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Implementation of Convolutional Neural Network (CNN) Based Fingerprint Recognition and Matching System

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Abstract:
One of the well-known mysteries is that fingerprint verification isn't enough to prevent a drop in image quality. Poor picture quality, caused by spurious and missing features, has a detrimental effect on system performance. Consequently, a fingerprint identification system relies heavily on accurately assessing the quality and veracity of the captured fingerprint images. The feasibility of a polynomial-based vault for different biometric traits is investigated in this paper, which presents a biometric matching and authentication system. After passing through a Gabor filter, the feature points extracted from the biometric data are transformed into Eigen spaces. This project explains how to use the MATLAB environment to scan an input image fully using a pixel window in order to determine its edges. The method relies on CNNs, or Convolution Neural Networks. Thanks to the MATLAB Graphical User Interface (GUI), the image may be imported more simply and the final output can be viewed at different processing stages. Despite their widespread usage because to their excellent temporal performances, minutiae-based approaches aren't always up to snuff when it comes to partial fingerprints or low-quality pictures. Therefore, a fresh approach is needed to compare partial input fingerprints to previously stored templates. This study recommends classifying inputs as either partial or high quality so that different matching strategies may be used for each group. We provide a structure matching method for whole fingerprints that accounts for essential details. For partial fingerprint matching, nevertheless, a convolutional neural network ML technique is recommended, which makes advantage of correlation between ridge regions and a set of details.

Keywords: Topics discussed include forensics, fingerprint detection, the Hough transform, algorithms for matching minutiae, and the fast Fourier transform.

INTRODUCTION

A polynomial is the outcome of an equation including more than two algebraic terms, especially if those terms include different powers of the same or many variables. The foundation of the majority of fingerprint recognition systems are algorithms that conform to minute minutiae. The frequent use of minutiae based techniques is a result of their outstanding temporal performances. Having said that, they could not be used at all for partial fingerprints and don't work well with low-quality images. Therefore, a fresh approach is needed to compare partial input fingerprints to previously stored templates. The technique provided in this paper involves separating low-quality inputs from partial ones and then applying a different matching strategy for each. We provide a structure matching method for whole fingerprints that accounts for essential details. In contrast, a fuzzy logic method that associates a set of details with spaces between ridges proposes partial fingerprint matching. The phrase "biometric recognition" encompasses a wide range of methods for determining an individual's identity based on their distinct set of physiological and behavioural characteristics. Many authentication and identification applications make use of biometric traits such as fingerprints, iris scans, faces, veins, voices, handwriting, and hand shape. One of the most common biometric features is the fingerprint. In 2009, fingerprint-based

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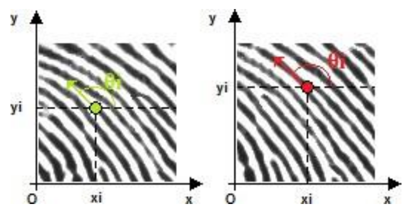
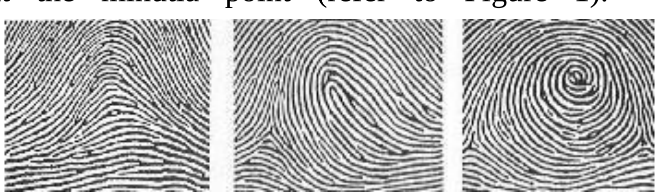
technology had a market share of around 67%, making it the undisputed leader in biometrics [1]. By 2014, the biometric industry's annual revenues will have almost doubled, according to the same report.
A fingerprint is an image of the epidermis of a fingertip that is made by rubbing the tip of the finger on a hard surface. The alternating ridges and furrows (or valleys) that make up a fingerprint make them clearly identifiable [2]. The distance between valleys and ridges is around 500 µm, while ridge widths may vary between 100 and 300 µm [3]. Ridges that would later become fingerprints begin to develop during the third or fourth month of pregnancy. A pair's chances of fingerprints being identical are 1 in 1.9 × 1015, and they are completely mature by the seventh month [4].



