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Resnet-50 For Face And Iris-Based Authentication- A Comparative Study Using Svm And Naive Bayesian Classifiers

[1]Bharathi Pilar, [2]Safnaz
[1]Assistant Professor,[2]Research Scholar
[1]Department of Computer Science, [2]Department of Computer Science
[1]University College Mangalore, Karnataka, India, [2] University College Mangalore, Karnataka, India

Abstract : This study explores a deep learning-based approach to enhance the performance of biometric recognition systems, specifically focusing on authentication using face and iris images in the well known ResNet-50 deep learning model. Traditional feature extraction methods often rely on handcrafted features and shallow models, which struggle with real-world variations such as lighting, pose, and occlusions, leading to limited generalization and accuracy. To address these challenges, the proposed method utilizes the ResNet50 convolutional neural net- work architecture for extracting robust and discriminative features from biometric images. ResNet50's deep residual connections enable the capture of complex patterns often missed by conventional techniques. The extracted features are then classified using two traditional machine learning algorithms—Support Vector Machines (SVM) and Naive Baye's (NB) for both face and iris images—chosen for their effectiveness in high-dimensional data classification and complementary strengths in pattern recognition. The findings suggest that the face images perform better com- pared to iris images for authentication in both classifiers, however, the Naive Bayesian classifier is found to outperform SVM in both modalities. The conclusion reached is by combining deep learning models with classical machine learning classifiers, the reliability and scalability of bio- metric identification systems are enhanced. Moreover, a multimodal approach for authentication may yield better performance as each modality adds to the performance of the identification task.

IndexTerms **–** Biometric, identification, face, iris, ResNet-50

I. Introduction

In recent years, the demand for secure and reliable biometric identification systems has grown significantly, highlighting the need for advanced techniques in face and iris recognition [1]. These biometric modalities are widely used due to their uniqueness and permanence, but accurately extracting discriminative features from such physiological traits remains a substantial challenge in real-world applications. Traditional methods often depend on handcrafted features and shallow machine learning models, which struggle to adapt to complex variations such as lighting conditions, facial expressions, pose changes, aging, and partial occlusions [2]. Consequently, these limitations hinder the accuracy and scalability of biometric systems in unconstrained environments [3], [4] A key issue in face and iris recognition systems is the difficulty in extracting robust and invariant features that are invariant across subjects and environments [5]. Many existing techniques rely on traditional image processing methods or shallow machine learning models, which may not fully exploit the rich information available in biometric images. As a result, classification accuracy often suffers when dealing with large datasets or noisy input data, reducing the reliability of these systems for large-scale deployment [6]. Furthermore, the reliance on shallow classifiers or simple models limits their ability to handle large, high-dimensional data and accurately represent the intrinsic characteristics of biometric traits, like those found in face and iris images [7].

To overcome these issues, this study proposes a deep learning-based approach that takes advantage of the ResNet-50 architecture for feature extraction. ResNet- 50's residual learning capabilities enable the model to learn deep, abstract representations that are more robust to variations and better capture the unique characteristics of biometric data. Once features are extracted, classification is performed using Support Vector Machines(SVM) and Naive Bayes(NB) classifiers, two well-established machine learning algorithms known for their efficiency in high-dimensional spaces and complementary decision-making strategies [8]. This study investigates the use of deep learning models for feature extraction and traditional machine learning models for classification in biometric recognition using face and iris image data. Specifically, a CNN-based architecture, ResNet-50- known for its ability to handle complex data through residual connections, is used for feature extraction from two widely used biometric datasets: the IITD face and iris datasets. ResNet-50 extracts robust and discriminative features from both categories of images. Once features are extracted, traditional machine learning algorithms—SVM and Naive Bayes—are applied for classification. SVM is effective in handling complex decision boundaries, while Naive Bayes offers a probabilistic approach that performs well across various classification tasks.

The primary objective of this study is to evaluate the effectiveness of combining deep learning-based feature extraction with traditional machine learning classifiers for biometric systems. A comparative analysis of the performance of the proposed method on the bench- marked IITD data set [9], for two modalities- face and iris with a focus on classification accuracy is performed. Through extensive experimentation and comparison, the study aims to provide valuable insights into the practical applications of these techniques in face and iris recognition systems and also aims to propose multimodal systems for authentication, as two modalities have been experimented individually and results have been found to be good for each modality.

