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Finger-Vein-based Biometric Recognition using Deep Neural Networks

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***Abstract*—Finger-vein-based biometric recognition has recently attracted the attention of many stakeholders, due to the convenience of its acquisition modality and its robustness against digital impersonation. A finger-vein corpus, has been collected from 100 subjects to test the proposed framework. Convolutional and recurrent neural networks are jointly employed for recognition purposes. The obtained experimental results show that, although in a very challenging scenario, the proposed system guarantees high levels of performance.**

I. Introduction

In the last decades, the use of biometric characteristics has become a prominent and well-accepted solution in secure and user-convenient recognition applications [1]. Biometrics traits such as fingerprint, face, signature, iris, and voice have been successfully employed in access control and border control, financial-transactions-related applications, as well as for person verification on personal devices, to cite a few examples. However, many of these biometric identifiers are exposed to the public and therefore prone to presentation attacks [2].

On the contrary, vein patterns are subcutaneous structures and therefore intrinsically more robust against such threat than other more commonly-used biometric traits. Because of this appealing characteristic, in the last few years the use of vein patterns is becoming more and more popular. A standard device for the acquisition of vein patterns is composed by a near-infrared (NIR) illuminator and a NIR camera. The hemoglobin in the blood absorbs infrared light, therefore blood vessels appears as dark lines in the acquired images. In our work, we take a step forward and introduce, for the first time in literature, an innovative on-the-fly, contactless, and low-cost vein-based biometric recognition system that allows the finger-vein structure to be acquired while the user is walking and passing four fingers over the acquisition system, with an increase of user convenience and of the throughput of the recognition system. Deep learning approaches involving both convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are here exploited to extract discriminative features from the acquired vein pattern's videos, and guarantee a high level of recognition performance. To the best of our knowledge, this is the first work in literature exploiting an on-the-fly technology for finger-vein-based biometric recognition.

The paper is structured as follows: an introduction on finger-vein-based recognition is given in Section II and an overview of the state-of-the-art works regarding deep-neural-network (DNN) approaches applied in the framework of vein-based biometric recognition is provided in Section III. The detailed description of the adopted architecture is given in Section IV. Eventually, the achieved results and the conclusions are detailed in Section V and VI respectively.

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II. Finger-Vein-based Biometric Recognition

The high convenience in the data acquisition process, the higher security in terms of presentation attack and liveness detection, as long as the always-improving performance offered by vein-based recognition system, are leading to an increasing interest in the design and use of such technology. In the recent years, different kinds of vein information, such as finger vein [3], palm vein [4], [5], wrist vein [6], and hand-dorsal vein [7], [8], have been studied with the purpose of application to biometric recognition.

In general, nearly every vein-based biometric system share the same configuration, consisting of the image acquisition, pre-processing, feature extraction, and matching steps. The vein image is captured by using a NIR illuminator and a NIR camera. Due to the different absorption properties of the hemoglobin compared to the tissues in the hand, veins appear as a network of dark lines in the images. Rotation and vertical translation of the hand could affect the acquisition step, and the acquired pictures are generally characterized by low contrast and poor quality, thus implying the need of pre-processing steps, such as normalization and image enhancement. Besides, a region of interest (ROI) containing the vein pattern is generally extracted from the enhanced image, and taken into account in the feature extraction stage. The feature extraction approaches used in vein-based biometrics can be broadly categorized into five classes:

- **geometry-based methods** (GB): geometric information, such as shape or topological structure, is extracted from the vein images and used as discriminative features for the users. Most of the aforementioned techniques follow the framework of segmenting the vein pattern from the background, with discriminative information then extracted from the obtained network. Global topology-based methods, such as line-like [22], [23] and curvature [24] models, fall within this category. Local geometry-based models, such as vein knuckle shapes, endpoints and crossing points [25], [26], [27] of vein structures, belong to this category as well;
- **subspace-learning-based methods** (SL): techniques exploiting appearance-based methods, such as linear discriminant analysis (LDA) [28], principal component analysis (PCA) [29], [30] or two-dimensional PCA [31], [32];
- **statistical-based techniques** (SB): statistical features as the local binary histogram and moments are exploited to

TABLE I
STATE-OF-THE-ART WORKS ABOUT FINGER-VEIN-BASED BIOMETRIC IDENTIFICATION SYSTEMS.

