A Novel Approach for Automatic Enhancement of Fingerprint Images via Deep Transfer Learning

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***Abstract*—For any Automated Fingerprint Identification System, the quality of its images is vital to ensure the proper accuracy of the whole system. When the quality of an image is not satisfactory, enhancement processes may be applied to help the extraction of the fingerprint features. There are several enhancement techniques, and their suitability depends on the features of the original fingerprint image. Choosing the best enhancement method is crucial because these procedures do not always improve the image quality, and may even worsen it. This work addresses this topic and presents a classifier based on Convolutional Neural Networks (CNNs) that automatically chooses the most suitable enhancement method for a specific image and applies it, but only if necessary. Our solution avoids an excessive human effort to select the best enhancement process and also requires no further training. We evaluated our proposal using FVC's datasets, and results show the benefits of CNN-based feature extractors and that our solution was able to improve the quality of digital printing through the adaptive application of enhancement filters.**

***Index Terms*—Deep Learning, CNN, Image Enhancement, Classification, Fingerprint, Biometrics**

I. Introduction

Currently, fingerprints are the most popular biometric features used for personal identification, as they present an easy to use, reliable and cost-efficient way to authenticate an individual since a human fingerprint is unique and remains invariant over time [1]. The general structure of a biometric recognition system consists of four main stages [2]. First, the acquisition of biometric traits is the process of getting a digitalized image of a person using a specific capturing device. Second, pre-processing is allowed to improve the overall quality of the captured image. Third, the features of data are extracted using different algorithms. Finally, the matching of the extracted characteristics is generally applied to perform the recognition of the individual.

The performance of fingerprint-based systems directly depends on the reliability and precision of the feature extraction stage [3]. Matching algorithms are based on features pairing found into fingerprints. Abbood et al. [4] suggest that the reliability of extracted features is related to fingerprint quality. On the other hand, Schuch et al. [5] indicate that applying image enhancement filters improves extracted features reliability.

Fingerprint image enhancement is defined as the process of applying techniques to emphasize fingerprint in images, and thus improving their perceptibility to facilitate the identification of ridge valley structures and hence their features [6]. Several methods of fingerprint image enhancement were developed over the years, such as those based on local histogram equalization [7], frequency domain filtering [2], and Gabor filter [8].

Choosing the best enhancement technique to apply in a given image is challenging because the best method for a specific type of image may decrease the quality for other images. Besides, some images should not even use any filter because they already have excellent quality. According to Gonzalez and Woods [9], there is no general theory of image enhancement, so when processing an image for visual interpretation, the viewer is the ultimate judge of how well a particular method works. Indeed, there are two problems when deciding the best enhancement technique for an image. First, the manual process is laborious and sometimes impractical, and second, when an unknown type of image appears, we need to test every method to determine which one is the best for this new case.

In this work, we propose a solution for both problems using an automatic image enhancement classifier based on Convolutional Neural Networks (CNNs). For every given image, the classifier is responsible for answering which enhancement method is the most suitable. This automated process mitigates problems mentioned above, given that no human intervention is required, and the neural network classifies new images based on their inner features, without requiring further training.

We evaluated the proposed solution using the Fingerprint Verification Competition (FVC) 2000, 2002, and 2004 datasets to assess how well CNNs can be used to predict the best enhancement technique for each image. The results indicate an advantage in terms of the feature extraction capacity of CNN-based feature extractors. Besides, We observed that the proposed approach was able to improve the quality of digital images through the adaptive application of enhancement

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filters, indicating promising results.

The remainder of this paper is organized as follows. Related works are presented in Section II. The background of the methods and metrics used in this work are described in Section III. Section IV provides information about the fingerprint image enhancements used. The evaluation methodology is specified in Section V. Experiments and the results obtained are listed in Section VI. Finally, Section VII presents closing remarks and the future work.

II. Related Works

Specialized literature on biometrics by fingerprint presents approaches to improve the quality of fingerprint through the utilization of enhancement filters. Recent works, with a focus on fingerprint image quality improvement, are highlighted in this section.

Klir [10] evaluated five different image enhancements applied in fingerprints from database FVC 2000 DB1_A. The results obtained were correlated using the NFIQ1 score by classifying the resulting images according to its quality. The authors found that the Difference of Gaussians filter had the highest impact on the images from this single database.

Schuch et al. [11] presented an extensive quantitative evaluation of seven fingerprint image enhancement methods. All methods were applied in 14 databases, including FVC's databases. Biometric performance is tested using two well-known feature extraction algorithms, and the performance of the enhancements was evaluated and compared by calculating NFIQ1 and NFIQ2 quality scores. The authors concluded that the type of enhancement filter should be chosen according to the characteristics of the image, in addition to suggesting five filters that present better results.

