IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Fingerprint Re-Creation Using Convolutional Autoencoders For Ridge Pattern Restoration

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Abstract: The ability to reconstruct fingerprints is an important element in biometric security systems, as well as forensic investigations. The purpose of this research is to study whether a convolutional autoencoder, modelled off a U-net architecture, could be used to reconstruct fingerprints from quality degraded or incomplete fingerprints. The model was also trained with pre-processing of a publicly available fingerprint dataset to convert the data to greyscale, resize them to uniform dimensions and normalize them. The model implemented a hybrid loss of Mean Squared Error (MSE) and Structural Similarity Index Measure (SSIM) loss to promote an accurate pixel match as well as structural similarity. Reconstruction results showed some promise in reconstructing core ridge structures of a fingerprint and highlighted the potential for digitized images of convolutional autoencoders to reconstruct and apply to fingerprint image reconstruction tasks.

***Keywords* -** Convolutional autoencoders, U-Net, biometric security, deep learning, image restoration, SSIM, MSE, pattern recognition, and fingerprint reconstruction

I. Introduction

Fingerprint reconstruction is an essential step in forensic applications such as biometric systems and criminal investigation. Many times, fingerprints are degraded due to poor capturing, or physical distortion, which demands reconstruction for proper recognition. The inadequate effects of the traditional approaches lie in that they have difficulties in recovering the detailed geometry. Convolutional autoencoders (CAEs), a subfield of deep learning, offer powerful tools for fingerprint image restoration. In this work, we demonstrate the use of a CAE to reconstruct fingerprints using the U-Net architecture, which is known for its skip connections and retention of spatial features. For pixel-level accuracy and perceptual quality, the system uses a hybrid loss function that combines mean squared error (MSE) and structural similarity index measure (SSIM). As a result, the system is suitable for practical applications.

II. Related Work

Recent advances in fingerprint reconstruction have centered on convolutional autoencoders (CAEs), which capture compact latent features of minutiae and ridge patterns. Saponara et al. [1] recently demonstrated that a deep CAE trained end-to-end can generate high-quality fingerprint images by learning to represent both the overall ridge flow and the detailed local bifurcation patterns. Building on this, de Sousa Neto et al. [2] proposed a fully convolutional autoencoder with both skip connections and residual learning layers that effectively reduced noise and reconstruction artifacts from low quality input. Raswa et al. [3] even showed that pixel wise MSE with a perceptual SSIM loss had greater robustness to extreme degradation, suggesting the importance of multi loss optimization, to preserve structural fidelity. Sparse-encoding approaches have also been explored to handle partial or latent prints; for example, Saponara et al. [4] imposed sparsity constraints on the latent space to enable plausible reconstruction from incomplete ridge fragments.

Generative adversarial networks (GANs) proved to be an effective supplementary tool for fingerprint generation and restoration. Bouzaglo and Keller [5] implemented an adversarial model for augmenting ridge textures, replacing lost or missing details with real features. Svoboda et al. [6] utilized a GAN discriminator along with a convolutional reconstruction network, conducting adversarial training to regularize the generation process and improve continuity in fine-scale minutiae, especially for latent or partial prints. The applications prove the strength of GANs to describe complicated fingerprint distributions, though many tend to work in a stabilizing way once proper regularization has been achieved to prevent instability.
In addition to strict reconstruction, various studies have combined feature-enhancement and hybrid architectures to improve downstream matching accuracy. Myshkovskyi and Nazarkevych [7] proposed a multi-scale CNN preprocessor to sharpen ridge endings and bifurcations prior to reconstruction, while Maiti et al. [8] employed an autoencoder to extract the valid finger region from background noise, enhancing overall reconstruction resolution. Bhilavade et al. [9] combined cross-domain learning with a CAE to cope with heterogeneous sensor data, recording state-of-the-art reconstruction and recognition accuracy. Lastly, Nagaraj and Channegowda [10] showed that layer-wise pretraining using stacked autoencoders can generate more discriminative latent features, a method with potential for initializing CAEs in data-starved forensic applications.

III. METHODOLOGY

The method begins with data preparation—raw fingerprint images transformed into grayscale, resized to 224×224 pixels, normalized, and with realistic augmentations. We then construct a U-Net–type convolutional autoencoder with skip connections to preserve global ridge patterns and local minutiae. We train using an aggregate Mean Squared Error (MSE)+Structural Similarity Index Measure (SSIM) loss with Adam optimization and early stopping to balance pixel precision and perceived quality. We then evaluate reconstruction performance using Mean Squared Error, Structural Similarity Index Measure, and visual comparison.

3.1 Data Pipeline

We utilized an open-source fingerprint database, which is a collection of high-resolution grayscale images of different types of fingerprint patterns like arches, loops, and whorls. Our preprocessing pipeline included the following key steps:

- **Grayscale Conversion:** Images were converted to grayscale using the luminosity formula to provide a consistent input to the network.
- **Resizing:** All images were resized to 224×224 pixels in order to match the input size that the neural network demands.
- **Normalization:** Pixel intensity values were normalized to [0,1] range by dividing each by the maximum pixel value of all images.
- **Augmentation:** The methods of data augmentation were applied to simulate the real-world noise, including random rotation, shifting horizontally, and changes in brightness.
- **Train-Test Split:** The data was partitioned into 80% for training and 20% for validation with a random partition for ensuring strong model evaluation.