a)*termination* b)*bifurcation* Figure 1. Minutiae types

Although most furrows and ridges are parallel to one another, terminations and bifurcations are the two most typical types of minutiae. There are also tiny features like porosity, cores, deltas, and ridges that are either dots or islands. While terminations and bifurcations are the only types of minutiae used by the FBI's minutiae-coordinate model, these other types are legitimate as well [5]. In many cases, a minutia may be represented as a trigonometric triangle {xi, yi, θi}, where xi and yi are the coordinates of the minutia and θi is the angle between the horizontal axis and the tangent to the ridge line at the minutia point (refer to Figure 1).



arch *whorl* *loop*

Figure 2. Fingerprint typologies according to Henry System

Along with minutiae, another significant category of fingerprint characteristics is singularities, which are distinct patterns created by the ridges of the fingerprint. Still in use today for fingerprint classification, Sir Edward Henry's Henry Classification System [6] was developed in the late 1800s. Because of this, accessing information stored in the recognition system's database is a breeze. The three most prominent fingerprint types seen in Figure 2 are the arch, loop, and whorl. Tented arch, plain arch, right loop, left loop, and so on are all subclasses of these typologies.

A fingerprint recognition application's main phases are as follows: acquiring the fingerprint, pre-processing the picture, extracting features, classifying the fingerprint, and finally, matching the fingerprints.

At each stage of fingerprint identification, there are several ways and technologies to choose from. During fingerprint matching, an input fingerprint is compared to templates—pre-processed fingerprints—stored in a database.

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If you believe [7], there are essentially three ways fingerprints may be matched: (i) by correlation, (ii) by minutiae, and (iii) by ridge features. Reference [8] states that the fingerprint recognition approaches can be grouped into five categories: (i) based on singular points, (ii) structure-based, (iii) frequency-based, (iv) syntactic or grammar-based, and (v) based on mathematical frameworks. Many acceptable algorithms can match whole fingerprints with high quality. Partial or low-quality samples are more challenging to match.

Fingerprint images could be affected by variables such as significant rotationand/or displacement, non-linear distortion (which occurs when a two-dimensional image is used to represent a three-dimensional structure), fluctuating pressure, skin condition, and feature extraction errors [2]. Due to excellent temporal performance, minutiae based recognition systems are often used in commercial fingerprint identification applications. However, these methods are not ideal for partial fingerprints and do not work well with low-quality inputs [9]. The disappearance of core and delta singularities makes singularity-based recognition and indexing methods impractical [10]. Poor quality fingerprints may provide varied results when processed using various fingerprint identification methods. Fingerprint recognition systems may be categorised as either positive or negative. Positive recognition systems, similar to physical access control systems, operate on the assumption that end-users are cooperative and want to be acknowledged. When we look into a malicious system and see that a user (in this case, a thief) is on a watch list or has registered under many identities, we assume that they are not being helpful and are attempting to evade discovery. A positive recognition system has problems with low quality points since they lead to the wrong rejection of reasonable persons. However, low quality for a negative identification system has far-reaching consequences, as criminals may intentionally reduce fingerprint quality to fool the system into thinking it doesn't recognise their true identity. So that nasty people can't game the fingerprint system, negative fingerprint identification systems need to be able to detect low-quality fingerprints and make them even better. Both photometric and geometrical degradations may occur in fingerprint quality. Unclean sensor surfaces, imperfect skin, and complicated picture backgrounds may all lead to photometric deterioration (in latent fingerprints). Geometrical deterioration is mainly.

