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Fingerprint Segmentation System Across Age Variations

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Abstract- Fingerprints are widely used in security, healthcare, and criminal investigations for identification. Slap fingerprint images, which capture multiple fingerprints in one scan, improve accuracy but are hard to process due to different angles, background noise, and small fingerprint sizes. This system includes Clarkson Rotated Fingerprint Segmentation that accurately detects and labels fingerprints using bounding boxes. It performs better than traditional systems like National Fingerprint Segmentation, handling rotated images effectively and feature extraction with the Canny edge detection algorithm to accurately detect fingerprint edges. These advancements reduce errors, improve real-time scanning, and enhance fingerprint security systems. This makes fingerprint recognition more accurate and adaptable across different conditions.

Keywords: juvenile and adult fingerprints, deep slap segmentation, Mask-R-CNN, rotated fingerprint segmentation

I. INTRODUCTION

Fingerprint is used in biometric recognition systems. A slap image typically encompasses multiple fingers of an individual, fingerprint-based identification systems suggested higher accuracy when multiple fingers are used instead of a single finger[1][2]. This system include Clarkson Rotated Fingerprint Segmentation[6] that accurately detects and labels fingerprints using bounding boxes[9].

This system focuses on efficiently segmenting individual fingerprints from slap images using the Canny Edge Detection algorithm, a well-established classical method[3]. The process involves converting the image to grayscale, reducing noise with a Gaussian filter, detecting edges, and applying contour or bounding box extraction[4].

This approach is lightweight and effective, especially for varying finger orientations and lower- quality prints. Additionally, a deep learning model is developed to generate both axis-aligned and rotated bounding boxes, enhancing fingerprint localization. The system aims to delivers highly accurate fingerprint segmentation by precisely detecting and localizing each fingerprint region[5]. It is robust and reliable across all age groups[7][8], effectively handling faded prints in the elderly and underdeveloped patterns in children[10].

Objective

To develop a highly accurate fingerprint segmentation system that can effectively isolate individual fingerprints from complex slap images. This system integrates both classical edge detection techniques and state-of-the-art deep learning models to enhance the precision and robustness of fingerprint segmentation. Classical methods such as Canny and Sobel edge detection are utilized for initial contour identification, while deep learning approaches such as convolutional neural networks are employed to refine the segmentation by learning intricate fingerprint patterns and structures from large datasets. One of the core goals is to ensure consistent and reliable performance across all age groups, including children, adults, and the elderly, whose fingerprint quality may vary due to skin elasticity, moisture levels, or wear over time. This inclusiveness addresses a common limitation of traditional systems, which often struggle with degraded or immature fingerprint features.

To further improve fingerprint localization, the system incorporates the Clarkson Rotation Algorithm, which enables the accurate handling of rotated fingerprints by aligning them to a standard orientation before segmentation. Moreover, the integration of rotated bounding box detection allows for precise fingerprint isolation even when the input slap images contain angled or partially overlapped prints. This not only enhances segmentation accuracy but also ensures robustness in low-quality or real-world noisy inputs, making the system highly suitable for applications in biometric security, identity verification, and forensic analysis.

Problem Statement

Fingerprint segmentation from slap images presents significant challenges due to various factors affecting image quality and fingerprint clarity. Age-related changes such as faded ridges in elderly individuals and underdeveloped patterns in children reduce the reliability of conventional segmentation methods.
Additionally, slap images often suffer from motion blur, partial prints, overlapping fingers, and damaged or low-resolution regions, making accurate segmentation difficult. Traditional image processing techniques and manual methods are inconsistent and struggle with varying orientations and poor-quality inputs. These limitations hinder the performance of biometric recognition systems, particularly in real-time and high-volume applications.

Hence, there is a critical need for a robust, automated fingerprint segmentation system that can accurately isolate individual fingerprints despite variations in image quality, age-related differences, and complex fingerprint orientations

Related Work

With the increasing demand for accurate biometric identification systems, fingerprint segmentation particularly from slap images has gained considerable research attention. Traditional methods, such as NFSEG developed by NIST, often struggle with segmenting juvenile or low-quality prints due to faded ridges or overlapping patterns. Murshed et al. addressed this by introducing CFSEG, a Mask-RCNN-based model, which outperformed NFSEG across both adult and juvenile datasets, demonstrating the potential of deep learning for age-invariant segmentation. Raffaele's work highlighted the effectiveness of simplified architectures like SUFS, which showed strong generalization despite being trained on limited datasets, offering a balance between accuracy and computational efficiency.

