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Original Article

Detection of Gender Using Digital Forensic

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Abstract - *A fingerprint is defined as a pattern present in between the tips and joints of a finger. Fingerprint stays the same from the day of a person's birth to the day they die. Fingerprints are found near crime sites, on weapons, in excavated things etc. Gender can be estimated on the basis of features like ridge density patterns, some unique characters present in fingerprint and with the help of fingerprint patterns like loops, whorls, arches. Unknown fingerprint's Gender can be recognized. In the proposed system, different algorithms like Pre-processing, Image binarization, Thinning are used for feature extraction. This study proposes a trained model using an image classifier of a fingerprint instead of traditional analysis. Our proposed system aims to determine Gender using fingerprints. For an unknown fingerprint, different minutiae feature that is extracted basis on this decision can be taken whether it is male or female.*

Keywords - *CNN Classifier, Dactylography, Digital Forensic, Fingerprints, Image Processing, Minutiae Features.*

I. INTRODUCTION

Forensic as an adjective relates to a court of Law. The word "Forensic" denotes techniques for the investigation of crime. Forensic when combined with Science, i.e. to processes to solve the crimes. Another term, "Digital Forensic", is defined as the method of identification of Computer Evidence that can be used by the court of Law. It is the way of finding evidence in digital media like hard drives, floppy disks, pen drives. In the proposed system, we have used fingerprints as unknown evidence in digital form. In this study, we established an association between fingerprints and Gender. It has been said that every human has a different fingerprint, as there are some unique features present in it. These unique features are ridge density, bifurcation, core, delta, island, pore, ridge ending. Fingerprint patterns are classified into loops, whorls, arches. This classification was given by Sir Edward Henry. This method of classification is used for providing records of each criminal.

Types of Fingerprint Patterns:

A. Loops

In loops, some of the ridges make a backwards turn, but without a twist. There is one delta. There must be at least one ridge count between the inner and outer terminus.[1]

B. Whorls

In whorls, some of the ridges make a turn through at least one complete circuit. There are two deltas, one on the left and the other on the right.[1]

C. Arches

This pattern can be of two types: [1]

a) ***Plain Arch:*** In this pattern, the ridges run from one side to the other, making no backward turn. There is usually no delta. But when delta appears, no ridge must intervene between the inner terminus and outer terminus.[1]

b) ***Tented Arch***: In this pattern, the ridges near the middle may have an upward thrust, arranging themselves as they were on both sides of an axis towards which adjoining ridges converge.[1]

Minutiae features are:

- ***Ridges***: Thin lines present on the surface of a finger.
- ***Bifurcation:*** Those ridges that form branches.
- ***Core:*** The centre from where ridges flow.
- ***Delta:*** The ridges that form Y-endings.

