Fingerprint Matching Using Pores Extracted with Machine Learning

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***Abstract*—Fingerprint recognition is widely used for biometric applications due to its uniqueness and convenience. However, traditional systems often overlook level 3 features, particularly pores, which can improve precision, especially in partial or latent fingerprints. The integration of these features is highly beneficial in contexts such as forensic analysis, where complete fingerprint patterns are not always available. This work proposes a pore detection model, which is a convolution neural network with U-Net architecture followed by a pore matching algorithm, applied to the dataset L3-SF, a collection of extremely realistic, labeled synthetic fingerprints. The results demonstrated high effectiveness, achieving high accuracy in pore detection and matching even in partial fingerprint images, outperforming many existing methods and, consequently, the power of deep learning applied to biometrics.**

I. Introduction

The growing and widespread use of biometric recognition in our society no longer allows for manual identification. In this context, fingerprints stand out for their unique convenience and immutable properties. In addition to facilitating personal identification in the civil context, fingerprints also play a crucial role in forensic applications, aiding in the investigation of crimes. [1].

Fingerprint features are commonly categorized into three different levels of detail. Level 1 refers to ridge flow and overall pattern type. Level 2 features include minutiae points, such as ridge endings and bifurcations. Level 3 features are associated with fine details, such as pores, ridge edge contour and more. However, level 3 features are only available in 1000 dpi images, and since the majority of fingerprint images are captured at 500 dpi, traditional Automatic Fingerprint Recognition Systems (AFRS) are typically designed to work only with level 1 and level 2 details, leaving pore information underutilized [1]. But with the constant evolution of fingerprint scanners, the technology to produce 1000 dpi fingerprint images is now much more accessible than it was when most current AFRS systems were developed. Since 20 to 40 pores are enough to identify a person [2], and each centimeter of ridge contains 9 to 18 pores, using them enables faster detection and matching, even from partial fingerprints.

In the literature, pore extraction algorithms can be divided into feature-based or learning-based [3]. Those that use features are very robust and do not adapt to varying pore shapes across individuals, so in this scenario, learning-based extraction comes into play. Most of these algorithms rely on convolutional neural networks (CNNs), which are powerful tools for image recognition due to their ability to automatically extract features through multiple convolutional layers. However, traditional CNN architectures may not be ideal for this task [4], as extracting pore coordinates from a fingerprint is fundamentally an image segmentation problem. Standard CNNs often involve subsampling operations, which can reduce spatial resolution and compromise the precise localization required for pore detection.

The various studies that propose pore extraction algorithms often fail to evaluate their models' ability to perform fingerprint matching using only a small portion of the image. Most focus exclusively on detection accuracy, neglecting the subsequent matching task and ignoring potential real-world applications. To address this gap, our work not only presents a deep learning-based pore extraction model but also introduces a pore-level matching algorithm capable of comparing partial fingerprint regions based on the extracted pores.

The objective of this paper is to develop a computer vision approach capable of accurately extracting pore coordinates from fingerprint images using deep learning techniques and to evaluate its effectiveness in matching fingerprints based solely on level-3 features. This work is organized as follows: the II section presents related papers, the III section presents materials, and the proposed method is presented in the IV section. The results and discussion are in the V section, and the conclusions are in the VI section.

II. Related Works

Recognizing the potential benefits of incorporating fingerprint pore information, numerous academic researchers have laid a strong foundation for advancements in this area. In [5], Mohammed Ali *et al.* propose a two-part fingerprint pore detection scheme, where the first part is a CNN and the second is a post-processing method to find the centroid of each pore and filter out false positives. The CNN is built with three hierarchical layers feature extraction, and each of these layers generates a heatmap that is concatenated in the last stage. After the final stage, the image is binarized so every pixel gets a value of 0 or 1. Then, a threshold variable is defined over a number of windows, making the value locally adaptive. This threshold, combined with Euclidean distance, filters out false positives, based on its distance to other pores. The researchers used the PolyU High-Resolution-Fingerprint database to train and evaluate their CNN model, achieving a true positive rate of 96.69% and a false positive rate of 4.16%, and all of that with a great reduction in the number of numerical operations.