I. LITERATURE REVIEW

The primary goal of edge detection is to locate the image pixels that correspond to the edges of the objects recognised in the image. The standard method for determining whether a pixel is an edge component involves taking its first and second derivatives and comparing them to a predetermined threshold. The final result is a binary image that only comprises the edge pixels that were detected. We can document major events and changes in the world's qualities by detecting abrupt changes in image brightness. When a picture's brightness varies, it's likely due to changes in the material's properties, the scene's lighting, the surface's orientation, or the depth of field. Shashank Mathur and Anil Ahlawat created a fuzzy relative pixel value technique for edge identification by using a series of fuzzy criteria to compare pixel values with nearby pixels. This allowed them to examine the pixel magnitude gradient in the window. For picture scanning, the method employs the windowing approach with a 3*3 pixels mask. However, a rule-based strategy was not used [11].Yinghua Li, Bingqi Liu, and Bin Zhou, three researchers from China's Ordnance Engineering College, characterised fuzzy technology as a new development with possible uses in several fields.

the domain of visuals, with fuzzy boosting serving as an integral part of fuzzy technology. Edge detection using Sobel differential arithmetic was the last step in this process, which began with establishing the fuzzy characteristic plane of the original picture [12]. Fuzzy augmentation came next. Yasar Becerikli1 and Tayfun of Turkey's Kocaeli University's Computer Engineering Department in Izmit state

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that edge detection is an area of great importance in the realm of image processing. Edge detection is the cornerstone of image segmentation, registration, and identification, as per their study. Their approach states that when it comes to the final image's edge thickness, a fuzzy rules-based solution provides greater flexibility [13]. Christ Jesus Jacques Miosso and Adolfo Bauchspiess demonstrated that first-order linear filters are the methods often employed for edge identification in digital pictures. Most natural photographs taken in less-than-ideal lighting circumstances have wildly varying contrast levels, and these filters fail to provide acceptable results when applied to such images [14]. A lookup table and an edge magnitude and direction approach were presented by In-So Kweon, Wang-Heon Lee, and Dong-Su Kim of South Korea's Department of Electrical Engineering and Computer Science using 3x3 perfect binary pixel patterns. They reasoned that there was no need to alter human online thresholds since their algorithm was more adaptable to the dynamic environment [5]. Using fuzzy logic concepts, this work focuses on constructing an algorithm for picture edge recognition. The most basic scanning mask that could be employed was a 2*2 pixel window. Fuzzy inference in MATLAB environment system has been As seen in Figure 1. As an example, our group is demonstrating three separate fingerprints of the same finger. Normal fingerprints are on the left, while severely distorted fingerprints are on the right. Based on the VeriFinger 6.2 SDK, the left two have a much higher match score than the right two. The distortion, rather than the overlapping region, is to blame for this colossal difference. You can see that the overlapping area is the same in both situations since the rectangles are green and red. Figure 3 shows normal fingerprints on the left and the most severely distorted one on the right.