Wang et al. [12] measured the biometric performance in terms of Equal Error Rate (EER) and the execution speed of five different fingerprint image enhancements. They carried out the experiments in database FVC 2000 DB1_B and found that classical feature extractor reached promised results.

On the other hand, recent approaches use Convolutional Neural Networks (CNN) to improve the quality of fingerprint images. Raff [13] proposed a CNN-based method to enhance noisy fingerprint images based on image reconstruction. This process improved matching results when performed on FVC 2000, FVC 2002, and FVC 2004 databases. Sahasrabudhe and Namboodiri [14] trained a Restricted Boltzmann Machine (RBM) with a set of high-quality images manually selected. The enhancement step is based on the reconstruction of the characteristics of the fingerprint image. However, in this approach, the authors evaluated the results in the same set of images whose characteristics had already been presented to the model in the training phase, which makes it challenging to analyze the generalization of the proposed solution. All approaches above, based on the image reconstruction techniques, can produce non-real characteristics in the original image, reducing the precision on the matching stage.

The most similar prior work to our own was published by Sharma and Dey [1], where the authors proposed an algorithm for improving the quality of fingerprint. It is based on five fingerprint types: dry, wet, dry-normal, wet-normal, and good quality images. The algorithm uses the fuzzy c-means technique as a classification model. The authors considered seven statistical attributes such as mean, variance, uniformity of contrast, and uniformity of the area of digital printing. They propose two stages: first, they classify each image in the groups defined previously and then apply histogram equalization, smoothing, and enhancement filters on a second stage. The authors, however, did not explore different types of image acquisition sensors and did not evaluate recent techniques for feature extraction from the image. Moreover, the use of simple statistical attributes may not be sufficiently representative of a set of samples in different sensors.

All the related works described the evaluation of several fingerprint image enhancement methods. Although they all presented the results of qualitative metrics, only the work of Schuch et al. [11] indicated the best enhancement for each database, and none of them tried to automatically classify the probably most suitable enhancement from an unknown image.

III. Background

A. Methods for enhancing image contrast

According to Schuch et al. [5], image enhancement algorithms applied to fingerprint can be classified into six classes. In this paper, we highlight four state-of-the-art algorithms that presented better results for reducing false match rate and also improved fingerprint quality. [4], [5]. Among these approach, the following stand out: (*i*) Wiener filter as a Noise statistics model, (*ii*) histogram equalization by Contrast Limited Adaptive Histogram Equalization (CLAHE) method as a signal domain model and its variant LCLAHE; (*iii*) energy normalization as an energy model, and (*iv*) cartoon-texture decomposition as a compositional model. Samples of enhanced fingerprint images are shown in Fig. 1.

1) Noise Statistics Approach: Greenberg et al. [15] were pioneers in proposing Wiener filter as a noise statistics model for enhancing fingerprint images [5], [11]. This method is based on noise estimation on the fingerprint image. So, estimated noise is calculated according to near pixels window to the central pixel, the noise can be estimated by local mean and variance, and it can be useful to expand the intensities difference between different pixels, improving the contrast. The function $w(n_1, n_2)$ defines the local estimate to improve pixel intensity and is given by the following equation:

$$w(n_1, n_2) = \mu + \frac{\sigma^2 - \nu^2}{\sigma^2} * (I(n_1, n_2) - \mu) \quad (1)$$

where ν^2 is noise estimated variance, I is the input image, n_1 and n_2 are coordinate into input image, and μ and σ^2 are the local mean and variance, respectively.

2) Histogram Equalization Approach: As an adaptive histogram equalization, Zuiderveld [16] proposed the CLAHE method based on the local scattering of pixel intensities. This method aims at finding a histogram as uniform as possible through a monotonic function that remaps the intensity values.

The redistribution of intensity values considers a local analysis, where the kernel defines the size of the parse window. Beyond this, the CLAHE method presents the clip limit parameter that limits pixels intensities and redistributes them to neighbor pixels, equalizing the histogram distribution. This procedure is particularly useful for highlighting the differences between papillary crest and background in a fingerprint image. In this paper, we adopt a variation from CLAHE called Laplacian CLAHE (LCLAHE) to improve our evaluations that combine a smoothed image with the Laplacian operator before CLAHE filter application.

3) Energy Normalization Approach: Hong et al. [2] proposed a reshaping of gray-scale values as an energy normalization. Distribution of the fingerprint image data is analyzed through the mean and the standard deviation calculus. The reshaping function $m(g)$ evaluates gray-scale images and applies the redistribution for image enhancing, according to Equation 2:

$$m(g) = \begin{cases} \mu_T + \sqrt{\frac{\sigma_T^2}{\sigma_S^2}(g - \mu_S)}, & if\ g > \mu_s \\ \mu_T - \sqrt{\frac{\sigma_T^2}{\sigma_S^2}(g - \mu_S)}, & \text{else} \end{cases} \tag{2}$$

where μ_T and μ_S are the mean of the target and source intensity, σ_T^2 and σ_S^2 is standard deviation, respectively.

