

## Introduction

**Problem:** In real-world applications, the captured face images are usually contaminated with noise, which significantly decreases the performance of face recognition. In this paper, we propose a cascaded noise-robust deep convolutional neural network (CNR-CNN) method for face recognition under noise.

## Contributions

- An effective CNR-CNN method is proposed for face recognition under noise. Instead of independently training the denoising sub-network and the face recognition sub-network, CNR-CNN jointly trains these two sub-networks in a cascaded manner.
- An efficient denoising sub-network is elaborately designed, which takes advantage of dense connectivity to connect the feature maps layer-by-layer.

## Proposed Method

1. The proposed CNR-CNN method consists of two sub-networks, i.e., a denoising sub-network and a face recognition sub-network. These two sub-networks are jointly trained in a cascaded manner.

The joint loss:

$$Loss_{denoise} = \frac{1}{2N} \sum_{i=1}^N \|R\hat{x}_i - (\hat{x}_i - x_i)\|_F^2$$

where N is the number of training samples,  $\{(\hat{x}_i, x_i)\}_{i=1}^N$  represents N noisy-clean training image pairs.

$$Loss_{id} = -\frac{1}{N} \sum_{i=1}^N \log \frac{e^{s \cdot (\cos \theta_{y_i} - m)}}{e^{s \cdot (\cos \theta_{y_i} - m)} + \sum_{j=1, j \neq y_i}^C e^{s \cdot \cos \theta_j}}$$

where C is the number of classes,  $\theta_{y_i}$  denotes the angle between the weight vector and the feature vector. The optimized parameter m and scaling factor s are empirically set to 0.35 and 30, respectively.

$$Loss = \lambda Loss_{denoise} + (1 - \lambda) Loss_{id}$$

where  $\lambda$  is a parameter used to adjust the tradeoff between the two sub-networks (we empirically set  $\lambda$  to 0.2).

2. Furthermore, we elaborately design a denoising sub-network, where the dense connectivity and local feature fusion are employed to efficiently reconstruct the faces contaminated with noise.

## Experiments

**Table 1.** Accuracy (%) of face verification on LFW dataset

	$\sigma = 0$	$\sigma = 15$	$\sigma = 25$	$\sigma = 35$	$\sigma = 40$	$\sigma = 45$	$\sigma = 50$
Base1	94.05	84.93	71.42	61.58	58.07	56.85	55.23
Base2	90.77	90.12	89.27	87.98	87.23	86.47	85.47
BM3D	<b>94.08</b>	92.68	91.25	88.87	87.83	86.95	85.38
WNNM	94.07	92.47	91.15	87.97	83.60	82.03	80.52
DnCNN	<b>94.08</b>	92.68	91.07	89.05	88.08	86.85	85.17
NR-Net	85.02	85.07	84.20	83.97	83.62	82.97	82.77
CNR-CNN	93.37	<b>92.98</b>	<b>92.05</b>	<b>91.57</b>	<b>91.42</b>	<b>91.00</b>	<b>90.02</b>

**Table 2.** The identification rate (%) on the FERET dataset

	$\sigma = 0$	$\sigma = 15$	$\sigma = 25$	$\sigma = 35$	$\sigma = 40$	$\sigma = 45$	$\sigma = 50$
Base1	98.49	68.26	7.15	0.94	0.88	0.82	0.75
Base2	98.12	97.30	95.61	91.28	89.90	86.95	81.30
BM3D	98.49	97.93	92.41	79.49	69.13	56.90	44.86
WNNM	98.49	98.18	91.84	75.85	66.75	55.90	44.98
DnCNN	98.49	97.93	93.35	80.87	72.96	63.17	50.75
NR-Net	90.28	87.39	80.99	72.08	66.75	62.30	53.83
CNR-CNN	<b>99.31</b>	<b>98.87</b>	<b>97.99</b>	<b>95.92</b>	<b>94.48</b>	<b>92.79</b>	<b>89.77</b>

