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Efficient Distorted Fingerprint Matching using OpenCV, and SIFT-FLANN Algorithm

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Abstract: This paper introduces an enhanced approach for distorted fingerprint matching, integrating OpenCV, SIFT analysis, and FLANN-based algorithms. By leveraging the robustness of SIFT in feature extraction and the efficiency of FLANN in nearest neighbor matching, our method aims to enhance accuracy and robustness in fingerprint recognition. Experimental evaluations on a dataset of distorted fingerprints demonstrate superior performance compared to some of the existing techniques, showcasing resilience against various distortions such as noise, rotation, and occlusion. Our method offers a reliable solution for real-world applications in security, forensics, and biometric authentication systems. In comparison to recent techniques, our approach significantly improves matching accuracy and computational efficiency, addressing the challenges of distorted fingerprint recognition effectively in modern contexts.

Keywords: Fingerprint Recognition, OpenCV, SIFT Analysis, FLANN-based algorithms, Distorted Image Recognition, Biometric Authentication, Feature Extraction.

I. INTRODUCTION

Biometrics, the science of identifying individuals based on unique biological traits, has become integral to modern security and identification systems. Among these modalities, fingerprint recognition stands out for its widespread adoption and reliability. By leveraging the distinctive patterns present on each person's fingertips, fingerprint recognition offers a robust means of authentication and identification.

Fingerprint recognition involves two primary processes:

1) *Enrollment:* During enrollment, an individual's fingerprint data is captured and stored in a database for future reference.
2) *Authentication:* Authentication, on the other hand, verifies the identity of individuals by matching the presented fingerprint with the stored template.

The utility of distorted fingerprint recognition extends beyond traditional security applications. In forensic investigations, it assists in identifying suspects or victims from partial or distorted prints found at crime scenes. The ability to accurately match distorted fingerprints enhances the investigative process and aids in solving crimes. This technology is particularly valuable in cases where conventional methods fail to provide conclusive evidence due to the condition of the fingerprint samples.

In healthcare, distorted fingerprint recognition ensures reliable patient identification, especially when dealing with elderly patients or individuals with medical conditions that may alter fingerprint characteristics. Accurate patient identification is crucial for maintaining medical records, preventing identity theft, and ensuring proper treatment and care. Implementing distorted fingerprint recognition systems in healthcare settings can streamline administrative processes and improve patient safety.

Moreover, distorted fingerprint recognition has significant implications in the authentication of historical documents. Old documents often bear fingerprints that may have deteriorated over time or been distorted due to handling or environmental factors. By effectively matching distorted fingerprints, this technology enables the verification of identities from historical records, contributing to the preservation of historical accuracy and integrity.

The versatility of distorted fingerprint recognition extends to diverse fields, including forensics, healthcare, and historical document authentication. Its ability to handle distortions and variations in fingerprint images makes it a valuable tool in various real-world applications, enhancing security, efficiency, and reliability in authentication and identification processes.

A. OpenCV Library

The selection of the OpenCV library for distorted fingerprint recognition stems from its robust functionality, versatility, and widespread adoption in the computer vision community. OpenCV, an open-source computer vision and machine learning software library, provides a comprehensive set of tools and algorithms for image processing, feature extraction, and pattern recognition.

Its extensive documentation, active community support, and cross-platform compatibility make it an ideal choice for implementing complex image processing tasks, such as fingerprint recognition.

In comparison to conventional techniques for distorted fingerprint recognition, the use of OpenCV offers several distinct advantages. Firstly, OpenCV provides a rich collection of pre-implemented algorithms for image enhancement, feature extraction, and matching, which significantly accelerates the development process. This library includes state-of-the-art techniques for feature detection and description, such as Scale-Invariant Feature Transform (SIFT) and Speeded Up Robust Features (SURF), which are well-suited for handling variations in fingerprint images caused by distortions. Additionally, the modular architecture of OpenCV allows for seamless integration with other libraries and frameworks, enabling the incorporation of advanced machine learning models and optimization techniques. This flexibility enables researchers and developers to experiment with novel approaches and adapt existing algorithms to specific use cases in distorted fingerprint recognition.