Paper	Database			Employed System		Performance
	Name	# Classes	Categ.	Feature Extraction	Matching	
Kumar et al. [9]	HKPU [9]	302 (156 users)	GB	Gabor filter & morphological proc.	XOR-based similarity scores	CIR = 90.08%
Van et al. [10]	SDUMLA [11]	636 (106 users)	SL	MFRAT[12] & GridPCA	Euclidian distance	CIR = 95.67%
Lu et al. [13]	SDUMLA [11]	636 (106 users)	SB	Polydirectional LLBP	Histogram intersection	CIR = 99.21%
Ong et al. [14]	SDUMLA [11]	636 (106 users)	GB	Minutiae	Genetic algorithm & k-modified Hausdorff distance (k-MHD)	CIR = 99.70%
Qui et al. [15]	SDUMLA [11]	636 (106 users)	SL	Pseudo-elliptical transform & 2D-PCA	Euclidean distance	CIR = 97.61%
	FV-USM [16]	492(123 users)				CIR = 97.02%
Xie et al. [17]	SDUMLA [11]	636 (106 users)		Block-based average absolute deviation (AAD)	Ensemble component-based extreme learning machines (EC-ELM) network	CIR = 97.76%
Banerjee et al. [18]	SDUMLA [11]	636 (106 users)	GB	Morphologically enhanced images	Affine registration based template matching algorithm (ARTeM)	CIR = 90.72%
Yang et al. [19]	HKPU [9]	302 (156 users)	GB	Anatomy Structure Analysis based Vein Extraction(ASAVE)	Integration Matching	CIR = 99.68%
Yang et al. [20]	HKPU [9]	302 (156 users)	GB	ASAVE[19] & indexing	Grouped Hamming Distance	CIR = 97.89%
	SDUMLA [11]	636 (106 users)				CIR = 95.25%
	MMCBNU_6000 [21]	600(100 users)				CIR = 94.83%
	FV-USM [16]	492(123 users)				CIR = 98.31%

extract discriminative information from vein structures. Methods based on local binary patterns (LBPs) [33], [34], local derivative patterns (LDPs) [35] and invariant moments [36] are examples of feature extraction techniques based on local statistics;

- **local invariant-feature-based methods** (LI): methods inspired by approaches stemming from computer vision, such as those using key points for the scale invariant feature transform (SIFT) as features [37], [38];
- **DNN-based models** (DM): a DNN consists of a sequence of processing layers and can be exploited as feature extractor or classifier module in a vein-based biometric system. A detailed overview of the state of the art exploiting DNN-based models in the field of vein-based biometric recognition system is provided in Section III.

An overview of the state of the art of finger-vein-based biometric identification systems is provided in Table I, where details about the employed database, as well as the employed feature extraction techniques, category and matching algorithms, together with the achieved recognition performance expressed as correct identification rate (CIR), are reported.

III. State-of-the-Art: DNN and Vein-Pattern-based Biometric Applications

In the recent past, deep learning techniques are being employed more and more in the field of biometric recognition, due to the promising achievable results in terms of recognition performance, spoofing attacks' detection, and ability in extracting discriminative features. Recently, CNNs have been specifically introduced in vein-based recognition scenarios, showing excellent performance when exploited for different tasks [59]. In this section, we present an overview of the most relevant papers about the application of deep learning methods in the field of vein-based biometrics. The related details are summarized in Table II.

A deep learning approach applied in a finger-vein-based biometric identification system has been first proposed by Radzi *et al.* [39]. The employed network's structure is based on the one proposed in [40], with the CNN fed with binary images obtained by thresholding the original vein pictures. A more recent work on finger-vein-based identification using CNNs is the one proposed by Das *et al.* [3], where stable and highly-accurate performance is achieved while dealing with finger-vein images of different quality.