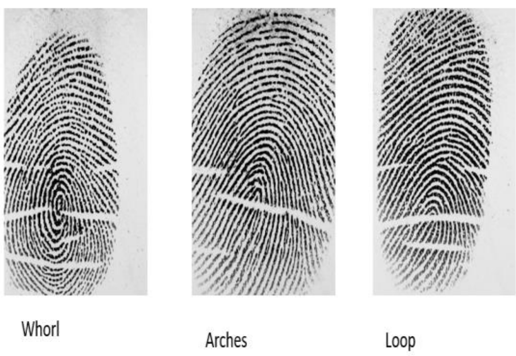


Fig. 1(a) Types of fingerprint patterns

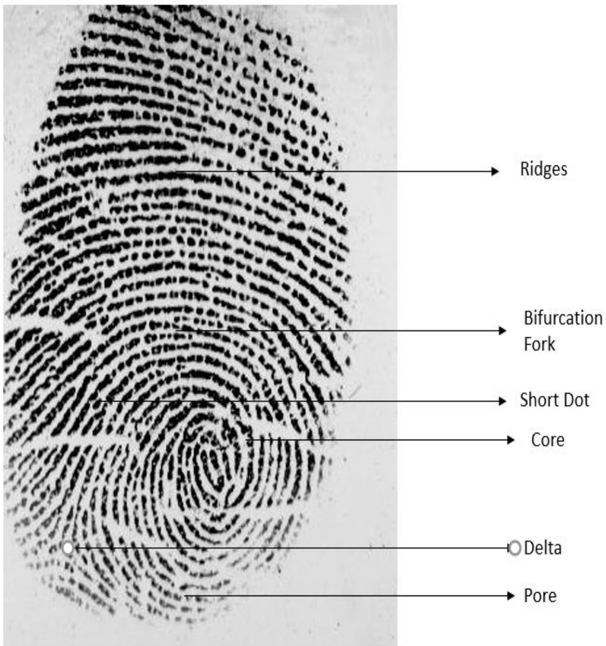


Fig. 2(b) Minutiae features

II. PROBLEM STATEMENT

According to S. S. Gornale, Basavanna M, Kruthi R (2015), "In crime complication court of law has accepted fingerprints verification is most believable and trustworthy proof for gender classification"[2]. Some difficulties in recognising the fingerprint deformities in ridge patterns due to cuts, dirt or even tear and wear. In the existing system, Fingerprints were obtained using a rolled method which was one of the most complicated tasks in acquiring high-quality images with distinct fingerprint ridges and minutiae. Early detection of the crime is a challenge in crime investigation. Repeatedly, fingerprints are the only evidence left at the crime scene for identification of the crime. The present study determines to identify Gender using digital technology like Image processing and Artificial Neural Networks. Thus, this study improves the accuracy and reality of fingerprints in crime investigation.

A. Objectives

- To Study Fingerprint Patterns.
- To study Minutiae Features for recognition of Gender.
- To implement different algorithms like Pre-processing, Image binarization, Thinning, Feature Extraction, Minutiae Matching.
- To train the model using Convolutional Neural Networks.
- To detect Gender using fingerprint

III. LITERATURE SURVEY

The methods used for identification of Gender a correlation between fingerprint patterns and blood group were manual. The methods used were ink method, rolled method, test tube method etc. The major problem in this was that they were not digitally sound. Our crime investigation says that our forensic department should be updated. Using this traditional method, unable to get accurate results. The following will highlight the literature review: According to Sandeep V. Binorkar1 Anand B. Kulkarni [3], this study was conducted with an intention to establish the relationship between the fingerprints and Gender of an individual. Fingerprints were obtained using the rolled method. According to Chandrakant P. Divate [4], this paper presents a brief review of the advanced research techniques in the area of gender classification. They have focused on a study of different biometrics of a person, which can be utilized for classifying a person as male or female and have presented a definite review of the present works. According to S. S. Gornale[2], in this work, minutia features are extracted for gender classification. Considering the minutiae details like intersecting points, ridge counts, number of blobs, terminating points and ridge counts. In general, this work is found to be acceptable and spirited results were observed, which are helpful and practically applicable in forensic anthropology. According to Nithin Mathew Sam [5], a study of fingerprints as a method of identification is known as Dactylography, or Dactyloscopy Dactylography is a progressing Science and new methods for the recording, lifting and developing of prints under different field conditions, including those from the decomposed body, are being introduced regularly. Identification using fingerprints is absolute and infallible. Since the turn of the century, fingerprints have been used as a very effective means of establishing the identity of the individual. The study of fingerprints as a method of identification is known as Dactylography. The present study was conducted on 100 males and 100 females of the South Indian Population aged between 18 and 81 years. Rolled fingerprints were obtained using pre-inked strips, and their patterns were identified. Each type of fingerprint pattern and its subtypes were identified and analysed for gender differences. According to P. Gnanasivam and R. Vijayarajan[6], a novel method of OSA technique was proposed for gender classification using the ridge count and fingertip size. Performance evaluation was done with the methods tested and the earlier methods by other researchers. For the proposed method, the spatial parameters, ridge count and fingertip size, and the OSA method were used for gender classification. An extensive analysis of both parameters was done, and it was found that all the values obtained were greater for males than females. An algorithm for assigning a score for each value of the parameters was discussed. This method produced a success rate of 88.41%, and 90.11% was achieved for the right-hand ring finger. A comparative performance evaluation was carried out with the other methods tested by the present researchers. Thus, the proposed method achieves better results than all the methods discussed. According to Suman Sahu, A. Prabhakar Rao and Saurabh Tarun Mishra [7], In this paper, the Gender through Fingerprints have been determined by using the Adaptive Neuro-Fuzzy Inference System (ANFIS) method. Fingerprints verification is one of the most reliable personal identification methods, and it plays a very important role in forensic applications like criminal investigation. Fingerprints have been used as a biometric for gender identification because of their unique nature and do not change throughout the life of an individual. To classify a given fingerprint image as male or female, we extracted the most significant features such as RV A and Frequency Domain Analysis (Frequency-based features such as Horizontal, vertical, diagonal & amplitude). These features were then used to train the ANFIS classifier. The experimental results showed that the proposed system could be used as a prime candidate in forensic anthropology with higher accuracy than NN and Fuzzy individually. According to Sudharshan Duth P Megha P Mirashi[8], Fingerprint contains ridge and valley, which together form distinctive patterns. A fingerprint Biometric trait is one of the important trait working with good results in gender classification. The plan agreements with the problem of gender classification using fingerprint images. The project proposed a technique for classifying Gender based on feature extraction. The related feature to be removed and differentiate the Gender is Gabor filters Minutiae extraction and ROI. The extracted feature is used to train an artificial neural network based on the extracted data.

