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Reconstruction of Fingerprints using Convolutional Autoencoders

Saatwik Bisaria[1], Aryan Aditya Singh[2], Sarita Yadav[3]
[1, 2, 3]*Department of Information Technology, Bharati Vidyapeeth College of Engineering*, New Delhi, India

Abstract: Phones unlock instantly when a finger registered with them is placed on the sensor, but it refuses to recognize the other unregistered finger, that's where the uniqueness of fingerprints becomes practically noticeable. Fingerprints can be used to identify a single person because they are unique to each person and do not change over time. Fingerprints consist of ridges that are elevated lines and grooves that are valleys between these lines. And hence fingerprints are patterns of ridges and furrows that are different for everyone.
Ridge patterns are what is imprinted on the surface when your finger touches it.If your fingerprints are taken and printed on paper, they can be used to match fingerprints that you might have left elsewhere.
Autoencoders are special types of neural network architectures in which the output is the same as the input. An autoencoder is a regression task where the network is asked to predict its input (in other words, model the identity function). These networks have a tight bottleneck of a few neurons in the middle, forcing them to create effective representations that compress the input into a low-dimensional code that can be used by the decoder to reproduce the original input. Using Autoencoders, we can find a possible way of recreating a fingerprint image with a dataset of already provided fingerprints which can be used as a tool for forensics , biometric investigations , genetics as well as genealogy purposes.
Keywords: Autoencoders, Image Reconstruction, Fingerprints, Biometrics, Forensics

I. INTRODUCTION

Fingerprints have been in use for over a century and have become the most extensively used form of biometric identification being used. Fingerprint identification is mainly used in machine learning. It is popular because of its low price of fingerprint sensors, easy access, non-intrusive scanning, and relatively efficient and fast performance.
Fingerprints have been used in criminal investigations for centuries as a means of identification. It is one of the most important means of detecting crimes because of its robustness and uniqueness.
The fingerprint is a pattern consisting of ridges and valleys of friction on the surface of the finger. The fingerprint expert digitizes or scans the printout obtained at the crime scene to match the printout, and the machine learning algorithms of the biometric identification system locate all the unique features and elevation points of the disputed printout. These unique feature sets are then compared to a stored database of fingerprints. Accurate and reliable identification is essential to detect crime. Biometrics has emerged as an excellent scientific tool for the research processes and investigation procedures. They have the potential to tackle crime . Thanks to the prevalence of various types of crime and advances in biometrics technology, biometrics will have a greater impact on future crime detection. However, if the latest knowledge of applied mathematics, statistics, and computer science is implemented in biometric science, significant improvements in cognitive systems can be expected.
One of the most important uses of fingerprints is to help investigators connect one crime scene involving the same person with another. Fingerprint identification also helps investigators track criminal records, previous arrests and convictions, and assist with decisions, parole, probations and amnesty. Convolutional neural networks (CNNs) are a neural network that consists of multiple convolutional layers and is used to process images, classifications, and segmentation. Moving on to the autoencoder, it is a part of the Neural Network architecture where the input and output remain the same. It works by compressing the input into a latent space notation and then generating an output from that notation.
After going through both terms, comes the convolutional autoencoder. The convolutional operator filters an input system to extract a certain part of its content. Convolutional autoencoders encode inputs into a set of simple signals and reconstruct the input from them. Hence, the output is the same as input.
Security is viewed as the most important aspect in any organisation and is also a matter of grave concern for any organisation , biometric identification systems are the most dependable when it comes to validating a person’s identity. In this research paper, we are reconstructing fingerprints using convolutional autoencoders.

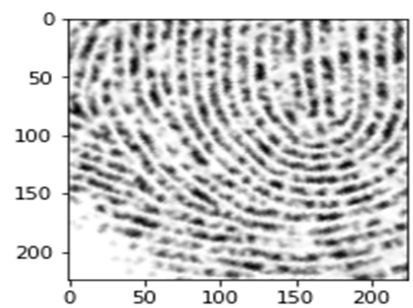
A. Dataset

FVC2000 is the First International Competition for Fingerprint Verification Algorithms. The first evaluation session was held in August 2000 and the results of the eleven participants were presented at 15th ICPR (International Conference on Pattern Recognition). This initiative is organized by D. Maio, D. Maltoni, R. Cappelli from Biometric Systems Lab (University of Bologna), J. L. Wayman from the U.S. National Biometric Test Center (San Jose State University) and A. K. Jain from the Pattern Recognition and Image Processing Laboratory of Michigan State University.