Hong *et al.* [42] have designed a finger-vein-based verification system exploiting a pre-trained model of VGG-16 [43] to perform biometric verification. The pre-trained network model is used for fine-tuning, having the difference between two finger-vein images as input, and databases with different image quality are taken into account. A deep CNN (D-CNN) architecture inspired by the VGG-16 model has also been exploited for biometric verification based on finger-vein by Huang *et al.* [44]. The modified CNN architecture is fed with a two-channel image resulting from the merging of two templates. An approach for finger-vein-based biometric verification using CNN and supervised discrete hashing (SDH) has been proposed in [46]. Different CNN architectures have been there tested, such a light CNN (LCNN) and a modified version of the VGG-Net-16, fed with pairs of vein images. The SDH scheme is also investigated for the aim of performance improvement and reduction of the template size. Fang et al. [48] have exploited a lightweight deep-learning framework for finger-vein verification. Mini-ROIs from the original image are extracted, based on the evaluation of the adopted network, and the original image and the mini-ROI are integrated trough

TABLE II
STATE-OF-THE-ART WORKS ABOUT APPLICATIONS OF DEEP LEARNING ALGORITHMS IN THE FIELD OF VEIN-BASED BIOMETRIC RECOGNITION SYSTEMS.

Paper	Biometric Identifier	Database Name	Database # Classes	CNN Features Reference	CNN Features Aim	Performance
Radzi et al. [39]	Finger-vein	Own	300 (50 users)	[40]	Biometric Identification	CIR = 100%
Das et al. [3]	Finger-vein	HKPU [9]	302 (156 users)	-	Biometric Identification	CIR = 95.32%
		FV-USM [16]	492 (123 users)			CIR = 97.53%
		SDUMLA [11]	636 (106 users)			CIR = 97.48%
		UTFVP [41]	360 (60 users)			CIR = 98.33%
Hong et al. [42]	Finger-vein	Own (Good Quality)	120 (20 users)	VGG-16 [43]	Biometric Verification	EER = 0.396%
		Own (Middle Quality)	198 (33 users)			EER = 1.275%
		SDUMLA [11] (Low Quality)	636 (106 users)			EER = 3.906%
Huang et al. [44]	Finger-vein	Own (Training)	300.000	VGG-16 [43]	Biometric Verification	-
		FVRC2016 - DS1 [45] (Testing)	1000			EER = 0.42%
		FVRC2016 - DS2 [45] (Testing)	1000			EER = 1.41%
		FVRC2016 - DS3 [45] (Testing)	1000			EER = 2.14%
Xie et al. [46]	Finger-vein	HKPU [9]	302 (156 users)	LCNN [47]	Biometric Verification	EER = 0.11%
				VGG-16 [43]		EER = 0.12%
Fang et al. [48]	Finger-vein	MMCBNU_6000 [21]	600 (100 users)	[49]	Biometric Verification	EER = 0.10%
		SDUMLA [11]	636 (106 users)			EER = 0.47%
Jalilian et al. [50]	Finger-vein	UTFVP [41]	360 (60 users)	U-net [51]	Biometric Verification	EER = 4.53%
						EER = 0.41%
				RefineNet [52]		EER = 2.95%
						EER = 1.80%
		SDUMLA [11]	636 (106 users)	SegNet [53]		EER = 2.54%
						EER = 2.17%
Kim et al. [54]	Finger-vein, Finger-shape	SDUMLA [11]	636 (106 users)	VGG-16 [43],	Biometric Verification	EER = 3.37%
		HKPU [9]	302 (156 users)	ResNet-101 [55]		EER = 1.08%
Wang et al. [56]	Hand-dorsal Vein	Own	200 (200 users)	VGG-16 [43]	Biometric Verification	EER = 0.06%
Zhang et al. [57]	Palm-Vein	Own	600 (300 users)	Inception ResNet v1 [58]	Biometric Verification	EER = 2.74%

a two-stream network. Jalilian *et al* [50] have used three different fully CNN (FCN) architectures, inspired by the U-net [51], RefineNet [52], and the SegNet [53] respectively, in order to extract the finger-vein patterns from NIR finger images. The problem of efficient training and configuration settings for the employed networks has also been studied, by training the considered FCN architectures with a varying number of manual and automatically generated labelled images. Wang *et al.* [56] have proposed a hand-dorsal vein recognition model constructed by adopting the VGG-16 model pre-trained on a large-scale database as a universal feature descriptor. A task-specific selective convolutional features (SCF) model based on spatial weighting is proposed to obtain the discriminative features, and spatial pyramid pooling (SPP) is introduced to obtain the final feature representation. Kim *et al.* [54] have proposed a deep CNN-based finger-vein and finger shape multimodal biometric system. The adopted CNN structure is the same of ResNet-50 and ResNet-101 [55], and it is fed with the spectrogram image of the ROI in case of the finger shape, and the difference between the enrolled and the input images in case of finger-vein. Two different CNNs are used in order to obtain the matching scores for finger shape and finger vein and the final matching score results from the score-level fusion of the scores. The ResNet architecture has also been exploited by Zhang *et al.* [57] in the framework of a palm-vein-based verification system. The authors applied a modified version of the Inception ResNet-v1 DNN to extract features, later used for identification and verification.