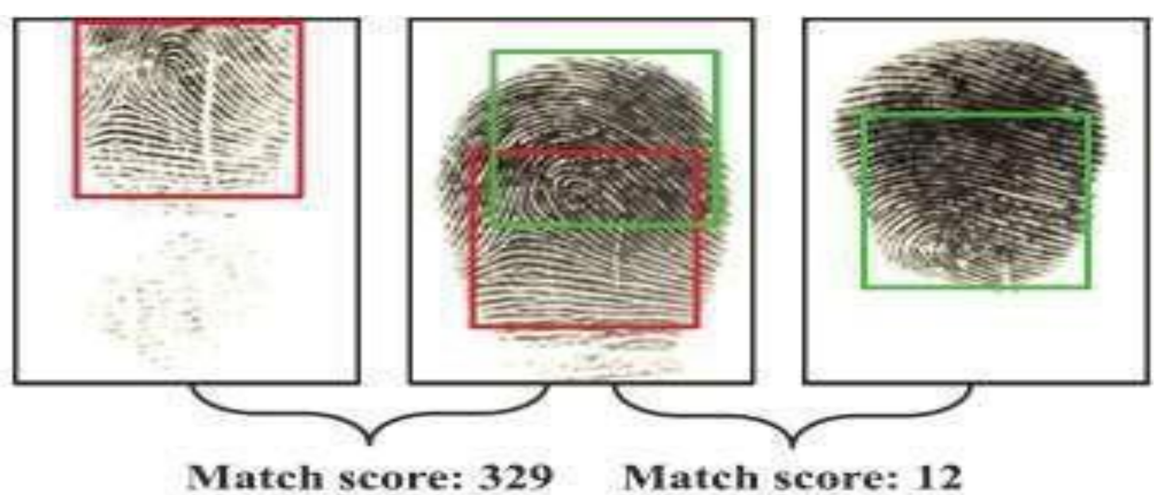

Fig 3: Three impressions of the same finger.

Disadvantages of the Existed Techniques

- Consuming More Time due to too many surveys.
- Less Accuracy.
- Privacy Issues.
- Classification issue.

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II.

III. PROPOSED METHODOLOGY

The primary goal of the research is to uncover the possibility that the distorted fingerprint is created by subjecting the normal fingerprint to an unidentified distortion field d. For over a hundred years, latent fingerprints discovered at crime scenes have been a crucial signal for forensic detection. However, there have been instances when inaccurate latent fingerprint identification led to false convictions. To properly match contactless 2D fingerprints with their matching contact-based fingerprints, this study provides a novel CNN-based architecture. When it comes to biometric identification systems, fingerprint scanning has been around the longest, has the most sophisticated technology, and the most users. Particularly distinctive to each fingerprint are the features, including ridge bifurcation and ridge ending. Picture capture, feature extraction, and matching are only a few of the many elements that go into an AFIS's mind. Latent fingerprints, which are often seen at crime scenes and usually have indistinct ridges and insufficient finger regions, are notoriously difficult for traditional algorithms to interpret. We will provide a CNN-based fine-tuning matching algorithm in the method for obtaining accurate matching values. The fingerprint's bifurcation and tip are its finer features. To create a minutia-score map with a fixed stride from raw fingerprints, a fully convolutional network (FCN) may be used. You may utilise the minutia-score map to make suggestions down to the pixel level, up to a certain point. The next step is to train a convolutional neural network (CNN) to classify the ideas and evaluate their qualities. Furthermore, by visualising our trained model, we can see that we have successfully extracted features while preserving accuracy. fingerprint's hidden ridges and valleys. The design of our network is seen in Figure 5. Without using exhaustive search, the suggested CNN-based minutiae algorithm may discover the correspondences between the input pattern of minutiae and the stored pattern of template minutiae. The proposed system is tested using Fast Fourier Transform and Hough Transform.

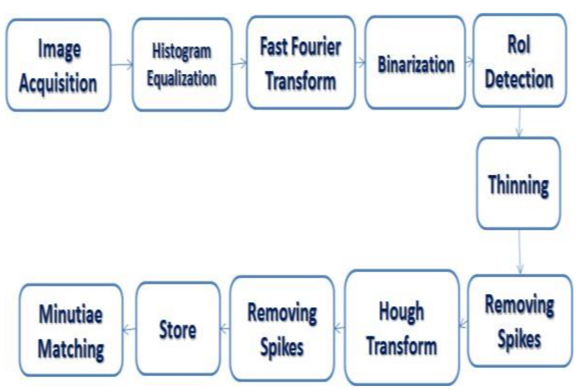

Figure 4: The Proposed Simulation Procedure in MATLAB.

3.1 The Matching Procedure

Feature Extraction is an important step in fingerprint-based recognition systems. In this paper, a CNN Fingerprint Feature Extraction Algorithm is presented. It is applied to latent fingerprints which have been previously obtained from real gray-scale, noisy fingerprints in the Image-Preprocessing stage, also by using CNNs.