4) Decompositional Approach: Cartoon-texture decomposition is a decompositional model based on two sets of the input image proposed by Buades et al. [17]. The first set represents a texture component and contains the relevant information; for instance, on fingerprint images, this component represents the papillary crests. The second set is called cartoon component and expresses the most common and least relevant information, for instance, the pixel set that represents the background region. The main idea behind this method is to identify the sensibility of the input image regarding smoothing operations and use it to improve the contrast. Buades et al. [17] proposed generating the cartoon component C and texture component T, after removing component C from input image, enhancing the relevant information. The following equations define these components:

$$C(x) = w(\lambda_\sigma(x))(L_\sigma * I)(x) + (1 - w(\lambda_\sigma(x))I(x)) \tag{3}$$

$$T(x) = I(x) - C(x) \tag{4}$$

where, $(L_\sigma * I)(x)$ represents a nonlinear low-pass and high-pass filter that depends of weighted value $w(x) : [0, 1] \longrightarrow [0, 1]$ defined by smoothing local total variation [17].

B. Estimating fingerprint quality

Good-quality fingerprints have discernible patterns and features that allow the extraction of features. Several factors may affect the quality of fingerprint images, such as the user's skin condition (e.g., scars, blisters, wet or dry skin), scanner limitation or imperfection, or even impurities on the scanner surface. A widely used fingerprint quality control software is the well-known NIST Fingerprint Image Quality software (NFIQ1) developed by the US National Institute of Standards and Technology [18]. The first version of the NFIQ tool was published in 2004 as part of the NIST Biometric Image Software (NBIS). The software is supplied as an open-source and was designed to predict the quality of fingerprint samples by classifying fingerprints into five different quality classes: 1 (excellent quality) up to 5 (very poor quality). It uses multilayer perceptron (MLP) neural network models with 22 hidden units to map fingerprint images to the quality score.

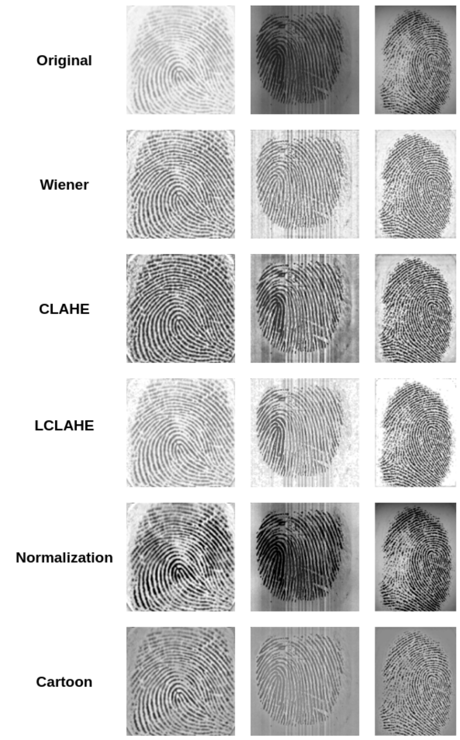


Fig. 1: Samples of enhanced fingerprints by the use of different methods. The first row represents the original images.

C. Evaluation Metrics

For the sake of improving our results analysis, in this work, we propose an analysis methodology based on the indexes obtained from the confusion matrix. The confusion matrix produces basic indices that include True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN), from which other evaluation metrics can be derived. The evaluation of results considers the metrics described as follows.

Accuracy (Acc) presents a hit rate as a relation between the number of correctly predicted samples and the total samples. This metric indicates the proximity between the predicted set by the evaluated model and reference set, according to Equation 5.

