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OPTIMIZED FINGERPRINT IMAGE DENOISING AND SEGMENTATION USING SPECTRAL-RESIDUAL ATTENTION ZERO-SHOT CONVOLUTIONAL NEURAL NETWORK

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ABSTRACT

Fingerprint recognition is extensively applied in biometrics security and forensic because it is unique and permanent. In reality, however the real fingerprint images are usually corrupted with noise and low contrast, and fractured ridges, which greatly decreases the reliability of the recognition. The objective of this work is to enhance the quality of fingerprint images and the segmentation by using a unified deep learning system. The main aim is to maintain the ridge continuity and minutiae data and deal with low-quality fingerprints and partially corrupted ones. So, this research proposed to use a hybrid method that involves the use of Decompress Zero-Shot Convolution Neural Network (DZOC) to implement fingerprint denoising and Spectral-Residual Attention Zero-Shot CNN (SRC-NET) to perform ridge segmentation. DZOC is based on compression reconstruction approach in which a residual is learned to avoid noise without destroying fine ridge information. SRC-NET is then applied to the denoised output and uses spectral-residual analysis and attention to appropriately identify the ridges versus background noise without using labeled training data. The effectiveness of the proposed framework is also shown in an experimental analysis, in which the SRC-NET attains a segmentation accuracy of 95.07, which is higher than existing models of segmentation. The findings validate the hypothesis that the proposed DZOC and SRC-NET framework can greatly increase the level of fingerprint clarity and reliability in segmentation. In general, the method offers a powerful and scalable approach to the real-world fingerprint recognition systems to be used with noisy and low-quality acquisition conditions.

Keywords: *Biometric Security, Convolution Neural Networks, Denoising, Fingerprint Recognition, Image Enhancement, Zero-Shot CNN*

1. INTRODUCTION

Fingerprint recognition is widely utilized biometric technologies since it is permanent, unique, and easy to obtain and thus it is very applicable in security, authentication and forensic investigations. but in practice fingerprint images are usually subject to some form of degradation like noise, low contrast, smearing, partial occlusion, and discontinuous ridge structures. these problems can greatly decrease the quality of fingerprint images thus affecting the ridge clarity, minutiae extraction and the overall recognition accuracy adversely. previous research has determined that the quality of fingerprint images directly correlates with the matching reliability and system performance [1].

Although existing fingerprint enhancement and segmentation algorithms exist, most current algorithms have a hard time with highly degraded fingerprint images, particularly those that have been acquired in uncontrolled or unfavorable circumstances. current methods tend to lose fine ridge information and are not resistant to noise, resulting in erroneous segmentation and sub optimal recognition results. The feature-based verification systems like Harris and Surf are also limited in noisy environments [2], whereas minutiae-based machine learning systems are highly reliant on the quality of the images and the effectiveness of preprocessing [3]. Moreover, a significant portion of current deep learning solutions is not designed to perform both operations simultaneously, with some primarily designed to either denoise or segmentate, instead of to perform both.

The latest developments in deep learning have shown promising outcomes in enhancing and recognizing fingerprints. Invertible denoising networks have been proposed to reduce the computational complexity, whereas high-speed spectral denoising methods have been proposed to enhance the precision of a fingerprint [4]. M-net cnn-based architectures [5] have demonstrated excellent results in fingerprint denoising and in painting problems [6], and stacked convolutional autoencoders have been used to optimize latent fingerprint segmentation [7]. Furthermore, single-point detection networks based on customized semantic segmentation networks are created [8], and automated latent fingerprint identification end-to-end deep learning models have been proposed [9]. local combinations of minutiae-based features have been further refined to give higher identification accuracy [10]. deep feature collaboration technique has also been used with complex biometrical structures such as 3d finger knuckle patterns [11] and hybrid feature learning techniques have been used to detect fake fingerprint detection [12]. contributions to interpretability have been provided using explainable deep learning models in related domains [13], and optimised CNN-based quality improvement methods have been provided to improve the quality of latent fingerprints [14].

Nonetheless,it can be costly in terms of the large size of labeled datasets, and massive computational power, as well as not being adaptable to low-quality and partially corrupted fingerprints. thus, an urgent requirement is still the existence of a strong, versatile, and computationally efficient framework that is able to perform the simultaneous enhancement and segmentation of fingerprint images in demanding environments.

1.2 Research Objectives:

In order to eliminate these limitations, this research aims to:

Develop an effective fingerprint noise remover algorithm that preserves ridges and minutiae details in a very compromised image.

A powerful segmentation technique that can be useful in differentiating between ridges and noisy backgrounds without necessarily large numbers of labeled data.

Suggest a combined deep learning model that combines denoising and segmentation to enhance the overall performance of fingerprint recognition.

Compare performance of the proposed model to the popular performance measures .

1.3 Significance of the study:

The significance of this research is that it will enhance the reliability and robustness of fingerprint recognition systems under real world situations. The proposed solution improves the level of clarity of ridges and maintains valuable information on the existence of the minutiae, which are important in the matching and identification of the person, by performing the denoising and segmentation tasks in one integrated framework. Besides, the zero-shot and attention-based mechanisms decrease the reliance on big labeled data by enabling the system to be scaled and used in real-time. This piece of work helps in improving the development of biometric security mechanisms and especially in situations where the quality and noise of the finger print data is low and thus enhancing the usefulness of biometric security mechanisms in both forensic and authentication field.

This research proposed a hybrid architecture that integrates decompress zero-shot convolutional neural network to denoise fingerprints and spectral-residual attention zero-shot CNN to segment the ridges accurately to meet these goals. The proposed model will address the shortcomings of current approaches by delivering high-quality images, more accurate segmentation, and better generalization in different settings of fingerprints.

