Restoring Altered Fingerprint Images With Convolutional Auto-Encoders

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***Abstract*—This paper explores the application of convolutional auto-encoders in the restoration of altered fingerprint images returned to their original states. Employing a methodical approach, this research outlines the process, methodology, and implementation of the auto-encoding techniques. Challenges and obstacles encountered during the project are delineated, as is a comprehensive analysis of the obtained results. The research in this paper hopes to highlight the efficacy and limitations of this approach, offering insight into its practical implications in the real world.**

***Index Terms*—convolutional autoencoders, fingerprint restoration, image processing, student research, pattern recognition, deep learning**

I. Introduction

Amidst the complex and evolving landscape of biometric security, fingerprints reign as the cornerstone of authentication and identification. Their ubiquity and uniqueness, allow for secure authentication under the correct conditions. This prompts an intriguing challenge: the integrity of these identifiers in the face of alterations.

The acquisition of fingerprints, a core process in fingerprint recognition, relies on various methods such as optical, capacitive, or ultrasonic sensors to capture the unique ridge patterns and minutiae points. However, despite the advancements made in fingerprint scanning technologies, the collected fingerprint images may exhibit imperfections or damages that can compromise the accuracy of identification [1]. The primary factor contributing to imperfect fingerprint acquisition is the variability in scanning conditions. Factors such as humidity, temperature, or surface conditions of the scanner, can have a detrimental impact on the quality of the captured image [2]. Moreover, the physiological characteristics of the individual may further contribute to imperfections in fingerprint image quality. Variations in skin conditions, such as scars, calluses, and dryness, can affect the clarity and completeness of fingerprint scans. Additionally, the angle, pressure, or positioning of the finger during scanning can introduce distortions, leading to partial or fragmented images.

To tackle the challenges aforementioned, I have implemented a convolutional auto-encoder. Convolutional auto-encoders are a specialized class of neural networks designed for image processing and restoration, making them a natural candidate for fingerprint restoration. Unlike traditional auto-encoders, convolutional auto-encoders leverage the use of convolutional layers, allowing them to capture spatial relationships within the fingerprint image. The architecture of an auto-encoder is comprised of two main components: an encoder and a decoder. The encoder compresses input data into a latent representation, extracting essential features and patterns. Afterward, the decoder takes the encoded data to reconstruct the original input image.

In the context of fingerprint image restoration, convolutional auto-encoders hold immense promise. Their ability to preserve intricate details while handling image-specific features enables them to capture the complex patterns inherent in fingerprint images. The decision to employ a convolutional auto-encoder in this research stems from its ability to capture intricate features. By leveraging these networks, a solution to imperfections and alterations within fingerprint acquisition may be present.

II. Related Work

In the domain of fingerprint image processing, numerous techniques have been proposed to address the challenges associated with image alterations and degradations. Previous research utilizing methods such as filtering and enhancement has demonstrated efficacy.

A. *Previous research*

Saponara et al. [3] propose a convolutional neural network auto-encoder architecture to reconstruct fingerprint images using a CNN architecture. This paper goes into depth about the pre-processing of the input images, the auto-encoder architecture and layers, testing methodologies, and the impact on several different datasets.

Kuo et al. [2] propose a method to restore fingerprints under low-temperature conditions utilizing a convolutional neural network training method with ridge loss. The 2-stage training method generates a ridge map of the input image, then restores the missing ridge pattern and removes noise based on the ridge map generated from stage 1. This method uses an encoder-decoder model to extract ridge map features and restore the image.

Both Saponara et al. [3] and Kuo et al. [2] stand as pivotal works within the domain of fingerprint image restoration and reconstruction. These papers lay the foundation upon which my research derives.

III. Methods and Implementation

A. Dataset Description

The fingerprint dataset used in this research was collected from the Sokoto Coventry Fingerprint Dataset (SOCOFing), designed for academic research purposes. The dataset consists of 6,000 fingerprint images from 600 African subjects, containing unique labels for gender, hand and finger names, and synthetically altered versions of the corresponding fingerprints. Each fingerprint has three varying levels of alterations with z-cuts, central rotation, and obliteration of the image. These alterations range from easy, smaller alterations that retain a majority of the original fingerprint data, to hard, large alterations that impose major modifications to the original fingerprint [4].

