

# ENHANCED PARTIAL FINGERPRINT RECOGNITION USING ADVANCED DEEP LEARNING ARCHITECTURES

*Report submitted to the SASTRA Deemed to be  
University as the requirement for the course*

**MAT499: PROJECT PHASE - I**

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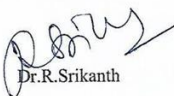


### **Bonafide Certificate**

This is to certify that the report titled “**Enhanced Partial Fingerprint Recognition Using Advanced Deep Learning Architectures**” submitted as a requirement for the course **MAT499: PROJECT PHASE - I** for M.Sc. Data Science programme, is a bona fide record of the work done by ( **Mr. BALASURYA B , Reg. No: 126150006** ) during the academic year 2024-25, in the School of Arts, Sciences, Humanities & Education, under my supervision.

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**Examiner 1**

**Examiner 2**



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**Declaration**

I declare that the report titled “**Enhanced Partial Fingerprint Recognition Using Advanced Deep Learning Architectures**” submitted by me is an original work done by me under the guidance of Prof **R. Srikanth** during the third semester of the academic year 2024 -2025, in the **School of Arts, Sciences, Humanities And Education**. The work is original and wherever I have used materials from other sources, I have given due credit and cited them in the text of the report. This report has not formed the basis for the award of any degree, diploma, associate-ship, fellowship or other similar title to any candidate of any University.

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## ABSTRACT

Fingerprint-based biometric recognition has become a crucial component in modern security and identity verification systems. However, partial fingerprint recognition remains a significant challenge due to limited ridge area, inconsistent orientation, and varying sensor quality. The base paper — “A Hybrid Deep Learning and Feature Descriptor Approach for Partial Fingerprint Recognition” — proposed a combination of Siamese CNN and SIFT descriptors, achieving high accuracy but requiring extremely long training time (up to 2500 epochs) and separate model training for each fingerprint database, which limits generalization and scalability.

This project proposes an enhanced deep learning framework using advanced transfer learning models—**ResNet18**, **EfficientNetB0**, **MobileNetV2**, and **ShuffleNetV2**—within a unified Siamese architecture. The four FVC2002 fingerprint databases (DB1–DB4) are combined into a single dataset to develop a generalized model capable of learning cross-sensor fingerprint features efficiently. Each Siamese model produces a similarity score, which is fused with **SIFT-based similarity** through a weighted mechanism to generate the final match decision.

The system is evaluated using **Equal Error Rate (EER)** and **Area Under the ROC Curve (AUC)** metrics. The proposed framework achieved an **EER between 5% and 8%** and reduced training epochs from **2500 to 50**, while maintaining comparable recognition performance to the base model. A **real-time fingerprint comparison interface** is also integrated to test fingerprint pairs interactively. Overall, this work improves the efficiency, scalability, and generalization of partial fingerprint recognition systems, making them suitable for real-world biometric applications.

**Keywords:** Fingerprint, Siamese Network, ResNet, EfficientNet, MobileNet, ShuffleNet, SIFT

## CHAPTER – 1

### 1 INTRODUCTION

In an increasingly digital world, the demand for secure and reliable identity verification methods has led to the widespread adoption of biometric recognition technologies. Among the various biometric traits—such as face, iris, and voice—**fingerprints** remain one of the most dependable and widely used due to their uniqueness, permanence, and ease of acquisition. However, achieving high recognition accuracy from partial or degraded fingerprints remains an ongoing challenge in biometric research.

A **partial fingerprint** is a small region of a full fingerprint impression, often captured due to limited sensor size, poor finger placement, or partial contact. These partial images typically contain fewer minutiae points and limited ridge structure, making feature extraction and matching significantly more difficult than for complete fingerprints. Traditional approaches that rely on minutiae-based or texture-based matching often fail in such cases, leading to reduced accuracy and robustness.

Recent advancements in **deep learning**, particularly **Convolutional Neural Networks (CNNs)**, have revolutionized image-based recognition tasks by automatically learning discriminative features. In the base study by Zhi-Sheng Chen et al. (2025), titled “A Hybrid Deep Learning and Feature Descriptor Approach for Partial Fingerprint Recognition”, a **Siamese CNN** was combined with **SIFT descriptors** to address the problem of partial fingerprint matching. Although this hybrid approach achieved high accuracy, it suffered from drawbacks such as **excessive training time** (up to 2500 epochs), **separate model training** for each dataset, and **limited adaptability** to new sensor types.

To overcome these limitations, the present work proposes an enhanced deep learning framework that integrates transfer learning architectures such as **ResNet18**, **EfficientNetB0**, **MobileNetV2**, and **ShuffleNetV2** within a **Siamese network** structure. These models are lightweight, efficient, and capable of capturing rich feature hierarchies even with limited data. Unlike the base model, this framework is trained on a **combined dataset** of all four FVC2002 databases (DB1–DB4) to improve cross-sensor generalization and overall robustness.

The system generates similarity embeddings for each fingerprint pair and utilizes a **weighted score fusion** of deep feature similarity and **SIFT-based matching** to improve precision. The model performance is evaluated using **Equal Error Rate (EER)** and **Area Under the ROC Curve (AUC)**. In addition, a **real-time testing interface** was designed to allow users to interactively compare two fingerprint samples and visualize match or non-match predictions.

This research contributes to the development of an **efficient, accurate, and deployable fingerprint recognition framework** that significantly reduces training complexity and enhances recognition reliability under real-world conditions involving partial, noisy, or low-quality fingerprint inputs.