IV. CNN ARCHITECTURE

A sequence of finger-vein images is fed into the matching system after resizing and normalization to zero mean and unit variance. Each element of the sequence is processed by the same CNN model, The neural network architecture of the proposed approach is discussed in details in the following section.

A. *Proposed CNN Topology*

The CNN adopted in the proposed system, shown in Figure 1, has been specifically designed for finger-vein-based recognition tasks, with its configuration (sizes, kernels, etc.) set considering finger geometry and orientation. The proposed networks, called Vein-CNN or shortly V-CNN throughout the

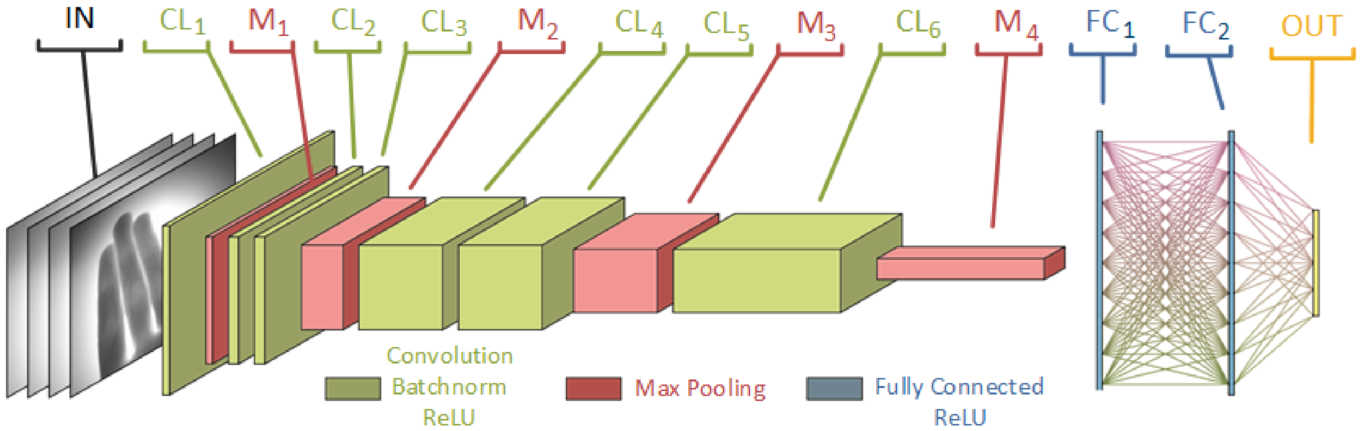

Fig. 1. V-CNN Architecture.

paper, has 6 convolutional layers, 4 max pooling layers, 2 fully-connected layers and an output layer, with 13 layers in total as summarized in Table III. The details of the V-CNN topology are explained as follows:

- *IN*: the input layer takes data with a size of $[320 \times 360 \times N_c]$, with finger vein images of size $[320 \times 360]$ and N_c channels for each image. We may have either $N_c = 1$ or $N_c = 4$ in the proposed configurations, while a resizing is needed to bring the finger-vein images to the required input size;
- *Group-1 ($CL_1 - M_1$)*: the first hidden layer group is composed of 64 convolutional filter of size $[3 \times 3 \times 64]$, followed by a batch normalization, a rectifier linear unit (ReLU), and a max-pooling layer of size $[2 \times 2]$. After the convolution and down-sampling, $[160 \times 180 \times 64]$ low-level features are extracted from the input data;
- *Group-2 ($CL_2 - CL_3 - M_2$)*: the second hidden layer group consists of two layers of 128 convolutional filters, each of which followed by a batch normalization and a ReLU. Kernel size for the former one is chosen as $[11 \times 5]$ in order to capture patterns along finger orientation, mostly close to vertical position in our database. After 2-layered convolution and down-sampling with max-pooling layer of size $[2 \times 2]$, Group-1's output is transformed into $[80 \times 90 \times 128]$ features;
- *Group-3 ($CL_4 - CL_5 - M_3$)*: the third hidden layer group consists of two layers of 256 convolutional filters, each followed by a batch normalization and a ReLU. Differently from the previous hidden layer group, the size of the kernel for the first convolutional layer here is chosen as $[5 \times 11]$ in order to capture patterns across fingers. After 2-layered convolution and down-sampling with max-pooling layer of size $[2 \times 2]$, Group-2's output is transformed into $[40 \times 45 \times 256]$ features;
- *Group-4 ($CL_6 - M_4$)*: the forth hidden layer group is composed of 512 convolutional filters of size $[3\times3\times512]$, followed by a batch normalization, a ReLU, and a max-pooling layer of size $[5\times5]$. After convolution and down-sampling, the output of previous group is transformed into $[8 \times 9 \times 512]$ low-level features.
- *Group-5 ($FC_1 - FC_2$)*: the fifth hidden layer group contains two fully-connected layers, each followed by a ReLU and a dropout regularization where 50% of hidden units are dropped in order to reduce overfitting while training. This layer group converts previous group's activation map into a $[1024 \times 1 \times 1]$ feature map x;
- *OUT*: the output layer consists of N_I neurons, where N_I is the number of unique identities/subjects in the database. A fully-connected network is generated in this layer, giving as outputs the probabilities of $1 - to - N_I$ matches for the considered subjects.