$$Acc = \frac{TP + TN}{TP + TN + TP + TN} \tag{5}$$

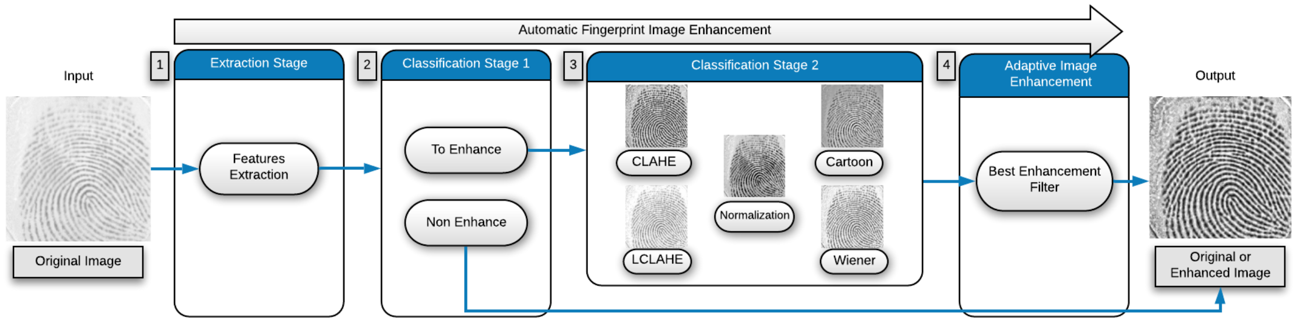


Fig. 2: The flow of the proposed methodology for improving the fingerprint quality via automatic enhancement.

Precision produces a ratio between all truly positive classifications and the total positive predictions the model presented, indicating a ratio of the hit to the positive class. It can be used in a situation where False Positives are considered more harmful than False Negatives. On the other hand, Recall or Sensibility can be used in a situation where False Negative is considered more harmful than False Positive. Here, the positive class represents fingerprint samples that require enhancements to improve their contrast. In its turn, F1 Score (F1-S) calculates the weighted harmonic mean between Precision and Recall and is presented by Equation 6. This metric presents values closer to the lowest values of the simple arithmetic mean of both metrics.

$$F1 - S = \frac{2 * Recall * Precision}{Recall + Precision} \tag{6}$$

Finally, to assess the quality of the resulting fingerprint image, the NFIQ1 quality score was calculated, whose quality indexes range from 1, highest quality, to 5, lowest quality.

IV. Automatic Fingerprint Image Enhancement

To improve the quality of fingerprint images, we propose an automatic image enhancement classifier composed of two stages, where the general idea is to apply enhancement filters only to the samples that will benefit from them. As illustrated in Fig. 2, the proposed approach receives a fingerprint image as input and, at the first stage of classification, decides whether the image needs to be enhanced to improve its quality or not. Once some images present a satisfactory quality, some enhancement procedures may add noise and decrease its overall quality.

The images needing enhancement go through the second classification stage that classifies the samples in five classes that represent fingerprint enhancements already consolidated in the literature: CLAHE, Normalization, Cartoon, Wiener, and LCLAHE. At the end of the classification process, the output will indicate the best enhancement to improve the fingerprint quality, or if it must be kept original. When the classifier indicates that enhancement is needed, the image is enhanced with the proper filter. Finally, the output is comprised of the original or improved image.

In this work, we propose the use of CNN as feature extractors using the concept of transfer learning, which relates to the descriptive power of a CNN previously trained in a dataset with a high number of heterogeneous samples and which is applied to a set of samples not yet known by the model. To validate the proposed solution, we evaluated the use of several feature extractors and classifiers to identify the most suitable for improving fingerprints quality.

V. Evaluation Methodology

A. Feature Extraction

The use of CNN as feature extractors produces results known as deep features. In this work, we propose the use of such features to extract information from the fingerprint images for automatic classification of the best contrast enhance filter.

1) Classical features extractors: The Gray Level Co-Occurrence Matrix (GLCM) is a feature extractor based on image texture analysis. This extractor is based on the descriptors of Haralick [19]. GLCM is calculated from the co-occurrence of pairs of pixels in the image based on the distance D in a θ direction from the reference pixel.

The Local Binary Patterns (LBP), proposed by Ojala and Pietik [20], is a method that is also based on image texture analysis. The LBP is calculated from an analysis of the local neighborhood of a reference pixel. The operation assigns a binary label to each neighboring pixel, within a neighborhood with distance D, according to the intensity level of the reference pixel. The set of local binary standards defines the attributes of the sample.

Based on the analysis of the invariant moment of the image, Hu [21] proposed a family of feature extractors inspired by the central moments. These extractors are invariant in scale, rotation, and translation and make up a set of seven moments.

2) Deep features extractors: On this paper, we evaluate CNN models DenseNet169 and DenseNet201 proposed by Huang et al. [22], and also CNN MobileNet proposed by Howard et al. [23]. These architectures were trained from the ImageNet dataset [24], which consists of 1.2 million images, and grouped into 1000 categories. The training methodologies

