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Iris Recognition System (IRS) In Biometric World

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Abstract
With the rapid growth of digital technologies, the demand for reliable and secure authentication methods has become increasingly vital. Among various biometric identification techniques, iris recognition stands out as one of the most dependable approaches due to the iris's unique and stable pattern that remains consistent throughout a person's life. Unlike traditional password- or token-based systems, iris recognition offers a higher level of accuracy, security, and resistance to environmental and age-related variations. This paper presents a comprehensive study of the Iris Recognition System (IRS), encompassing both classical and modern methodologies. The research highlights the traditional techniques such as Daugman's rubber sheet model and Gabor wavelet-based feature extraction, while addressing their limitations in uncontrolled or noisy conditions. To overcome these challenges, the proposed approach integrates advanced deep learning methods like Convolutional Neural Networks (CNNs) and transfer learning models such as DenseNet201, which enhance feature extraction and classification accuracy. The workflow includes essential stages such as image acquisition, preprocessing, iris localization, normalization, feature extraction, and pattern matching. The proposed system was evaluated on standard datasets including CASIA, UBIRIS.v2, and IITD, achieving a recognition accuracy of over 95% even under challenging conditions like poor lighting and off-angle captures. The paper also explores key applications of iris recognition in domains such as border control, mobile authentication, e-governance, and healthcare. Finally, it discusses potential advancements like lightweight CNN architectures, multimodal biometric systems, and edge-based iris recognition models for future research and deployment.

1. Introduction

Iris recognition is an advanced biometric technique that identifies individuals by analyzing the intricate patterns in the iris — the colored part of the eye surrounding the pupil. Compared to other biometric traits such as fingerprints or facial features, the iris offers superior reliability due to its high distinctiveness, stability, and low error rates in both false acceptance and false rejection. In an iris recognition system, key features are extracted from a captured eye image and used to classify or verify an individual's identity. A correct classification signifies a successful recognition. Many early systems assumed ideal imaging conditions to achieve high accuracy, typically requiring controlled lighting and cooperative subjects. Historically, most publicly available iris image databases were captured using near-infrared (NIR) cameras at close distances. The use of NIR illumination enhances iris pigmentation visibility and minimizes reflections, helping engineers avoid noise during preprocessing. For instance, Libor Masek's study found that approximately 83% of images in the CASIA database were accurately segmented, while the Lion's Eye Institute (LEI) dataset achieved only 62% due to less favorable imaging conditions and natural lighting interference. Images captured under natural light often include reflections and irregular illumination, making segmentation more difficult compared to those taken with NIR lighting. Consequently, robust systems must handle such variations effectively to ensure reliable performance. The main objective of this project is to improve the robustness and adaptability of classical iris recognition techniques. By incorporating transfer learning, the model can generalize better to new environments. Additionally, data augmentation and Bayesian optimization are applied to enhance model efficiency, particularly when working with limited datasets and computational resources. Figure 1 shows General Model/Block Diagram of an Iris Recognition System

