CONTRIVER®, Mysore

Department of computer science

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TRAINING CERTIFICATE

*This is to certify that **Sri. BM PRATEEK KUSHALAPPA(****CR0170BE8*****).*** *MS Ramaiah Institute of Technology in partial fulfillment for the award of "**Training Certificate**" in* ***Department of computer science*** of the ***CONTRIVER, Mysore*** *during the year* 2022-2023. *It is certified that he/she as undergone internship during the time period from 07/02/2023 to 01/04/2023 of all working days corrections/suggestions indicated for internal validation have been incorporated in the report deposited to the guide and trainer. The training report has been approved as it satisfies the organizational requirements in respect of Internship training prescribed for the said qualification.*

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Abstract

The use of contactless fingerprint recognition systems are gaining popularity due to the convenience and hygiene benefits they offer. Unfortunately, limited research has been done on how these systems perform when compared to contact-based systems. This study compares the effectiveness of contactless versus contact-based fingerprint identification systems using a CNN-based architecture.

The proposed framework uses a pre-trained CNN model to extract deep features from both contactless and contact-based fingerprint images. A classification model is then used to predict the individual's identification using the extracted features. On a dataset that is available to the public, the framework is assessed.

Furthermore, an extensive analysis is done to understand the factors that affect the performance of contactless fingerprint recognition systems. Significant factors that affect the performance of contactless fingerprint recognition systems are the quality of the contactless fingerprint image and the distance between the finger and the sensor.

Chapter 1: Introduction

Fingerprint recognition is a widely used biometric technology for personal identification due to its uniqueness and reliability. Conventional contact-based fingerprint identification systems require the user to press their finger against a sensor, which can be uncomfortable and unsanitary, especially in locations with a lot of traffic. As a result, contactless fingerprint recognition technologies have grown in acceptance since they offer a more practical and hygienic substitute.

The effectiveness of contactless versus contact-based fingerprint identification devices has not been thoroughly researched. Hence a framework needs to be developed that can accurately compare the performance of contactless and contact-based fingerprint recognition systems.

This study compares the effectiveness of contactless versus contact-based fingerprint identification systems using a CNN-based framework. Using a pre-trained CNN model, the framework extracts deep characteristics from fingerprint photos taken via contactless and contact-based technology. The individual's identity is then predicted using a classification model and the extracted features.

The proposed framework conducts a thorough study of a publicly available dataset in order to evaluate the performance of contactless fingerprint recognition systems. The findings of this study help guide future developments in contactless fingerprint identification technology and offer valuable insights into how well contactless and contact-based systems perform.

Chapter 2: Objectives

The main objective of the proposed CNN-based framework is to compare the performance of contactless and contact-based fingerprint recognition systems. Specifically, the objectives of this study are:

1. To develop a CNN-based framework that can accurately extract deep features from contactless and contact-based fingerprint images.
2. To evaluate the performance of the proposed framework on a publicly available dataset and compare the performance of contactless and contact-based fingerprint recognition systems.
3. To analyze the factors that affect the performance of contactless fingerprint recognition systems, such as the quality of the contactless fingerprint image and the distance between the finger and the sensor.
4. To provide insights into the performance of contactless and contact-based fingerprint recognition systems and inform future improvements in contactless fingerprint recognition technology.

Chapter 3: Literature Survey

Steven.et.al [1] In this paper presents an end-to-end automated system, called C2CL, comprised of a mobile finger photo capture app, preprocessing, and matching algorithms to handle the challenges inhibiting previous cross-matching methods; namely i) low ridge-valley contrast of contactless fingerprints, ii) varying roll, pitch, yaw, and distance of the finger to the camera, iii) non-linear distortion of contact-based fingerprints, and vi) different image qualities of smartphone cameras. The preprocessing algorithm segments, enhances, scales, and unwarps contactless fingerprints, while the matching algorithm extracts both minutiae and texture representations. A sequestered dataset of 9, 888 contactless 2D fingerprints and corresponding contact-based fingerprints from 206 subjects (2 thumbs and 2 index fingers for each subject) acquired using the mobile capture app are used to evaluate the cross-database performance of the proposed algorithm. Experimental results on 3 publicly available datasets show substantial improvement in the state-of-the-art for contact to contactless fingerprint matching (TAR in the range of 96.67% to 98.30% at FAR=0.01%).