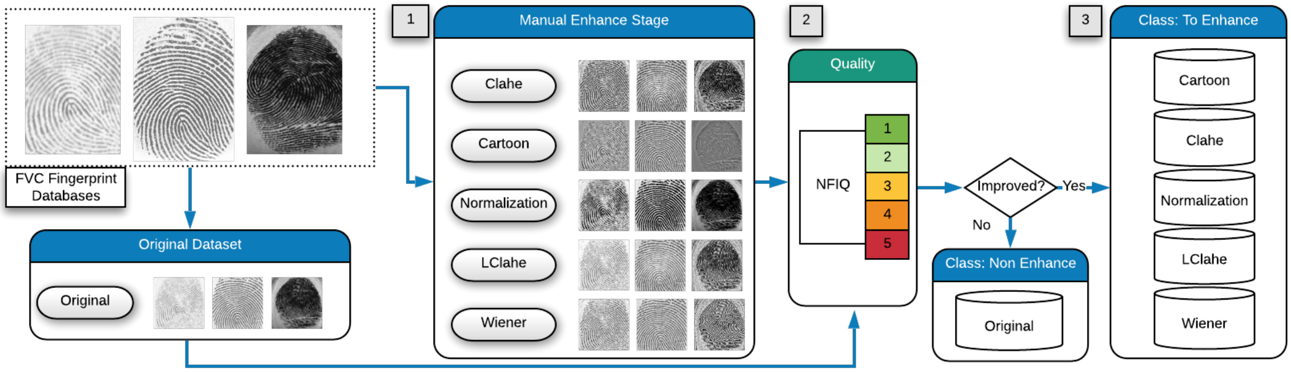


Fig. 3: Construction flow of the training dataset based on NFIQ quality score.

used by each architecture are documented in detail in their respective articles.

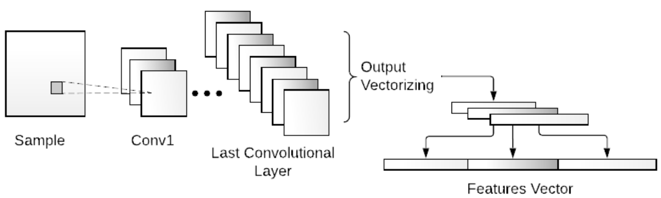


Fig. 4: Deep feature extraction from CNN Architectures.

According to Fig. 4, the vector of deep features can be obtained by removing the fully connected layer, and the exit of the previous chamber is then transformed into a one-dimensional matrix. This one-dimensional matrix can be used as a sample feature vector. In this way, a pre-trained CNN does not act as a classification model, but as a feature extractor whose representativeness potential was previously trained with a different set of data of fingerprint images.

B. Classification

1) Preparation of the training dataset: The FVC 2000, 2002, and 2004 datasets describes by [5], have a total of 7920 fingerprint samples spread in multiple databases (DB), excluding synthetic samples. In this work, we use samples that have the following source: six different optical readers, two different capacitive readers, and a thermal reader. Table I presents, for each DB, properties of the fingerprints and the name of the sensor device used to capture them.

TABLE I: FVC dataset description with sensors list.

FVC	DB	Sensor type	Image size
2000	DB1	Optical “S.D. Scanner”	300x300
	DB2	Capacitive “TouchChip”	256x364
	DB3	Optical “DF-90”	448x478
2002	DB1	Optical “TouchView II”	388x374
	DB2	Optical “FX2000”	296x560
	DB3	Capacitive “100 SC”	300x300
2004	DB1	Optical “V300”	640x480
	DB2	Optical “U.are.U 4000”	328x364
	DB3	Thermal “FingerChip”	300x480

To prepare the training dataset, we made copies of the FVC datasets and applied five kinds of enhancement filters for each image of the datasets. Then, we performed an NFIQ1 quality evaluation on original and enhanced images. Afterward, based on the NFIQ1 score, we classified the images in two classes: the images that have improved in quality by applying any enhancement and those that have not improved quality. Lastly, we separated the first group of images according to the enhancement that improved the image quality. Fig. 3 illustrates this process.

2) Training: In order to evaluate the representativeness of the extracted features for the classification of both sets “To Enhance” and “Non Enhance” for Stage 1, and “CLAHE”, “LCLAHE”, “Cartoon”, “Normalization”, “Laplace”, and “Wiener” for Stage 2, the generated images were classified using four consolidated ML techniques: k-NN [25], RF [26], MLP [27], and SVM [28] with RBF kernels.

In the classification process, MLP classifier performed its training using the Levenberg-Marquardt method, and with the neurons varying from 2 to 1000 in the hidden layer. We used a grid search to determine the number of neighbors for the k-NN classifier, where the k value was varied using the odd values from 3 to 15.

The SVM classifier with RBF kernels is defined as γ, where this hyperparameter was varied from 2^{-15} to 2^{3}. For the RF classifier, the criteria function was varied for Gini and entropy, the minimum number of samples that is necessary to split an internal node ranged from 1 to 6, the lowest amount of samples requested to be at a leaf node also ranged from 1 to 6, and the number of estimators was 3000.

The hyperparameters for MLP, SVM, and RF were determined through a 20-iterations random search over a cross-validation process with 10-folds.