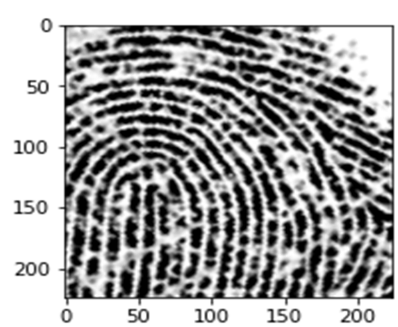
FVC2000 competition attempted to establish the first common benchmark, allowing companies and academic institutions to unambiguously compare performance and track improvements in their fingerprint recognition algorithms. Three databases were created using different state-of-the-art sensors and a fourth database was artificially generated; 11 algorithms were extensively tested on the four data sets. We believe that FVC2000 protocol, databases, and results will be useful to all practitioners in the field not only as a benchmark for improving methods, but also for enabling an unbiased evaluation of algorithms.

DB	Sensor Type	Image Size	Set A (wxd)	Set B (wd)	Resolutio n
DB1	Low-cost Optical Sensor	300x300	100x8	10x8	500 dpi
DB2	Low-cost Capacitive Sensor	256x364	100x8	10x8	500 dpi
DB3	Optical Sensor	448x478	100x8	10x8	500 dpi
DB4	Synthetic Generator	240x320	100x8	10x8	about 500 dpi

There are 800 images taken from the dataset (Fingerprint Dataset for FVC2000_DB4_B) available on kaggle which are DB4 type images. The images are resized to 224 * 224 pixels for further processing. Following are the sample images from the dataset -



(1) Sample image 1



(2) Sample image 2

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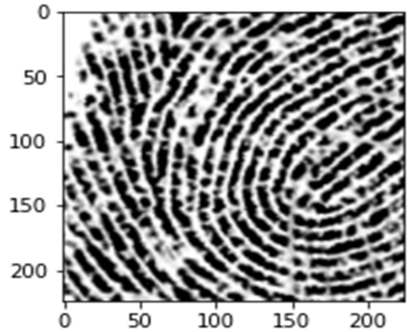


(3) Sample image

B. *Biometrics*

Biometrics are usually classified as

1) Physiological and
2) Behavioural

As far as physiological biometrics are concerned, fingerprints and DNA are considered crucial elements that cannot be copied. This is because the fingerprints or toes are unique and each individual has their own set of fingerprints. In addition, fingerprints for individuals never change from birth to death.

Physiological biometry mainly includes facial recognition, fingerprinting, hand geometry, iris recognition, and DNA. Behavioral biometry includes keystroke, signature and voice recognition.

C. *Fingerprint Analysis*

Fingerprints are the most reliable human identification factor that can be used for personal identification and which, due to their uniqueness and consistency, are widely used in biometric authentication systems. Fingerprint recognition systems play a crucial role in many situations where a person needs to be verified or identified with high certainty.

Fingerprints may look complicated in nature, but they have a pattern that can be divided into arcs, loops, or cores. Furthermore, the arch, loops, and core consist of a ridge end and a ridge bifurcation, which are known as minutiae.

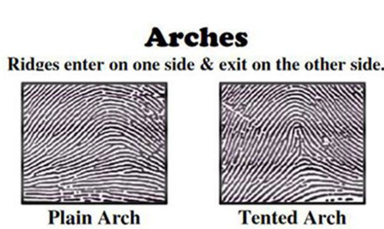
Minutiae are considered to be the most important characteristic used to compare fingerprints. It was previously known that the minutiae did not have enough information to reconstruct the original fingerprint image. However, it is now possible to carry out the reconstruction using a convolutional autoencoder neural network architecture.

D. *Distinguishing Features of Fingerprints*

The first encounter with fingerprints makes them look complicated. They are used by forensic scientists and law enforcement agencies. Fingerprints can look complicated, but it is true that they have general ridge patterns and each person's fingerprints are unique, allowing them to be systematically classified.