As already mentioned, the described network has been specifically designed to deal with the finger-vein images generated in the proposed system. In order to test its effectiveness, in Section V its behavior is compared against three different state-of-the-art CNN architectures, namely VGG-19 [43], Densenet-201 [60] and Inception-v3 [61], selected due to their superiority shown over ImageNet Large Scale Visual Recognition Challenge Datasets in different years [62], [63].

B. Network Initialization and Optimization

For all the CNN architectures considered in this study, a cross-entropy (CE) loss function is preferred for back-propagation, and stochastic gradient descent (SGD) with a batch size of 32 is used for training optimization. During the SGD optimization, *i)* learning rate is started from 0.001 and divided by 10 after each 30 epoch iteration, *ii)* momentum is chosen as 0.9 for accelerating the gradient vectors in the right directions, and *iii)* L_2 regularization penalty (weight decay) is set to 0.01. As poor initialization of neural network weights can divert the learning steps to a wrong path, following weights are preferred for CNN models in our experiments: *i)* random initialization with a normal distribution $\mathcal{N}(0, 2/n)$ for convolutional layers, where $n = K_w \times K_h \times N_{C_{out}}$ and K_w, K_h are kernel sizes, $N_{C_{out}}$ is output channel size, *ii)* unit weight initialization for batch normalization, and *iii)* random initialization with a normal distribution $\mathcal{N}(0, 0.01)$ for fully-connected layers.

V. Experimental Tests

In order to evaluate the effectiveness of the proposed framework for the designed several tests have been performed

TABLE III
PROPOSED CNN CONFIGURATION (V-CNN).

Abbreviation	Layer Type	Number of Filter	Size of Feature Map	Size of Kernel	Number of Stride	Number of Padding
IN	Image Input Layer	-	$320 \times 360 \times N_c$	-	-	-
CL_1	Convolutional Layer-1	64	$320 \times 360 \times 64$	3×3	1×1	1×1
M_1	Max-Pooling Layer-1	1	$160 \times 180 \times 64$	2×2	2×2	0×0
CL_2	Convolutional Layer-2	128	$160 \times 180 \times 128$	11×5	1×1	5×2
CL_3	Convolutional Layer-3	128	$160 \times 180 \times 128$	5×5	1×1	2×2
M_2	Max-Pooling Layer-2	1	$80 \times 90 \times 128$	2×2	2×2	0×0
CL_4	Convolutional Layer-4	256	$80 \times 90 \times 256$	5×11	1×1	2×5
CL_5	Convolutional Layer-5	256	$80 \times 90 \times 256$	5×5	1×1	2×2
M_3	Max-Pooling Layer-3	1	$40 \times 45 \times 256$	2×2	2×2	0×0
CL_6	Convolutional Layer-6	512	$40 \times 45 \times 512$	3×3	1×1	1×1
M_4	Max Pooling Layer-4	1	$8 \times 9 \times 512$	5×5	5×5	0×0
FC_1	Fully Connected Layer-1	1024×1				
FC_2	Fully Connected Layer-2	1024×1				
OUT	Output Layer	$N_I \times 1$				

over a database collected at our Institution.