Kauba.et.al [2] In this paper provides a comprehensive and in-depth engineering study on the different stages of the fingerprint recognition toolchain. The insights gained throughout this study serve as guidance for future work towards developing a contactless mobile fingerprint solution based on the iPhone 11, working without any additional hardware. The targeted solution will be capable of acquiring 4 fingers at once (except the thumb) in a contactless manner, automatically segmenting the fingertips, pre-processing them (including a specific enhancement), and thus enabling fingerprint comparison against contact-based datasets. For fingertip detection and segmentation, various traditional handcrafted feature-based approaches as well as deep-learning-based ones are investigated. Furthermore, a run-time analysis and the first results on the biometric recognition performance are included.
To evaluate the different stages of the recognition toolchain, two datasets acquired in a contactless manner in real-life scenarios were created. The main focus of the evaluation was on fingertip detection and segmentation. In addition, some light was shed on different aspects of interoperability: (i) the estimation and correction of the

image resolution in terms of DPI, (ii) a first evaluation of the performance of the comparison of contactless FPs with contact-based ones using state-of-the-art FP recognition software, and (iii) the influence of different fingerprint enhancement methods employed during the fingerprint preprocessing stage. To enable this evaluation, contact-based samples from the same subjects were acquired.
It turned out that, for practical applications (outdoor use with an inhomogeneous background), only the DL-based segmentation approaches were suitable. Furthermore, it became apparent that an accurate DPI correction is an essential step towards contactless to contact-based interoperability. Our recognition performance results were promising, but with the current prototype, they were not accurate and reliable enough for operational police use.

Attrish.et.al [3] In this paper proposes an approach for developing a contactless fingerprint recognition system that captures finger photo from a distance using an image sensor in a suitable environment. The captured finger photos are then processed further to obtain global and local (minutiae-based) features. Specifically, a siamese convolutional neural network (CNN) is designed to extract global features from a given finger photo. The proposed system computes matching scores from CNN-based features and minutiae-based features. Finally, the two scores are fused to obtain the final matching score between the probe and reference fingerprint templates. Most importantly, the proposed system is developed using the Nvidia Jetson Nano development kit, which allows us to perform contactless fingerprint recognition in real time with minimum latency and acceptable matching accuracy. The performance of the proposed system is evaluated on an in-house IITI contactless fingerprint dataset (IITI-CFD) containing 105 train and 100 test subjects. The proposed system achieves an equal error rate of 2.19% on IITI-CFD. Apart from standard image processing and state-of-art feature extraction algorithms, deep learning models can be used to improve matching accuracy to even better. With the advancement in sensing technology and computation power, the contactless domain has an enormous market scope. The results show that contactless biometric systems can also achieve similar accuracy, which other systems claim in the commercial market.

Lin.et.al [4] In this paper proposes a multi-Siamese CNN architecture for accurately matching contactless and contact-based fingerprint images. In addition

to the fingerprint images, hand-crafted fingerprint features, e.g. minutiae and core point, are also incorporated into the proposed architecture. This multi-Siamese CNN is trained using fingerprint images and extracted features. Therefore, a more robust deep fingerprint representation is formed from the concatenation of deep feature vectors generated from multi-networks. In order to demonstrate the effectiveness of the proposed approach, a publicly available database consisting of contact-based and respective contactless fingerprints is utilized. The effectiveness of the proposed approach is demonstrated by the comparative experimental results on a publicly available dataset. The comparative experimental results presented in this paper suggest that this approach outperforms several CNN-based methods and traditional minutiae-based methods for cross-fingerprint matching.
Despite the promising results, there are several limitations. Firstly, the complexity of the proposed framework is high due to training multiple CNNs. Secondly, although significant performance improvement is achieved by the proposed approach the results are still below the expectations for the deployments. Thirdly, only one database is utilized for evaluation due to the lack of publicly available databases. In addition, the size of the user database is not large enough for training deep CNN without an overfitting problem. Therefore generating/using large-size fingerprint databases is required to ensure the effectiveness of the proposed approach.