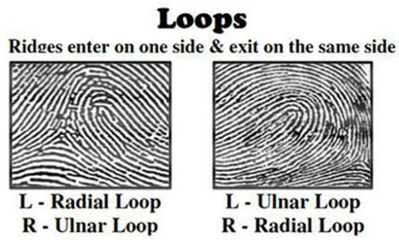
Fingerprints have three basic ridge patterns:

1) *Arches*



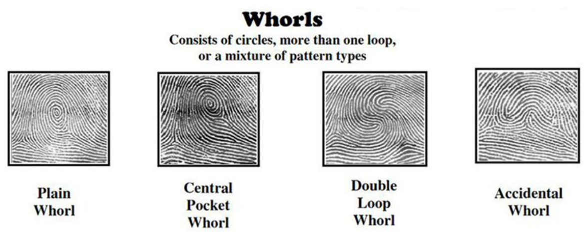
In this type of pattern, the ridges enter on one side and exit on the other side. It is estimated that 5% of the world's population have arches in their fingerprints.

2) Loops



This type of pattern has protrusions on one side and outlets on the same side. It is estimated that 60-65% of the world's population has loops in their fingerprints.

3) Whorls/Core



It consists of circles, more than one loop or mixture of patterns. It is estimated that 30-35% of the world's population has navels in their fingers.

The uniqueness of a fingerprint is exclusively determined by the local ridge characteristics and their relationships. The ridges and valleys in a fingerprint alternate, flowing in a local constant direction. The two most prominent local ridge characteristics are:

The uniqueness of the fingerprint is determined exclusively by the characteristics of the local ridge and their relationships. The ridges and valleys are in the fingerprint alternate and flow in a local constant direction. The two most important features of the local ridge are

a) Ridge ending and,

b) Ridge bifurcation.

The ridge ending is defined as the point where the ridge suddenly ends. Ridge bifurcation is defined as the point at which a ridge branches or runs onto ridge branches. Together, these functions are called ***minutiae***.

Minutiae points

The set of minutiae points is considered to be the most prominent feature of the fingerprint representation and is widely used in the comparison of fingerprints. The minutiae set was believed to not contain sufficient information to reconstruct the original fingerprint image from which the markers were extracted. Recent studies, however, have shown that it is indeed possible to reconstruct fingerprint images from their minutiae.

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II. METHODOLOGY

Autoencoder is an artificial neural network that learns how to efficiently compress and encode data then learns how to reconstruct the data back from the reduced encoded representation to a representation that is as close to the original input as possible.

This neural network model is trained to attempt to copy its input to its output. Internally, it has a hidden layer *h* that describes a code used to represent the input. The network may be viewed as consisting of two parts:

1) An encoder function that produces latent representation

$$h=f(x)$$

2) A decoder function that produces a reconstruction

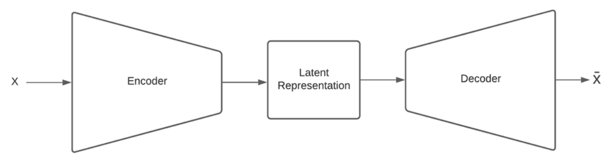
$$r=g(h).$$

If an autoencoder succeeds in simply learning to fit

$$g(f(x)) =x$$

everywhere, then it is not useful. Instead, autoencoders are designed to be unable to learn to copy perfectly. Usually they are restricted in ways that allow them to copy only approximately, and to copy only input that resembles the training data. Because the model is forced to prioritize which aspects of the input should be copied, it often learns useful properties of the data.

The general architecture of autoencoders is presented in the figure given below.



The general structure of an autoencoder, mapping an input x to an output (called reconstruction) *r* through an internal representation or code *h*. The autoencoder has two components: the encoder f (mapping x to h) and the decoder g (mapping h to r).

Autoencoders in their traditional formulations do not take into account the fact that a signal can be viewed as a sum of other signals. Convolutional Autoencoders instead use the convolution operator to take advantage of this observation. They learn to encode the input in a series of simple signals and then try to recreate the input from them.

In the general continuation case, a convolution is defined as the integral of the product of two functions (signals) after one of them has been inverted and shifted:

$$f(t)*g(t)\overset{def}{=}\int_{-\infty}^{\infty}f(\tau)g(t-\tau)d\tau$$

As a result, a convolution produces a new function (signal). The convolution is a commutative operation, therefore

$$f(t)*g(t)=g(t)*f(t)$$

In the 2D discrete space, the convolution operation is defined as:

$$O(i,j)=\sum_{v=-\infty}^{\infty}\sum_{u=-\infty}^{\infty}F(u,v)I(i-u,j-v)$$

In the image domain where the signals are finite, this formula becomes:

$$O(i,j)=\sum_{u=-2k-1}^{2k+1}\sum_{v=-2k-1}^{2k+1}F(u,v)I(i-u,j-v)$$

Where:

a) O(i,j) is the output pixel, in position (i,j)
b) 2k+1 is the side of a square, odd convolutional filter
c) F is the convolutional filter
d) I is the input image