Organization: the research is designed in such a way that section 2 performs topical work and background review in the area of fingerprint denoising and segmentation. Section 3 demonstrates the proposed dzoc and src-net architecture, algorithm and architecture description. In section 4, the experimental arrangement is given and the results are given. The results are provided in section 5 with the gains made on the accuracy of minutiae extraction and segmentation. The research is concluded in section 6 where the contributions are brought to a close. The materials used are provided at the end.

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2. BACKGROUND STUDY

Fingerprint recognition has received much interest in the field of biometric security because it is very reliable in authentication and forensic use. Various methods have been proposed by various researchers to enhance the quality of images, segmentation and spoof detection of fingerprints. But current approaches have struggled to process low quality, noisy and real world fingerprint data.

Ruzicka et al. (2025) [15] proposed a deep neural network architecture known as TipSegNet to perform fingertip segmentation in contactless fingerprint imaging. This model was effective in isolating the fingertip region and enhanced the recognition performance. Nevertheless, the technique was restricted to the contactless fingerprints and was not easily generalized to the available rolled and slap fingerprint images.

Wan et al. (2020) [16] proposed XFinger-Net, an attention-gate U-Net-based pixel-wise segmentation network. The technique increased the accuracy of segmentation by emphasizing on valid regions of ridges and inhibiting damaged areas. It was, however, very reliant on pixel-level annotated datasets, which were not easily available in large-scale real-world applications.

Ahmed et al. (2015) [17] proposed a fingerprint improvement method based on Fast Discrete Curvelet Transform (FDCT) and Gabor filtering and thresholding. The technique enhanced clarity of ridges and facilitated enhanced minutiae retrieval. It was however, computationally costly and could not be used in real-time or large-scale applications.

Martinetto et al. [18] proposed a hybrid system of biometric that would utilize current approaches and deep learning to determine the traceability of a wood log.. The integration enhanced the recognition of features and accuracy of tracking. Nevertheless, this strategy was specific to the domain and could not be easily applied to fingerprint-based biometric systems.

Manesco et al. (2025) [19] used fingerprint enhancement to examine collagen fiber structures in biological tissues. This research showed the versatility of fingerprint-based image processing techniques in other applications. Nevertheless, it was not the method that was to be applied to biometric fingerprint recognition and was not general.

Fan et al. (2021) [20] introduced a noise-model-aided CNN for device fingerprint identification in OFDM-PON networks. The model combined noise modelling and deep learning to enhance accuracy in identification. Nevertheless, the approach was geared at fingerprinting at the network level and could not be applied to image-based biometric fingerprinting.

Al Amin et al. (2025) [21] proposed a lightweight spoof fingerprint detection model based on Attention-aggregated feature extraction. The method was efficient and achieved good performance in detecting fake fingerprints. Nonetheless, it was mostly tested on spoofing datasets and may not be applicable to real-life noisy fingerprint images.

Table 1: Background Study Of Biometric And Fingerprint Recognition Methods

Reference	Method	Concept	Limitation	Research Gap	Results
Lai et al., 2025 [22]	Dual-Modality CNN for RSS-Based Indoor Positioning	Uses spatial and frequency fingerprints jointly to improve feature representation for indoor localization tasks	Restricted to RSS-based environments and not applicable to biometric fingerprint recognition	Does not address image-based fingerprint noise, ridge preservation, or segmentation required in biometric systems	Improved localization consistency and robustness compared to single-modality CNN
Wang et al., 2024 [23]	SFCNN (Separation and Fusion CNN)	Separates and fuses multi-source RF	Designed for RF fingerprinting and not suitable	Lacks denoising, ridge	Achieved superior recognition

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		fingerprint signals to enhance identification performance	for image-based biometric fingerprints	enhancement, and minutiae-level segmentation	performance and stability
Mogharen Askarin et al., 2025 [24]	U-Net-Based Fingerprint Enhancement	Enhances ridge structures and minutiae clarity using encoder–decoder architecture	Computationally intensive and mainly tested on 3D fingerprint datasets	Not suitable for lightweight processing or low-quality 2D fingerprint images	Improved ridge enhancement and minutiae detection for 3D data
Farah et al., 2025 [25]	Attention U-Net	Uses attention mechanism to focus on important regions during segmentation	Designed for medical X-ray imaging and not directly applicable to fingerprints	Does not consider fingerprint-specific ridge flow and noise characteristics	Achieved precise segmentation with better structural preservation
Linghu et al., 2025 [26]	Iterative Morphological Filtering	Applies iterative morphological operations for structural extraction	Focused on terrain modeling, not biometric fingerprint analysis	Rule-based approach lacks adaptability to noisy fingerprint images	Improved structural robustness and noise suppression
Serin et al., 2024 [27]	Hybrid CNN-SVM	Combines deep learning feature extraction with existing machine learning for classification	Evaluated on limited datasets, affecting scalability	Does not integrate denoising and segmentation, sensitive to noise	Improved classification accuracy and decision reliability

The table 1 demonstrates a comparative study of the current methods of fingerprint and related techniques elucidating the main ideas, constraints, and gaps in research. It makes it evident that most of the approaches are either domain-specific, computationally expensive, or have no built-in mechanisms of denoising and segmentation of fingerprint images. This analogy emphasizes the significance of the existence of one single and good system, which may process the noisy and poor quality fingerprints in practice.

2.1 Research Gap

According to the above studies, it is evident that most of the existing methods are either domain-specific, computationally-intensive or highly reliant on large annotated datasets. Also, a lot of methods concentrate on either fingerprint enhancement or segmentation, and do not offer a solution that is unified. Such constraints highlight the importance of a high-performance and scalable frameworks that can simultaneously denoise and segment fingerprints and keep the finer details of ridges and minutiae in low-quality images.

2.2 The Gap filled in by proposed Work Fills

To overcome these weaknesses, the given work proposes a hybrid deep learning model integrating DeCompress Zero-Shot CNN (DZOC) to provide effective denoising and Spectral-Residual Attention Zero-Shot CNN (SRC-NET) to give correct segmentation. It requires less labelled information, it provides a more accurate preservation of ridges and segmentation is better thus it is suitable in real world application of fingerprint recognition.