Furthermore, the performance and efficiency of OpenCV-based solutions surpass traditional methods due to its optimized implementation and parallel processing capabilities. By leveraging hardware acceleration and parallel computing architectures, OpenCV can efficiently process large volumes of fingerprint data, leading to faster and more accurate recognition results.

Overall, the use of the OpenCV library for distorted fingerprint recognition offers a compelling alternative to conventional techniques, providing enhanced performance, flexibility, and scalability. Its rich feature set, extensive documentation, and active development community make it a valuable asset for researchers and practitioners seeking to advance the state-of-the-art in biometric authentication and identification systems.

B. Scale-Invariant Feature Transform - SIFT (Feature extraction algorithm)

The Scale-Invariant Feature Transform (SIFT) algorithm has garnered significant attention in the field of computer vision for its robustness to scale, rotation, and illumination changes, making it a compelling choice for matching distorted fingerprint images. When confronted with variations in fingerprint patterns caused by distortions such as noise, rotation, or occlusion, traditional matching algorithms may struggle to accurately identify corresponding features. In contrast, SIFT offers a distinctive advantage by extracting invariant keypoints and descriptors that are resilient to such distortions, enabling reliable matching across disparate conditions. SIFT's efficacy in matching distorted fingerprint images stems from its underlying principles. By identifying distinctive keypoints and generating descriptors based on local image gradients, SIFT encapsulates unique structural information unaffected by variations in orientation or scale. This characteristic makes it particularly well-suited for handling distorted fingerprints, where traditional methods may falter due to the complexity of the matching task. Compared to alternative algorithms, SIFT stands out for its robustness and versatility in fingerprint recognition tasks. While other techniques such as Speeded Up Robust Features (SURF) and Oriented FAST and Rotated BRIEF (ORB) offer similar capabilities in feature detection and description, SIFT maintains a distinct advantage in challenging scenarios characterized by significant distortions or variations in scale. Additionally, SIFT's patented design and extensive validation in academic and industrial settings reinforce its reputation as a reliable and effective solution for distorted fingerprint matching. Despite its strengths, SIFT may exhibit limitations in terms of computational efficiency and scalability, particularly when applied to large-scale fingerprint datasets. In such cases, alternative algorithms such as SURF and ORB may offer superior performance due to their computational simplicity and reduced computational overhead. However, in scenarios where accuracy and robustness are paramount, SIFT remains a preferred choice for matching distorted fingerprint images, offering unparalleled resilience to challenging conditions. ORB is the fastest algorithm while SIFT performs the best in most scenarios [2]. The subsequent table illustrates the results of comparing images with their rotated counterparts using various algorithms, highlighting SIFT's superior performance in terms of match percentage. This empirical evidence further underscores SIFT's efficacy and underscores its role as a leading solution for distorted fingerprint recognition.

TABLE I

Results of Comparing the Image with its Rotated Image

	Time (sec)	Kpnts1	Kpnts2	Matches	Match Rate (%)
SIFT	0.16	248	260	166	65.4%
SURF	0.03	162	271	110	50.8%
ORB	0.03	261	423	158	46.2%

C. Fast Library for Approximate Nearest Neighbors - FLANN

The Fast Library for Approximate Nearest Neighbors (FLANN) matcher algorithm has emerged as a powerful tool in the realm of computer vision, offering efficient and scalable solutions for nearest neighbor search tasks. FLANN's suitability for distorted fingerprint recognition stems from its ability to rapidly identify approximate nearest neighbors in high-dimensional feature spaces, a critical requirement for matching complex and varied fingerprint images.

FLANN's superiority over traditional matching algorithms lies in its capacity to handle large-scale datasets and high-dimensional feature spaces with minimal computational overhead. By employing tree-based data structures such as KD-trees and randomized k-d forests, FLANN achieves accelerated search performance while maintaining a high degree of accuracy, making it particularly well-suited for matching distorted fingerprint images.

Compared to alternative algorithms such as brute-force matching or hierarchical clustering, FLANN offers distinct advantages in terms of efficiency and scalability. Brute-force matching, while straightforward, suffers from prohibitively high computational complexity, especially in scenarios involving large datasets or high-dimensional feature descriptors. Hierarchical clustering, on the other hand, may struggle to maintain accuracy in high-dimensional spaces and may be sensitive to variations in data distribution.