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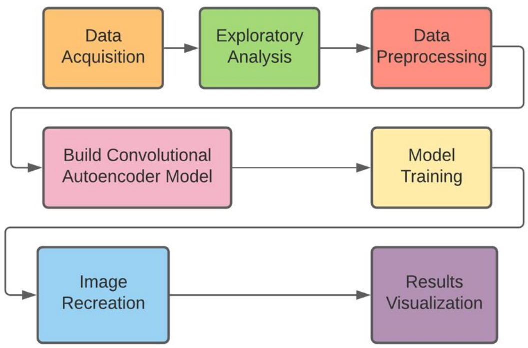
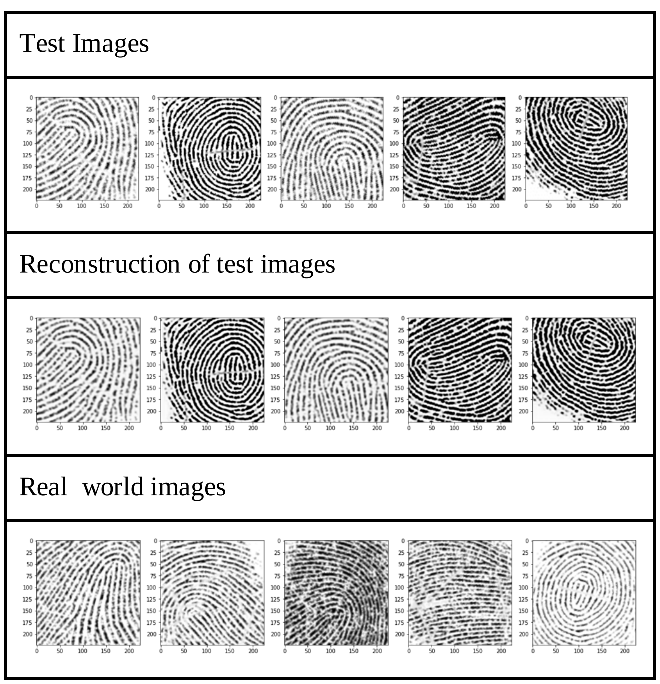
Convolutional Autoencoders approach the task of filter definition from a different perspective, instead of manually designing convolutional filters, we let the model learn the most suitable filters that minimize reconstruction error.
These filters can then be used for any other computer vision task.
Convolutional Autoencoders are the state-of-art tools for unsupervised learning of convolutional filters. Once these filters are learned, they can be applied to any input to extract features. These features can then be used to perform any task that requires a compact representation of the input.
To aid our methodology we used Keras, an open-source neural-network library written in Python. It is capable of running on top of TensorFlow. We chose Keras as it follows best practices for reducing cognitive load: it offered consistent & simple APIs, it minimizes the number of user actions required for common use cases, and it provides clear and actionable feedback upon user error.

III. IMPLEMENTATION



We import the python packages and load the dataset. We performed exploratory analysis on our dataset to obtain valuable insights on the data.
We preprocessed the images to work better with the neural networks.We changed the dimensions of image to 224 * 224. After preprocessing the data and converting it into usable form, an autoencoder model is built with an encoder input network and a decoder output network. The encoder network generates a latent representation of the input data and the decoder layer generates an output.



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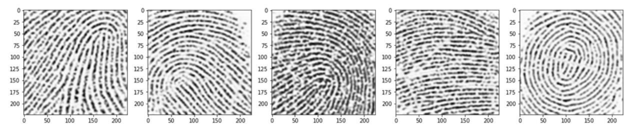
Reconstruction of real world images


Table denoting the initial fingerprint images v/s the output fingerprint images by convolutional autoencoders.

As it can be observed that our model seems to be working effectively on real world images too, which is impressive as this model can now be used to create matching or nearly-matching identical fingerprints for real world data. Thus, it is applicable to the fields of cybersecurity and forensics.

We can observe that the recreated outputs have fine and detailed information which represents the fingerprint itself and were found comparable to the original ones. Hence, we have successfully recreated fingerprints using a convolutional autoencoder model.