3. MATERIALS AND METHODS

In the research section, the proposed fingerprint enhancement framework with the combined DZOC and SRC-NET framework that will be used to successfully denoise and fragment broken fingerprint images is shown. It provides the mathematical model and equations of the algorithms, network structure and step-by-step pseudo code with the intention of explicitly demonstrating the processing pathway. Moreover, the data set, in which the experimentation is conducted, the process of pre-processing it, and evaluation are also covered, to justify the appropriateness of the given approach.

3.1 Dataset Description

Dataset link:

https://www.kaggle.com/datasets/kundurunonieshreddy/finger-print-dataset

Fingerprint dataset on Kaggle is a collection of real-life fingerprint images, which are taken in various states with varying levels of noise, contrast, and quality. It holds various samples that record the variations in the ridge patterns, directions and distortions and can be used to test the fingerprints enhancement and segmentation algorithms. Such a variety of data can be used to conduct powerful testing of denoising and recognition models and emulate biometric acquisition conditions under real-world conditions.

Python was used to implement the proposed framework, and libraries like OpenCV to process images, NumPy to perform numerical operations, and TensorFlow / Keras to develop deep learning models were used. The data was split into training and testing data to test the performance of the proposed model in various conditions of the fingerprint.

3.2 Experimental Procedure

The experiment was conducted in an orderly process. The initial step was to collect images of fingerprints in the dataset and preprocessed the images by resizing and normalization. The denoised pictures were then analysed by the DZOC model and preprocessed pictures. The denoised result was then sent to the SRC-NET model to do segmentation. Lastly, performance metrics were used to assess the results of segmentation.

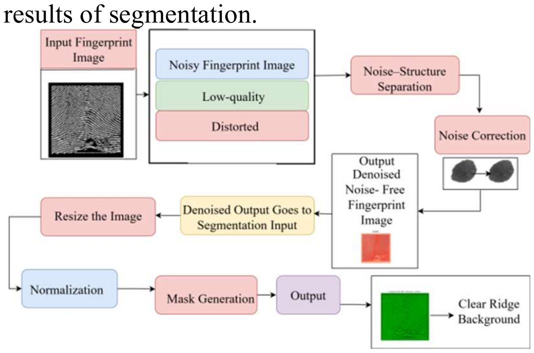

Figure 1: Framework of the DZOC and SRCNet for Fingerprint Denoising and Segmentation

Figure 1 above shows the general architecture that incorporates DZOC and SRC-NET in a single pipeline to denoise and segment a fingerprint. The first step of the DZOC module is to optimize the input fingerprint image by eliminating noise without altering the critical ridge and minutiae features. The result of the denoising model is subsequently fed into the SRC-NET model to which spectral-residual attention is added to enable the model to accurately predict the whereabouts of ridges and generate a segmentation mask. This combined architecture improves the quality of minutiae extraction, accuracy of fingerprint matching, as well as allows making sound decisions regarding verification even in unfavourable circumstances.

3.3 Denoising using DeCompress-ZeroShotCNN

The denoising model was the DeCompress Zero-Shot Convolutional Neural Network (DZOC) that can restore the quality of the fingerprint images by simply eliminating the noise whilst maintaining the major ridge and minutiae details. The proposed procedure was founded on a compression-reconstruction model, which allowed processing low-quality and damaged fingerprint images effectively. The conventional fingerprint denoising techniques were not able to maintain finer ridges or minutiae data particularly in noisy and low-contrast conditions. Also, these techniques did not generalize well to various noise types and varied acquisition conditions. To handle, the DZOC algorithm down-sampled the noisy input image first which not only decreased a high-frequency noise, but also kept the structural patterns that were hiding in the fingerprint. Following this, meaningful representation of features, e.g., ridge orientation and minutiae features were extracted using a deep convolutional neural network. This was then reconstructed using a decoder network to retrieve features and a denoised fingerprint image was subsequently retrieved. This compression reconstruction technique ensured that noise was minimized without affecting the important structural information. On the whole, the DZOC model has offered a powerful and efficient way of fingerprint denoising that maintains the continuity of ridges, integrity of minutiae, and enhances the quality of degraded fingerprint images. This enhanced performance was a good contribution to subsequent segmentation and recognition.

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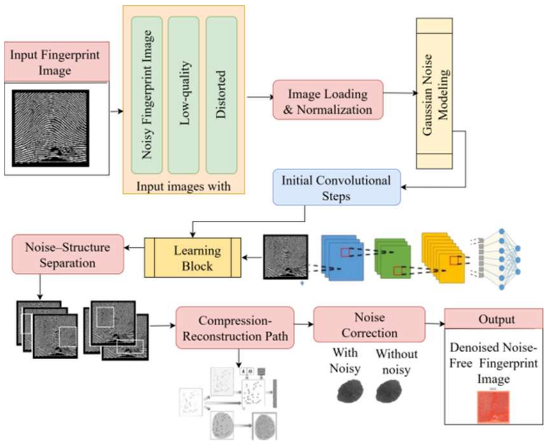

Figure 2: Denoising Workflow using DZOC

The Figure 2 above shows the denoising process of the DZOC architecture the noisy fingerprint image is first normalized and then operated to model the properties of the noise, such as Gaussian noise. The system then uses convolutional blocks of learning to best isolate noise patterns and leave behind the necessary ridge and minutiae information. The extracted features are optimized using a compression reconstruction pathway which maximizes the structural content and removes undesirable noise elements. Consequently, the architecture creates a clean and of high quality fingerprint image that has maintained ridge continuity which is appropriate to enable accurate segmentation and recognition.