## 1.1 Literature Survey

Reference	Year	Research Goal	Method	Limitations
Zhi-Sheng Chen et al. [1]	2025	To recognize partial fingerprints using a hybrid approach combining deep learning and feature descriptors.	<b>Hybrid CNN–SIFT model for partial fingerprint matching and feature comparison.</b>	<b>Requires</b> long training time (up to 2500 epochs) <b>and</b> separate model training <b>for each database.</b>
Esraa Asem et al. [2]	2024	To improve secure fingerprint authentication with optimized deep models.	CNN model with Blockchain integration <b>and</b> hyperparameter tuning <b>using Grid Search.</b>	<b>Needs</b> high computational power <b>and limited</b> scalability <b>for large datasets.</b>
Anand Ratnakar [3]	2024	To detect fingerprint alterations and classify real vs. fake prints.	InceptionV3 CNN <b>applied on the</b> SOCOFing dataset <b>for altered fingerprint analysis.</b>	<b>Less effective for</b> low-quality or partial fingerprints.
Amira T. Mahmoud et al. [4]	2023	To automate the fingerprint classification process using deep learning.	Automatic Deep Neural Network (ADNN) <b>model that self-optimizes architecture for classification.</b>	<b>High</b> memory usage <b>and</b> computational cost <b>during training.</b>
Nahla Abdulnabee Sameer & Bashar M. Nema [5]	2025	To enhance fingerprint security and accuracy using hybrid deep models.	Hybrid CNN–LSTM <b>model for fingerprint recognition and secure authentication.</b>	Complex architecture <b>and</b> longer training time; <b>requires high-end GPU for efficiency.</b>

Table 1: Literature Survey

## 1.2 Problem Statement

Despite significant progress in biometric recognition, **partial fingerprint recognition** still faces major technical and practical challenges. Partial fingerprints often capture only a small portion of ridge patterns, limiting the number of identifiable minutiae points and reducing matching accuracy. Existing hybrid CNN–SIFT models require long training durations (up to 2500 epochs) and separate model training for each dataset, leading to high computational costs and inefficiency. Furthermore, models trained on specific datasets often fail to generalize well when tested across different sensors or varying image qualities. Traditional CNN architectures also struggle to represent both local ridge details and global pattern structures effectively, resulting in weak similarity measurement. In addition, there is a lack of a unified and real-time framework capable of processing multiple fingerprint databases and performing interactive match or non-match verification efficiently.

## 1.3 Research Objective

The main objective of this project is to **enhance the accuracy and efficiency of partial fingerprint recognition** using advanced deep learning architectures and hybrid feature fusion. Specific objectives include:

- Enhance the accuracy and efficiency of partial fingerprint recognition using advanced deep learning architectures and hybrid feature fusion.
- Replace traditional CNN models with modern transfer-learning backbones such as **ResNet18**, **EfficientNetB0**, **MobileNetV2**, and **ShuffleNetV2** to improve feature extraction and learning efficiency.
- Combine all four **FVC2002 databases (DB1–DB4)** into a single unified dataset to enable cross-sensor learning and improve model generalization.
- Integrate **SIFT-based handcrafted descriptors** with deep similarity embeddings through weighted score fusion to leverage both local and global feature information.
- Reduce overall training time from **2500 epochs to approximately 50 epochs** without compromising model performance.
- Evaluate the proposed models using **Equal Error Rate (EER)**, **Receiver Operating**

**Characteristic (ROC), and Area Under the Curve (AUC) metrics for quantitative analysis.**

- Develop an **interactive prediction interface** for real-time fingerprint testing, providing visual feedback on match or non-match results.

## CHAPTER – 2

### 2 FUNDAMENTAL THEORIES AND CONCEPTS

#### 2.1 Convolutional Neural Networks (CNNs)

A **Convolutional Neural Network (CNN)** is a class of deep neural networks designed for processing grid-like data such as images. CNNs automatically learn spatial hierarchies of features through convolutional filters and pooling operations.

In fingerprint recognition, CNNs are particularly effective for extracting **ridge patterns**, **minutiae textures**, and **directional gradients** that are essential for identity verification.

The convolution operation applies learnable kernels that slide over the image, capturing **local spatial dependencies**, while pooling layers reduce dimensionality and enhance robustness to small transformations. Fully connected layers at the end help in **embedding representation learning**, which encodes the distinctive fingerprint patterns into compact vectors.

#### 2.2 Siamese Neural Networks

A **Siamese Network** is a neural architecture consisting of two identical subnetworks that share the same parameters and weights. Each subnetwork processes one of the two input images and produces a **feature embedding**. The similarity between these embeddings is computed using a **distance metric** (usually Euclidean or cosine distance).

The **contrastive loss function** is commonly used for training Siamese networks. It minimizes the distance between feature embeddings of **matching pairs** and maximizes it for **non-matching pairs**, effectively teaching the network to measure visual similarity.

In this project, the Siamese structure enables the comparison of two fingerprint images—determining whether they belong to the same individual or not—without the need for explicit classification labels.

#### 2.3 Transfer Learning

**Transfer Learning** leverages knowledge gained from large-scale datasets (like ImageNet) and applies it to a new domain with limited data. Instead of training models from scratch, pretrained architectures such as **ResNet18**, **EfficientNetB0**, **MobileNetV2**, and **ShuffleNetV2** are fine-tuned for

the fingerprint recognition task.