Fig. 1. Dataset showcasing level of alterations: real, easy, hard

B. Dataset Preparation

The implementation utilizes a fingerprint image dataset consisting of genuine ('Real') and altered fingerprint images ('Altered'). Both sets of images are loaded and pre-processed to ensure uniformity in size (100 x 100 pixel width and height) and a gray-scale format for further processing. Images from both 'Real' and 'Altered' datasets are normalized to a scale between 0 and 1 for compatibility with the neural network architecture. After normalization, the dataset is split into 80% for training and 20% for testing.

C. Auto-encoding Model

The auto-encoder model is a neural network architecture utilizing the capabilities of the Tensorflow and Keras libraries. These libraries allowed for efficient development and training of the auto-encoder model, streamlining the process of constructing and optimizing the architecture. The overall model consists of three convolutional layers within the encoder, each followed by a pooling layer. The decoder contains three corresponding layers, each followed by an up-sampling layer. This creates a model with a total of six convolutional layers.

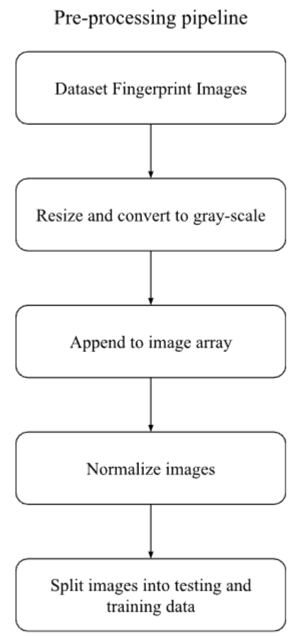

Fig. 2. Pre-processing pipeline for fingerprint images

TABLE I
AUTO-ENCODER MODELING LAYERS

LAYER (TYPE)	OUTPUT SHAPE	Param #
InputLayer	100 x 100 x 1	0
Conv2D	100 x 100 x 32	320
MaxPooling2D	50 x 50 x 32	0
Conv2D	50 x 50 x 64	18496
MaxPooling2D	25 x 25 x 64	0
Conv2D	25 x 25 x 128	73856
Conv2D	25 x 25 x 128	147584
UpSampling2D	50 x 50 x 128	0
Conv2D	50 x 50 x 64	73792
UpSampling2D	100 x 100 x 64	0
Conv2D	100 x 100 x 1	577
Total Params:	314,625	

The architecture is optimized with the RMSprop optimizer and trained using the mean squared error (MSE) loss function since the MSE loss function penalizes larger errors more severely, and accurate reconstruction of the fingerprint image is the goal. The model comprises an encoder and a decoder, where the encoder learns to extract meaningful features from the 'Altered' fingerprint images, compressing them into latent space representation. The decoder then reconstructs these compressed representations, aiming to restore the image as close to the original 'Real' fingerprint image.

Training involves feeding the 'Altered' fingerprint images into the model, iterative adjusting the network's weights to minimize the difference between the reconstructed output and the 'Real' fingerprint images. This process is monitored over multiple epochs by assessing the loss metrics, providing insights into the convergence and performance of the model. Once the auto-encoder is trained, it is leveraged to reconstruct the altered fingerprint images. A subset of test images is chosen to provide a visual comparison between the original input image and the reconstructed image. The reconstructed images are saved for further evaluation.

To quantitatively evaluate the accuracy of the reconstructed images, a Structural Similarity Index (SSIM) metric is employed. This metric measures the similarity between the reconstructed fingerprint images and their unaltered counterparts. A higher SSIM score indicates a closer resemblance between the reconstructed and original images.

IV. RESULTS

The model exhibited promising performance when trained on highly specific datasets, specifically comprising a singular fingerprint, with alterations made to that specific fingerprint. The model demonstrates proficient restoration capabilities for altered fingerprints within the training set. Notable, it excelled in restoring alterations in singular fingerprint instances that were meticulously trained and fine-tuned to learn the intricacies of these alterations. The model achieves a notable average SSIM score of 96% when compared to the original fingerprint within its trained scope.