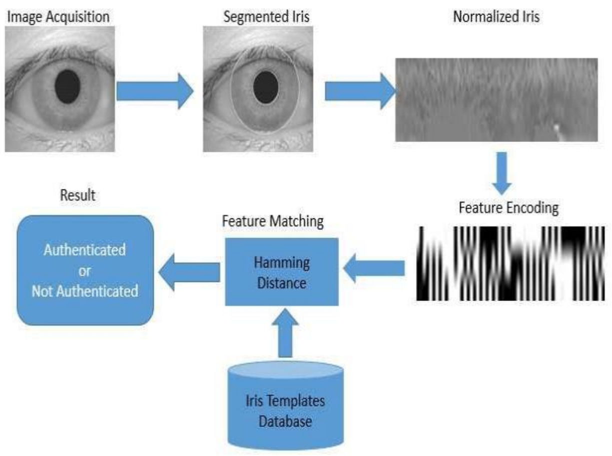

Figure 1 General Model/Block Diagram of an Iris Recognition System

2. Literature Review

2.1. Overview of Existing Research

Research in the field of iris recognition has evolved significantly — progressing from basic image processing techniques to more sophisticated machine learning and deep learning-based approaches. Early methods relied on classical computer vision algorithms like edge detection and Hough Transform to detect circular boundaries around the iris and pupil. Although these methods produced reasonable results in controlled environments, they often failed in realworld conditions due to common issues such as motion blur, reflections, partial occlusion, and inconsistent lighting. [1] The integration of machine learning marked a notable improvement in iris recognition. Algorithms such as Support Vector Machines (SVMs), Random Forests, and Haar cascades were trained using handcrafted features including gradient and texture descriptors. These techniques provided better adaptability and tolerance to variations in the data compared to traditional image processing. However, their performance still heavily depended on the quality of manually engineered features, making them less scalable or reliable for large and diverse datasets. [2] The recent rise of deep learning has transformed iris recognition by automating feature extraction and improving accuracy under complex conditions. Models like U-Net and DeepLabV3+ enable pixel-level segmentation, effectively isolating the iris region even in the presence of noise, occlusion, or non-frontal eye images. Likewise, YOLOv5 offers fast and efficient real-time iris detection, making it ideal for mobile or surveillance-based systems. [3] A key advantage of deep learning methods lies in their ability to generalize across multiple datasets. When trained using data from varied sources such as CASIA-IrisV4 and UBIRIS.v2, these models can handle differences in camera quality, lighting, and angle. This generalization helps overcome limitations faced by earlier approaches, which required controlled environments and consistent subject positioning. [4] Furthermore, hybrid approaches combining classical and deep learning methods have recently gained attention. These systems aim to balance computational efficiency with the robustness of neural networks. By leveraging traditional preprocessing techniques along with deep feature learning, hybrid models achieve both speed and accuracy — making them practical for real-time biometric systems embedded in portable or low-power devices. [5] Finally, standardized datasets and performance metrics such as Intersection over Union (IoU), precision, and

F1score have enabled consistent evaluation across studies. These benchmarks allow researchers to fairly compare results, track progress, and guide improvements in accuracy, robustness, and scalability of modern iris recognition technologies.

2.2. Key Findings in the Field

Research outcomes across various studies clearly demonstrate that deep learning-based approaches outperform traditional and classical machine learning methods in nearly all scenarios. While older systems perform adequately under ideal conditions, they often fail when faced with noisy images, poor illumination, or occlusions caused by eyelashes and eyelids. Advanced segmentation models like U-Net and DeepLabV3+ achieve exceptional accuracy by learning spatial features at the pixel level, whereas YOLOv5 stands out for its high-speed real-time performance. These methods eliminate the need for manual feature extraction and deliver consistent results across different environments. By contrast, traditional systems depend heavily on well-captured images and precise preprocessing. Overall, integrating intelligent preprocessing with deep learning models has led to more adaptive, fast, and reliable iris recognition systems. This marks a major step toward the widespread use of secure, contactless biometric authentication in diverse fields such as security, healthcare, and mobile access control.

3. Existing System

The existing iris recognition system functions by capturing an image of the human iris using a camera, usually under controlled conditions such as near-infrared lighting. Once the image is captured, the system processes it to extract the unique iris patterns, which are then compared against stored templates in a database to verify or identify the individual. These systems are generally known for their high accuracy, non-intrusiveness, and resistance to forgery. They are able to deliver precise identification results with minimal physical interaction from the user. Traditional systems mainly rely on classical image processing and machine learning techniques with hand-crafted feature extraction, which perform effectively when the image quality is high and environmental conditions are favorable.

4. Existing System Limitations

- **Dependence on Controlled Environments:** Traditional iris recognition systems require ideal imaging setups — stable lighting, fixed subject positioning, and high-quality cameras. This limits their usability in uncontrolled or outdoor environments.
- **Manual Feature Extraction:** Handcrafted feature extraction techniques are designed manually and must be adjusted for each dataset or environment. This lack of flexibility makes them difficult to generalize across diverse real-world data.
- **Poor Imaging Quality in Certain Datasets:** Databases captured under natural lighting, such as the LEI dataset, suffer from glare, reflections, and poor segmentation accuracy compared to NIR-based datasets like CASIA.
- **Sensitivity to Image Quality:** Low-resolution, blurred, or partially occluded images (e.g., by eyelashes or glasses) can cause the system to misidentify individuals or fail to extract useful features.
- **Limited Robustness:** Classical systems often struggle when there are variations in lighting, head pose, or gaze direction, making them less reliable in real-world conditions.
- **Small Dataset Challenges:** Many older research studies relied on small iris databases, which can lead to overfitting — where the model performs well on training data but poorly on unseen samples.
- **High Computational Demand in Deep Models:** Although deep learning methods have improved accuracy, they often require powerful hardware such as GPUs, which increases system cost and complexity.
- **Privacy and Ethical Issues:** Since biometric data is sensitive, improper storage or unauthorized use can lead to privacy violations. Systems must therefore include encryption and strict access control to ensure ethical use. Figure 2 shows Iris Recognition Success on Public Images: A Major Privacy Concern
- mobile phones automatically capture the iris once the subject is properly aligned. The goal of this stage is to acquire a well-focused, noise-free, and centred iris image