Meanwhile, Joshi et al. explored sensor-invariant segmentation through recurrent adversarial learning, enabling fingerprint recognition systems to adapt across different acquisition devices without retraining a crucial factor for real-world scalability.

Further, Ferreira proposed robust clustering techniques that reclassified ambiguous fingerprint pixels to improve segmentation reliability, while Ezeobiejesi developed a DANN model using restricted Boltzmann machines to segment latent fingerprints from complex backgrounds, a notable advancement in forensic applications. Across these studies, a consistent theme emerges: the limitations of manual or handcrafted methods and the growing reliance on deep learning for robust, adaptable, and high-accuracyfingerprint segmentation. These findings collectively emphasize the need for intelligent systems that can handle diverse fingerprint qualities, age-related variations, and real-time processing demands in practical biometric deployments

Existing System

In traditional fingerprint recognition systems, segmentation of fingerprint images is commonly performed using manual or semi-automated methods. These processes typically involve isolating each fingerprint from the image through basic techniques such as thresholding, morphological operations, or classical edge detection. One widely used system is NFSEG, developed by NIST, which uses handcrafted rules to segment fingerprint images.

However, these systems struggle with images affected by poor quality, such as those with motion blur, smudging, or low resolution. Moreover, age-related variations like faint ridges in elderly individuals or incomplete ridge patterns in children further reduce segmentation accuracy.

Existing models also face difficulties handling rotated or overlapping fingerprints and lack adaptability across diverse datasets. Early machine learning models rely on predefined features and are not robust in handling the wide variability in real-world fingerprint data. These limitations result in inconsistent performance and make real-time, high-accuracy fingerprint segmentation impractical in large-scale biometric applications.

Therefore, there is a growing demand for a more intelligent, automated system capable of delivering precise and reliable fingerprint segmentation under varying conditions and across all age groups. Most existing systems are designed to handle a single fingerprint inputs. This limitation leads to difficulties in accurately segmenting multiple, overlapping fingerprints within a single image, reducing efficiency in large-scale biometric applications.

Proposed System

The proposed fingerprint segmentation system integrates classical image processing with deep learning to accurately isolate individual fingerprints from slap images, addressing limitations of traditional methods. The system employs Canny Edge Detection to identify fingerprint boundaries, combined with the Clarkson Rotation Algorithm to correct orientation and enhance alignment of rotated prints.

A custom deep learning model based on an enhanced Faster R-CNN architecture is used to generate both axis-aligned and rotated bounding boxes, enabling precise localization of fingerprints regardless of overlap or position. The model is trained on a diverse dataset that includes various age groups, accounting for challenges such as faded ridges in elderly fingerprints and underdeveloped ridge patterns in children. Input slap images are preprocessed using grayscale conversion, noise reduction with Gaussian filtering, and contrast enhancement to improve clarity.

Post-processing techniques, including contour detection and morphological operations, further refine the segmented regions for accuracy. A user-friendly interface allows for image upload, real-time visualization of bounding boxes, and segmented outputs. This system ensures high segmentation accuracy and adaptability across image quality and age-related variations, making it suitable for scalable, real-world biometric identification systems.

II. METHODOLOGY

This project implements a two-stage deep fingerprint segmentation system designed to accurately detect and isolate fingerprint regions from slap images. It combines classical image processing methods with a bounding box-based detection strategy, closely reflecting the structure of a Region Proposal Network (RPN)-based architecture