FLANN's operational principle revolves around the construction of efficient index structures tailored to the specific characteristics of the input data. These index structures facilitate rapid approximate nearest neighbor search by partitioning the feature space into hierarchical regions, enabling efficient pruning and traversal during search operations. By exploiting the inherent structure of the data, FLANN minimizes the computational burden associated with exhaustive search methods, delivering superior performance in terms of search speed and accuracy.

In the context of distorted fingerprint recognition, FLANN's ability to efficiently handle high-dimensional feature descriptors and rapidly identify approximate nearest neighbors makes it an ideal choice for matching complex and varied fingerprint images. Its scalability, accuracy, and computational efficiency position FLANN as a leading solution for distorted fingerprint recognition, outperforming traditional matching algorithms and enhancing the reliability and performance of fingerprint recognition systems.

II. RELATED WORKS

Many studies have been done on different applications of biometric in our life. Biometrics provide higher security concerns with respect to old authentication methods such as pin, password, token, etc. Here are a few related works to SIFT, OpenCV and Fingerprint matching.

A.Jain et.al. [1] As biometric systems expand, security becomes critical. Threats like intrusion and function creep pose risks. This chapter outlines vulnerabilities and proposes countermeasures, emphasizing robust security in biometric technology.

[2] This study compares three image matching techniques across various transformations: scaling, rotation, noise, fisheye distortion, and shearing. Evaluation parameters include key point count, matching rate, and execution time. ORB proves fastest, while SIFT excels overall. ORB and SURF outperform SIFT at 90-degree rotations, and ORB and SIFT perform similarly with noise. Key points are centralized in ORB but distributed in SURF, SIFT, and FAST detectors.

[3] This paper introduces an image forensic technique for detecting copy-move forgery in images. It utilizes SIFT features extracted from irregular sized non-overlapping blocks of the forged image and employs FLANN matching to identify forged regions based on keypoint matching. The method demonstrates effectiveness against diverse attack scenarios including down-sampling, JPEG compression, and geometric transforms. Future research could extend this method to address other forms of forgery like image splicing, contrast changes, and noise addition. [4] The SIFT algorithm detects keypoints and computes descriptors, offering robustness to image translation and rotation. FLANN-based matching, though fast for large datasets, may not always yield optimal results. SIFT's complexity can lead to false matches. Future research could focus on eliminating duplicate images to enhance this work's effectiveness. [5] This paper introduces two novel detection-description techniques optimized for face recognition (FR) tasks. Experimental results on LFW and Face94 datasets demonstrate that the SURF-detector-SIFT-descriptor method outperforms others, detecting more features robustly, even under unconstrained scenarios. Although the SIFT-detector-SURF-descriptor method shows promise, it slightly lags in accuracy compared to SURF-detector-SIFT-descriptor, albeit with improved speed over classical SIFT and SURF. Further research aims to enhance algorithm accuracy by exploring additional detector/descriptor combinations across various benchmark databases. [6] This paper evaluates the performance of the SIFT matching algorithm against diverse image distortions like rotation, scaling, fisheye, and motion distortion. It calculates and presents false and true positive rates across numerous image pairs and examines the distribution of keypoint orientation differences for correct and incorrect matches. Future work will utilize these results to optimize the accuracy of SIFT matching further. [7] Computer Vision, a subset of Artificial Intelligence, involves training computers to analyze images and extract essential features.

OpenCV, a C++ library with Python bindings, offers diverse functionalities for computer vision tasks such as object detection, face recognition, and medical diagnosis. This paper highlights OpenCV's pivotal role in face detection and recognition, outlining popular algorithms, OpenCV modules, and applications in Python. It assesses recent literature leveraging OpenCV for human face detection and recognition across various domains, aiming to enhance human life. [8] Based on the results obtained from both fingerprint and iris images, iris recognition emerges as the superior system due to its highest average accuracy and inherent resistance to duplication or aging effects. However, scalability issues may arise with database size, leading to slower authentication processes. Future endeavors involve detailed implementations of both fingerprint and iris recognition, potentially integrating hardware solutions. Given vulnerabilities in fingerprint scanners, enhancing security through embedded crypto-biometric authentication schemes, particularly in banking systems, is crucial. Combining cryptography and biometrics can elevate security levels in person authentication processes.