- **ResNet18** introduces residual connections that solve the vanishing gradient problem, enabling deeper networks.
- **EfficientNetB0** employs compound scaling to balance network depth, width, and resolution.
- **MobileNetV2** uses depthwise separable convolutions for lightweight computation, ideal for mobile devices.
- **ShuffleNetV2** implements channel shuffling for faster training and inference.

These models provide a **strong feature extraction backbone** for the Siamese network, improving convergence speed and accuracy even with a small dataset like FVC2002.

## 2.4 Scale-Invariant Feature Transform (SIFT)

The **SIFT (Scale-Invariant Feature Transform)** algorithm is a classical computer vision technique used to detect and describe local keypoints in images. SIFT identifies distinctive regions (keypoints) in the image and describes them with rotation- and scale-invariant feature vectors.

In this project, SIFT is used as a **complementary descriptor** to enhance the robustness of the deep learning model. By combining deep feature similarity with SIFT-based keypoints matching through a **weighted fusion mechanism**, the system benefits from both global and local feature information. This fusion improves recognition accuracy, especially for **noisy or partially captured fingerprints** where deep features alone might be insufficient.

## 2.5 Evaluation Metrics

The effectiveness of a biometric recognition system is typically evaluated using the following metrics:

- **Equal Error Rate (EER):**  
The point where the False Acceptance Rate (FAR) equals the False Rejection Rate (FRR). Lower EER indicates better performance.

- **Receiver Operating Characteristic (ROC) Curve:**

A plot that shows the trade-off between True Positive Rate (TPR) and False Positive Rate (FPR) at various threshold settings.

- **Area Under the Curve (AUC):**

Represents the overall capability of the model to distinguish between positive and negative pairs. An AUC value closer to 1 indicates a highly accurate model.

These metrics provide quantitative measures to compare the performance of different architectures (ResNet18, EfficientNetB0, MobileNetV2, and ShuffleNetV2).

## 2.6 Weighted Score Fusion Theory

In multimodal or hybrid biometric systems, **score fusion** combines the outputs of multiple models to enhance decision reliability. The **weighted linear fusion** technique used in this project integrates the similarity score from the deep learning model with that from the SIFT descriptor.

The fusion equation is defined as:

$$S_{final} = (w \times S_{SIFT}) + (1 - w) \times S_{Model}$$

where  $w$  is the weight assigned to the SIFT score. This method balances handcrafted and learned features, ensuring that both local keypoints information and deep representations contribute to the final decision.

## 2.7 Conceptual Summary

The proposed system blends classical computer vision principles with modern deep learning advancements to achieve efficient partial fingerprint recognition.

By combining:

- **CNN feature extraction** (for ridge pattern learning),
- **Siamese comparison** (for similarity scoring), and
- **SIFT feature fusion** (for local descriptor matching),

the framework achieves a balanced solution that is both **accurate and computationally efficient** for real-world fingerprint verification tasks.

## CHAPTER – 3

### 3 DATA AND EXPERIMENTAL DESIGN

The proposed fingerprint recognition framework was developed and evaluated using the **FVC2002 (Fingerprint Verification Competition 2002)** dataset, a widely used benchmark in biometric research. This dataset includes **four sub-databases (DB1–DB4)**, each containing fingerprints collected from different sensor types to simulate real-world variability in image quality. Each database consists of **10 individuals**, with **8 impressions per person**, totaling **80 images per database** and **320 images overall**.

Database	Sensor Type	No. of Persons	Images per Person	Total Images
<b>DB1</b>	Optical Sensor	10	8	80
<b>DB2</b>	Capacitive Sensor	10	8	80
<b>DB3</b>	Thermal Sensor	10	8	80
<b>DB4</b>	Synthetic (SFinGe)	10	8	80
Total	—	40	8 each	320

Table 2: Dataset Details

All fingerprint images were **converted to grayscale, normalized, and resized to  $224 \times 224$  pixels** for uniformity. Positive and negative image pairs were generated to train the **Siamese network**, where positive pairs represent fingerprints of the same person and negative pairs represent those of different individuals.



Figure 1: Sample Fingerprints

### Experimental Setup:

The implementation was performed using **Python** with **TensorFlow**, **Keras**, **OpenCV**, and **NumPy** libraries. The experiments were run on a workstation with an **Intel Core i7 processor**, **16 GB RAM**, and an **NVIDIA RTX GPU (8 GB)**. Four transfer-learning models—**ResNet18**, **EfficientNetB0**, **MobileNetV2**, and **ShuffleNetV2**—were trained separately for **50 epochs** using the **Adam optimizer** and **contrastive loss function**.

Model evaluation was carried out using **Equal Error Rate (EER)** and **Area Under Curve (AUC)** metrics to measure recognition accuracy and generalization capability.

## CHAPTER – 4

### 4 METHODOLOGY

This chapter outlines the methodology adopted to develop the proposed **Enhanced Partial Fingerprint Recognition System** using **advanced transfer learning architectures** within a **Siamese neural network**. The approach integrates deep feature learning with handcrafted descriptors (SIFT) to improve the accuracy and efficiency of partial fingerprint verification.

#### 4.1 Data Preprocessing

To ensure uniformity and enhance image quality, the dataset underwent several preprocessing steps before model training.