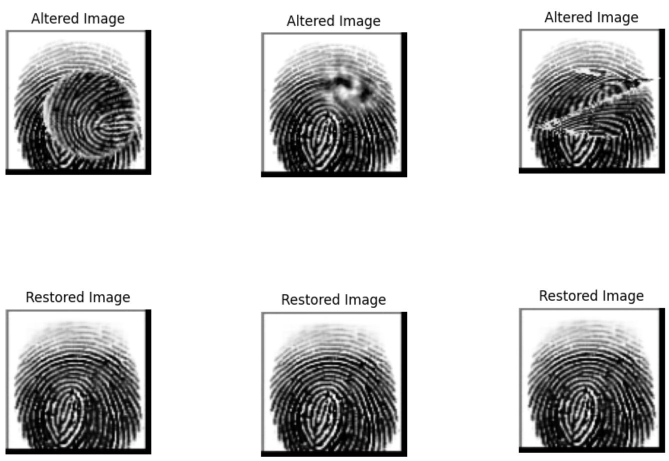

Fig. 3. Results on a specifically trained fingerprint

However, this specificity proved to be a double-edged sword. When presented with an untrained input image or utilized on a broader dataset beyond its training scope, the auto-encoder's performance is significantly degraded. The model struggles to generalize its learned features, resulting in flawed and distorted outputs. In instances where the model was given input with alterations diverging from its training data, the model would produce reconstructions that bore little resemblance to the original fingerprint, often yielding distorted outputs. The average SSIM score for training on a specific fingerprint with unfamiliar data was 22%.

Moreover, broadening the training dataset to encompass a more diverse range of fingerprints led to over-fitting issues. In Figure 6, the top graph demonstrates the training progress of the mode when trained on a specific fingerprint and its alterations. The absence of a divergence between the training

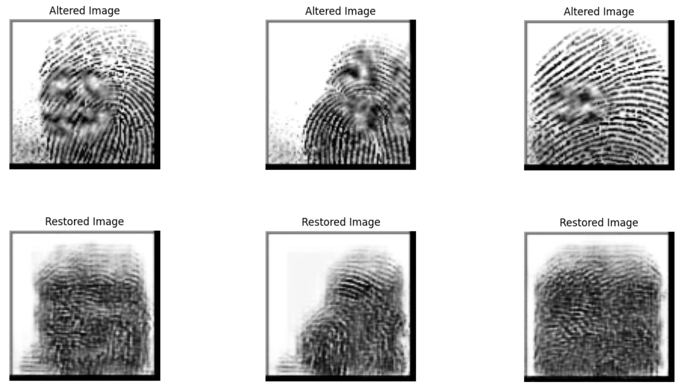

Fig. 4. Results on unfamiliar fingerprints

and validation loss curves indicates a balanced learning process. The model effectively learns the nuances of the provided fingerprint alterations, thus being able to accurately recreate fingerprint images close to the original fingerprint. Conversely, the bottom graph showcases the outcome of training the model on a broad, unlabeled dataset containing multiple different fingerprints and fingerprint alterations. The evident divergence between the training and validation loss curves signals a sign of over-fitting.

The auto-encoder struggled to discern relevant patterns with the abundance of diverse features in each fingerprint. Consequently, this over-fitting compromises the model's ability to generalize, affecting its performance on new, unseen data. Had labels been used to discern which features belonged to which fingerprint, perhaps the model would have been able to generalize the information, applying the appropriate features to the correct fingerprint. The average SSIM score for broad dataset training was 23%.