[9] An efficient fingerprint matching approach is presented, boasting a 40-fold improvement over existing systems. The method categorizes fingerprints into four major classifications: whorl, arch, left-loop, and right-loop. However, a drawback of the existing system is noted: it requires the database to contain only one print per individual and cannot handle matching fingerprints from different fingers. Further study is needed to address this limitation, as the current turnaround time of 20-25 minutes is lengthy, and matches typically yield multiple templates rather than a single match. [10] This paper demonstrates the application of SIFT features in palmprint authentication, utilizing point-wise matching and geometric constraints to enhance accuracy. Additionally, an extension of SAX to 2D images is proposed for palmprint authentication. Fusion techniques further improve authentication accuracy. Implementation in C++ yields rapid feature extraction and matching, suitable for real-time applications. Future work will focus on refining preprocessing steps, matching strategies, exploring graph matching for face authentication, and studying advanced fusion methods.

III.PROPOSED MODEL

This proposed model effectively demonstrates the use of SIFT and FLANN algorithms for distorted fingerprint recognition, showcasing their capabilities in identifying corresponding keypoints and descriptors between sample and fingerprint images, leading to accurate and reliable matches. This approach holds promise for enhancing the performance of fingerprint recognition systems in real-world applications. Following are the stages involved in our model:

A. Image Acquisition Stage

The image acquisition stage plays a crucial role in obtaining distorted fingerprint images for analysis and matching. Distorted fingerprints can be acquired from various sources, including healthcare settings, old documents, and forensic investigations, each presenting unique challenges and considerations.

1) *Forensics:* In forensic investigations, distorted fingerprint images are often obtained from crime scenes, evidence materials, or latent prints recovered from surfaces. Distortions in fingerprint patterns may occur due to factors such as smudging, partial impressions, or overlapping prints, making it challenging to extract accurate and reliable fingerprint features. Forensic experts employ specialized techniques such as latent print development, chemical enhancement, and digital enhancement to enhance the visibility and quality of distorted fingerprint images. These techniques enable forensic examiners to identify and analyze distorted fingerprints for investigative purposes, including suspect identification, crime scene reconstruction, and evidence linking.
2) *Healthcare:* In healthcare settings, distorted fingerprint images are often obtained during routine patient registration or identification processes. Factors such as aging, medical conditions, and environmental factors can contribute to distortions in fingerprint patterns. Additionally, variations in fingerprint quality due to factors like moisture, dirt, or injury may further complicate the acquisition process. Despite these challenges, healthcare practitioners rely on fingerprint biometrics for patient identification to streamline administrative processes, prevent identity theft, and ensure accurate medical record-keeping.
3) *Old Documents:* Distorted fingerprint images can also be extracted from old documents, including historical records, archival materials, and personal artifacts. Over time, fingerprints imprinted on paper documents may deteriorate due to handling, exposure to environmental elements, or natural aging processes. As a result, the quality and integrity of fingerprint images may be compromised, leading to distortions and degradation..

Recognition of these distorted fingerprints holds immense potential in streamlining patient identification processes, preserving historical accuracy through document authentication, and aiding forensic investigations by enhancing suspect identification and crime scene reconstruction. Once the fingerprint is obtained it can be imaged and we can digitally enhance it using filters and noise reduction techniques for further matching process.

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B. Image Resizing

Image resizing plays a crucial role in our distorted fingerprint recognition model by standardizing the dimensions of fingerprint images, thereby facilitating consistent analysis and comparison across varying datasets. It helps ensure that fingerprint images of different sizes are compatible with the feature extraction and matching algorithms, enhancing the accuracy and reliability of the recognition process. Resizing fingerprint images to a uniform size is essential for several reasons. Firstly, it simplifies the computational complexity of feature extraction algorithms by reducing the variability in image dimensions. This enables efficient processing and analysis of fingerprint images, leading to faster and more reliable recognition results. Additionally, resizing helps mitigate the impact of distortions caused by scaling, ensuring that fingerprint features are accurately represented and preserved during matching.