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3.3 CNN Based Fingerprint Matching Algorithm

Basically the finger print matching process has four fundamental steps

1. Fingerprint Reading,

2. Image Preprocessing,
- *Enhancement*
- *Binarization*
- *Segmentation*

3. Feature Extraction.
- Thinning
- Minutiae Marking/Edge Detection & Direction

4. Post- Preprocessing
- Remove Spurious Spikes

After the Feature- Extraction stage, a set of representative features of the enrollee fingerprint (the minutia template) is stored in the database. During the recognition mode, a fingerprint to be recognized undergoes the same three processing steps as in the enrollment mode. The result, *a test minutia template*, is compared with a minutia template from the database in the *Feature-Matching* stage. A match score which measures the degree of the similarity between the two

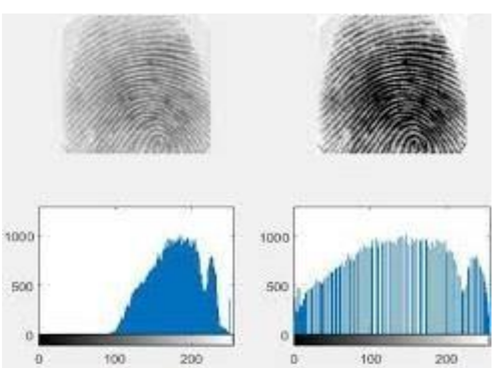

Figure 5: Histogram Equalization.

minutia templates is calculated. Higher values indicate higher confidence in a match. In short, the main problem in fingerprint recognition is to decide how similar two fingerprints, i.e., their minutia templates, are.

3.4 Fingerprint Image Enhancement

Fingerprint Image enhancement is to make the image clearer for easy further operations. Since the fingerprint images acquired fromsensors or other medias are not assured with perfect quality, those enhancement methods, for increasing the contrast between ridges and for rows and for connecting the false broken points of ridges due to insufficient amount of ink, are very useful for keep a higher accuracy to fingerprint recognition. In this Project the Image Enhancement is done by using FFT.

3.4.1 Histogram Equalization

Histogram equalization is to expand the pixel value distribution of an image so as to increase the perception information. The original histogram of a fingerprint image has the bimodal type, the histogram after the histogram equalization occupies all the range from 0 to 255 and the visualization effect is enhanced.

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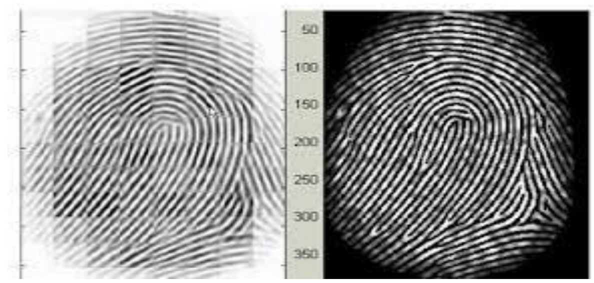
3.4.2 FFT

A Fast Fourier transform (FFT) is an algorithm that computes the discrete Fourier transform (DFT) of a sequence, or its inverse (IDFT). Fourier analysis converts a signal from its original domain (often time or space) to a representation in the frequency domain and vice versa. The FFT is a complicated algorithm, and its details are usually left tothose that specialize in such things. In this project FFT is used for Image Enhancement.

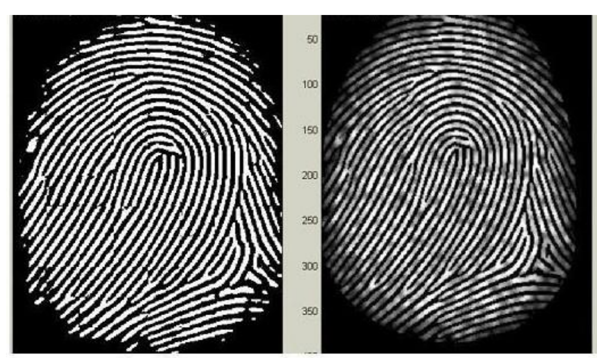


(a) (b)

Figure 6: Image Enhancement by FFT (a). Distorted Finger Print Image, (b). After applying of FFT.