Furthermore, the research of Wang *et al.* [4] contributes significantly to this matter, since it proposes a Fully Convolutional Network (FCN) instead of a CNN, since FCN architectures can outperform in image segmentation tasks, and since extracting the pore region from a fingerprint is a segmentation, this approach offers several advantages. The specific architecture used in this study was U-Net, and it works by processing the image and then downsampling it through a series of convolution, followed by an upsampling path that gradually restores spatial resolution, using skip connections from the downsampling path. This process is applied using a sliding window of size 120×160 pixels, generating multiple samples from a single fingerprint image. Each sub-sample is then validated to reduce the number of false detections, particularly in cases where overlapping occurs.

In [6] Junjian Cui *et al.* suggests a fingerprint pore matching algorithm using polar histograms to generate descriptors for each pore. The relative distances and angles of each pore relative to its neighbors are encoded to form polar descriptors that fall within a defined radius. Correspondences between the reference and target images are computed using Chi-square distance based on their descriptors, and refined using the Random Sample Consensus (RANSAC) algorithm. The method was able to achieve an Equal Error Rate (EER) of 10.46%, outperforming previous pore-based approaches.

III. Materials

A. Hardware and Software

For this work we used a computer with Intel(R) Xeon(R) CPU W-1250 @ 3.30GHz coupled with NVidia Quadro P1000 video card 4 Gb of VRAM and 64 GB DDR4 @ 2666 MT/s was used. The computer uses Ubuntu 24.04 LTS operating system and the main tool for building the convolutional network model was Pytorch library.

B. L3-SF

The dataset used for this work was L3-SF [7]. This dataset is composed of 740 synthetic high resolution labeled fingerprint images. Since acquiring real fingerprint images with both high resolution and labeled pores is challenging, this synthetic alternative is valuable due to its nearly identical similarity to a real fingerprint. The images in this dataset were generated using a Cycle-Consistent Adversarial Network (CycleGAN), trained on data from the PolyU HRF dataset. As shown in Figure 1, the synthetic fingerprints exhibit a striking visual similarity to real fingerprint images.

IV. Proposed Method

The method proposed here is composed of two main blocks: the model block with pre-processing, training and validation steps, then the pore matching block, as we can see in figure 2. Initially, each image is divided into four quadrants, creating new images to augment the dataset. Then,

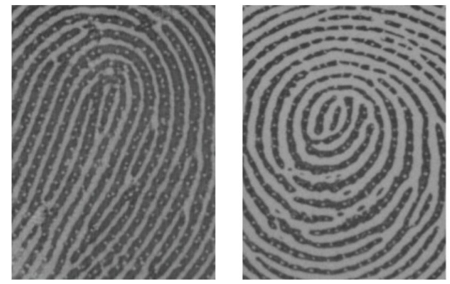

Fig. 1. Comparison between a synthetic fingerprint (L3-SF) and a real fingerprint (PolyU HRF).

each image undergoes Contrast Limited Adaptive Histogram Equalization (CLAHE) for better contrast. Finally, from the acquired dataset, pore coordinate labels generate heatmap images with pore zones, where pixel values vary 0-1 based on distance to the pore. The training step is done through a U-Net architecture, that receives the image and the heatmap to create a model capable to segment pore regions. With the output image from the model, a pore matching algorithm that uses polar histograms is used to find matches using only a cropped windows of a fingerprint image.

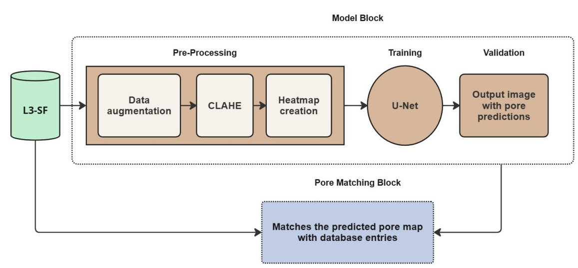

Fig. 2. Proposed method

A. Data processing

To carry out the training with the L3-SF dataset, sample count was increased by dividing each original image into four 256x256 pixel quadrants, ensuring a size big enough to achieve minimal information loss, and increasing the sample size from 720 to 2880. Subsequently, each new image underwent CLAHE, a process that divides the image into blocks and equalize the variation of intensity based on that in order to maintain stable contrast. For each processed image, associated pore coordinate labels were used to generate heatmaps. This process employed a Gaussian window, where a variable x was added to each coordinate, resulting in pixel values ranging from 0 to 1 based on distance to the pore. These heatmaps are used as the training labels required by the U-Net model. The details of the processing flow is showed in Figure 3.