In our model, image resizing is achieved using OpenCV's “resize” function, which allows us to adjust the dimensions of fingerprint images while preserving their aspect ratio. By specifying the desired scaling factor or target dimensions, we can resize fingerprint images to a standardized size suitable for further processing. This ensures consistency in the feature extraction and matching stages, enhancing the robustness and performance of our distorted fingerprint recognition model.

C. Feature Extraction

In our distorted fingerprint recognition model, the Scale-Invariant Feature Transform (SIFT) algorithm plays a pivotal role in feature extraction by detecting and describing distinctive key points within fingerprint images. SIFT operates by analyzing the image at multiple scales, ensuring robustness to changes in size and orientation. It starts by identifying potential keypoints at stable locations in the image, such as ridge endings and bifurcations in fingerprint ridges.

Once candidate keypoints are identified, SIFT computes descriptors for each keypoint by analyzing the local image gradients within a surrounding region. These descriptors encode the unique structural characteristics of the fingerprint, capturing details about the orientation, intensity, and distribution of features. Importantly, SIFT descriptors are invariant to changes in scale, rotation, and illumination, making them highly robust against distortions commonly encountered in fingerprint images. By extracting keypoints and descriptors using SIFT, our model obtains a rich and informative representation of fingerprint features, enabling accurate and reliable matching across diverse conditions.

D. Verification and Matching

In our model, the Fast Library for Approximate Nearest Neighbors (FLANN) matching algorithm is employed for efficient and accurate matching of distorted fingerprints in the database to the provided distorted fingerprint. FLANN operates based on the principle of approximate nearest neighbor search, which involves finding the most similar data points in a high-dimensional space efficiently. FLANN achieves this by constructing index structures such as KD-trees or randomized k-d forests, which enable rapid search and retrieval of approximate nearest neighbors.

During the matching process, FLANN compares the descriptors extracted from the distorted fingerprint to those stored in the database, seeking approximate matches that are close in feature space. By efficiently pruning the search space and exploiting the hierarchical structure of the index, FLANN can identify potential matches quickly and accurately, even in the presence of distortions or variations in fingerprint images. This approach enhances the robustness and scalability of our model, enabling reliable recognition of distorted fingerprints against a large database of fingerprint templates.

E. Calculating BestScore

In our model, the best score is determined by evaluating the ratio of high-quality matches between the provided distorted fingerprint and each fingerprint template in the database, relative to the total number of keypoints detected. Initially, the best score is set to zero, indicating no matches found yet. As the matching algorithm progresses and evaluates matches between the distorted fingerprint and each template in the database, the best score is updated whenever a template yields a higher match score than the current best score. Following the retrieval of matches, the number of high-quality matches is divided by the total number of keypoints detected in either the distorted fingerprint or the template, depending on which count is smaller. This ratio is then multiplied by 100 to yield the match score percentage. The template with the highest match score is considered the best match for the provided distorted fingerprint, representing the closest match in the database.

$$\boldsymbol{Best\_Score} = \left[\frac{\boldsymbol{No.of\ Matchpoints}}{\boldsymbol{Total\ no.of\ Keypoints}}\right] \times \mathbf{100}$$