IV. CONCLUSION AND FUTURE WORK

In this paper we have proposed a convolutional autoencoder for fingerprint reconstruction. An autoencoder model is created with encoding and decoding layers, modeling the challenge of image reconstruction by extracting primary input image content and recovering and returning well-refined details as the output image. Experimental results show that our convolutional autoencoder model achieves great performance in the quality of reconstructed images. We finally conclude that use of convolutional autoencoders is a viable and feasible option in the reconstruction of fingerprint images.

As for the future work, preparing a larger dataset with more types of sensors would make this more effective. Also generative adversarial network (GAN's) architecture can be considered for application for this problem statement.

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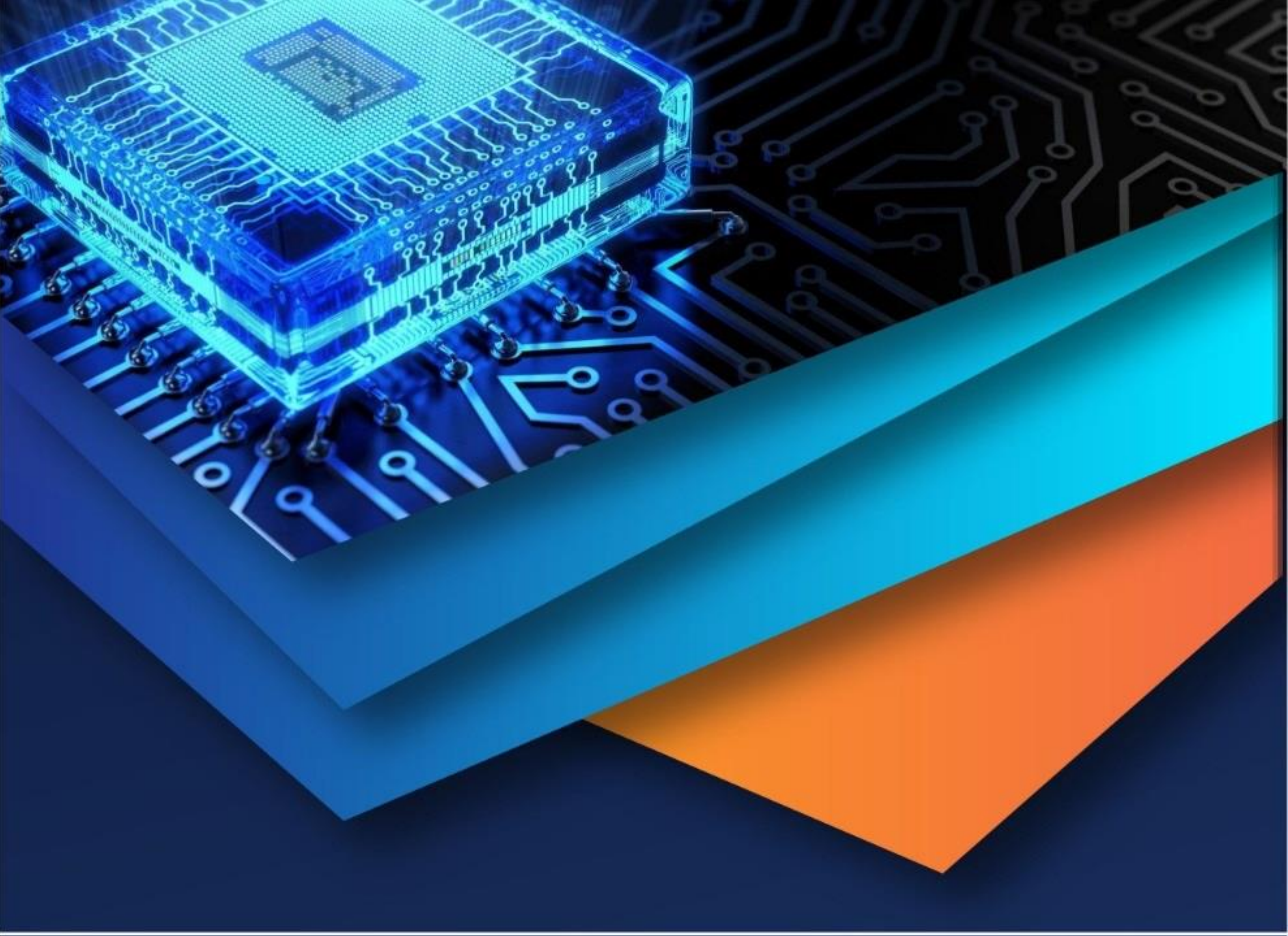

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