye orientation detection.

The experimental results showed that the proposed architecture achieved promising levels of accuracy and a high capacity for minimizing loss during training. However, comparative analyses of the training and validation environments revealed varying indicators of overfitting and bottlenecks in the classification of overlapping feature distributions, particularly when data size decreased or pixel features converged between live and fake groups. This indicates a continued need to improve generalization capabilities to maintain stable performance when handling unseen data through the application of regularization strategies and advanced preprocessing.

The flexibility of this architecture enables promising applications in real-world security and biometric scenarios. Future studies are recommended to expand dataset sizes and enhance their geographical diversity, while also integrating attention mechanisms and visualization techniques such as Grad-CAM to better understand the decision-making process within the network’s hidden layers. These improvements can contribute to enhancing the reliability and performance of biometric verification systems.

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