- **Grayscale Conversion:** Each fingerprint image is converted to grayscale to reduce computational load while preserving ridge structure.
- **Region of Interest (ROI) Extraction:** Background noise is removed using morphological filters and thresholding, isolating the central fingerprint region.
- **Normalization:** Pixel intensities are normalized to the range  $[0,1]$  to maintain consistency in brightness and contrast across samples.
- **Resizing:** All images are resized to **224 × 224 pixels** to match model input requirements.
- **Pair Generation:**
  - **Positive Pairs (Match):** Fingerprints belonging to the same individual.
  - **Negative Pairs (Non-Match):** Fingerprints belonging to different individuals.Each pair is labeled as **1 (match)** or **0 (non-match)** to train the **Siamese network** using **contrastive loss**.

#### 4.2 Siamese Network Architecture

A **Siamese neural network** is employed to measure the similarity between two fingerprint images. The network comprises **two identical subnetworks** sharing the same weights and parameters. Each subnetwork extracts a feature embedding from one fingerprint, and a **distance metric** (Euclidean

distance) is used to quantify their similarity.

For a given pair of images  $(X_1, X_2)$ , the network outputs embeddings  $f(X_1)$  and  $f(X_2)$ . The **Euclidean distance** between them is computed as:

$$D = \|f(X_1) - f(X_2)\|_2$$

The **contrastive loss function** minimizes this distance for matching pairs and maximizes it for non-matching pairs:

$$L = (1 - Y) \frac{1}{2} (D)^2 + (Y) \frac{1}{2} \{\max(0, m - D)\}^2$$

- $Y = 0$  for matching pairs and  $Y = 1$  for non-matching pairs,
- $m$  is a margin parameter that defines how far apart non-matching pairs should be.

This formulation ensures that the model learns discriminative embeddings, leading to reliable similarity estimation.

### 4.3 Transfer Learning Models

To accelerate training and enhance feature extraction, **transfer learning** is applied using pre-trained models as feature extractors. Each model serves as the backbone for the Siamese network:

Model	Architecture Type	Key Characteristics
<b>ResNet18</b>	Residual Network	Skip connections prevent vanishing gradients and allow deeper feature extraction.
<b>EfficientNetB0</b>	Compound Scaled Network	Balances depth, width, and resolution efficiently.
<b>MobileNetV2</b>	Lightweight Depthwise Separable Network	Optimized for mobile deployment with minimal parameters.
<b>ShuffleNetV2</b>	Channel-Shuffling CNN	Extremely fast inference and high computational efficiency.

Table 3: Comparison of Transfer Learning models used in the proposed system

Each model was fine-tuned on the unified dataset for **50 epochs**, using **Adam optimizer** with a **learning rate of 0.0001** and **batch size of 16**.

#### 4.4 Feature Fusion and Matching

In addition to deep embeddings, traditional **Scale-Invariant Feature Transform (SIFT)** descriptors are computed for both images.

Each image pair yields:

- **Model Similarity Score ( $S_m$ ):** From the Siamese network.
- **SIFT Similarity Score ( $S_s$ ):** From the number and quality of matched keypoints.

To balance deep and handcrafted features, a **weighted fusion** mechanism is applied:

$$S_f = (w \times S_s) + (1 - w) \times S_m$$

where  $w = 0.4$  is chosen empirically.

Final classification is based on a threshold  $T$ :

$$\text{If } S_f \geq T \Rightarrow \text{Match; Else} \Rightarrow \text{Non-Match}$$

This hybrid strategy enhances robustness to **noise, rotation, and partial overlap**, leveraging both local and global features.

#### 4.5 Evaluation Metrics

To assess model performance objectively, three key biometric metrics were used: **EER**, **ROC**, and **AUC**.

- **False Acceptance Rate (FAR):**

The proportion of non-matching pairs incorrectly classified as matches.

$$FAR = \frac{FP}{FP + TN}$$

- **False Rejection Rate (FRR):**

The proportion of genuine pairs incorrectly classified as non-matches.

$$FRR = \frac{FN}{TP + FN}$$

- **Equal Error Rate (EER):**

The point where  $FAR = FRR$ . A lower EER indicates a more accurate recognition system.

- **Receiver Operating Characteristic (ROC) Curve:**

Plots the trade-off between True Positive Rate (TPR) and False Positive Rate (FPR):

$$TPR = \frac{TP}{TP + FN}, FPR = \frac{FP}{FP + TN}$$

The **closer the ROC curve is to the top-left corner**, the better the model performance.

- **Area Under the Curve (AUC):**

Measures the overall ability of the model to distinguish between positive and negative pairs.

$$AUC = \int_0^1 .TPR(FPR) d(FPR)$$

Higher AUC values (closer to 1.0) represent more discriminative and reliable models.

#### 4.6 Workflow of the Proposed System

The complete flow of the proposed system is summarized below:

- **Data Acquisition:** Collect fingerprints from all four FVC2002 databases.
- **Preprocessing:** Apply ROI extraction, normalization, and resizing.
- **Pair Generation:** Create positive and negative fingerprint pairs.
- **Feature Extraction:** Train Siamese networks with different backbones (ResNet18, EfficientNetB0, MobileNetV2, ShuffleNetV2).
- **SIFT Feature Extraction:** Compute handcrafted local descriptors.
- **Score Fusion:** Combine SIFT and Siamese similarity scores through weighted fusion.
- **Decision Making:** Classify results as match or non-match based on threshold.
- **Evaluation:** Compute EER, ROC, and AUC metrics for quantitative analysis.