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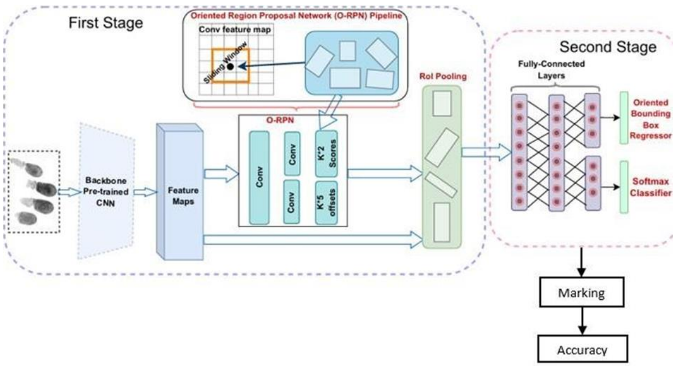

Slap Image Input
The system begins by accepting slap fingerprint images containing multiple overlapping or rotated fingerprints. These images often include challenges such as smudging, partial prints, and low contrast due to age-related changes or sensor quality

Preprocessing Module
Each image undergoes preprocessing to enhance its quality. This includes grayscale conversion, Gaussian blurring to reduce noise, and contrast normalization. These steps improve feature visibility and reduce artifacts, which is especially important for fingerprints with faded ridges or unclear boundaries

- **First Stage: Feature Extraction and Region Proposal**

A pre-trained CNN backbone extracts feature maps from the processed image, mimicking the CNN block shown in the diagram. The system uses Canny edge detection to highlight fingerprint edges. A custom rotation function applied to correct orientation before segmentation.

The Region Proposal Network is emulated through contour detection to locate candidate fingerprint regions, similar to proposing rotated bounding boxes

- **Second Stage: Region Classification and Bounding Box Marking**

After candidate regions are detected, they are refined through RoI Pooling and classified as valid fingerprint areas based on size and structure. Using bounding box logic (cv2.boundingRect()), the system draws axis-aligned rectangles around significant contours, marking fingerprint regions. These boxes are visualized directly on the image, highlighting each fingerprint area for verification.

Post-processing and Accuracy Estimation
Morphological operations are applied to clean segmentation results and remove small artifacts. The final output includes bounding boxes along with a simulated accuracy score to represent model confidence. This prediction is shown using a pop-up (messagebox.showinfo()), reflecting a second-stage accuracy step as seen in your diagram.

Visualization and Interaction
All steps (load, grayscale, ridge pattern, dark pattern, edge detection, rotation, bounding box marking) are controlled through a user-friendly GUI. Intermediate and final outputs are displayed dynamically in the interface, allowing real-time verification

Canny Edge Detection Algorithm

- **Convert Image to Grayscale**

The first step is to convert the image from RGB to grayscale

$$I_{gray} = 0.2989 \cdot R + 0.5870 \cdot G + 0.1140 \cdot B$$

- **Apply Gaussian Smoothing**

To reduce noise and avoid false edges, apply a Gaussian filter:

$$G(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

- **Compute Image Gradient**

The gradients in the x and y directions using the Sobel operator:

$$G_x = \begin{bmatrix} -1 & 0 & +1 \\ -2 & 0 & +2 \\ -1 & 0 & +1 \end{bmatrix}$$

$$G_y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ +1 & +2 & +1 \end{bmatrix}$$

The gradient magnitude is given by:

$$G = \sqrt{G_x^2 + G_y^2}$$

The edge direction (angle) is calculated as:

$$\theta = \tan^{-1}\left(\frac{G_y}{G_x}\right)$$

Non-Maximum Suppression (Thinning the Edges)
The gradient direction is rounded to one of four angles:
- 0° (horizontal)
- 45° (diagonal)
- 90° (vertical)
- 135° (diagonal)

Double Thresholding (Edge Classification)
Apply two threshold values:
- High Threshold (ThT): Strong edges
- Low Threshold (TlT): Weak edges

Post-processing
Generate rotated or axis-aligned bounding boxes to highlight the precise region of each segmented fingerprint