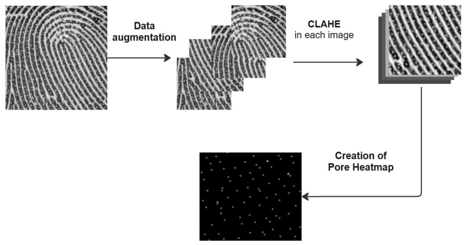

Fig. 3. Fingerprint processing steps

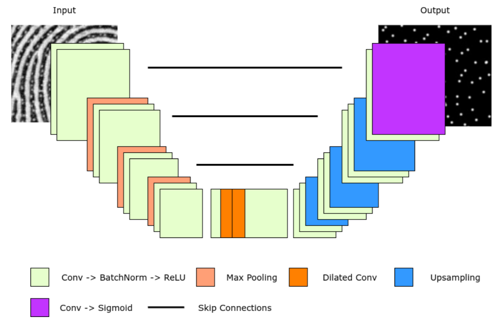

Fig. 4. EnhancedPoreUNet architecture.

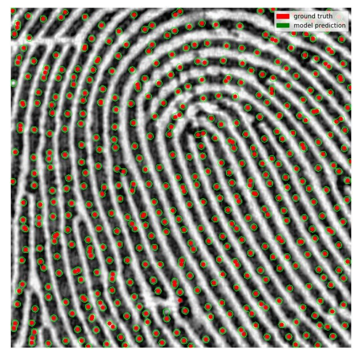

Fig. 5. Pore segmentation result.

B. U-Net

A Fully Convolutional Network (FCN) is a Machine Deep Learning algorithm primarily used for semantic segmentation. A derivative of this approach yields U-Net, a state-of-the-art approach specifically designed for biomedical image segmentation [8]. The U-Net architecture features a distinct ”U” shape, comprising a contracting path (encoder) that captures context and an expanding path (decoder) that enables precise localization. Crucially, skip connections are employed to propagate contextual information from the encoder to the decoder, facilitating the recovery of spatial details during upsampling.

In this project, we implemented a modified U-Net, called EnhancedPoreUNet, as the backbone for segmenting pore regions in fingerprint images. Unlike prior works that rely on standard CNNs, our model achieves higher efficiency and performance by leveraging the U-Net encoder-decoder structure. The encoder consists of three blocks, each with two 3×3 convolutional layers followed by batch normalization and ReLU activation, with 2×2 max pooling to downsample the feature maps. The number of channels increases progressively from 32 to 128. At the core, a bottleneck block expands features to 256 channels and integrates two parallel dilated convolutions (rates 2 and 4) to enhance contextual awareness without sacrificing resolution. These outputs are summed and regularized using dropout (rate 0.5).

The decoder mirrors the encoder, using ConvTranspose2d layers to upsample the feature maps and concatenate them with corresponding encoder outputs through skip connections, preserving spatial precision. Subsequent convolutions reduce the channel depth from 128 to 32, and a final 1×1 convolution followed by a sigmoid function produces a probability map. The result is a binary mask highlighting pore locations in white (1) against a black background (0). The model is trained using a Combined Loss Function, a weighted sum of Binary Cross-Entropy and Dice Loss, effectively addressing the pixel-level accuracy and the class imbalance of sparse pore regions. The full architecture is illustrated in 4

An example of the model’s predicted pore mask overlaid on a fingerprint image is shown in Figure 5, illustrating the intended segmentation output of the proposed method.

C. Train and validation

This model was developed specifically for this work and was trained from scratch. The training process employed the AdamW optimizer with an initial learning rate of 0.001 and a weight decay of 1e-4 to mitigate overfitting. A combined loss function (CombinedLoss), balancing Binary Cross-Entropy (BCE) and Dice Loss with a BCE weight of 0.5, was used to optimize the model.

The dataset was partitioned into an 80/10/10 training, validation and test split, respectively. The model was trained in batches of 16 images over a maximum of 30 epochs. To manage learning effectively, a ReduceLROnPlateau scheduler was implemented, which reduces the learning rate by a factor of 0.5 if the validation loss does not improve for 2 epochs (patience = 2). An early stopping mechanism was also integrated, halting training if the Intersection over Union (IoU) does not improve for 4 consecutive epochs, ensuring efficient training and preventing overfitting. A validation step was performed in each epoch to monitor prediction and save the best model based on IoU.