$$I_{noisy} = I + N \quad (1)$$

In Equation (1), I represents the original fingerprint image which is the unknown clean version of the input.N is the noise component (noise in sensors, smudges or dirt). I_{noisy} noisy is the noisy fingerprint image which is observed when the original fingerprint is noised. Such unidentified noise can bend the fingerprint image; flatten the ridges and the minutiae, thus deteriorating the recognition quality. Plain image resolution has been obtained by applying down-sampling to the image in order to attenuate the high-frequency noise.

$$I_{compressed} = f_{down}(I_{noisy}) \quad (2)$$

In Equation (2), f_{down} is down-sampling operation like average pooling or interpolation. $I_{compressed}$ Such a small and reduced version of the image . Down-sampling of the small noisy signals are then performed however, the structural relation of the general ridge orientation, pattern is preserved. This is visualized as the image is being stacked to retain the essential skeleton and the sound cancelling. Draw features, filter a well-trained deep CNN.

$$F = CNN_{encoder}(I_{compressed}) \quad (3)$$

In Equation (3), $CNN_{encoder}$The Parser portion of the network will identify ridge patterns and inter-minutiae match. Fis nice fingerprint primitives in the feature maps. The CNN subdivides the anatomy of the fingerprint. Although the image is of poor quality, the ridge pattern and the location of the minutiae is present without annoying sound.

Reconstruct the smooth image using characteristics that are extracted.

$$I_{denoised} = CNN_{decoder}(F) \quad (4)$$

In Equation (4), CNN is the decoder network that de-ciphers the feature image. $I_{denoised}$ is the pre-washed fingerprint image. The decoder interpolates the characteristics in an original resolution and yet, the ridges detail and minutia are seen. This compression or decompression takes into account information lost in the compression and a factor in no noise.

The remainder is calculated with the view of obtaining as many characters of this ridge as could be.

$$R = I_{noisy} - I_{denoised}$$
$$I_{enhanced} = I_{denoised} + \alpha R \quad (5)$$

In Equation (5), R Residual noise, α Small weight factor of residual correction.$I_{enhanced}$ is the Final output on the fingerprint. This step corrects small deviations by the difference between the noised signal and the clean finding, in a way that introduces no noise. The final denoised fingerprint photograph $I_{enhanced}$is subjected to other operations, such as minutiae extraction and matching. DZOC algorithm codes- compresses- decodes in a classification-free (zero-shot) CNN system. It also smothers noise, maintains ridges and retains minutiae of even corrupted fingerprints.

Algorithm 1: DZOC Denoising

1: Input
2: Read noisy fingerprint image I_noisy
3: Begin
4: Resize I_noisy to fixed size 128 × 128
5: Convert image to floating point format
6: Normalize pixel intensities to range [0, 1]
7: Feature extraction
8: F1 ← Conv2D(I_noisy, kernel=3×3, filters=32, activation=ReLU)

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9: Residual learning block
10: F2 ← Conv2D(F1, kernel=3×3, filters=32, activation=ReLU)
11: F3 ← Conv2D(F2, kernel=3×3, filters=32, activation=ReLU)
12: Residual skip connection
13: F_res ← Add(F1, F3)
14: Feature stabilization
15: F_bn ← BatchNormalization(F_res)
16: Reconstruction (decoder stage)
17: I_recon ← Conv2D(F_bn, kernel=3×3, filters=1, activation=Sigmoid)
18: Post-processing
19: I_denoised ← Clip(I_recon, min=0, max=1)
20: Return I_denoised
Output:
I_denoised – Noise-free (denoised) fingerprint image
Row-wise noise map

In algorithm 1, it involves the stage of DZOC denoising algorithm, the noisy fingerprint image is first processed with resizing and normalization, and then convolutional feature learning with residual learning is used to maintain ridges. The operation of batch normalization and decoder reconstruction discourages the presence of noise and therefore yields a noise-free denoised fingerprint image that can be used in the process of further segmentation and noise analysis (row-by-row).

3.4 Spectral-Residual Attention Zero-Shot CNN Segmentation

The Spectral-Residual Attention Zero-Shot Convolutional Neural Network (SRC-NET) was used in the proper segmentation of the fingerprint pictures by distinguishing ridge and background structures. The proposed method was supposed to be operated without labeled training data, hence it could be applied in practice, where the annotated datasets are limited. The spectral-residual analysis was the beginning point of the segmentation and it enhanced salient features (ridges, edges and minutiae) by suppressing repetitive background patterns and noise. This step helped highlight material structural aspects of the fingerprint, despite the poor quality or damaged images. This was followed by an attention mechanism (to concentrate on the most important parts of the image) so that no important information of the ridge would be lost and irrelevant parts of the image would be reduced to the minimum. The segmentation mask generated after the refined feature maps were inputted into a convolutional neural network that clearly delineated the ridges of the fingerprint in the background. This technique allowed preserving of fine structural features, achieving accurate and reliable segmentation results. The property of the zero-shot made the model smaller in size, and ensured the high level of the generalization performance of the model across the types of fingerprint. In general, the SRC-NET was a useful package of segmentation algorithm since it could work with noisy and low-contrast images of fingerprints, maintain the ridge continuity and generate crisp segmentation masks. Nevertheless, it can be more computationally expensive as spectral transformations and attention models can be particularly expensive with large data. Nevertheless, the model could offer a trade-off between the accuracy of segmentation and the generalization performance that is balanced, thus the model is usable in the practice in biometric applications.