**Table 3.** The identification rate (%) on the FEI dataset

	$\sigma = 0$	$\sigma = 15$	$\sigma = 25$	$\sigma = 35$	$\sigma = 40$	$\sigma = 45$	$\sigma = 50$
Base1	<b>98.65</b>	58.45	5.75	1.45	1.15	1.25	1.15
Base2	94.35	93.35	89.80	87.10	87.45	78.90	74.40
BM3D	<b>98.65</b>	95.00	87.55	74.70	70.95	61.65	54.35
WNNM	<b>98.65</b>	94.85	85.95	70.65	67.75	55.20	47.25
DnCNN	98.55	94.60	86.45	71.80	67.35	55.35	47.00
NR-Net	79.25	76.60	70.95	62.70	64.35	51.45	48.15
CNR-CNN	98.20	<b>97.45</b>	<b>95.70</b>	<b>93.10</b>	<b>93.80</b>	<b>88.75</b>	<b>84.70</b>

We compare the proposed method with several state-of-the-art methods, including BM3D, WNNM, DnCNN and NR-Network, respectively. To show the robustness of the proposed method, we set seven different levels of noise (i.e.,  $\sigma \in [0, 50]$ ).

## Contact Us

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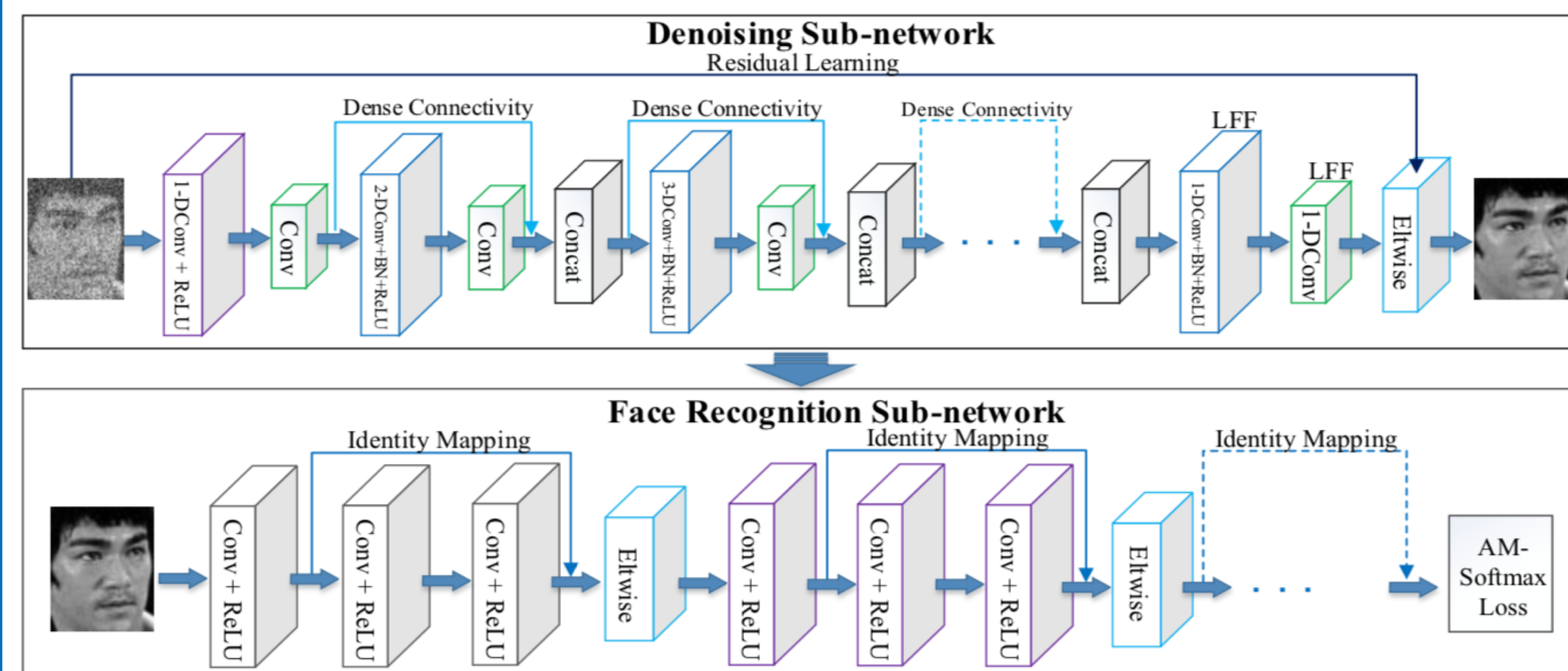


Fig. 1. Architecture of the proposed CNR-CNN.