During the experiments all preprocessing steps have been executed on MATLAB (R2017b), and PyTorch 0.4.0 has been preferred to build network architectures with a system configuration of 32Gb RAM, Titan V graphics card, i7-3.4GHz processors and Windows 10 operating system.

A. CNN Comparisons

The proposed framework is here compared against three different state-of-the-art CNN architectures, namely VGG-19, Densenet-201, and Inception-v3, following the same training strategies employed for the tests previously described.

As a result of comparison over CNN-only architectures, the highest identification accuracy scores are commonly accomplished with V-CNN when 4-layer input tensors are preferred as templates.

In order to show the effectiveness of our approach, we have considered two alternative methods for fusing the information derived from multiple frames, yet without exploiting any temporal information Specifically, we have implemented a score-level fusion (SF) as well as a decision-level fusion (DF) strategy over the features extracted by the CNN processing individual frames. In more detail, SF is performed by averaging the likelihoods obtained as predictions from the CNN models for each of the nine separate frames in an acquisition sequence. Majority voting is instead performed to implement DF once the predictions for each frame are provided by the CNN. The improvements obtained using SF and DF over the acquired sequences of images are shown in Figure 2. Both SF and DF increase the accuracy in between 2%-5% when considering two acquisition sessions for training. Nevertheless, adding more training sessions slightly reduces the relevance of the improvement on the identification accuracy. In addition, both SF and DF result in similar patterns over identification performances, which means that the two approaches are not significantly different from each other (p-value= 0.415801 in terms of paired t-tests).

To sum up, among all the CNN architectures evaluated in this study, V-CNN and and Densenet-201 perform better than the others.

VI. CONCLUSIONS

We have proposed a novel CNN architecture, namely V-CNN, customized for finger-vein identification. Despite its simplicity, the proposed V-CNN outperforms other state-of-the-art CNN architectures.

VII. ACKNOWLEDGEMENTS

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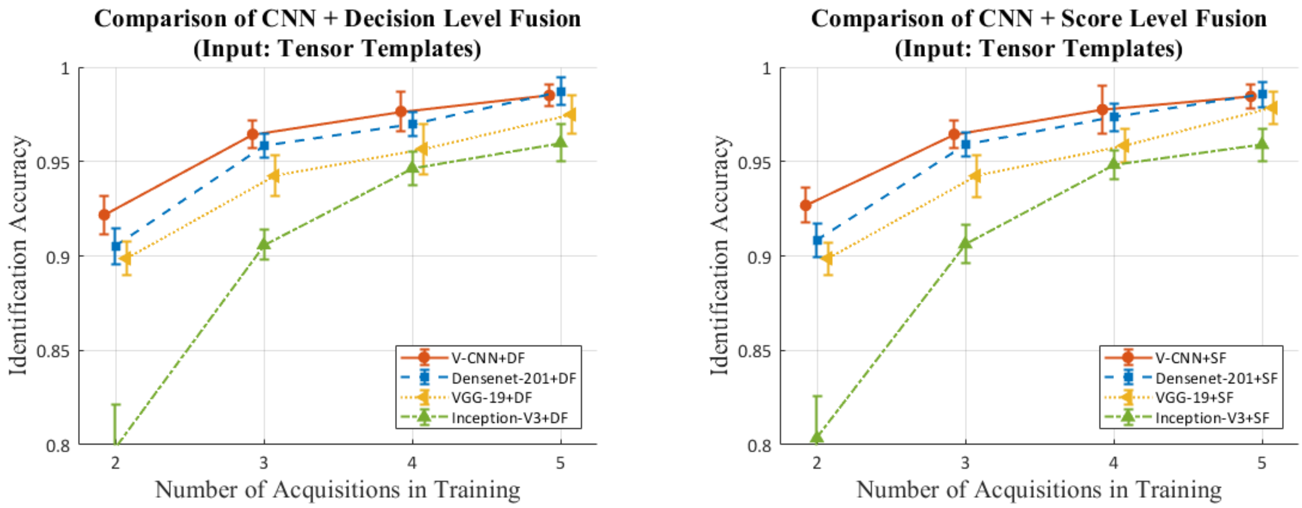

Fig. 2. Performance comparison of simple fusion techniques based on DF (left) and SF (right) over CNN-based feature extracted from frames of a sequence, for different training acquisitions and using 4-layer input templates.

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