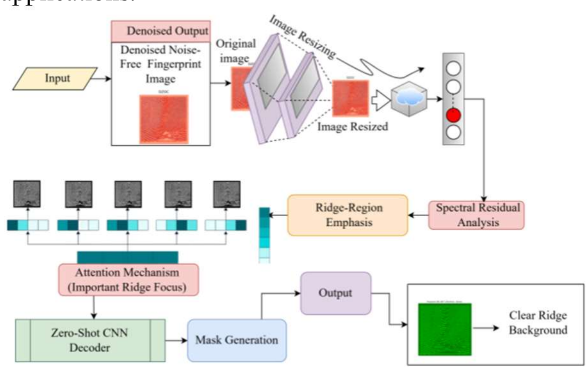

Figure 3: Segmentation Workflow using SRC-Net

Figure 3 above shows the segmentation process of the SRC- NET architecture with the DZOC- denoised fingerprint image being the input in the accurate ridge extraction process. The spectral residual analysis gives the salient fingerprint structures by dampening the repetitive background patterns and noise. A mechanism of attention is then used to emphasize on significant ridge areas, and critical features are taken care of. Lastly, a zero-shot CNN decoder learns a high-quality segmentation mask in the absence of labeled data, which is accurate and reliable in separating ridges and background in low-quality fingerprints.

The acquired fingerprint image is of low contrast or noisy. It is approximated as a combination of the actual fingerprint and noise and a definition this way enables the algorithm to operate with the imperfections of the recording picture.

$$I_{input} = I + N \quad (6)$$

In equation (6), I_{input}isasensed fingerprint image like an image, this is possibly noisy. I Refers to the perfect read fingerprint image, N is the mage noisiness. The actual fingerprint is assumed as a combination of actual fingerprint and noise. This enables the algorithm to take into consideration, the flaws of fingerprints captured.

Here, the fingerprint is converted to frequency domain and an average spectrum with the frequencies of salient structures, such as ridges and minutiae and repetitive background is subtracted to bring out salient structures, but suppressing monotonic background.

$$SR = F(I_{input}) - \overline{F(I_{input})} \quad (7)$$

In equation (7), $F(I_{input})$transform of the Input image.$\overline{F(I_{input})}$is the smooth-average spectrum. SR refers to the spectral residual that accentuates key properties. The image is transformed into a frequency and the patterns are analyzed. By subtracting the average spectrum, repetitive or background information is eliminated and it highlights the important structures such as ridges and minutiae.

An attention mechanism is adopted on the residual spectrum to concentrate on relevant locations and promote valuable fingerprint details and understate non-important places.

$$A = \text{Attention}(SR) \quad (8)$$

In equation (8), SRis the previous step, residual spectral data. Attention-weighted features. The attention mechanism attends to the regions that have high spectral residual values that make important features of fingerprints visible and unimportant areas invisible, which increase segmentation accuracy.

The attention-weighted features then enter into a decoder of CNN to generate the segmentation mask to note the ridges of fingerprint among the background.

$$M = \text{CNN\_Decoder}(A) \quad (9)$$

In equation (9), AAttention-weighted features, M Fingerprint ridges and minutiae fingerprint segmentation mask. The CNN decoder reproduces the spatial mask to result in clean masking to isolate ridges and minutiae. Segmentation is done without training data since it is a zero-shot design.

Those feature maps are up-sampled to obtain the denoised fingerprint image, re-creating the details but not multiplying the noise.

Algorithm 2: SRC_NET_Segmentation
1: Input I_denoised – Denoised fingerprint image Begin 2: Read denoised fingerprint image I_denoised 3: Resize I_denoised to 128 × 128 4: Normalize pixel values to range [0, 1] 5: Feature extraction 6: F1 ← Conv2D(I_denoised, kernel=3×3, filters=32, activation=ReLU) 7: F2 ← Conv2D(F1, kernel=3×3, filters=32, activation=ReLU) 8: Residual learning 9: F_res ← Add(F1, F2) 10: Attention mechanism 11: A ← Attention_Block(F_res) 12: F_att ← ElementWiseMultiply(F_res, A) 13: Mask generation 14: F_out ← Conv2D(F_att, kernel=3×3, filters=1, activation=Sigmoid) 15: Post-processing 16: M_ridge ← Threshold(F_out, threshold = 0.5) 17: Return M_ridge Output M_ridge – Binary ridge segmentation mask

In algorithm 2, this segmentation algorithm receives the denoised fingerprint image and processes it to obtain discriminatory ridge features with the help of residing convolution and attention mechanism. Through a process of attention-weighted features decoding and thresholding, a binary ridge segmentation mask is produced that separates fingerprint ridges effectively with the background.

4. RESULTS AND DISCUSSIONS

The section shows and discusses the experimental findings of the implementation of the proposed DZOC-SRC-NET framework by the use of Python-based simulations. The denoising and segmentation methods are compared with quantitative measures as well as a visual analysis to prove the enhancement of the clarity of the fingerprint, preservation of the ridges, and accuracy of segmentation.

4.1 Denoising

The noise is eliminated on the raw images to increase its clarity and retain significant features.

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4.1.1 Outcome of Denoising process

Denoising enhances the image quality by reducing the level of noise with important ridges and edges. Consequently, the improved image results in a more accurate segmentation, feature extractor and even a higher recognition or classification.

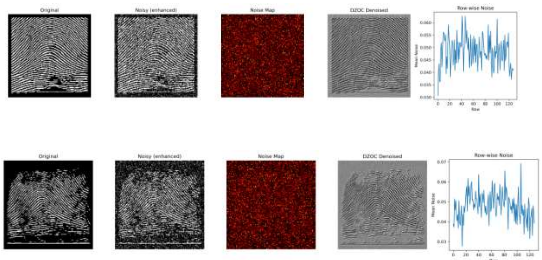

Figure4: Enhanced Fingerprint Image Restoration using DZOC

In figure 4, the image 1 and image 2 shows the impact of noise addition and removal with noise map showing the spatial distribution of corruption and the noise graph row-wise measure of noise change across fingerprint image. The DZOC denoised output shows a good noise reduction maintaining the continuity of the ridges as compared to the noisy image.