The structure of the paper is as follows: Section 2 re- views related work in the field of biometric recognition and feature extraction methods. Section 3 describes the ResNet-50 model. Section 4 presents the methodology, including the preprocessing steps, ResNet-50 model for feature extraction, and the classifiers used. Section 5 details the experimental setup, followed by results and discussion. Finally, Section 6 concludes the paper with directions for future research.

LITERATURE REVIEW

Angadi et al. [10] proposed a face recognition system that addresses challenges such as pose, illu- mination, expression, and occlusion by using facial images with these variations. The system represents facial images as connected graphs, extracting features such as spectral properties, energy, and texture of the graph using CS-LBP. Global features like face length and width are also incorporated into the symbolic data structure. The experimental results on the AR face and VTU-BEC-DB databases show identification rates of 95.97% and 97.20%, respectively.

Kumar et al. [11] proposed that automatic face recognition plays a crucial role in various applications, including face recognition, facial expression analysis, head pose estimation, and human-computer interaction. This technology involves detecting digital images of humans based on their location and size within the digital print. It is a key advancement in the field of computer technology.

Y. Bouzouina et al. [12] developed a biometric bimodal system that combines face and iris modali- ties for person verification. The face recognition uti- lizes Discrete Cosine Transform (DCT) and Principal Component Analysis (PCA), while the iris recognition is enhanced by precise segmentation using the Snake method. Feature fusion is achieved using Gabor filters and Zernike moments, optimized with a Genetic Algorithm. The system's performance, tested on the CASIA- IrisV3-Interval database, achieved a recognition rate of 98.8%.

Rahman et al. [13] proposed a multimodal biometric system combining face and iris recognition to improve identification efficiency. The study addresses the challenges of unimodal systems, such as noisy sensor data and spoofing, by fusing two modalities using matching score and decision level fusion tech- niques. PCA is used for face recognition, while the Daugman method is employed for iris recognition. The proposed system outperforms existing fusion methods, demonstrating significant performance improvements in biometric identification.

Yadav and Srinivasulu [14] introduced a multi- biometrics recognition system integrating offline sig- natures, fingerprints, and iris attributes through deep learning methods. While demonstrating strong perfor- mance in feature and score accuracies, the system's robustness and general applicability are limited due to insufficient investigation into biases, dependencies on specific datasets, and the influence of hyperparameters. These factors are crucial in determining the system's reliability across diverse operational environments and datasets. Future research efforts should focus on ad- dressing these gaps to enhance the system's effective- ness and reliability in practical applications of biometric recognition.

Alay and Al-Baity [15] combined three separate CNN models tailored for identifying face, iris, and finger vein biometrics, utilizing both feature-level and score-level fusion techniques to achieve commendable accuracy. Despite these successes, the study's applica- bility beyond its specific context was hindered by a no- table gap in comprehensive analysis. Specifically, there is a lack of thorough exploration into the generalization capabilities of their approach across different datasets or scenarios. Furthermore, the study did not extensively probe potential weaknesses inherent in their selected CNN models, which could impact the robustness and reliability of their findings in varied real-world applica- tions. These limitations underscore the need for further research to enhance the robustness and generalizability of multimodal biometric systems utilizing deep learning approaches.

II. ResNet-50

ResNet-50 is a deep convolutional neural network with 50 layers, introduced by He et al. [16] in 2015. It is a variant of the ResNet (Residual Network) family, which introduced the concept of residual learning to ease the training of deeper networks. A key innovation in ResNet-50 is the use of identity shortcut connections, which skip one or more layers. The ResNet-50 architecture consists of a stem layer followed by four stages, each containing a stack of residual blocks with bottleneck designs.

3.1Architecture

The following table details the architecture which is illustrated in Fig 1.

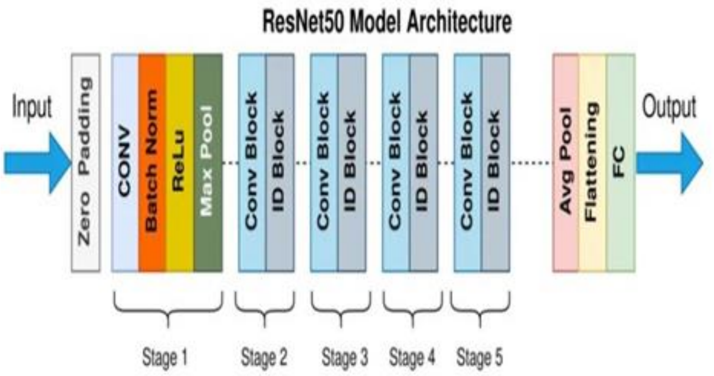

Figure 1. ResNet-50 Architecture-picture courtesy [17]