3) Classification Stage 1: Does the sample need enhancement?

Many images do not improve quality when applying the enhancement filters, where they can lose quality. This is because contrast enhancement filters, in addition to improving the contrast of the image, often also enhance noise and produce false key points. This behavior hinders the recognition stage and contributes to false positives. The rise of false features and increased noise after applying the filters in some situations, increasing the risks of decreasing the quality and eventually false matching. In this sense, it is necessary to identify the need to apply or not a contrast enhancement filter.

In this paper, we propose the first stage of classifying samples between "To Enhance" and "Non Enhance" classes. Given the intrinsic imbalance of the data set regarding the need for enhancement, this step was modeled as a binary classification problem. Therefore, from a fingerprint sample, this stage automatically identifies whether or not to apply the enhancement. If it is not necessary ("Non Enhance" class), the flow ends while preserving the original characteristics of the sample. Otherwise, the sample is directed to stage 2 to identify the best contrast enhancement filter. Fig. 2, step 2, illustrates the first stage of this methodology.

4) Classification Stage 2: Which enhancement method to apply to the sample?

Choosing the better enhancement filter is a critical decision in images that need to improve contrast, as different filters can result in different levels of quality according to fingerprint features. At this stage, samples that need contrast are classified into one of five classes: "CLAHE", "LCLAHE", "Cartoon", "Normalization", and "Wiener". Each class corresponds to a contrast enhancement filter.

VI. Results and Discussion

The proposed approach was evaluated on a computer with an Intel(R) Core(TM) i7-9750H CPU @ 2.60GHz, 16 GB of RAM, a GeForce GTX 1660 Graphics Processing Unit (GPU), and a Linux LTS 18.04 operating system.

The feature extraction stage considered three classical methods (GLCM, HU, and LBP), and three recently proposed CNNs architectures previously trained (DenseNet169, DenseNet201, and MobileNet). Table II shows the number of features identified by each approach.

TABLE II: Number of features for each extractor.

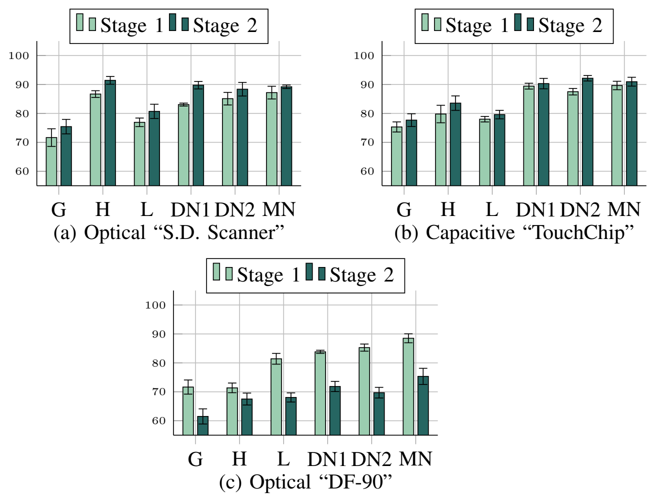
Approach	Extractor	Number of features
Classic	LBP	48
	GLCM	14
	Hu Moments	7
Transfer Learning	Densenet 169	1664
	Densenet 201	1920
	MobileNet	1024

Stages 1 and 2 considered classification models already consolidated in the literature: MLP, NN, RF, and SVM. Once each image bank has specific characteristics, training and tests were carried out for each database of each FVC year.

The results show that for the Optical scanner "S.D. Scanner", the combination of the HU extractor and the RF classifier showed average accuracy, considering stage 1 and stage 2, above 89%, although the combination MobileNet with NN indicating the best accuracy for stage 1.

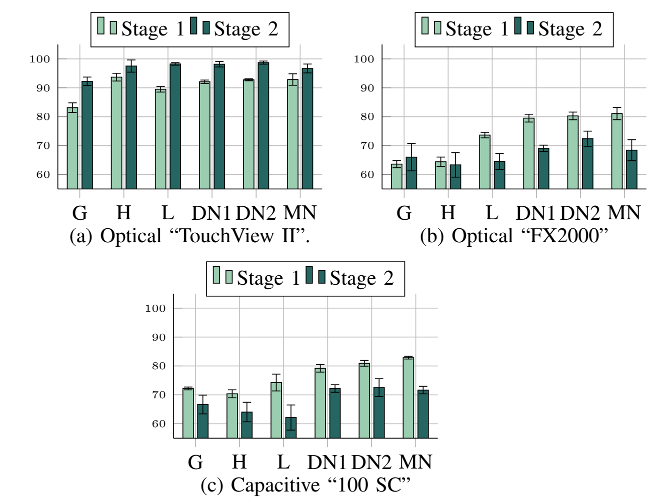
On the other hand, for the Capacitive "TouchChip" and Optical "DF-90" scanner, the best results were presented by combining MobileNet with NN, presenting an average accuracy of 90.3% and 88.5%, respectively. Fig. 5 presents the best indexes according to feature extractors for each type of reader referring to the FVC 2000.