IV. SYSTEM METHODOLOGY

A. Minutiae Extraction

a) ***Preprocessing***

Pre-processing is one of the main steps in any image processing task. In this post, we need to get the foreground region and remove the background (because it does not contain information). Histogram Equalization is used for pre-processing.

b) Image Binarization

Image Binarization is for thresholding. The Otsu thresholding will automatically choose the best generic threshold for the image to obtain a good contrast between foreground and background information. This is because the image contains a bimodal distribution (which means that we have an image with a 2-peak histogram) of pixel values.

c) Thinning

Once we have a binary image, we are actually already set to go to calculate our feature points and feature point descriptors. However, in order to improve the process a bit more, we suggest to skeletize the image.

d) Minutiae Marking

When we got this skeleton image, the following step would be to look for crossing points on the ridges of the fingerprint, which are being then called minutiae points. We can do this by a key point detector that looks at a large change in local contrast, like the Harris corner detector. Since the Harris corner detector is both able to detect strong corners and edges, this is ideally for the fingerprint problem, where the most important minutiae are short edges and bifurcation, the positions where edges come together.

e) FAST Algorithm for Corner Detection

FAST is an algorithm proposed originally by Rosten and Drummond for identifying interest points in an image. An interesting point in an image is a pixel that has a well-defined position and can be robustly detected. Interest points have high local information content, and they should be ideally repeatable between different images. Interest point detection has applications in image matching, object recognition, tracking etc. The idea of interest point detection or corner detection (both are interchangeably used in literature) is not new.

B. Algorithm for Feature Matching

a) Brute Force Matcher

Brute-Force matcher is simple. It takes the descriptor of one feature in the first set and is matched with all other features in the second set using some distance calculation

C. Block Diagram

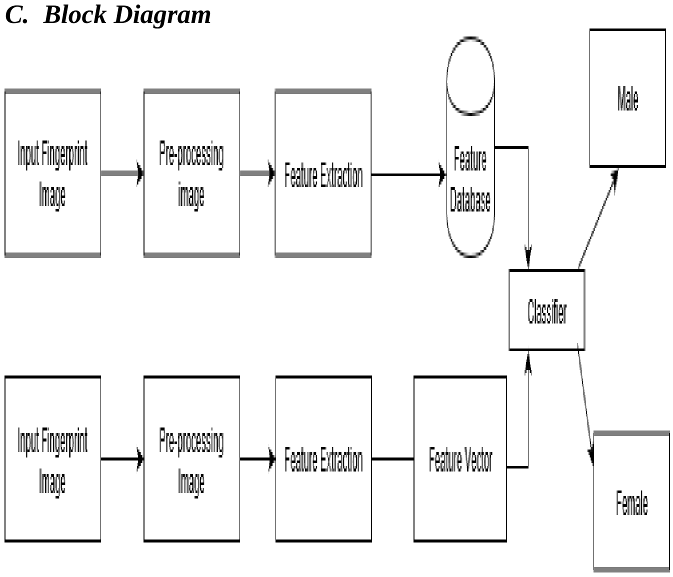


Fig. 1 System architecture

D. CNN Classifier

In an end-to-end manner, it is shown that each step in the pipeline presented by them is aimed at making the generated salient map more accurate than the ground lives data. Convolutional neural network (Ann) is a kind of depth machine learning method derived from an artificial neural network (Ann), which has achieved great success in the field of image recognition in recent years. The training algorithm of a neural network is based on the error backpropagation algorithm (BP), which is based on the decrease of precision. However, with the increase of the number of neural network layers, the number of weight parameters will increase sharply, which leads to the slow convergence speed of the BP algorithm. The training time is too long. However, the CNN training algorithm is a variant of the BP algorithm. By means of local connection and weight sharing, the network structure is more similar to the biological neural network, which not only keeps the deep structure of the network but also greatly reduces the network parameters so that the model has good generalization energy and is easier to train. This advantage is more obvious when the network input is a multi-dimensional image so that the image can be directly used as the network input, avoiding the complex feature extraction and data reconstruction process in a traditional recognition algorithm. Therefore, convolutional neural networks can also be interpreted as a multilayer perceptron designed to recognize two-dimensional shapes, which are highly invariant to translation, scaling, tilting, or other forms of deformation[9-15].