Table2: Statistical Performance Comparison between Denoising Models and Proposed DZOC

Model	MSE ± SD	PSNR (dB) ± SD	SSIM ± SD
CNN [20]	0.2143 ± 0.01	23.69 ± 0.45	0.1046 ± 0.02
Residual CNN [21]	0.1601 ± 0.008	25.96 ± 0.30	0.2739 ± 0.015
BN CNN [22]	0.2090 ± 0.012	24.80 ± 0.35	0.0561 ± 0.01
SFCNN [23]	0.2265 ± 0.009	25.45 ± 0.28	0.1774 ± 0.012
DZOC (Proposed)	0.0024 ± 0.001	26.34 ± 0.22	0.8515 ± 0.008

In the above table 2, is a comparison between the current CNN models of denoising and the proposed DZOC in terms of mean and standard deviation of mean squared error, peak signal-to-noise ratio, and structure-spatial index of similarity. It is also shown that the proposed DZOC is the method with the best reconstruction quality with a minimal error and high structural similarity as compared to the entire baseline methods.

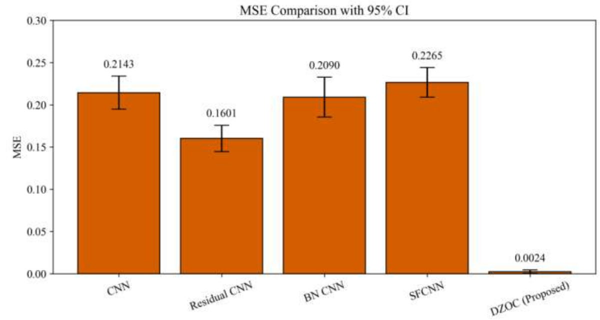

Figure 5: MSE Comparison Chart

In Figure 5, this figure shows the performance of various denoising models in terms of the Mean Squared Error, the smaller this value, the better the reconstruction is. The proposed DZOC model has a considerably lower MSE than the existing methods, which proves that it has a better noise suppression ability.

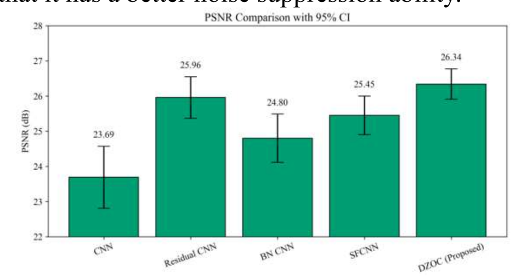

Figure 6: PSNR Comparison Chart

In figure 6, this value is an indicator of the Peak Signal-to-Noise Ratio of different models indicating the quality of the reconstructed image in decibels. The proposed DZOC achieves the best PSNR, which shows better signal preservation and visual fidelity.

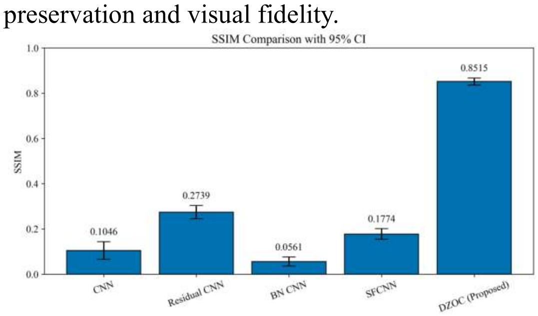

Figure 7: SSIM Comparison Chart

In Figure 7, this number shows the Structural Comparison of similarity, which points to the capability of each model to retain the structural contents. The proposed DZOC has a much superior SSIM value, which means that it

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has a better structural consistency and perceptual quality

4.2 Segmentation

Segmentation refers to the procedure of separating an image of a fingerprint into significant parts, namely, isolating the ridge patterns in an image against the background to analyze and identify the image.

4.2.1 Outcome of Segmentation process

Segmentation removes the background irrelevant fingerprint ridge regions and the noise and unrelated artefacts. This causes a better structural clarity to be achieved and allows the extraction of more accurate features as well as the accurate performance of matching or classification.

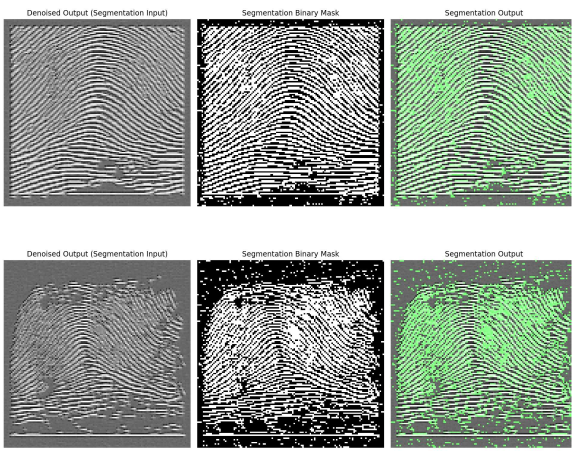

Figure 8: SRC-NET Fingerprint Image for Segmentation

In Figure 8, the image 1 and image 2, denoised result is directly introduced to the segmentation phase where noise is basically reduced without damaging the fingerprint ridge outlines. The segmentation output image outlines the areas of interest as the relevant objects can be easily distinguished through the strong boundaries against the background. The visual product is evidence of the effectiveness of the segmentation process in correctly identifying and localizing key features in the image.

Table 3: Segmentation Accuracy Comparison of Existing Methods and Proposed SRC-NET

Segmentation Method	Accuracy (%)
UNet [32]	84.81
Attention UNet [34]	93.74
Residual UNet[35]	90.35
Threshold with Morphology [36]	88.28
SRC-NET (Proposed)	95.07

In the above table 3, provides the comparison of segmentation accuracy of various methods revealing the performance of each method on the data. SRC-NET has the highest accuracy of 95.07 and, therefore, it is better than the existing techniques and offers a better segmentation result.