D. Pore matching

The pore matching algorithm used in this work builds upon the polar histogram method introduced by [6], and uses only pores to find pairs between two fingerprints. Input images are randomly cropped into windows ranging from 2% to 16% of the original size, then passed through the U-Net model to extract binary pore masks. Pore centroids are identified via connected component analysis.

Each pore is described by a polar histogram that encodes the relative distances (20 bins) and angles (24 bins) of its neighboring pores, providing rotation and translation invariance. A

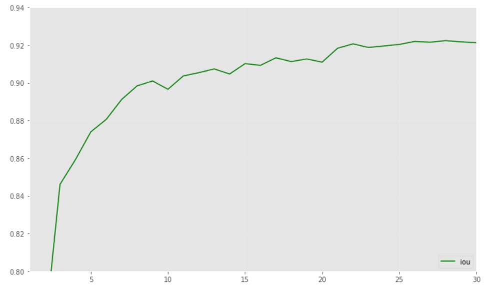

Fig. 6. IoU value over the epochs.

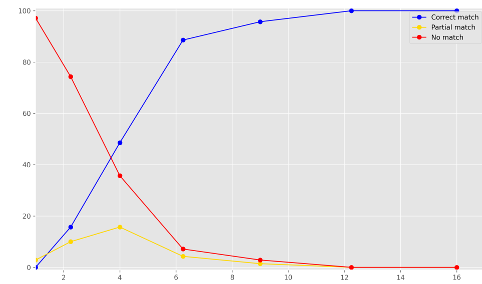

Fig. 7. Fingerprint matching performance by window size in percentage.

TABLE I
FINAL RESULTS OF TESTS WITH THE MODEL

Rate of True (RT)	0.9162
Rate of False (RF)	0.0153
IoU	0.9229

similarity matrix is constructed using Chi-square distances between descriptors, and RANSAC is applied to filter out geometrically inconsistent matches. The final result is a ranked list of scores indicating the best matches across the fingerprint database. This method is efficient and particularly effective for partial fingerprint matching.

V. RESULTS AND DISCUSSION

The combination of the EnhancedPoreUNet and the L3-SF dataset yielded strong performance results. Throughout training and validation, the accuracy consistently remained above 98%, while the loss values steadily declined to a range between 20% and 25%. Most notably, the IoU metric increased significantly, reaching 92% within just 30 epochs. This upward trend can be visualized in Figure 6.

Some metrics were used for the analysis of the proposed model, among them Rate of True (RT), Rate of False (RF) and IoU with results presented in Table I.

After training the model, we proceeded to evaluate the pore matching algorithm. For this evaluation, 10% of the dataset (70 images) was used. Each image was cropped to a region of the original fingerprint image. We then analyzed the matching scores for each fingerprint by generating three classification labels: (i) when the highest-scoring image corresponds to the original fingerprint (correct match), (ii) when the original fingerprint appears within the top-10 highest-scoring results (partial match), and (iii) when the original fingerprint is not found among the top-10 (no match). The results of these test can be seen at 7. As we can see, with a partial image that contains only 14% of the original image, we get over 95% chance of a correct match.

Although the final RT achieved in this work was below the state-of-the-art benchmark of 96.69% reported in [5], it outperformed many existing models. For instance, it achieved a significantly lower RF than the 13.89% reported in [4] or 4.18% in [5]. This demonstrates the robustness and practical potential of the proposed model. Furthermore, regarding pore matching performance based on the window size of fingerprint images, no prior studies were found addressing this specific aspect.

A final point concerns the dataset used. This work did not suffer from the use of a synthetic dataset, but it would certainly be an improvement to test these results on a real database.

VI. CONCLUSIONS

Using pores as discriminatory features enhances biometric fingerprint analysis, with applications in spoof detection, forensics, and efficient authentication. This work proposed a general framework for pore-based recognition, where the EnhancedPoreUNet model, trained on the L3-SF dataset, achieved an IoU of 92.29% and an RT of 91.62%. The system also matched 90% of fingerprints using just 12% of the image.

Future improvements include testing on diverse sources like latent prints to ensure a more general applicability. Increasing training epochs may reduce loss, though this likely requires a deeper U-Net to prevent overfitting. Enhancing the matching algorithm to better handle opacity and rotation differences is also a key direction.

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