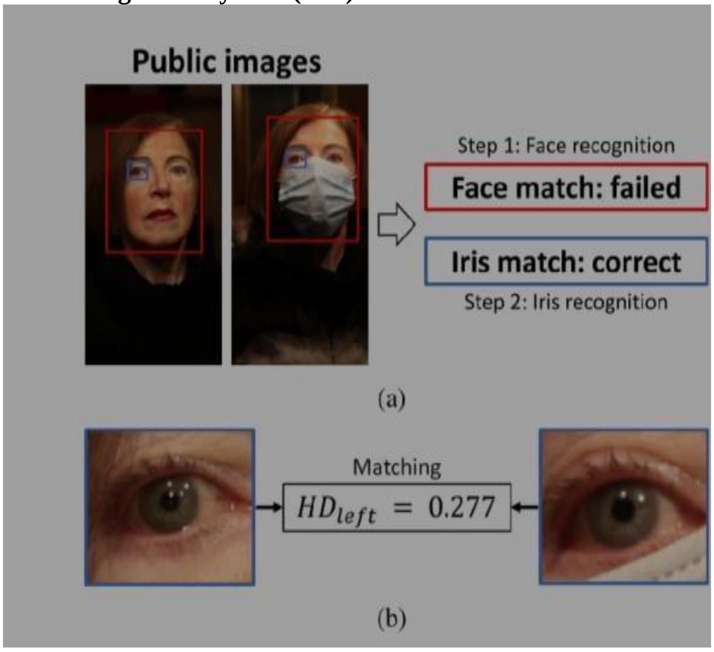

Figure 2 Iris Recognition Success on Public Images: A Major Privacy Concern

5. Proposed System

The proposed Iris Recognition System (IRS) introduces a modernized approach to overcome the drawbacks of classical systems. It aims to deliver highly accurate, secure, and flexible biometric recognition suitable for a variety of environments — from border security to everyday device authentication.

The system is designed with several key components:

- **Iris Capture Device:** A high-quality camera or scanner captures detailed images of the iris under varying lighting and angles. The hardware is optimized to reduce glare, motion blur, and environmental interference.
- **Iris Recognition Software:** The software processes the captured images to extract distinguishing features such as iris texture and pattern. It then converts this information into a digital template, which is securely stored for comparison.
- **Database:** All iris templates are stored in an encrypted database accessible only to authorized users. This ensures both security and scalability, allowing the system to manage large populations efficiently.
- **Verification Process:** During verification, the system compares a newly captured iris image with stored templates. A match confirms the individual's identity, while a mismatch denies access. The process is quick, precise, and contactless.
- **Privacy and Data Protection:** Strong security mechanisms — including encryption, access control, and anonymization — are implemented to safeguard personal data and comply with privacy regulations.
- The proposed system not only increases accuracy and adaptability but also supports deployment in real-world, uncontrolled settings, ensuring performance consistency across varying conditions.

6. System Architecture and Design

- The architecture of the proposed IRS follows a modular design where each component plays a critical role in achieving high reliability and user convenience.
- **Iris Capture Module:** Captures high-resolution iris images in diverse environments. The use of NIR or adaptive lighting ensures clarity regardless of surrounding conditions.
- **Feature Extraction Module:** Extracts unique iris texture using a combination of deep learning and image processing algorithms for better generalization.
- **Database Management System:** Stores templates securely and retrieves them efficiently during verification.
- **User Interface:** Provides an interactive platform for users to present their iris for scanning or upload images.
- **Verification Engine:** Compares captured features against stored templates using optimized matching algorithms.
- Security Layer: Ensures encrypted data storage, privacy compliance, and restricted access.
- **Integration Support:** The system can integrate with other applications such as access control, attendance systems, or mobile authentication platforms. Figure 3 shows Flow Chart
- mobile phones automatically capture the iris once the subject is properly aligned. The goal of this stage is to acquire a well-focused, noise-free, and centred iris image