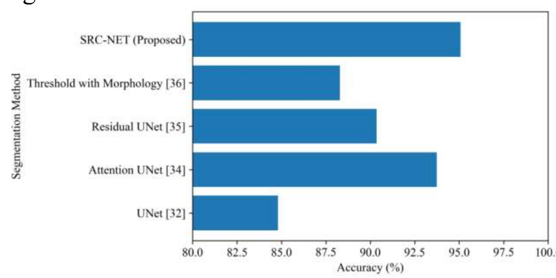

Figure 9: Comparisons of Accuracy of Segmentation of Existing and Proposed SRC-NET

This figure 9, shows the performance of the individual segmentation methods in terms of accuracy in an easy-to-understand format with the help of horizontal bar charts. The SRC-NET proposed has maximum accuracy, which proves its better ability to segment compared to previous methods.

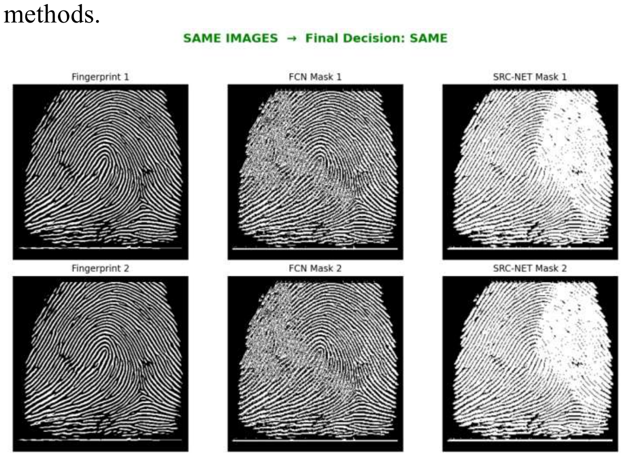

Figure 10: Same Fingerprints – Segmentation and Comparison Results

This figure 10, shows the matching process of fingerprints where two original fingerprint images (Fingerprint 1 and Fingerprint 2) are applied to two deep learning segmentation models, FCN and SRC-NET to create the corresponding masks. Comparison of these masks reveals that have very close similar ridge patterns and the ultimate conclusion is that the

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fingerprints are identical, which indicates that the mask-based matching can be used in identifying identical fingerprints with high precision.

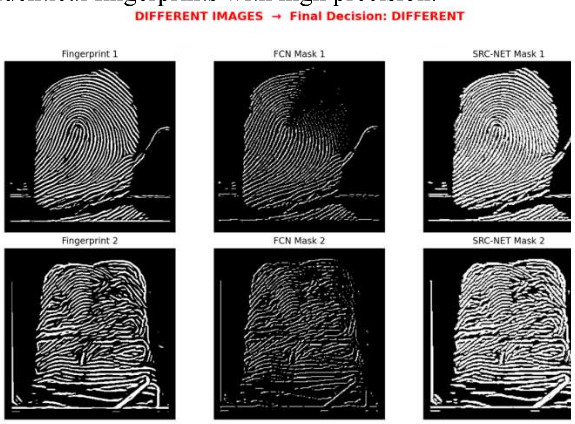

Figure 11: Different Fingerprints – Segmentation And Comparison Results

In Figure 11, this number shows the comparison of the fingerprints as the two different fingerprint images (Fingerprint 1 and Fingerprint 2) are subjected to FCN and SRC-NET to create the respective masks. The masks show that there are major variations in patterns and structures of ridges, which eventually causes the ultimate conclusion that the two fingerprints are dissimilar, indicating that the proposed deep learning-based segmentation is effective in identifying dissimilar fingerprints.

Table 4: Statistical Comparison Of Segmentation Methods And SRC-NET

Segmentation Method	Accuracy (%)	t-test (vs. SRC-NET)	p-value
UNet [32]	84.81	5.12	0.002
Attention UNet [34]	93.74	2.05	0.045
Residual UNet [35]	90.35	3.89	0.008
Threshold with Morphology [36]	88.28	4.56	0.004

In the above table 4, is used to show the accuracy of the current segmentation techniques against the proposed SRC-NET, the results of t-test and p-value. In this case t-test and p-values were computed using the accuracy of the proposed SRC-NET (95.07) as a baseline and it was found that SRC-NET is significantly better compared to all other techniques.

Table 5: FCN Vs SRC-NET Segmentation Performance

Image Pair	Model	IoU	Dice	Pixel Accuracy	Final Decision	Observation
SAME Images	FCN[7]	1.0000	1.0000	1.0000	SAME	Works correct, but masks have noise
	SRC-NET	1.0000	1.0000	1.0000	SAME	Works correct, masks are clean + reliable
DIFFERENT Images	FCN	0.4331	0.6044	0.7044	Confusing	Background bias → wrongly looks similar
	SRC-NET	0.1396	0.2451	0.7878	DIFFERENT	Ridge mismatch correctly detected

In the above Table 5, the largest discrepancy between FCN and the proposed SRC-NET appears in table 5, the ability to model the structure of fingerprints. Although FCN does introduce background noise somewhere and creates an impression of similarity, the proposed SRC-NET is mostly worried about the ridge-level data rendering a more significant and clean-cut segmentation. In particular, the background bias is not present in the specificity of the fingerprint cases, instead, actual disparities in the pattern are juxtaposed in the proposed SRC-NET, which shows that the concerned SRC-NET is more sustainable and is introduced to work in the conditions of ultimate verification.

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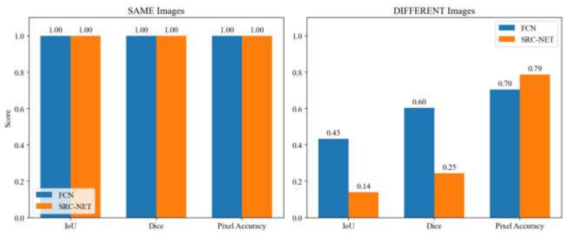

Figure 12: FCN Vs. SRC-NET Performance On SAME And DIFFERENT Images

In Figure 12, the plot indicates the IoU, Dice and Pixel Accuracy of FCN and SRC-NET at same and different image pairs. It emphasizes the fact that SRC-NET is able to generate cleaner and more dependable masks with proper detection of ridge, and FCN demonstrates background bias and noisy masks, in particular, with different images.