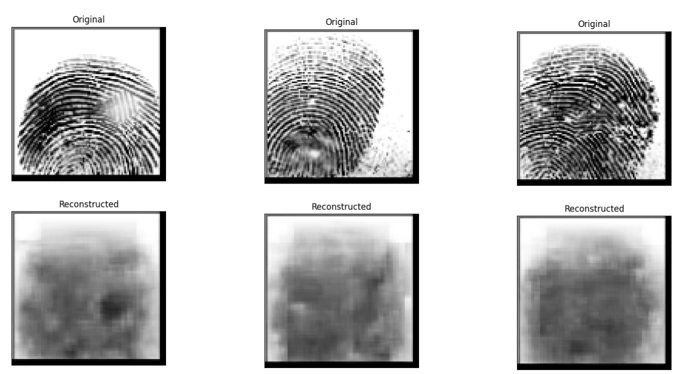

Fig. 5. Results on broad dataset

TABLE II
STRUCTURAL SIMILARITY INDEX SCORES

DATASET TYPE	**SSIM SCORE**
Specific Dataset	96%
Specific Dataset (Unfamiliar Inputs)	22%
Broad Dataset	23%

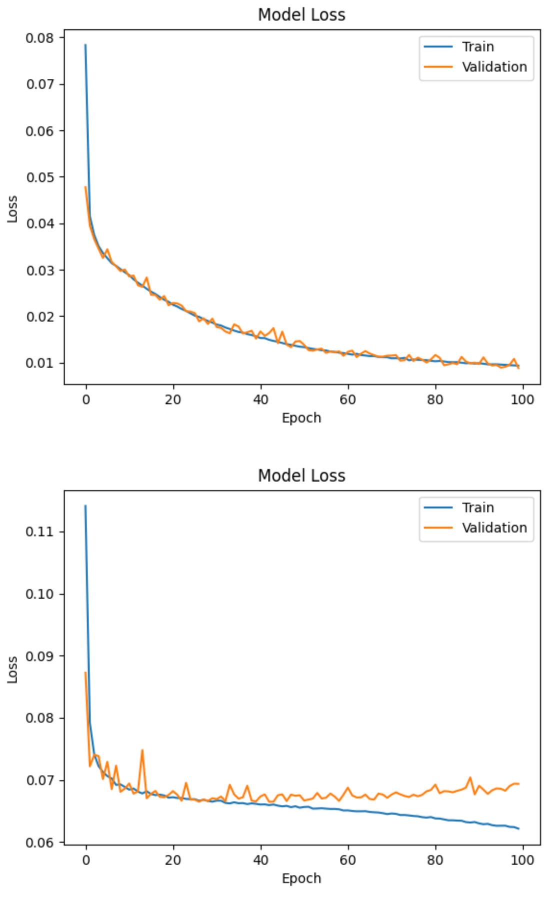

Fig. 6. Training on specific dataset (top) v.s. broad dataset (bottom)

V. Conclusions, Limitations, and Future Works

Convolutional auto-encoders show promising results within the realm of fingerprint image restoration. Their inherent capacity to intricately capture details through the encoder and subsequently reconstruct images using this encoded information positions them as a compelling solution for fingerprint restoration tasks. The model developed in this project demonstrates substantial potential, particularly when trained on meticulously curated datasets. However, the observed limitations when confronted with broader datasets hint at a crucial area for improvement: the employment of data labeling. The introduction of appropriate labels could potentially enhance the model's capacity to generalize its learning across broader fingerprint datasets.

While convolutional auto-encoders exhibit promise in controlled settings, the practicality within real-world context is restrained by the volume of training data and computational resources required. Future endeavors might focus on refining the models to operate efficiently within the practical limits of data and computational power, thus paving the way for deployment in real-world scenarios.

Being a single student-driven endeavor, the project's scope and depth to my knowledge, time constraints, and resources. My initial lack of familiarity with convolutional neural networks, the Tensorflow and Keras libraries, posed a learning curve, requiring additional time for comprehension and implementation. Difficulties arose during the setup phase with Tensorflow and Keras, delaying the actual development of the model. Training the models demanded a substantial amount of time and resources, impacting the pace of experimentations and modifications I could make to the model. My initial results were not ideal, an hour of training the model, only for the model to produce subpar results. Each iteration of the auto-encoder model meant retraining with the new parameters; this in bulk, took up a majority of the time spent on the project. Despite the setbacks and initial frustrations encountered, the experience and knowledge gained from this project are invaluable. My understanding of neural networks, image processing, and fingerprint biometrics has vastly improved.

Fig. 7. Example of subpar early auto-encoder results

References

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