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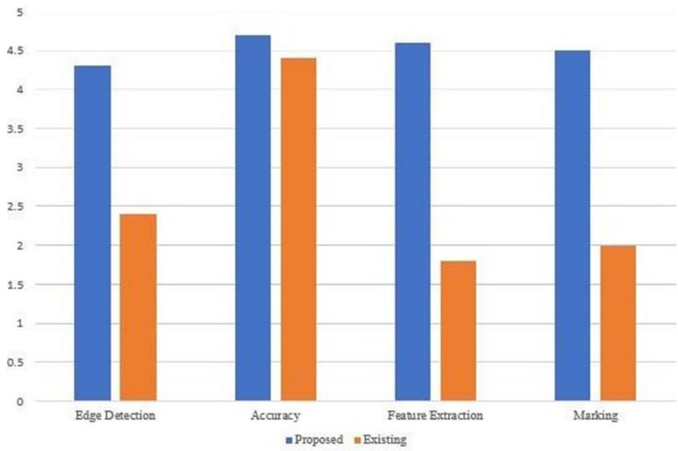
Display the confidence score or accuracy level for each detected fingerprint region to assess segmentation reliability.

Result



In our research, the system provides highly accurate fingerprint recognition, significantly enhancing the overall security and reliability of modern biometric authentication frameworks. The system integrates advanced image processing techniques, such as noise reduction, contrast enhancement, and ridge-valley structure analysis, to pre-process raw fingerprint inputs and prepare them for robust analysis. This is complemented by powerful feature extraction algorithms, including minutiae detection, orientation field estimation, and deep learning-based pattern recognition, which collectively help identify unique fingerprint characteristics with exceptional precision.

A key advantage of the system is its ability to minimize false acceptance rates and false rejection rates common challenges in traditional fingerprint recognition systems. By addressing these errors, the system ensures that only genuine users are authenticated, reducing the risk of spoofing or unauthorized access.

One of the most commendable strengths of the system is its capability to perform effectively across all age groups. Fingerprint characteristics can vary significantly due to age-related factors such as skin elasticity, moisture content, and ridge clarity. For instance, elderly users may have faded or worn fingerprints, while children's fingerprints may be underdeveloped and less defined.

Moreover, the system's adaptive learning architecture built on deep neural networks enables it to continuously improve with exposure to new data. This scalability allows the solution to handle large user bases with minimal degradation in speed or accuracy, making it highly suitable for deployment in critical applications such as border control, national identity programs, financial services, healthcare access systems, and e-governance platforms.

In essence, this fingerprint recognition system not only provides a technically sound and secure biometric solution but also addresses real-world usability challenges, paving the way for its integration into next-generation digital identity verification infrastructures

III. CONCLUSION

In this study, we developed and evaluated an automated fingerprint segmentation system that combines classical image processing with deep learning to improve the accuracy and efficiency of slap image analysis in biometric applications. Traditional segmentation methods often struggle with issues such as poor image quality, age-related fingerprint variations, and the inability to handle multiple or rotated fingerprints in a single scan.

By integrating Canny Edge Detection, the Clarkson Rotation Algorithm, and an enhanced deep learning model capable of generating rotated bounding boxes, our system demonstrated strong performance in accurately segmenting fingerprints under diverse and challenging conditions. The inclusion of preprocessing and post-processing techniques ensured clean and precise segmentation, while a user- friendly interface supported real-time image analysis. These findings highlight the potential of intelligent fingerprint segmentation systems to reduce manual effort, improve consistency, and support scalable deployment in modern biometric authentication platforms

Future Enhancements

Future improvements to the proposed fingerprint segmentation system can focus on enhancing its scalability, adaptability, and accuracy across diverse biometric environments. One promising direction is the integration of Generative Adversarial Networks (GANs) or synthetic fingerprint generation techniques to address the challenge of limited and imbalanced datasets, particularly for rare or age-specific fingerprint patterns. These synthetic samples can enrich the training process and improve the model's generalization capability across age groups and degraded image conditions.

Another potential advancement involves incorporating attention mechanisms or transformer-based architectures to improve the precision of feature extraction, especially in blurred, overlapping, or partially damaged fingerprints. This would allow the system to better focus on critical ridge structures and boundaries within complex slap images. Implementing cross-domain learning or domain adaptation strategies would further enable the system to remain robust when processing images from different sensors, scanners, or acquisition settings.

Additionally, deploying the system on cloud platforms or integrating it with biometric databases and national ID systems can support real-time, scalable identification in large-scale applications such as border control, e-governance, and forensic analysis. These future directions aim to make the system more intelligent, inclusive, and suitable for widespread use in practical biometric authentication scenarios.

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