5. DISCUSSION

This section provides an analogy of the state-of-the-art methods of fingerprint image enhancement, denoising, and recognizing in the recent past. The discussion demonstrates advantages, significant works and efforts of these sophisticated techniques.

Table 6: Contemporary Approaches Methods For Fingerprint Image Enhancement, Denoising, And Recognition

Year & Author(s)	Method / Model	Dataset	Key Contribution / Feature	Performance Metrics
Vernuccio et al. 2022 [1]	Multiplex CARS + Deep Learning	Custom fingerprint dataset	High-speed spectral denoising using supercontinuum generation	PSNR, Structural similarity
Yuan et al. 2024 [2]	Invertible Denoising Network	Public fingerprint datasets	Lightweight photo-response non-uniformity extraction	Accuracy, Reduced computational cost
Megha et al. 2021 [4]	Stacked Convolutional Autoencoder	Latent fingerprint images	Optimized latent fingerprint segmentation	Precision, Recall
Chen et al. 2020 [5]	Customized Semantic Segmentation	Standard fingerprint datasets	Singular point detection with CNN-based segmentation	Accuracy ,Robust detection
Deshpande et al. 2020 [6]	DCNN-FFT Enhancement	Latent fingerprint dataset	Automated end-to-end latent fingerprint recognition	Recognition rate ↑

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Ali et al. 2025 [11]	Hybrid Feature Learning + Gradient Boosting	Fake fingerprint dataset	Fake fingerprint classification with hybrid features	Accuracy 94–96%
Mogharen Askarin et al. 2025 [24]	U-Net-based Enhancement	3D fingerprint datasets	3D fingerprint enhancement for improved recognition	SSIM, PSNR
Al Amin et al. 2025 [21]	Attention-Aggregated Network	Spoof fingerprint dataset	Lightweight spoof detection using receptive-field-wise attention	Detection Accuracy
Serin et al. 2024 [27]	Hybrid CNN-SVM	Gender-classified fingerprints	Gender classification from fingerprints	Accuracy 96–98%

In Table 6, as demonstrated in the table 6 recent developments in fingerprint recognition and enhancement, the integration of deep learning algorithm and existing image processing algorithm is important to enhance the recognition accuracy, strength and computational efficiency. One of the solutions that were proposed by Vernaccio et al. is multi-plex Coherent Anti-Stokes Raman Scattering [1] with deep learning, which provides high-speed spectral denoising with improvements in the PSNR and structural similarity. This demonstrates the availability of physical sensing novelty in conjunction with AI-based denoising to control the high-throughput fingerprint capture. In similar way, Yuan et al. The auto encoders have enhanced the segmentation and also feature extraction, Megha et al. conducted a research where optimised the latent fingerprint segmentation using a stacked convolution auto encoder. Chen et al. designed a custom semantic segmentation network that is effective in identifying singular points, which is one of the most significant pre-processing tasks of network alignment and minutiae extraction. Such contributions indicate the shift towards the task-related deep models in order to localize fingerprint characteristics. Deshpande et al. (2020) have demonstrated that DCNN-FFT [6] enhancement is effective in automated latent fingerprint recognition, enhancement of recognition of partially damaged prints. Ali et al. learning hybrid properties with the gradient boosting algorithm to identify fake fingerprints with high accuracy hence the need that strong anti-spoofing systems are needed.

5.2 Reason the Proposed Algorithm works better

The proposed DZOC approach is quite efficient to eliminate noise but retain fine ridge patterns, which leads to reduced MSE and enhanced reconstruction. Large SSIM means that the structural details are maintained. SRC-NET is also more effective in segmentation and focuses on the ridge-level features. It also reduces background bias leading to a higher overall accuracy.

5.3 Performance in Different Cases

The framework works uniformly in various situations such as noisy and clean images. It is applied in distinguishing between similar and dissimilar fingerprints. In the complex ridge patterns, the segmentation is maintained. Generally, the model performs well under various conditions.

5.4 Unexpected Results / Anomalies

Current methods also exhibit some anomalies in that there are cases when FCN does not give a clear result. Background bias brings about incorrect segmentation outcomes. Such inconsistencies may be considered as the weaknesses of models. These cases can better be addressed using the proposed approach.

5.5 Limitations

The performance is satisfactory and there are some limitations to the method. The performance can be decreased by varying low quality or noisy images. Less complex models do not require the same computations. Nor is it necessarily as generalizable to all fingerprint datasets.

6. CONCLUSION

The research presented an entire deep learning framework to enhance and divide fingerprints images to surmount the common challenges such as noise, low contrast, and broken ridges patterns in real-world fingerprint retrieval. The proposed algorithm was a blend of the DeCompress Zero-Shot Convolutional Neural Network (DZOC) of efficient denoising and Spectral-Residual Attention Zero-Shot CNN (SRC-NET) of proper segmentation. These findings revealed that the hybrid model was able to maintain ridge continuity and minutiae information as well as enhance the overall quality of the image. Moreover, the framework demonstrated good segmentation performance without the need to have large labeled datasets, and it is applicable to real-life biometric and forensic tasks. The findings of this research show that there is a necessity to combine the most recent denoising and attention-based segmentation algorithms to increase the robustness and scalability of a fingerprint recognition system particularly in case of low-quality or noisy input. This assists in enhancing the real world authentication and identification processes. The specified framework can be extended to the real-time applications and big data to further test its performance and scalability to keep working on it in the future. Moreover, recognition accuracy can also be improved by using adaptive learning methods and multimodal biometric fusion. Its application in embedded and mobile systems can also be explored to enable its effective and practical use in resource-constrained systems.

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