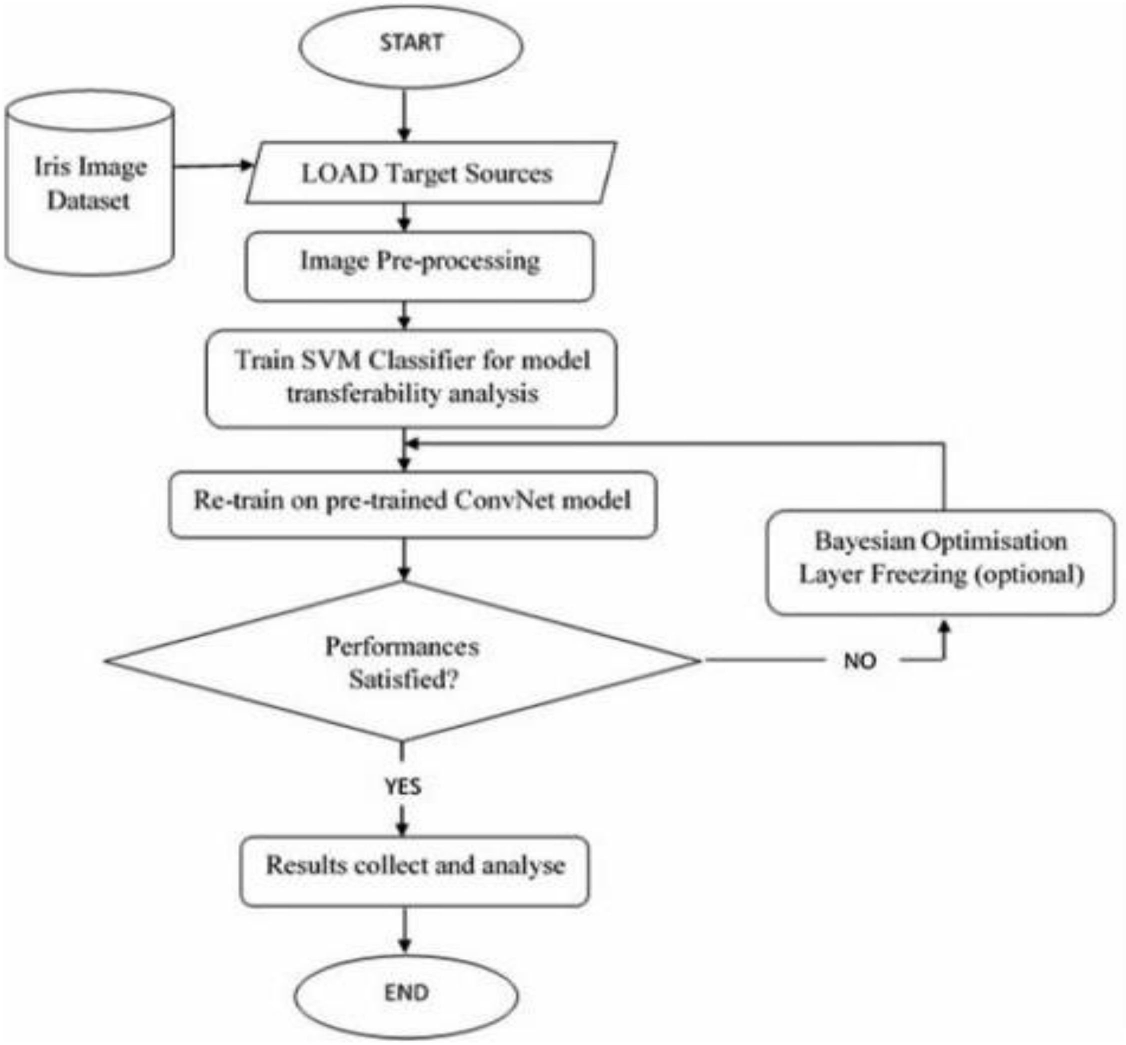

Figure 3 Flow Chart

7. Methodology and Implementation

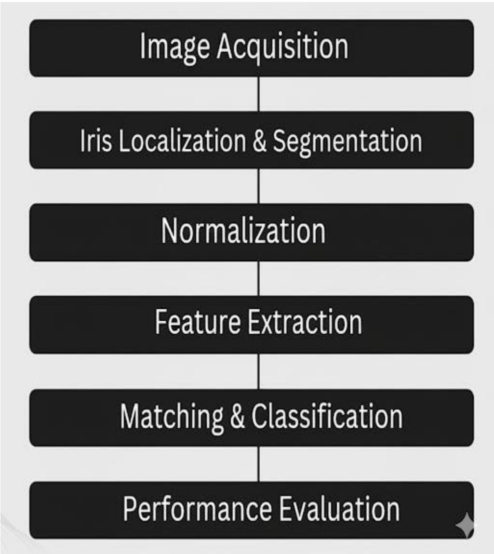

Figure 4 Workflow of the Iris Recognition System

7.1. Image Acquisition

The Image Acquisition phase is the foundation of the entire system, as the quality of the captured image directly determines the effectiveness of subsequent processes like segmentation, normalization, and feature extraction. During this step, high-resolution images of the human eye are captured using specialized iris scanners or high-definition cameras. Most practical systems utilize near-infrared (NIR) illumination, which enhances contrast between the iris and the pupil, minimizes reflections, and clearly exposes iris textures. In cost-effective systems, regular webcams may be used, though they often require additional preprocessing due to lighting inconsistencies. The captured image should ideally have a resolution of at least 640×480 pixels, ensuring fine details of the iris are visible. The eye must be centered, free from motion blur, and unobstructed by eyelids, eyelashes, or spectacles. However, challenges often arise due to uneven lighting, glare, and natural eye movement. To overcome these issues, modern acquisition systems integrate autofocus, auto-exposure, and multi-frame capture technologies. Multiple images are captured in quick succession, and the best-quality frame is automatically selected using Image Quality Assessment (IQA) techniques. Additionally, denoising filters and histogram equalization may be applied to improve contrast and clarity. Datasets such as CASIA-IrisV4 and UBIRIS.v2 are commonly used for testing because they provide images taken under both controlled and uncontrolled conditions. In real-world applications, iris scanners embedded in devices such as airport gates, ATMs, or mobile phones automatically capture the iris once the subject is properly aligned. The goal of this stage is to acquire a well-focused, noise-free, and centred iris image suitable for accurate feature extraction and pattern recognition.

7.2. Iris Localization and Segmentation