V. EXPECTED RESULTS

Based on the proposed system, we have done a CHI-Square analysis to get the expected results manually. After getting proper confirmation about the difference between male and female fingerprints, further, we have used CNN Classifier to train the model and obtain the accuracy.

A. *Chi-Square Analysis(χ2-Test)*

The Chi-square test is intended to test how likely it is that an observed distribution is due to chance. It is also called a "goodness of fit" statistic because it measures how well the observed distribution of data fits with the distribution that is expected. A Chi-square test is designed to analyze categorical data. The estimated result identifies males or females based on the fingerprint patterns. With the count of 200 males and 200 females, Chi-Square Analysis is performed as follows:

- ***Null hypothesis H0***: Null Hypothesis rejected (Loops are not found in males and whorl are not found in females) There is no association between the gender and fingerprint pattern

- ***Alternative hypothesis H1***: Null Hypothesis accepted (Loops are found in males and whorl are found in females) There is an association between the Gender and fingerprint pattern.
- Observed Value: [[38, 16, 36], [27, 28, 43]] Degree of freedom =2
- Expected Value:[[31.11 ,21.06,37.81] [33.88, 22.93, 41.18]]
- Probability=0.950, critical=5.991, stat=5.424
- Significance=0.050, p=0.066
- Hence Concluded: “Null Hypothesis accepted (Loops are found in males and whorl are found in female). There is an association between the Gender and fingerprint pattern.”

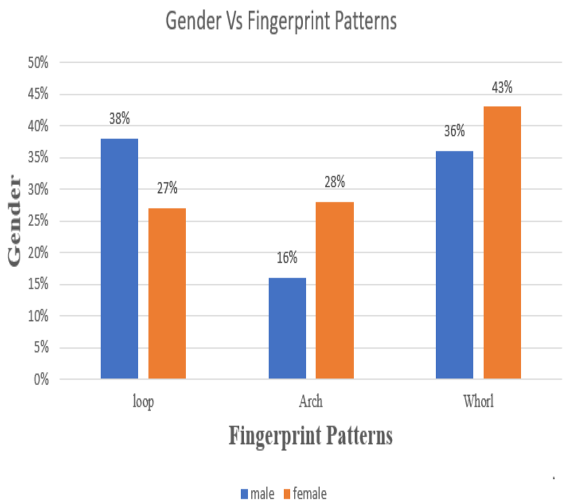


Fig. 2 Identification of gender-based on fingerprint patterns

After applying Opencv Algorithms on fingerprint images, we get Minutiae Features in the below figures.