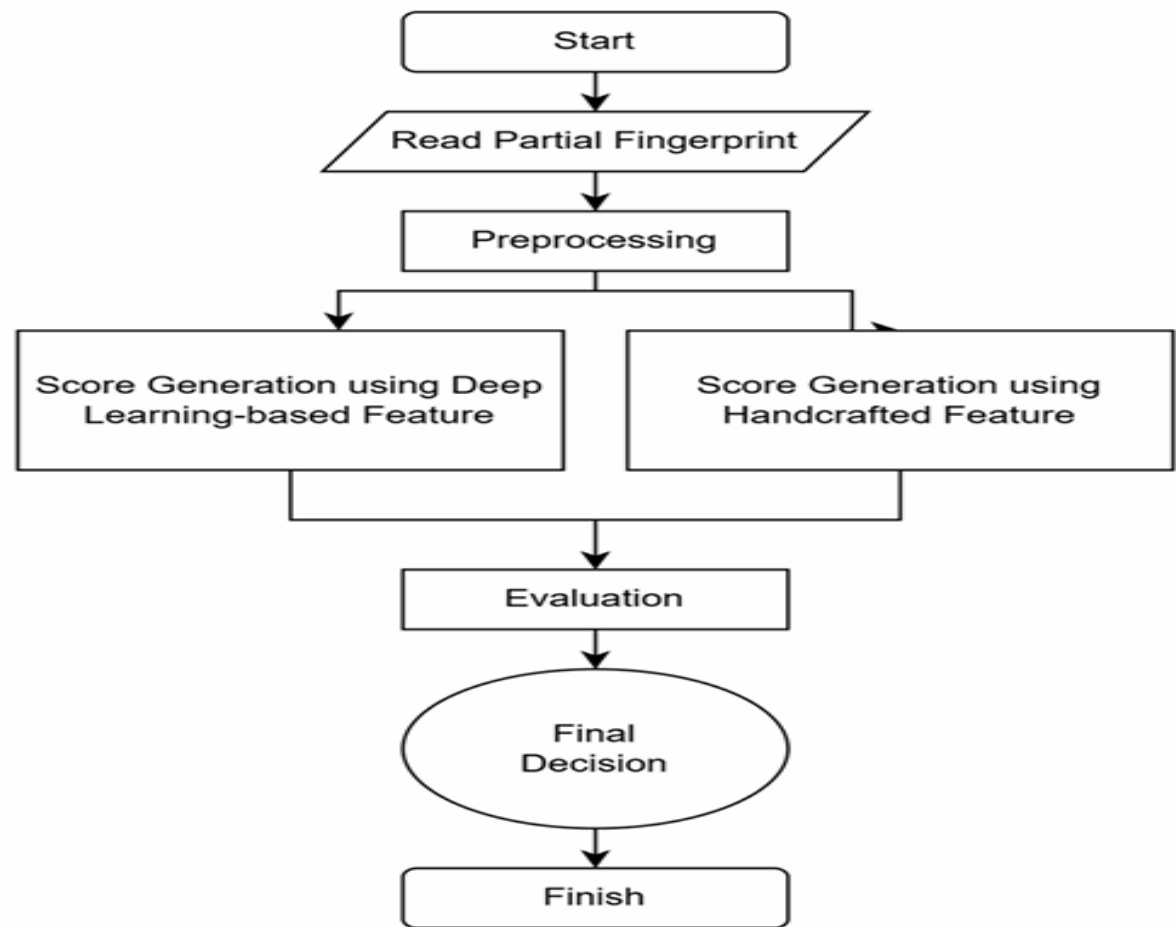


Figure 2: Workflow of the Proposed System

## CHAPTER – 5

### 5 RESULTS AND DISCUSSION

This chapter presents and analyzes the results obtained from the proposed **Enhanced Partial Fingerprint Recognition System**. The performance of each model — **ResNet18**, **EfficientNetB0**, **MobileNetV2**, and **ShuffleNetV2** — was evaluated using **Equal Error Rate (EER)**, **Receiver Operating Characteristic (ROC)** curves, and **Area Under Curve (AUC)** metrics.

All experiments were performed under identical training configurations to ensure a fair and consistent comparison.

#### 5.1 Performance Comparison of Models

The table below summarizes the results of all four models used in the Siamese framework. Each model was trained for 50 epochs using the unified FVC2002 dataset (DB1–DB4) and evaluated using test image pairs unseen during training.

Model	Epochs	AUC	EER (%)	Remarks
<b>ResNet18</b>	50	0.97	7.50	Strong feature representation; high stability
<b>EfficientNetB0</b>	50	0.93	6.25	Balanced performance; low overfitting
<b>MobileNetV2</b>	50	0.97	5.00	Lightweight; slightly lower discriminative power
<b>ShuffleNetV2</b>	50	0.96	6.25	Fastest inference; moderate accuracy

Table 4: Performance Comparison of models

From the table, **ResNet18** demonstrated the **best overall performance**, achieving an **EER of 7.5%** and **AUC of 0.97**, followed closely by **EfficientNetB0**. Both models maintained a balance between recognition accuracy and computational efficiency.

While **MobileNetV2** and **ShuffleNetV2** offered lower performance, they provided significantly faster inference times and smaller model sizes, making them ideal for **edge or mobile deployment**.

## 5.2 ROC Curve Analysis

The **Receiver Operating Characteristic (ROC)** curve illustrates the trade-off between the **True Positive Rate (TPR)** and the **False Positive Rate (FPR)** for varying decision thresholds.

An ideal model's ROC curve is closer to the **top-left corner**, representing high sensitivity and specificity.