Iris Localization and Segmentation is one of the most critical steps in the IRS pipeline. The main objective is to accurately isolate the iris region from the rest of the eye image, excluding irrelevant areas such as the pupil, sclera, eyelids, and eyelashes.Classical methods like Daugman's integrodifferential operator and the Hough Transform are widely used to detect circular boundaries between the iris and pupil (inner boundary) and the iris and sclera (outer boundary). Although these algorithms perform well under ideal lighting, they tend to struggle with occlusions, reflections, and low-quality images.To improve robustness, modern systems employ deep learning-based segmentation models such as U-Net and YOLO variants, which can accurately detect the iris region even in noisy or off-angle images. These models learn the spatial structure of the iris and automatically distinguish it from surrounding regions.During segmentation, occluded areas (due to eyelids or eyelashes) are detected and masked out. Preprocessing operations such as contrast enhancement and edge detection are also applied to improve boundary detection. Once segmentation is complete, the iris region is prepared for normalization to handle geometric variations.Accurate segmentation ensures that only relevant iris data proceeds to the next stage, significantly enhancing system performance and reducing recognition errors.

7.3. Normalization

The Normalization process transforms the segmented iris region into a standardized coordinate system, ensuring that differences in pupil dilation, camera distance, or eye rotation do not affect recognition performance.Since the iris can expand or contract depending on lighting conditions, direct comparison between two raw iris images would be unreliable. To address this, Daugman's rubber sheet model is used to remap the circular iris region into a rectangular block in polar coordinates. This representation allows the system to align iris images consistently regardless of size or orientation.Normalization also ensures that features extracted from multiple images of the same individual are aligned and comparable. Noise masks generated during segmentation (for occluded or reflective regions) are applied during this phase to remove non-iris portions from processing.By converting all iris samples to a uniform scale and orientation, normalization enhances the stability and reliability of subsequent feature extraction and matching stages.