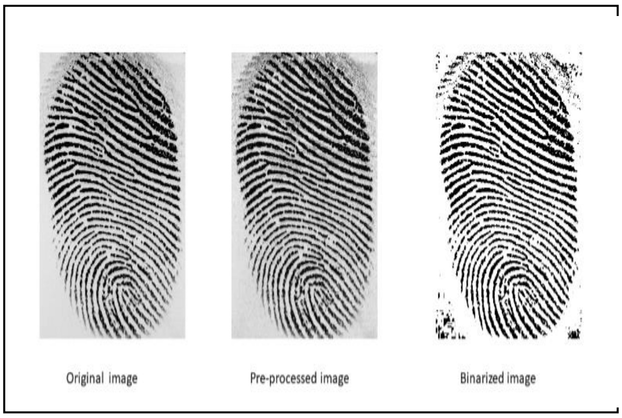


Fig. 3 Original image, pre-processed image, binarized image

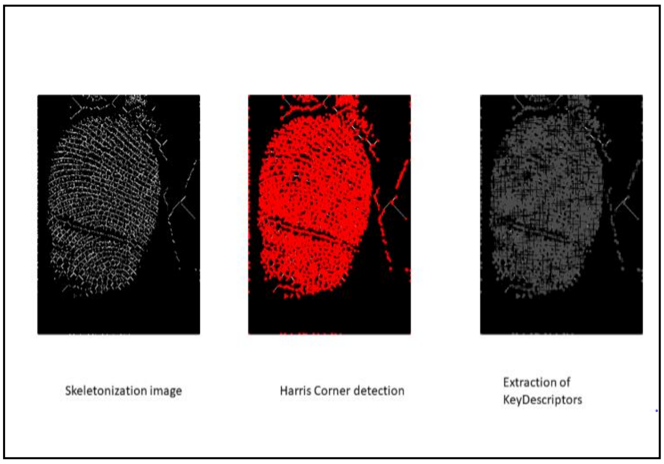
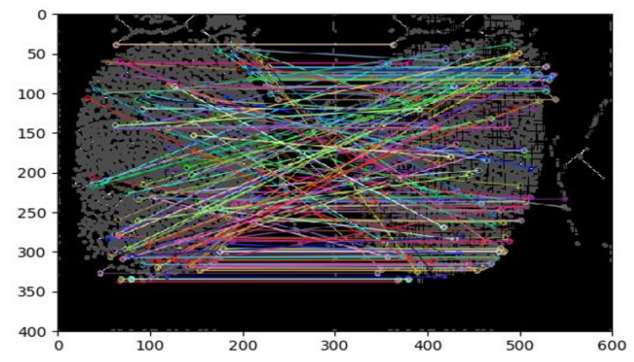


Fig. 4 Thinning image, key features extracted image



Fingerprint Matching

B. Results Using CNN Classifier

A CNN consists of an input layer, an output layer, as well as multiple 3 hidden layers. The hidden layers of a CNN typically consist of convolutional layers, pooling layers, fully connected layers and normalisation layers (ReLU). Additional layers can be used for more complex models.

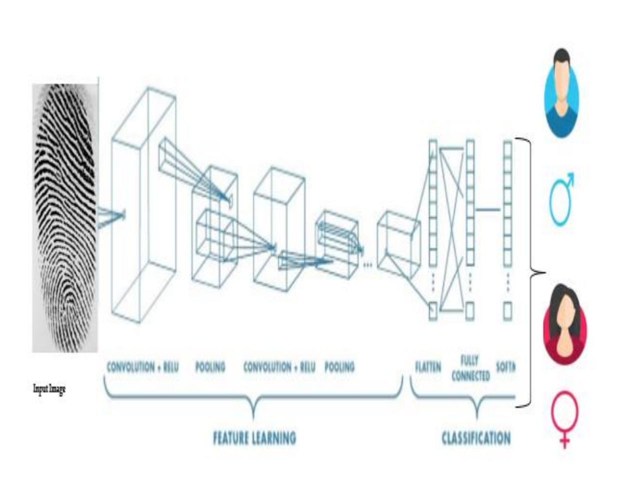


Fig. 6 Typical CNN architecture [15]

This CNN model is used extensively in modern Machine Learning applications due to its ongoing record-breaking effectiveness. Linear algebra is the basis for how these CNNs work. Matrix vector multiplication is at the heart of how data and weights are represented [13]. Each of the layers contains a different set of characteristics for an image set. For instance, if a face image is input into a CNN, the network will learn some basic characteristics such as edges, bright spots, dark spots, shapes etc., in its initial layers. The next set of layers will consist of shapes and objects relating to the image, which are recognizable such as eyes, nose and mouth. The subsequent layer consists of aspects that look like actual faces, in other words, shapes and objects, which the network can use to define a human face. CNN matches parts rather than the whole image, therefore breaking the image classification process down into smaller parts (features). A 3x3 grid is defined to represent the features extraction by the CNN for evaluation. The following process, known as filtering, involves lining the feature with the image patch. One by one, each pixel is multiplied by the corresponding feature pixel, and once completed, all the values are summed and divided by the total number of pixels in the feature space. The final value for the feature is then placed into the feature patch. This process is repeated for the remaining feature patches followed by trying every possible match-repeated application of this filter, which is known as a convolution. The next layer of a CNN is referred to as "max pooling", which involves shrinking the image stack. In order to pool an image, the window size must be defined (e.g. usually 2x2/3x3 pixels), the stride must also be defined (e.g. usually 2 pixels). The window is then filtered across the image in strides, with the max value being recorded for each window. Max pooling reduces the dimensionality of each feature map whilst retaining the most important information. The normalization layer of a CNN also referred to as the process of Rectified Linear Unit (ReLU), involves changing all negative values within the filtered image to 0. This step is then repeated on all the filtered images, and the ReLU layer increases the non-linear properties of the model. The subsequent step by the CNN is to stack the layers (convolution, pooling, ReLU) so that the output of one layer becomes the input of the next. Layers can be repeated, resulting in a "deep stacking".