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F. Proposed Model Flowchart

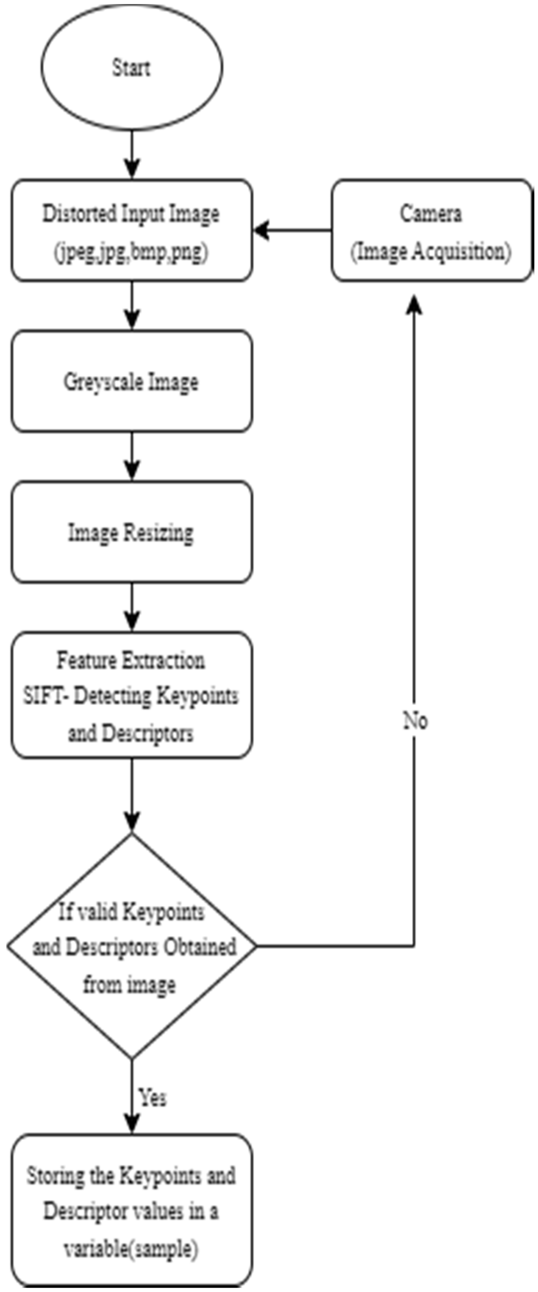

Fig. 1 Distorted Image Acquisition and Preprocessing

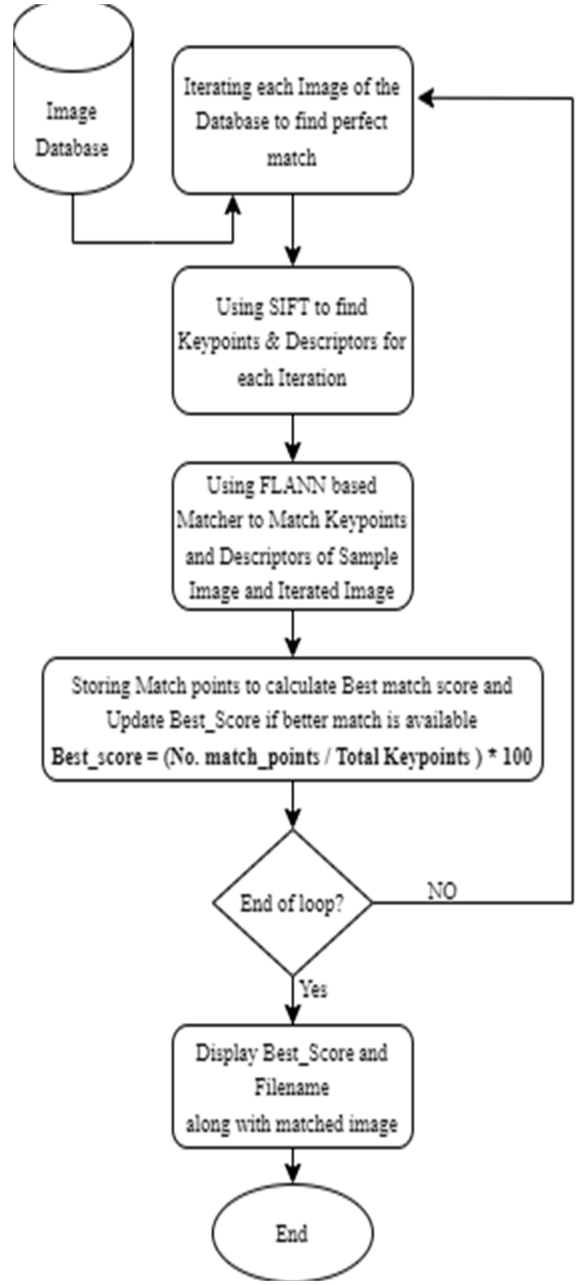

Fig. 2 Matching and Best Score Calculation from Image Database

G. Program Code for the Proposed Model

Following is the code in Python which is implemented on Google Colab for the proposed model

```
# Importing necessary libraries, including OpenCV (cv2), Python Imaging Library (PIL)
import cv2
import os
import PIL.Image

# Loading the sample fingerprint image and resizing it.
sample=cv2.imread("/content/Real/jpeg-optimizer_Left-Hand_Thumb (1).jpg")
sample=cv2.resize(sample,None,fx=2.5,fy=2.5)
```