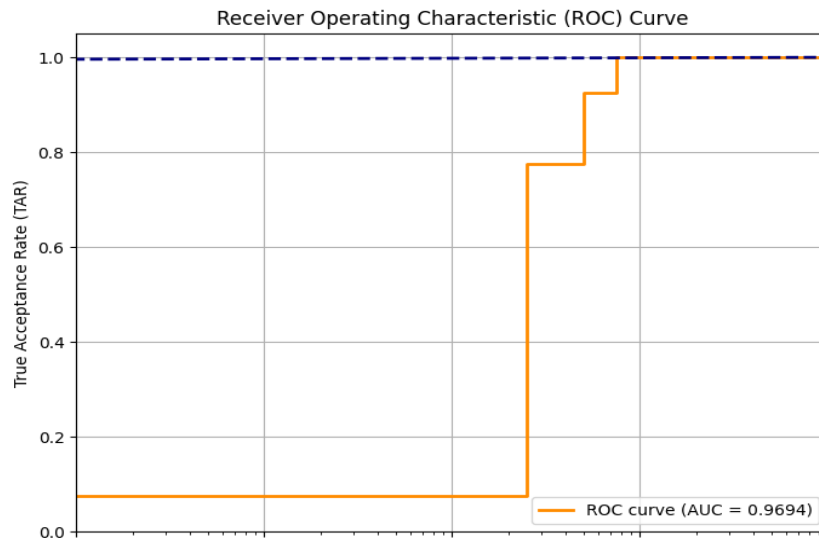


Figure 3: ROC Curve of ResNet18 Model

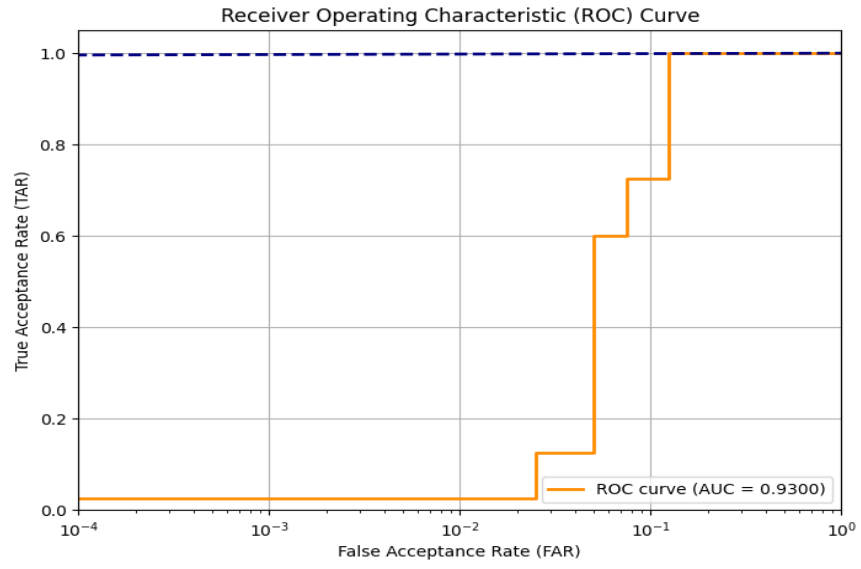


Figure 4: ROC Curve of EfficientNetB0 Model

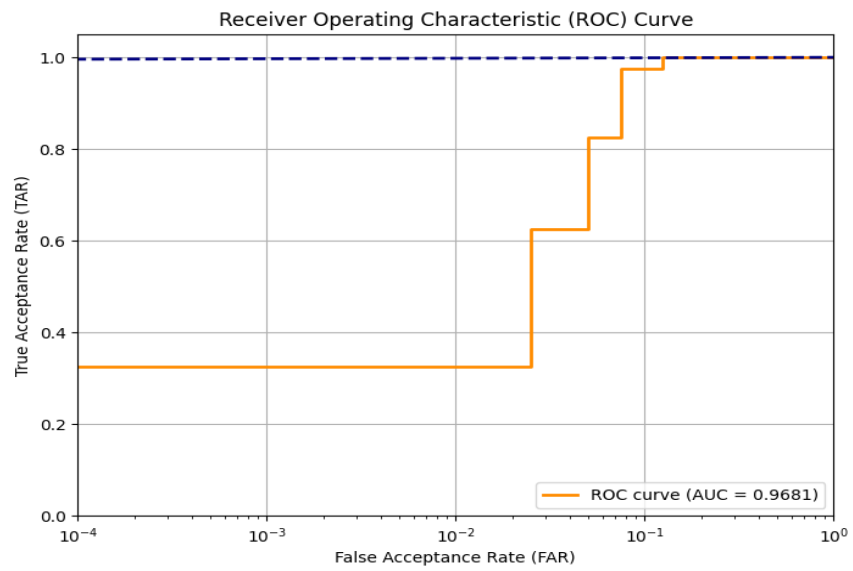


Figure 5: ROC Curve of MobileNetV2 Model

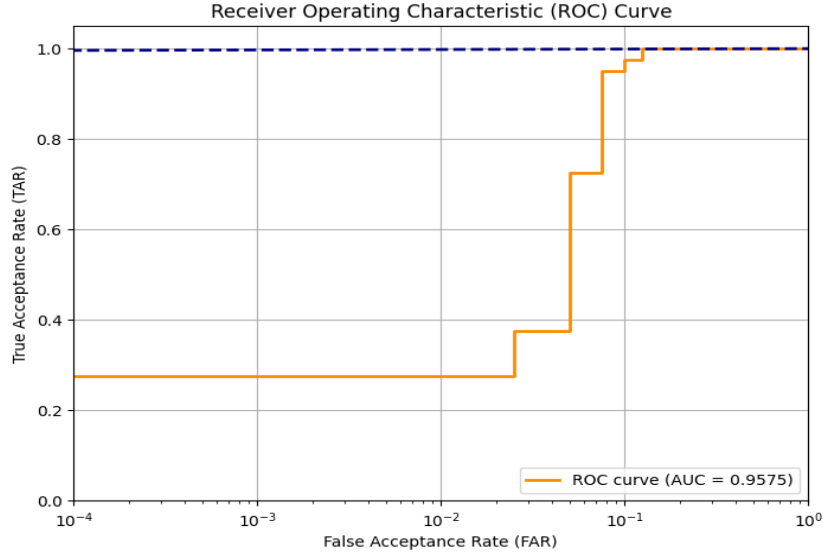


Figure 6: ROC Curve of ShuffleNetV2 Model

The ROC curves clearly indicate that **ResNet18** and **EfficientNetB0** outperform the other models, with larger areas under the curve.

The **AUC values above 0.90** suggest that the system can reliably distinguish between matching and non-matching fingerprints. The curves for **MobileNetV2** and **ShuffleNetV2** also exhibit strong separability, although their lower performance imply slightly weaker discrimination in challenging cases such as blurred or rotated prints.