The final layer within the CNN architecture is called the fully connected layer, also known as the classifier. Within this layer, every value gets a vote on determining the image classification. Fully connected layers are often stacked together, with each intermediate layer voting on phantom "hidden" categories. In effect, each additional layer allows the network to learn even more sophisticated combinations of features towards better decision making [16].

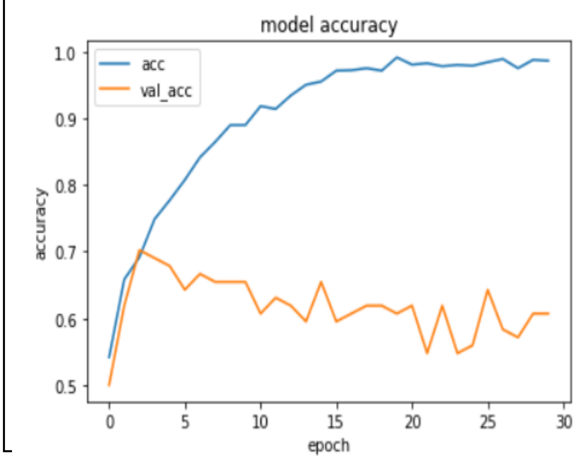


Fig. 7 Model accuracy graph

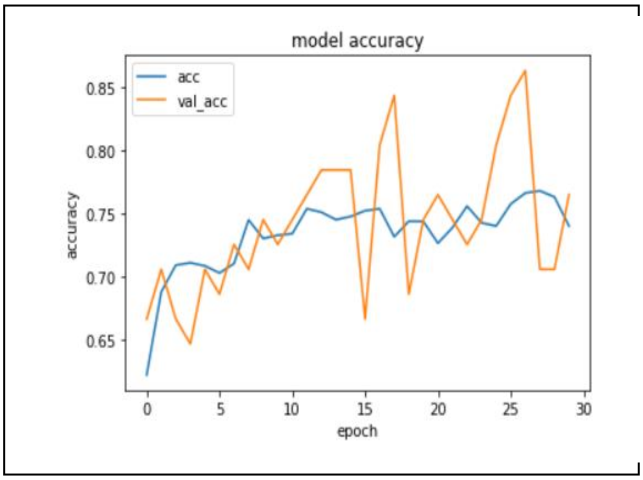


Fig. 8 Model accuracy more than 85%

VI. CONCLUSION

From the above analysis, Gender can be concluded. Based on research, it's found that in females, most patterns found are whorl followed by arches, while in male fingerprints, the most found patterns are loops followed by whorls. This was one of the parameters that can be used for gender detection. Another unique parameter is ridge density. It is found that the fingerprint possessing ridge density < 13 ridges/25 mm2 is most likely to be male, and ridge count > 14 ridges/25 mm2 are most likely to be female. The model gives an accuracy of more than 85%.

VII. FUTURE SCOPE

With our proposed research work, further research can be done in areas where we can get clues from fingerprint patterns related to a criminal's religion so that we can get more details about that criminal. Another research can be done for the patients who want to avoid diabetics. Like, fingerprint research can be done to predict diabetics in humans. Many more fields of research can do to predict career interest with the help of fingerprints. Also, one will be able to understand the hobbies and personalities of Humans with the help of a fingerprint.

VIII. APPLICATIONS

Fingerprints are especially important in the criminal justice realm. Investigators and analysts can compare unknown prints collected from a crime scene to the known prints of victims, witnesses and potential suspects to assist in criminal cases. For example, A killer may leave their fingerprints on the suspected murder weapon. A bank robber's fingerprints may be found on a robbery note. In an assault case, the perpetrator may have left fingerprints on the victim's skin. A burglar may leave fingerprints on a broken windowpane. A thief's fingerprints may be found on a safe [18]. Biometrics bring security and convenience wherever they're deployed, but in some instances, they also bring increased organization. In the field of healthcare, this is particularly true. Health records are some of the most valuable personal documents out there, doctors need access to them quickly, and they need to be accurate [19].

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