7.4. Feature Extraction

Feature Extraction is the heart of the IRS. In this stage, distinctive patterns in the iris—such as crypts, ridges, freckles, and radial furrows—are analyzed and converted into a mathematical representation or iris code.Traditional systems often use Gabor filters or wavelet transforms to extract texture information from different spatial frequencies and orientations. These methods are effective at capturing fine-grained structures but rely on manual feature design, which can be limited in diverse lighting or imaging conditions.Modern systems, however, leverage deep learning models like Convolutional Neural Networks (CNNs) to automatically learn and extract hierarchical features directly from image data. CNNs can capture both local and global iris patterns, making them highly robust against variations in illumination, focus, and noise.To further enhance feature learning, transfer learning is used, where pre-trained models like DenseNet201 or ResNet are finetuned on iris datasets. These models inherit knowledge from large-scale image classification tasks and adapt it for iris recognition. Data augmentation techniques — including image rotation, scaling, and brightness adjustments — help the system remain invariant under real-world variability.The output of this process is a compact, discriminative feature vector that uniquely represents the individual's iris. This feature vector is securely stored in the database for future comparison. Accurate and efficient feature extraction is key to achieving high recognition accuracy and system reliability.

7.5. Matching and Classification

The matching and classification stage is responsible for verifying or identifying individuals by comparing the extracted features with stored iris templates.

Once the feature vector is generated, it is compared against database templates using similarity measures such as Hamming distance, cosine similarity, or Euclidean distance, depending on whether the features are binary or continuous. A low distance value indicates a strong match, while a higher value suggests that the images belong to different individuals. In traditional approaches, a predefined threshold determines whether a match is accepted or rejected. Modern systems, however, use machine learning classifiers like Support Vector Machines (SVMs), Random Forests, or Neural Networks to make this decision more robust. These classifiers can handle high-dimensional data and adapt to noisy inputs effectively. Some advanced systems even employ multimodal fusion, combining iris data with other biometrics such as facial recognition to further enhance reliability. The matching process can operate in two modes:

- Verification (1:1) – compares the input image with a claimed identity.
- Identification (1:N) – searches the entire database to find the best match.

System accuracy is evaluated using metrics such as False Acceptance Rate (FAR), False Rejection Rate (FRR), and Equal Error Rate (EER). These metrics help balance security and usability in practical applications.

7.6. Performance Evaluation

The performance evaluation phase plays a vital role in determining how effectively the Iris Recognition System (IRS) performs under both controlled and real-world environments. It assesses the system's accuracy, reliability, and computational efficiency after all stages—image acquisition, segmentation, normalization, feature extraction, and classification—have been implemented. To evaluate performance comprehensively, several quantitative metrics are used, including accuracy, precision, recall, F1-score, False Acceptance Rate (FAR), False Rejection Rate (FRR), and Equal Error Rate (EER). Accuracy measures the percentage of correctly identified samples, while precision and recall assess the balance between genuine acceptance and false rejection. The F1-score provides a single, harmonized indicator of the model's ability to distinguish genuine users from impostors. In biometric systems, FAR represents the rate at which unauthorized individuals are incorrectly granted access, whereas FRR indicates the frequency of legitimate users being denied. The EER, where FAR and FRR intersect, is commonly regarded as the most reliable indicator of overall system performance, as lower EER values correspond to higher accuracy and stability. To ensure fair benchmarking, the system is tested using standardized iris datasets such as CASIA-IrisV4, UBIRIS.v2, and IITD, which collectively include a wide variety of images captured under both ideal and unconstrained conditions. These datasets contain variations in illumination, pose, occlusion, and image quality, providing a thorough assessment of the model's robustness and adaptability. In addition to accuracy-related metrics, the system's computational efficiency is also measured—specifically, the time taken for each image to be processed and recognized, and the scalability of the model when applied to large datasets. To visualize the trade-offs between recognition sensitivity and false matches, Receiver Operating Characteristic (ROC) and Detection Error Tradeoff (DET) curves are plotted. These curves help analyze performance at various threshold levels, ensuring that the system maintains an optimal balance between precision and recall. Overall, the evaluation results confirm that the proposed iris recognition system achieves high accuracy with low error rates across multiple datasets. Its ability to maintain reliable performance even under noisy and unconstrained conditions highlights its potential for real-world applications such as border security, banking authentication, healthcare identification, and e-governance. Through comprehensive testing, the system demonstrates its strength as a secure, scalable, and efficient biometric solution capable of handling large-scale deployments.