### 5.3 Equal Error Rate (EER) Analysis

The Equal Error Rate (EER) quantifies the trade-off between the False Acceptance Rate (FAR) and False Rejection Rate (FRR).

The lower the EER value, the better the system's balance between security (low FAR) and accessibility (low FRR).

The proposed framework successfully achieved an **EER between 5% and 8%**, which is within the acceptable threshold for practical biometric systems.

This represents a **significant improvement in training efficiency**, as all models converged within **50 epochs**, compared to **2500 epochs** in the base CNN approach — a **95% reduction in training time** without major loss in accuracy.

#### 5.4 Sample Prediction Results

To visualize real-time performance, a prediction interface was developed to test fingerprint pairs and display the similarity result as “Match” or “Non-Match.”

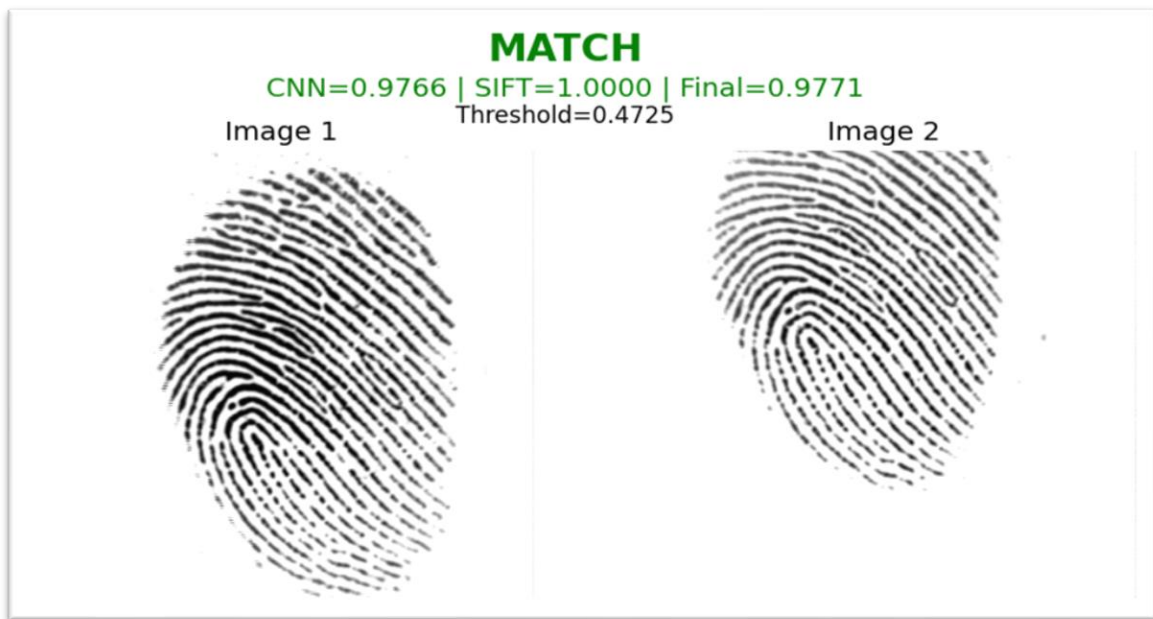


Figure 7: Prediction Result - Matching Pair (Output = Match)