3.2 Model Architecture

The used model is a U-Net-type convolutional autoencoder, which is well-suited to its capacity for handling fine spatial information in image reconstruction tasks. The architecture has an encoder, bottleneck, and decoder, with skip connections to preserve high-level features across the network.

- **Encoder:** The encoder consists of four convolutional blocks, and each of these is followed by batch normalization, ReLU activation, and dropout for regularization. Max pooling comes after each of the blocks with the aim of downscaling the feature maps and thus reducing spatial dimensions but expanding the depth of feature extraction. The filters used in the encoder are escalated from 32 to 256.
- **Bottleneck:** The bottleneck layer is one convolutional layer with 512 filters, a dense representation of the most important features of the image.
- **Decoder:** The decoder is the reverse of the encoder, using upsampling and convolution layers to reconstruct the fingerprint image. Skip connections are added to each layer, merging features from the corresponding encoder layers to preserve spatial information lost due to downsampling.
- **Output Layer:** The last layer outputs a single-channel grayscale image with pixel values ranging from 0 to 1 through a 1×1 convolutional operation combined with a sigmoid activation function.

3.3 Loss Function and Optimization

The model was trained using a hybrid loss function:

$$L_{total}=MSE+(1-SSIM) \quad \text{Eq. (1)}$$

where MSE (Mean Squared Error) punishes pixel-wise errors, and SSIM (Structural Similarity Index) guarantees the perceived quality of the reconstructed image. The model was trained using the Adam optimizer with a learning rate of $1\times10-4$ and early stopping to avoid overfitting. Training was performed for 200 epochs with a batch size of 8.

3.4 Training Procedure

The model was trained on the extended dataset using the following process:

1. **Data Augmentation:** Online augmentation was performed with the use of Keras's ImageDataGenerator, applying random rotations, shifts, and flips to improve generalization.
2. **Model Training:** The model was trained for 200 epochs. Early stopping was used if the validation loss did not improve for 20 epochs in a row. The model checkpoint was saved at every epoch for possible recovery.
3. **Evaluation:** Model performance was assessed on a test validation set with the use of MSE and SSIM to measure reconstruction quality.

3.5 Evaluation Metrics

To measure the performance of the model quantitatively, the following were used:

- **Mean Squared Error (MSE):** Computes the average of the squared differences between the original and estimated pixel values.
- **Structural Similarity Index (SSIM):** Measures perceptual similarity between two images in terms of structure, luminance, and texture. designations.

IV. Results and Evaluation

The suggested study provides a comprehensive analysis of the effectiveness of the U-Net–based convolutional autoencoder in the restoration of degraded fingerprint images. Quantitative assessment is done using standard error measures, and qualitative comparison is done through visual comparisons.

4.1 Quantitative Evaluation

The model was validated on a held-out validation set consisting of 20% of the whole dataset. Table 4.1 displays the evaluation metrics used and the values achieved. Figure 4.1 depicts the Training vs. Validation Loss for 20 epochs since the values stabilized after 20 epochs and the early stop function used in the code terminated the process.

Table 4.1: Evaluation Metrics

Metric	Value
Average MSE	0.053497
Average SSIM	0.379390

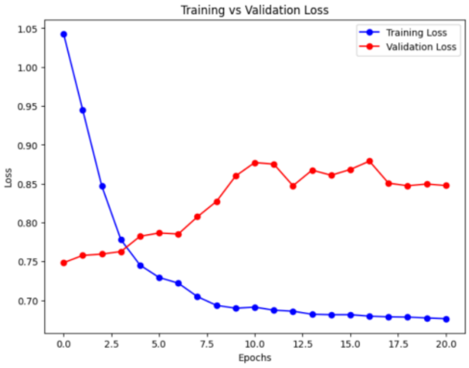

Figure 4.1: Training versus Validation Loss

4.2 Qualitative Analysis

Reconstructed images preserve high global ridge flow, though there is a slight smoothing of finer minutiae details. We would need to skip connections in the U-Net function to effectively minimize blurring over normal autoencoders. Figure 4.2 depicts the re-constructed fingerprints. There are clear differences between the images from the dataset in the first row compared to the resulting images in the second row. The ridges are reconstructed effectively and there is contrast between the background and the fingerprint to highlight the reconstruction better.

Figure 4.2: Top row depicts the fingerprints selected for reconstruction and the Bottom row depicts the final results after reconstruction.

V. Future Enhancements

While the suggested U-Net–based convolutional autoencoder demonstrates proficiency in reconstructing fingerprints, there exist several modifications that could enhance both its precision and utility. A key enhancement entails augmenting the input resolution beyond 224×224 pixels, which would facilitate a more detailed capture of intricate ridge and minutiae features—especially advantageous in forensic applications.

Coupling domain-specific restrictions into the loss function, i.e., minutiae-aware or orientation-consistency losses, has the potential to guide the model towards structurally more accurate reconstructions. Hybrid models, coupling generative adversarial networks (GANs) for visual realism and preservation of fine-grained detail, represent promising areas for future work. Increasing the size of the training dataset to encompass prints from different sensors and amounts of distortion will enhance generalizability. Transfer learning or domain adaptation techniques have the potential to further facilitate cross-environment performance.

To facilitate deployment, enhancing the model for edge devices through the utilization of lightweight architectures (such as MobileNet) or through quantization techniques may allow for real-time functionality within mobile or embedded systems. Furthermore, the implementation of privacy-preserving strategies, including federated learning, should be contemplated to train models securely utilizing sensitive biometric data. Collectively, these improvements will bolster the model's scalability, robustness, and appropriateness for practical biometric applications.

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