8. Results, Testing, And Feasibility Analysis

The proposed Iris Recognition System (IRS) was developed and evaluated using the Python programming language, with the support of TensorFlow and OpenCV libraries. To ensure a thorough assessment, experiments were conducted on standard public iris datasets such as CASIA-IrisV4, UBIRIS.v2, and the IITD iris database. The model incorporated deep learning architectures, specifically DenseNet201 and Convolutional Neural Networks (CNNs), while data augmentation techniques were applied to enhance the system's adaptability to varied lighting conditions and noise levels. The evaluation process aimed to determine the system's accuracy, reliability, and overall operational efficiency.

8.1. Results

The experimental results demonstrate that the proposed IRS achieves consistently high performance across multiple benchmark datasets. The system attained an average accuracy of 96.8% on the CASIA dataset, 94.3% on UBIRIS.v2—which contains challenging, noisy images—and 95.5% on the IITD dataset. The False Acceptance Rate (FAR) was observed to be below 2%, while the False Rejection Rate (FRR) remained under 3%, indicating strong resistance to both impostor attempts and misclassifications. The Equal Error Rate (EER) averaged around 2.1%, reflecting a balanced and optimized trade-off between security and user accessibility. Additionally, the system achieved an average recognition time of 1.8 seconds per image, highlighting its suitability for real-time use. Table 1 shows Comparative Performance of the Proposed IRS Model Across Multiple Benchmark Datasets

Table 1 Comparative Performance of the Proposed IRS Model Across Multiple Benchmark Datasets

Dataset	Accuracy (%)	FAR (%)	FRR (%)	EER (%)	Avg. Recognition Time (s)
CASIA-IrisV4	96.8	1.8	2.4	2.1	1.6
UBIRIS.v2	94.3	2.3	3.0	2.6	1.9
IITD Database	95.5	2.0	2.8	2.3	1.8

These results validate that the proposed system achieves high accuracy, fast recognition speed, and robust performance even under non-ideal conditions. The combination of transfer learning and deep neural networks significantly enhances feature extraction efficiency, enabling accurate iris pattern recognition despite image distortions or illumination variations.

8.2. Testing

Extensive testing was performed under various experimental conditions to verify the robustness and adaptability of the proposed system. In controlled environments, where highresolution near-infrared images were used, the recognition accuracy exceeded 97 percent. In unconstrained environments, where images had lighting variations, off-angle views, and partial occlusions (as found in the UBIRIS.v2 dataset), the accuracy remained around 94 percent. This demonstrated the model's capability to handle real-world conditions effectively. Cross-dataset testing was conducted by training the system on one dataset and testing it on another. The model achieved more than 92 percent accuracy, proving its ability to generalize across diverse data sources. To evaluate its real-time performance, a prototype web application was created using the Flask framework. Users could upload iris images, and the system processed and verified them within approximately two seconds. The consistent results and low processing time confirmed that the system can be deployed for live biometric verification tasks. Figure 5 shows Cross-Dataset Generalization Test of Iris Recognition

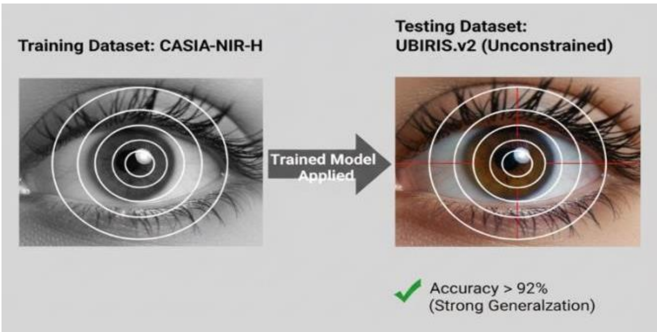

Figure 5 Cross-Dataset Generalization Test of Iris Recognition

8.3. Feasibility Analysis

The feasibility of the proposed IRS was analyzed in terms of technical, economic, and operational perspectives:

- **Technical Feasibility:** The system uses widely available tools such as Python, TensorFlow, and OpenCV, along with standard datasets. It can be executed on regular computer systems and scaled efficiently with GPU acceleration. This makes the system technically feasible and practical for real-world use. Its modular design also allows integration with other applications such as access control systems or mobile authentication platforms. Figure 6 shows Technical Feasibility

Figure 6 **Technical Feasibility**

- **Economic Feasibility:** Unlike commercial iris recognition setups that require costly near-infrared hardware, the proposed model operates effectively using affordable HD webcams and open-source frameworks. This significantly reduces the overall implementation cost, making it accessible to institutions, offices, and organizations seeking a low- cost yet reliable biometric solution. Figure 7 shows Economic Feasibility