Lin.et.al [5] In this paper develops a CNN-based framework to accurately match contactless and contact-based fingerprint images. Our framework firstly trains a multi-Siamese CNN using fingerprint minutiae, respective ridge map and specific regions of ridge map. This network is used to generate deep fingerprint representation using a distance-aware loss function. Deep fingerprint representations generated in such a multi-Siamese network are concatenated for more accurate cross-comparison. The proposed approach for cross-fingerprint comparison is evaluated on two publicly available databases containing contactless 2D fingerprints and respective contact-based fingerprints. The experimental results from two public datasets presented in section III.E illustrated that the proposed method can achieve outperforming results of many other promising deep learning methods. The experiments also indicated that the proposed method can achieve significantly improved performance over other minutiae-based fingerprint cross-comparison methods.

Unlike contact-based fingerprint cross-sensor comparison, the cross-comparison using contact-based to contactless fingerprints is more challenging. In practice, a lack of sufficient training data, i.e. contact-based and respective contactless fingerprints, in the proposed framework can significantly degrade the matching accuracy. Incorporating different data augmentation strategies like scale-based data augmentation and using more promising learning strategies including different stochastic optimization algorithms like Adagrad or Adam, are expected to improve the cross-comparison performance and should be considered in the extension of this work. Deep learning-based architecture which is specially designed to learn inter and intra-class variations for other cross-sensor problems, e.g. contact-based to rolled fingerprints offers significant potential to improve the accuracy and is suggested for further work.

Nirmal.et.al [6] In this paper develops a CNN framework for recognizing contactless fingerprint images–based on the database. The framework uses fingerprint minutiae and particular ridge map
regions to train a CNN first. Over several popular deep learning, The experiments presented in this paper achieve good results with greater accuracy. Experimental results obtained in this paper show the effectiveness of the proposed approach and illustrate a significant improvement in methods of fingerprint recognition. The proposed work also helps to mitigate the spoofing of fingerprints, thus providing greater security. The model is tested which achieved more accurate identification. Higher accuracy of recognition, low complexity and low storage requirements can make it popular for deployment. Accuracy is calculated by considering different threshold values. By experiments, for threshold=1, accuracy was seen as maximum. Although the proposed CNN-based approach achieves good performance for contactless fingerprint recognition, it is still
possible to improve identification accuracy by incorporating greater training sets as well as training strategies. A fingerprint spoofing mitigation is an important aspect of this model. The system thus provides more security.

Jawade.et.al [7] In this paper, proposes a cost-effective, highly accurate and secure end-to-end contactless fingerprint recognition solution. The proposed framework first segments the finger region from an image scan of the hand using a mobile phone camera. For this purpose, a cross-platform mobile application is developed for fingerprint enrollment, verification, and authentication keeping security, robustness, and accessibility in mind. The segmented finger images go through fingerprint enhancement to highlight discriminative ridge-based features. A novel deep convolutional network is proposed to learn a representation from the enhanced images based on the optimization of various losses. For matching, a two-way architecture is proposed based on the minimization of the various loss functions. The proposed multi-branch network surpasses existing algorithms including commercial systems on multiple challenging databases such as PolyU and ISPFD. a mobile application has been developed with an end-to-end pipeline ranging from data acquisition to fingerprint matching for contactless person authentication. It is strongly believed that end-to-end system design will help promote the widespread adoption of smartphone-based contactless fingerprint authentication. In turn, this can help alleviate the risk of virus transmission and other drawbacks of traditional contact-based fingerprint biometric enrollment.

Chapter 4: Problem Statement

Developing a CNN-based framework that can accurately compare the performance of contactless and contact-based fingerprint recognition systems and analyze the factors that affect the performance of contactless fingerprint recognition systems.