According to Fig. 6, the DenseNet201 feature extractor presented the best results for all types of readers using the FVC 2002 databases. Our results show an average accuracy of 95.7%, for the "TouchView II" Optical scanner with SVM classifier, 74.7%, for the "FX2000" Optical scanner with NN classifier and 77.2% for the "100 SC" Capacitive scanner with SVM.



(a) Optical "S.D. Scanner" (b) Capacitive "TouchChip" (c) Optical "DF-90"

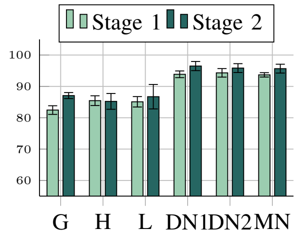
Fig. 5: Best Accuracy results for FVC 2000 dataset (G: GLCM, H: HU, L: LBP, DN1: DenseNet169, DN2: DenseNet201, MN: MobileNet).



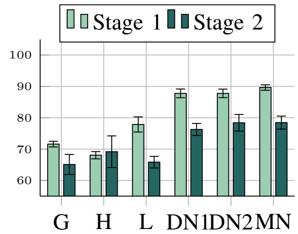
(a) Optical "TouchView II". (b) Optical "FX2000" (c) Capacitive "100 SC"

Fig. 6: Best Accuracy results for FVC 2002 dataset (G: GLCM, H: HU, L: LBP, DN1: DenseNet169, DN2: DenseNet201, MN: MobileNet).

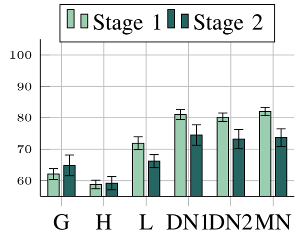
Finally, the MobileNet character extractor combined with the NN classifier presented the best average performance between stages 1 and 2 for the readers "Optical" U.are.U 4000 and Thermal "FingerChip", with an average accuracy of 84.1% and 77.9%, respectively. This results are presented on the Fig. 7.



(a) Optical "V300"

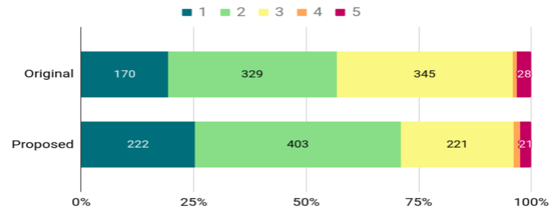


(b) Optical "U.are.U 4000"

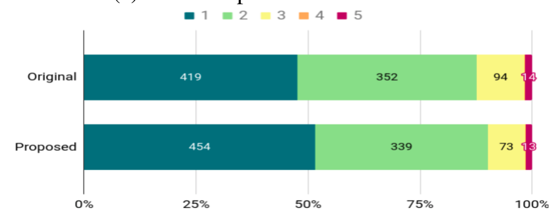


(c) Thermal "FingerChip"

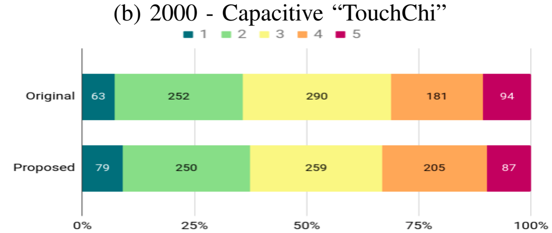
Fig. 7: Best Accuracy results for FVC 2004 dataset (G: GLCM, H: HU, L: LBP, DN1: DenseNet169, DN2: DenseNet201, MN: MobileNet).



(a) 2000 - Optical "S.D. Scanner"

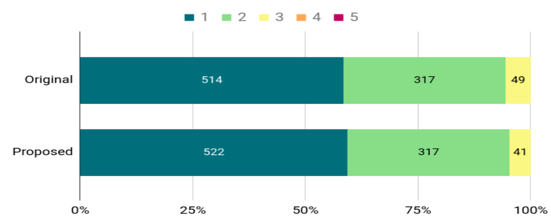


(b) 2000 - Capacitive "TouchChi"