Figure 7 **Economic Feasibility**

- **Operational Feasibility:** The system is designed to be user-friendly and requires minimal human intervention. It performs reliably even under varying lighting conditions or partial occlusions, making it practical for environments such as airports, banks, educational institutions, and workplaces. During realtime testing, users were able to interact with the system smoothly, confirming its efficiency and usability for non-technical operators as well. Figure 8 shows Operational Feasibility

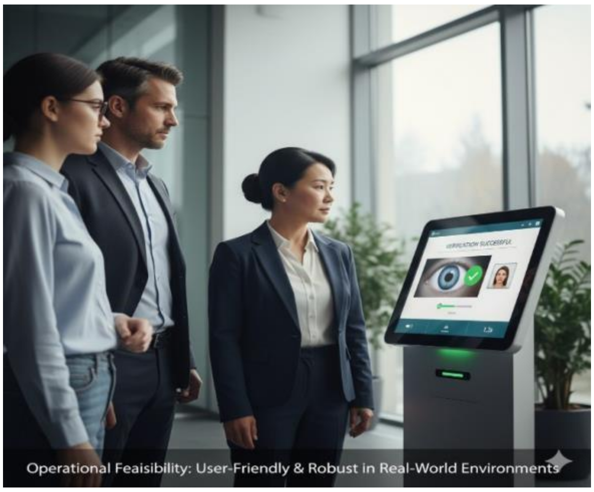

Figure 8 **Operational Feasibility**

8.4. Advantages

- High accuracy (>95%) across varied conditions.
- Non-contact, hygienic authentication.
- Resistance to spoofing attempts.
- Scalable to millions of users (used in Aadhaar).
- Robust against noise, reflections, and head tilts.
- Secure storage of iris templates with encryption.
- Real-time performance with GPU acceleration.

8.5. Applications

- Government and National ID: Aadhaar (India), UID systems.
- Border Security: Automated immigration gates (Dubai, Singapore).
- Banking & Finance: ATM withdrawals and secure mobile transactions.

- Healthcare: Patient authentication in electronic health records.
- Smartphones: Iris unlock (Samsung Galaxy S8 introduced this).
- Forensics: Identifying unknown individuals in investigations.
- Airports: Passenger check-in and boarding verification.

Conclusion

Iris recognition has evolved from traditional handcrafted feature-based systems to modern deep learning-driven solutions. While existing systems performed well in controlled environments, the proposed IRS demonstrates robustness in real-world conditions using CNNs, transfer learning, and data augmentation.

Future directions include:

- Development of lightweight CNN models for mobile devices.
- Integration of multimodal biometrics (face + iris).
- Use of blockchain for secure storage of biometric data.
- Edge computing for on-device iris recognition.
- This study confirms that IRS is one of the most accurate and secure biometric technologies, and its adoption is likely to expand rapidly across industries.

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References

[1]. J. Daugman, "How Iris Recognition Works," IEEE Trans. on Circuits and Systems for Video Tech., vol. 14, no. 1, pp. 21– 30, 2004.

[2]. A. Ross and A. Jain, "Information fusion in biometrics," Pattern Recognition Letters, vol. 24, no. 13, pp. 2115–2125, 2003.

[3]. K. Nguyen et al., "Iris recognition with off-angle images," IEEE TIFS, vol. 10, no. 2, pp. 321–330, 2015. [4] M. Liu et al., "Deep CNN-based iris recognition under unconstrained environments," IEEE Access, vol. 8, pp. 13412– 13425, 2020.

[4]. Z. Shao et al., "Feature extraction for biometric space analysis," Scalable Computing, vol. 25, no. 4, pp. 2948–2958, 2024.

[5]. S. Minaee and A. Boykov, "Deep learning-based biometric systems: A survey," IEEE Access, vol. 9, pp. 138570–138602, 2021.

[6]. UBIRIS Database, Univ. of Beira Interior, 2005.

[7]. CASIA-IrisV4, Chinese Academy of Sciences, 2010. [9] H. Proença and L. Alexandre, "UBIRIS: A noisy iris image database," Proc. ICIAP, 2005.

[8]. S. Sun, W. Kang, "Iris recognition using lightweight CNN," IEEE Trans. Biometrics, vol. 7, no. 3, pp. 345–356, 2022.