Table 1. Resnet-50 architecture

Layer Name	Details	Output Size
Conv1	7 × 7, 64, stride 2	112 × 112
MaxPool	3 × 3, stride 2	56 × 56
Conv2 x	1 × 1, 64 3 × 3, 64 1 × 1, 256 × 3 blocks	56 × 56
Conv3 x	1 × 1, 256 3 × 3, 256 1 × 1, 1024 × 6 blocks	28 × 28
Conv4 x	1 × 1, 128 3 × 3, 128 1 × 1, 512 × 4 blocks	14 × 14
Conv5 x	1 × 1, 512	7 × 7

	3 × 3, 512 1 × 1, 2048 × 3 blocks	
AvgPool	Global average pooling	1 × 1
FC (Dense)	1000-wayfully connected (softmax)	1000

3.2 Key Features

- Uses bottleneck residual blocks: each block has three layers (1 × 1, 3 × 3, 1 × 1).
- Identity shortcuts allow gradients to flow more easily, addressing the vanishing gradient problem.
- Achieves high accuracy on ImageNet [18] with relatively fewer parameters than equivalent plain networks

III. PROPOSED METHODOLOGY

This research presents and compares the performance of a highly reliable biometric recognition system that uses facial and iris image data. The block diagram depicting the process is shown in Fig 2.

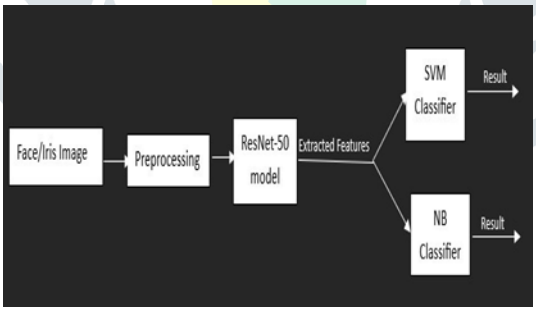

Figure 2. The block diagram of the proposed authentication system

4.1.Authentication using Face image

Face authentication is a biometric method used to verify a person's identity by extracting features from the face image which provide valid clues regarding whom it accounts to. Modern face recognition systems use deep learning models especially convolutional neural networks(CNNs) due to their ability to learn discriminative features from face images.

4.1.1 Preprocessing the Face Image

Before feeding a face image into ResNet-50, it undergoes several pre- processing steps:

1) Colour Conversion: RGB image is converted to gray scale to simplify processing.
2) Resizing: The face image is resized to 128 × 128 pixels.
3) Normalization: Pixel values are normalized to the range [0, 1].

The final pre-processed image is represented as a 2D tensor.

$$\text{Input} \in R128 \times 128$$

4.2 Iris-based authentication

Iris recognition is a biometric authentication method that uses the unique patterns in the colored ring surrounding the pupil of the human eye. Due to the high stability, uniqueness, and richness of iris textures, iris-based authentication is considered one of the most accurate and secure biometric techniques.

4.2.1 Preprocessing the Iris image

The general steps involved in iris-based authentication are:

1) Image Acquisition: A near-infrared (NIR) or visible-light camera captures a high-resolution image of the eye.
2) Segmentation: The iris region is isolated from the surrounding structures (pupil, sclera, eye- lids, and eyelashes). Techniques such as Hough transform or active contours may be used to detect circular boundaries.
3) Normalization: The segmented iris is trans- formed into a fixed-size rectangular block using a normalization technique such as Daugman's rubber sheet model. This compensates for differences in iris size due to pupil dilation or head tilt.
4) Resizing: The face image is resized to 128 × 128 pixels to simplify processing
5) Colour Conversion: RGB image is converted to gray scale to simplify processing.

4.3 System Description

The proposed biometric authentication system uses either a face or iris image as input. The overall process consists of several key stages:

1) Input Image: A high-resolution face or iris image is captured using a camera sensor under controlled lighting conditions.
2) Preprocessing: The input image undergoes preprocessing steps such as face/iris detection, alignment, resizing (typically to 128 × 128), and normalization as described in sections 4.1.1 and 4.2.1. These operations ensure that the input is consistent and suitable for the neural network.
3) Feature Extraction (ResNet-50): The pre-processed image is passed through the ResNet- 50 deep convolutional neural network. Instead of using the final softmax layer, the feature vector (embedding) is taken from the penulti- mate fully connected layer. This vector encodes the unique characteristics of the individual's biometric traits.
4) Feature Embedding: The extracted features are represented as a numerical vector in high- dimensional space. This serves as a compact and discriminative representation of the user's face or iris.
5) Model training and validation: The generated embeddings of images for each user are used to train and test the classification model. Evaluation metrics are computed for the trained model.
6) Decision: Based on the result of classification the features are decided to be bound to a specific person.