3.4.3 Finger Print Binarization

Fingerprint Image Binarization is to transform the 8-bit Gray fingerprint image to a 1-bit image with 0-value for ridges and 1-value for furrows. After the operation, ridges in the fingerprint are highlighted with black color while furrows are white. A locally adaptive binarization method is performed to binarize the fingerprint image. Such a named method comes from the mechanism of transforming a pixel value to 1 if the value is larger than the mean intensity value of the current block to which the pixel belongs shown in figure 7.



Finger 7: Image Binarization.

3.6 Fingerprint Image Segmentation

In general, only a Region of Interest (ROI) is useful to be recognized for each fingerprint image.

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Figure 8: RoI of Finger Print Image after Segmentation.

The image area without effective ridges and furrows is first discarded since it only holds background information. Then the bound of the remaining effective area is sketched out since the minutia in the bound region is confusing with those spurious minutia's that are generated when the ridges are out of the sensor.

3.5 Finger print Feature Extraction

The goal of the Feature-Extraction unit is to extract distinguishable features in fingerprints, as well as their attributes, in order to guarantee the Feature Matching. There are two main features in a fingerprint image: Thinning and Edge Detection, as shown in Fig.9 & 10. In a latent fingerprint, an ending is the end point of a line, while a bifurcation is the junction point of lines using Hough Transform.

Figure 9: Image Thinning.

For matching purposes, these so-called "minutiae" are usually denoted by their type, their location, and the direction of the adjacent ridge. Due to noisy original images and artifacts produced in the Image-Preprocessing stage, spurious minutiae will always be present. Therefore, after the minutiae are

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extracted, an important step, minutia reduction, is performed to eliminate the false minutiae in the Feature- Extraction stage. The spurious minutiae are normally eliminated by using empirically determined thresholds.

3.5.1 Minutiae Marking/Edge Detection

The next step in our algorithm is the alignment of the query fingerprint image with the template fingerprint image. The rigid transformation parameters (rotation, translation, and scale) are estimated by using the generalized Hough transform. The Hough transform is a feature extraction technique used in image analysis, computer vision, and digital image processing.

Figure 10: Edge Detection using Hough Transform.

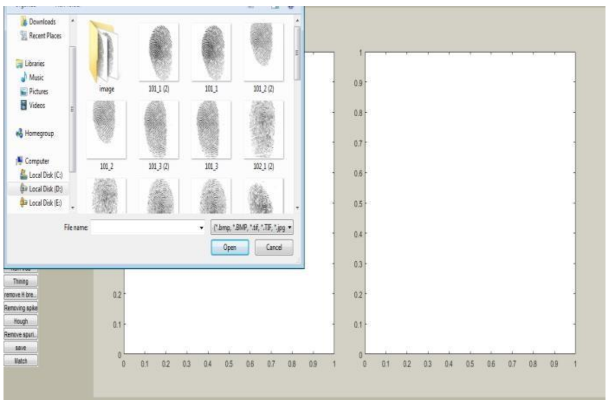

Figure 11: Image Acquisition.

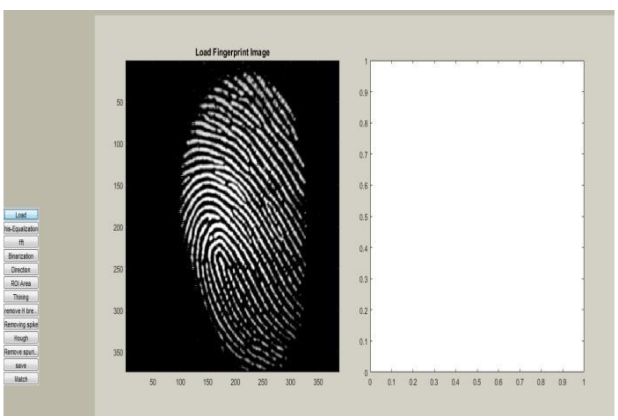

Figure 12: Loaded Input Image.