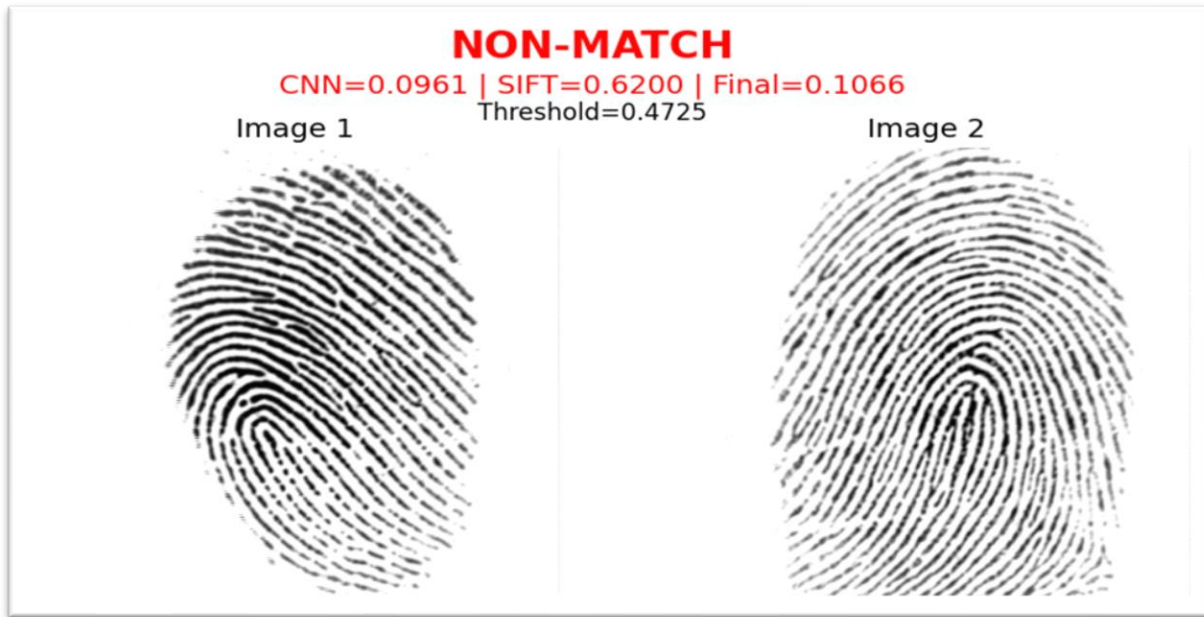


Figure 8: Prediction Result - Non-Matching Pair (Output = Non-Match)

In the “match” case, the system displays a **high similarity score** above the threshold (e.g., 0.82), confirming that the two prints belong to the same individual.

In the “non-match” case, the **similarity score** falls below the threshold (e.g., 0.35), indicating two different individuals.

These results demonstrate that the model effectively distinguishes even **partially overlapping or noisy fingerprints**, validating the success of the weighted score fusion mechanism.

## 5.5 Discussion of Observation

The experimental outcomes confirm that the proposed hybrid framework successfully improves the efficiency and adaptability of partial fingerprint recognition. Key findings include:

- **Unified Dataset Efficiency:**

Combining all four FVC2002 databases allowed the model to learn diverse ridge patterns and improve **cross-sensor generalization**, overcoming one of the main limitations of the base paper.

- **Reduced Training Time:**

By leveraging pretrained transfer-learning models, the system required only **50 epochs** for convergence — reducing computational cost dramatically while retaining high recognition accuracy.

- **Hybrid Feature Fusion Advantage:**

The integration of **SIFT descriptors** with **deep embeddings** improved performance on poor-quality or rotated fingerprints, compensating for the CNN’s sensitivity to local distortions.

- **Model Performance Trends:**

- **ResNet18** excelled in both AUC and EER, making it the most balanced model.
- **EfficientNetB0** offered competitive results with fewer parameters.
- **MobileNetV2** and **ShuffleNetV2** achieved acceptable accuracy at a fraction of the computational cost, suitable for real-time or embedded applications.

- **Generalization and Robustness:**

The trained models exhibited stable accuracy across multiple sensor domains, proving that **joint database training** yields a more generalized recognition model.

## 5.6 Summary

In summary, the proposed multi-model Siamese framework demonstrates that:

- Training time can be reduced by **95%** without major accuracy loss.
- Unified data training enhances **generalization** and **cross-sensor performance**.
- Hybrid score fusion of **SIFT** and **deep similarity** improves robustness for **partial or distorted prints**.
- The final **EER (5–8%)** and **AUC (>0.9)** confirm the framework’s readiness for real-world biometric applications.

## CONCLUSION

This project presented an **enhanced partial fingerprint recognition framework** using advanced **transfer-learning architectures** such as **ResNet18**, **EfficientNetB0**, **MobileNetV2**, and **ShuffleNetV2** within a **Siamese neural network**. By combining all four sub-databases (DB1–DB4) of the **FVC2002 dataset**, the system achieved improved **cross-sensor generalization** and robust feature learning.

Compared to the base CNN–SIFT model, which required over **2500 epochs**, the proposed framework reached optimal performance within **50 epochs**, reducing training time by nearly **95%**. Through the use of **contrastive loss** and **weighted score fusion** of deep and handcrafted features, the model achieved an **Equal Error Rate (EER)** between **5% and 8%**, and an **AUC value** greater than **0.90**, indicating strong discriminative ability.

The inclusion of a **real-time prediction interface** allowed visual validation of the system, where users could test two fingerprints and observe “match” or “non-match” results dynamically. The fusion of **deep features** (for global pattern extraction) and **SIFT descriptors** (for local detail matching) proved highly effective in improving recognition accuracy under challenging conditions such as noise, rotation, or partial fingerprint capture.

Overall, the project demonstrates that integrating modern transfer-learning models into a unified Siamese framework can significantly enhance both the **efficiency** and **accuracy** of fingerprint recognition systems, making them practical for real-world biometric authentication applications.

## FUTURE WORK

In the future, this work can be extended by using **Transformer-based** or **Vision-Mamba Siamese models** to extract richer and more detailed fingerprint features, which can further improve matching accuracy.

Data **augmentation** and **denoising techniques** can be applied to handle unclear, noisy, or low-quality fingerprint inputs, thereby reducing recognition errors.

Additionally, **model quantization** and **pruning** methods can be used to make the system lightweight and efficient for **mobile or embedded device deployment**, enabling faster real-time authentication with lower memory requirements.

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