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```
# Displaying Sample Image
from google.colab.patches import cv2_imshow
cv2_imshow(sample)
cv2.waitKey(0)
cv2.destroyAllWindows()

# Initializing variables
best_score=0
filename=None
image=None
kp1, kp2, mp=None, None, None

#Iterating over each fingerprint image in specified directory
for file in[file for file in os.listdir("/content/Real/real")]:
  fingerprint_image = cv2.imread("/content/Real/real/"+file)
  sift = cv2.SIFT_create()
# Computing Keypoints and Descriptors using SIFT
  kpts_1,dcps_1 = sift.detectAndCompute(sample, None)
  kpts_2,dcps_2 = sift.detectAndCompute(fingerprint_image , None)

# Using FLANN Based matching algorithm to perform matching between sample and database image.
  matches = cv2.FlannBasedMatcher({'algorithm':1, 'trees':10}, {'checks': 50}).knnMatch(dcps_1, dcps_2, k=2)
  match_points = []
  for p,q in matches:
    if p.distance < 0.1*q.distance:
      match_points.append(p)
  keypoints=0
  if(len(kpts_1) < len(kpts_2)):
    keypoints = len(kpts_1)
  else:
    keypoints = len(kpts_2)
# Calculating and Updating Best_Score
  if len(match_points) / keypoints * 100 > best_score:
    best_score = len(match_points) / keypoints *100
    filename = file
    image= fingerprint_image
    kp1, kp2, mp = kpts_1, kpts_2, match_points