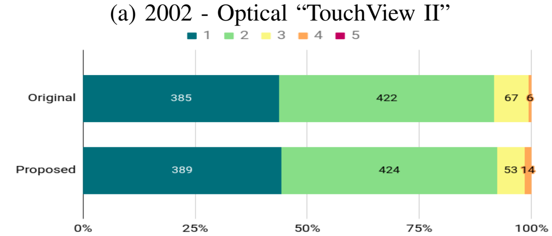


(c) 2000 - Optical "DF-90"

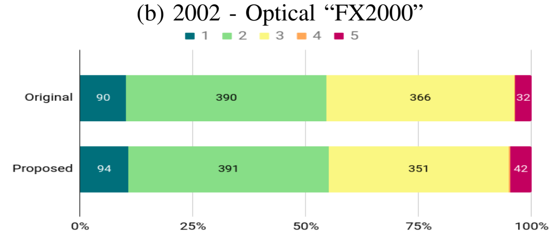
Fig. 8: NFIQ1 quality improvement for FVC 2000 datasets.



(a) 2002 - Optical "TouchView II"



(b) 2002 - Optical "FX2000"



(c) 2002 - Capacitive "100 SC"

Fig. 9: NFIQ1 quality improvement for FVC 2002 datasets.

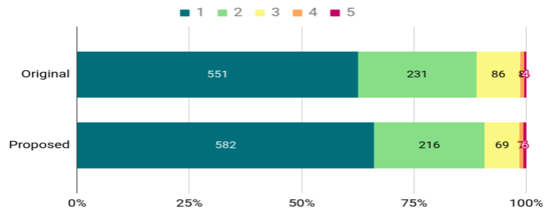
Regarding the improvement of the quality of fingerprint after performing the proposed methodology, the results were compared with the NFIQ1 quality indexes from the original samples. As shown in Fig. 8, 9 and 10, there was a noticeable improvement in the quality of the images originally classified as class 1 (best quality), observing the results of Fig. 8.a, there was an increase of 52 samples classified as best quality, from 170 to 222 samples. Similarly, there was a reduction of the number of samples with quality 4 and 5 (worst qualities), for example, in Fig. 8.c from 94 samples to 87 samples with quality 5. These results[1]., therefore, indicate that the automatic and adaptive selection of the enhancement filter to be applied to the image produces improvements in the quality of the fingerprint, thus indicating promising results in the study of quality improvement of fingerprints.

VII. Conclusion and Future Works

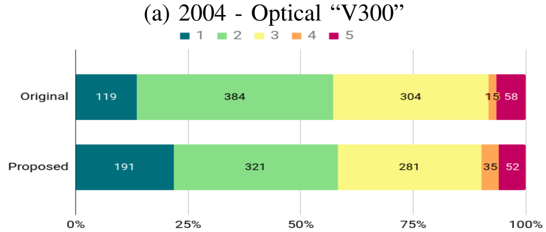
This work presents a new approach to automatically classify and improve the quality of fingerprint images. Although several fingerprint image enhancements are found in the literature, they can improve or lower the quality of the images. We use a two-stage process to decide whether the image needs to be enhanced, and if so, which method is the most suitable for this task. We compare two different types of feature extractors, classical and deep feature extractors, assessing the quality of the fingerprint using NFIQ1.

Except in one case in FVC 2004, there was no repetition of feature extractor and model for the two stages of the same reader. This fact indicates that every reader has different characteristics that are not adequately handled by a single enhancement method. Comparing both classical and deep feature extractors in the two stages of every reader, using CNNs gave

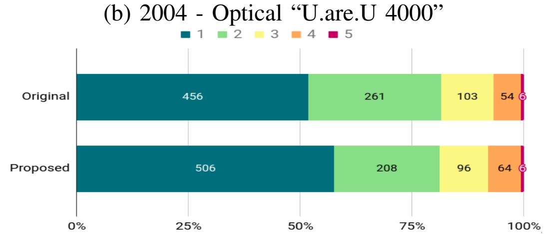
[1]We included more results of this work, considering more fingerprint scanner types, on this link: https://bit.ly/3dHjkMQ



(a) 2004 - Optical "V300"



(b) 2004 - Optical "U.are.U 4000"



(c) 2004 - Thermal "FingerChip"

Fig. 10: NFIQ1 quality improvement for FVC 2004 datasets.

the best results in all but one case. Traditional extractor HU with RF showed the best indices against other conventional methods. The best accuracy, on average, were presented by the DenseNet and Mobilenet networks, highlighting accuracy rates above 95% for "TouchView II" and "V300" readers.

Finally, considering all feature extractors, our results showed that the choice between different enhancement methods, based on the input images, can be aided by the proposed automatic classification. Our methodology can indicate a suitable combination to deal with fingerprint images from different sources. As future works, we want to evaluate fingerprint quality using NFIQ2. In addition to that, we want to explore different CNN architectures and study the best enhancements applicable in the fingerprint matching stage.

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