Chapter 5: Proposed Methodology

I. Flow diagram

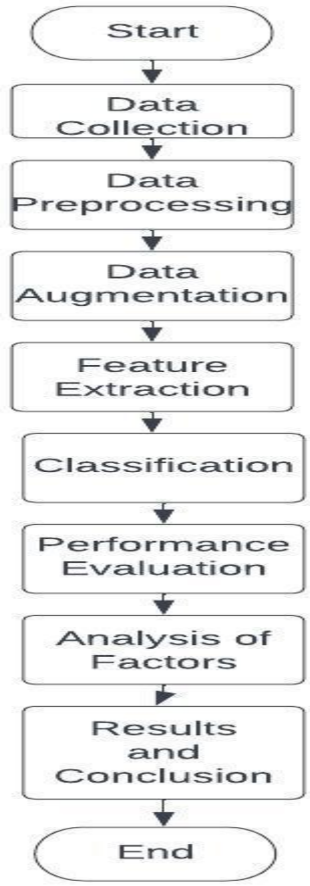

Figure 1

1. Data Collection
   - Collect contactless and contact-based fingerprint images from a publicly available dataset.
2. Data Preprocessing
   - Preprocess the fingerprint images using the OpenCV library.
   - Apply image enhancement techniques such as histogram equalization, denoising, and contrast stretching to improve the quality of the images.
3. Data Augmentation
   - Augment the preprocessed fingerprint images to increase the size of the dataset.

- Perform data augmentation techniques such as rotation, translation, and scaling to generate new variations of the fingerprint images.

4. Feature Extraction
    - Extract deep features from the preprocessed and augmented fingerprint images using a pre-trained CNN model.
    - The CNN model can be fine-tuned using the collected dataset or a pre-trained model can be used for feature extraction.
5. Classification
    - Use the extracted features to train a classification model such as SVM or Random Forest to predict the identity of the individual from the fingerprint image.
6. Performance Evaluation
    - Evaluate the performance of the proposed CNN-based framework on the collected dataset using metrics such as accuracy, precision, recall, and F1-score.
    - Compare the performance of contactless and contact-based fingerprint recognition systems.
7. Analysis of Factors
    - Analyze the factors that affect the performance of contactless fingerprint recognition systems such as the quality of the contactless fingerprint image, the distance between the finger and the sensor, and the effects of environmental factors such as lighting and temperature.
8. Results and Conclusion
    - Present the results of the study and draw conclusions about the performance of contactless and contact-based fingerprint recognition systems.
    - Provide recommendations for future improvements in contactless fingerprint recognition technology.

Chapter 6: System Requirements Specifications

To implement the proposed CNN-based framework for the comparison of contactless and contact-based fingerprint recognition systems, the following system requirements are needed:

1. Hardware
- A computer with a powerful graphics processing unit (GPU) for efficient training and testing of the deep learning model.
- A contactless fingerprint recognition sensor and a contact-based fingerprint recognition sensor for data collection and testing.
2. Software
- Python programming language for implementing the deep learning model and data preprocessing.
- Deep learning libraries such as Keras or TensorFlow for developing the CNN-based framework.
- OpenCV for preprocessing and augmenting the fingerprint images
- A database management system such as MySQL or MongoDB for storing and retrieving fingerprint data.

Chapter 7: Conclusion

In conclusion, the CNN-based framework for the comparison of contactless to contact-based fingerprints is an important area of research in biometric identification and security systems. The proposed methodology involves extracting minutiae and ridge-based features from both contactless and contact-based fingerprints and using a convolutional neural network to classify and match the features.

The framework has the potential to improve the accuracy and reliability of fingerprint recognition systems, particularly in situations where contact-based fingerprint sensors may not be feasible or practical. Furthermore, the system has the potential to be automated, which would reduce the need for manual analysis and improve the efficiency and speed of the system.

The literature survey indicates that there have been significant developments in the field of fingerprint recognition, with many researchers focusing on developing new algorithms and techniques for improving the accuracy and reliability of biometric identification systems. The use of CNN-based frameworks is an exciting area of research, with many potential applications in security, law enforcement, and other fields.

Overall, the CNN-based framework for the comparison of contactless to contact-based fingerprints has the potential to significantly improve the accuracy and reliability of biometric identification systems, and further research in this area is likely to lead to important advancements in the field of fingerprint recognition and security.

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