This system architecture ensures a robust and scalable framework for biometric authentication using modern deep learning techniques.

4.4 Classification

Support Vector Machine (SVM): SVM is a supervised learning algorithm which is particularly effective in high-dimensional spaces and used for classification. It finds the optimal hyperplane that maximizes the margin between the various classes. It is robust to overfitting, especially in high-dimensional data, and through the use of kernel functions it deals with non- linear data very effectively. It can handle complex decision boundaries which is considered as its primary strength. SVM is heavily used in face and iris recognition because it generalise well across varied biometric data.

Naive Bayes (NB): Naive Bayesian classifier is a probabilistic classifier based on Bayes' theorem, assuming feature independence within each class. Despite this simplifying assumption, it often performs surprisingly well in many real-world classification problems, especially when the dataset is large. It calculates the probability of a class given the features and assigns the class with the highest probability. Naive Bayes is computationally efficient, easy to implement, and works well for text and image classification tasks with large datasets. It is widely used in biometric systems due to its simplicity and effectiveness in handling noisy data.

IV. EXPERIMENTS AND RESULTS

5.1. Dataset

The dataset images are divided into an 80:20 ratio for training and testing purposes.

IIT Delhi Faces and Irises [19]

The IIT Delhi Iris Database includes iris images of the students and staff of IIT Delhi, New Delhi, India. It was created in Biometrics Research Laboratory in 2007 and the work is still going on. The current database is of 224 users, and the images are in bitmap (*.bmp) format. The images are collected from 176 males and 48 females in the age group 14-55. There are 1120 images in the database organized into 224 different folders each associated with the integer identification/number. The images have the resolution of these images is 320 X 240 pixels. They are acquired in the indoor environment.

The IIT Delhi near infrared face image database includes the images of faces collected from the students and staff at IIT Delhi, New Delhi, India. This database was created in 2007 and is still ongoing. The current database is collected from 102 users in the age group 17-50, and the images are in bitmap (*.bmp) format. The database of 612 images is organized into two folders of 306 images each. The acquired images have been sequentially numbered in each of the folders for every user with an integer identification/number. The resolution of these images is 768 X 576 pixels. These images have changes in the pose and expression. [9].

Table 2. Results for the proposed approach

Modality	Method	Accuracy	Precision	Recall	F1-Score
Face	SVM	90.20%	90.75%	90.05%	90.04%
Iris		88.70%	87.9%	88.01%	88.86%
Face	Naïve Bayes	91.50%	91.85%	91.22%	91.40%
Iris		89.40%	89.95%	89.50%	89.38%

5.2 Evaluation Metrics

The evaluation metrics for the proposed approach include precision, recall, and accuracy. Recall assesses the system's proficiency in accurately identifying positive samples among all of the dataset's real positive samples. Precision evaluates the proportion of correctly identified positive samples (faces and irises) relative to all samples classified as positive by the system. It gauges the system's accuracy, specifically in identifying positives. Accuracy, on the other hand, reflects the overall correctness of the system's predictions, encompassing both true positives (correctly detected faces and irises) and true negatives (accurately detected genuine faces and irises).

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

$$\text{F 1-score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Table 3. Comparative results for the proposed approach

Modality	Accuracy(%)
Kulkarni et al. [20]	93.33
Abdellatef et al. [21]	95.33
Therar H M et al. [22]	94.00
Brown et al. [23]	95.10
Proposed Method-Face	91.50

Naive Bayes classifiers with the indication that Face modality outperforms Iris using both classifiers. Table 3 presents a comparative analysis of accuracy results for different biometric systems. The proposed face modality system achieved an accuracy of 91.50%. The other biometric recognition systems which are compared with are found to be performing better using the handcrafted features. A deeper investigation into the use of deep learning models is required to fully utilise their capabilities.

V. CONCLUSION

This paper presented a comparative study of face and iris modality for authentication and in the study it is found that using ResNet-50 deep learning model, the face modality outperforms the iris modality for person authentication. Also it is found that both have comparable performance in the task and so we suggest a multimodal approach for better performance and is planned to be carried out as a future work.

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