#Displaying Image and Match point along with filename
print("BEST MATCH:"+ str(filename))
print("SCORE: "+str(best_score))
cv2_imshow(sample)
cv2.waitKey(0)
cv2.destroyAllWindows()
result= cv2.drawMatches(sample,kp1,image,kp2,mp,None)
result= cv2.resize(result,None,fx=4,fy=4)
cv2_imshow(result)
cv2.waitKey(0)
cv2.destroyAllWindows()
```

IV.RESULTS

The results obtained from the distorted fingerprint recognition process are presented herein, showcasing the best matching fingerprint image alongside the provided distorted image. Each result includes the filename of the matched fingerprint image from the database, providing a reference to the identified individual or record. Additionally, the corresponding best score percentage is displayed, indicating the degree of similarity between the distorted fingerprint and the matched image. By visually presenting the matched and distorted fingerprint images side by side, along with their associated metadata, the results offer a comprehensive overview of the recognition outcomes. These findings underscore the effectiveness and reliability of the proposed recognition model in accurately identifying and matching distorted fingerprints against a database of fingerprint images.

Fig. 3 Best Match filename and Score

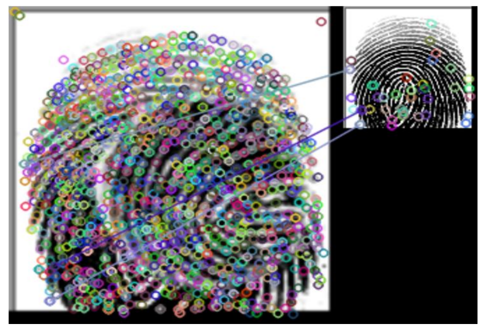

Fig. 4 Using drawMatches() function to show matched keypoints

V. CONCLUSIONS

In conclusion, the distorted fingerprint recognition model presented in this study demonstrates promising capabilities in accurately identifying and matching distorted fingerprints against a database of fingerprint images. By leveraging advanced algorithms such as the Scale-Invariant Feature Transform (SIFT) for feature extraction and the Fast Library for Approximate Nearest Neighbors (FLANN) for matching, the model achieves robust and reliable recognition outcomes. The results obtained showcase the effectiveness of the model in accurately identifying the best matching fingerprint image, as evidenced by the high match score percentages achieved. Looking ahead, future modifications to the model could focus on enhancing its scalability and efficiency to accommodate larger databases and handle real-time recognition scenarios. Integration of deep learning techniques for feature extraction and matching could also be explored to further improve recognition accuracy and adaptability to diverse fingerprint variations. Additionally, incorporating additional preprocessing steps to address common challenges such as noise, occlusion, and varying image qualities could enhance the model's robustness in real-world applications. Overall, the findings from this study lay the groundwork for further advancements in distorted fingerprint recognition and hold promise for enhancing the reliability and effectiveness of biometric identification systems in various domains.

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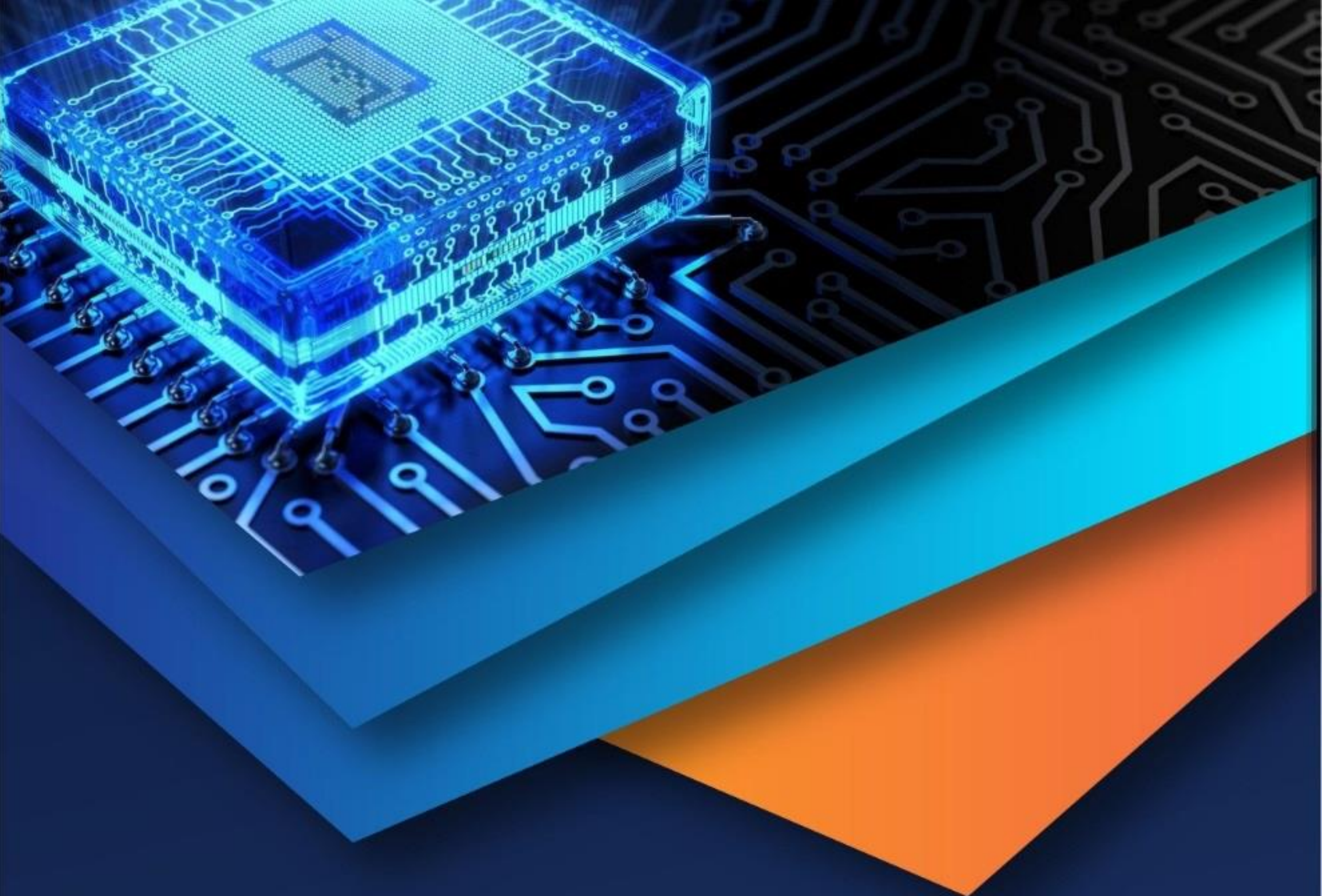

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