Figure 13: Image Enhancement by Histogram Equalization.

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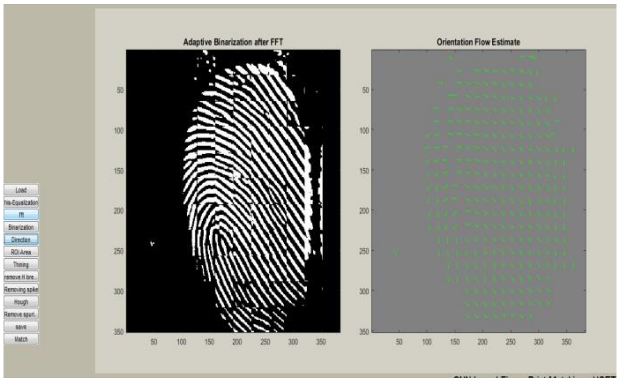

Figure 14: Orientation Flow Estimate.

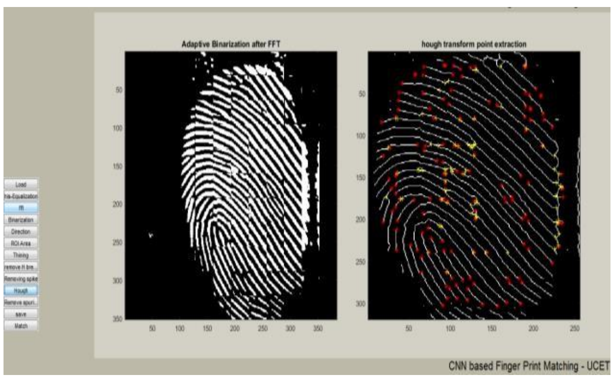

Figure 15: Hough Transform Point Extraction.

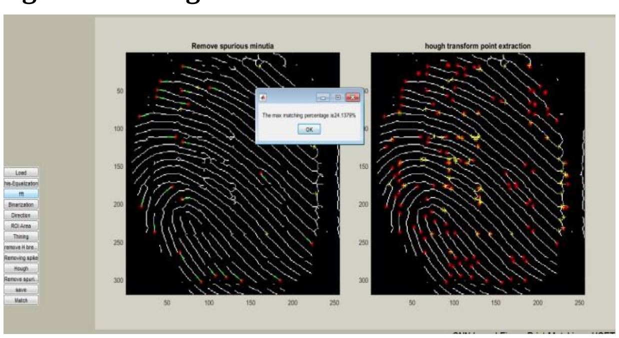

Figure 16: Final Minutiae Finger Prints Matching Percentage.

Using a voting system, the method seeks for flawed objects belonging to a certain class of shapes. Used for post-Edge Detection processing. It is a method for extracting an image's curves from a certain form or shapes. Straight lines, circles, parabolas, ellipses, and other regular curves may be found using the Classical Hough Transform.

IV. CONCLUSION & FUTURESCOPE

In this article, we provide a Minutiae Matching method that accomplishes the ML (CNN) Feature-Extraction stage of fingerprint recognition. With the help of this method, it is almost always able to identify the correct bifurcations, endings, and direction attributes, while eliminating the incorrect ones that may have been introduced by the original noise fingerprint or by previous processing stages. When utilising fingerprint matchers, the false non-match frequency is rather significant for fingerprints with extremely distorted fingerprints. Because of this, criminals and terrorists will be able to take advantage of a hole in automatic fingerprint recognition systems. To address this issue, it is necessary to develop reformation algorithms and implement fingerprint distortion inspection. The project showcases a new distorted picture. A new approach to matching latent to plain or rolled fingerprints may be developed by using the Fast Fourier Transform and the Hough Transform independently. When compared to FFT, the findings show that Minutiae is the superior matching method.

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