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Cascade CNN Framework for Low Resolution Image Classification

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Abstract
Low resolution images contain less visual information, so classifications of these images are difficult. For overcoming this problem, cascade CNN framework for low resolution image classification is proposed. In this framework, super resolution CNN (SRCNN) enlarges low resolution image into super resolution image. The convolutional features of these super resolution images are fused with low resolution convolutional features which are extracted by low resolution CNN (LRCNN) feature extractor. A deep neural network classifier is trained on these fused CNN features. This classifier classifies low resolution images using learned fused features. Proposed cascade framework has been evaluated on different benchmark image dataset MNIST, CIFAR10 and achieves competitive accuracy results.

Keywords: *Low resolution, cascade CNN, super resolution, feature fusion, image classification*

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INTRODUCTION

With the growth of generated data and limitation of computing power, low resolution images are generated and processed by many real-world applications, e.g. biometric, pedestrian recognition, object recognition [1–3]. Low resolution image contains less pixels and visual information in comparison to super resolution image. Low resolution degrades the visual information of images while they contain simple or complex visual information. The degradation of visual information is directly related to the classification of these images. For finding the relation between the degradation of visual information and classification, several research studies have been done. The performance of classification is reduced with the degradation of resolution of image [4, 5].

In literature, Chevalier *et al.* proposed LRCNN which leverages the benefit of super resolution layer to improve fine grain classification [6]. Further, they improve low resolution classification by integrating privileged information of CNN to fine grain classification [7]. Cai *et al.* also proposed a super resolution CNN framework to handle the classification of low resolution image [8]. Wei *et al.* presented an algorithm that learned a sparse image transformation by coupling the sparse structures of image pairs from both HR and LR spaces and successfully achieved competitive classification accuracy [9]. The idea of feature fusion of low and super resolution image has not been implemented for low resolution image classification.

For handling the low resolution image and its classification, Cascade CNN framework for low resolution image classification is proposed in this paper. The main idea behind this framework is to exploit the super resolution CNN for generating super resolution image from low resolution image by improving visual information and feature fusion. Here, the combination of low resolution and super resolution features contains more visual information while preserving its original low features. Thus cascade framework improves the classification of low resolution images. This framework is evaluated on standard MNIST [10], and CIFAR10 [11] image dataset and successfully achieves the competitive performance.

Remaining paper is organized as follows: Next part of the paper describes the proposed cascade framework for low image resolution image classification and its components. After that, the proposed framework is experimentally evaluated on standard image dataset MNIST and CIFAR10. This is folllowed by the part which concludes the paper.

PROPOSED FRAMEWORK

Proposed cascade CNN framework for low resolution image classification mainly consists of two modules: Feature extraction and Classification. Feature extraction module extracts the low resolution feature using LRCNN feature extractor and super resolution feature using SRCNN and CNN feature extractor. Extracted super resolution feature and low resolution feature are concatenated and fed into the classifier module. Classifier learns and classifies image accordingly. The architecture of this proposed framework is shown in Figure 1. The description of its components are given below.

Super Resolution CNN Feature

For extracting super resolution CNN feature from low resolution image, first image is converted into super resolution by super resolution methods. Several state of arts super resolution methods are available e.g. Deep convolutional super resolution [12, 13], sparse coding super resolution etc. [14, 15]. Here, SRCNN is adopted for super resolution image generation in proposed framework [12]. SRCNN directly learns an end to end mapping between the low resolution and high resolution images. The architecture of SRCNN is shown in Figure 2.

Super resolution feature is extracted from super resolution image by the trained convolutional neural network. This super resolution feature contains the extra visual feature. The benefit of this feature is to improve the classification predictability of classifier.

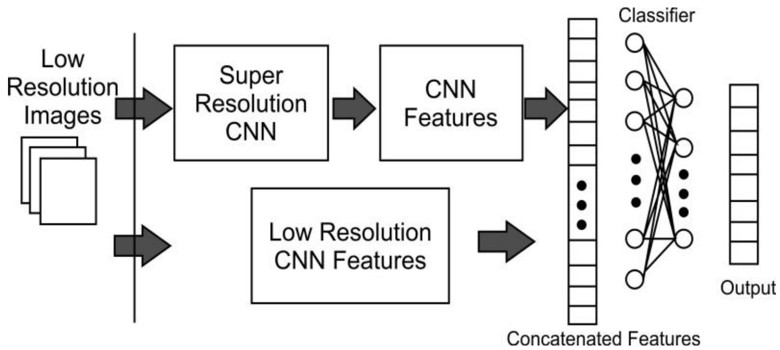

Fig. 1: *Architecture of Cascade CNN Framework for Low Resolution Image Classification.*

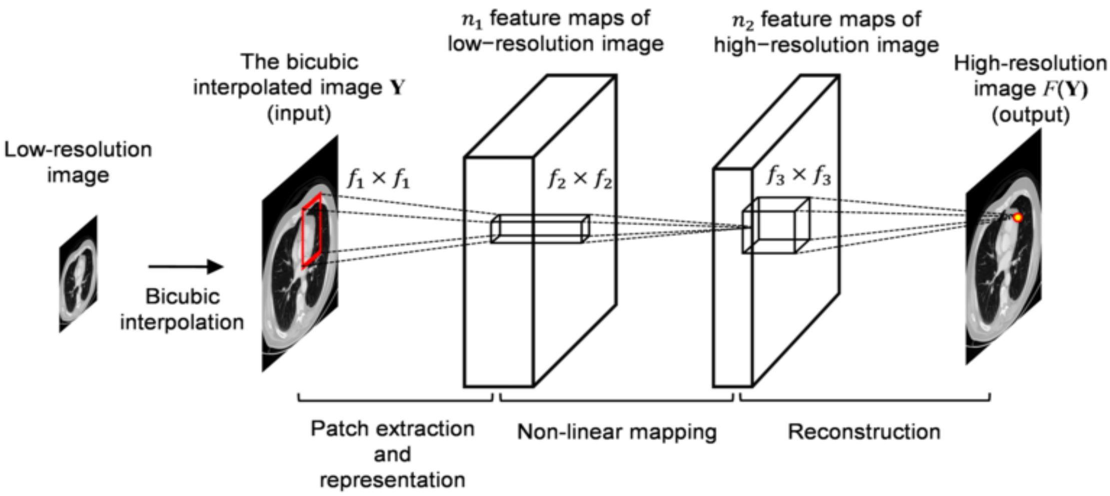

Fig. 2: *Architecture of SRCNN [12].*

Low Resolution CNN Feature
Low resolution feature is extracted from low resolution image by the trained convolutional neural network. Convolutional neural network learns automatically image spatial information and stores these spatial feature maps into their higher to lower layers. The benefit of this low resolution feature is to preserve original feature for the training of classifier.

Feature Fusion and Classification
To exploit the benefit of both low and super resolution, both features are fused with feature fusion method. Feature fusion is inspired by feature concatenation of subspace learning [16]. Here, both low and super resolution features are concatenated without dimension reduction and fed to neural network classifier. The classifier classifies it into its output class.

EXPERIMENT AND RESULTS
Experimental Setup
For generating low resolution image dataset from original image dataset (MNIST, CIFAR10), both dataset are resized into multiple low resolution dataset. For MNIST dataset, images of (28×28, 21×21, 14×14, 7×7) resolution are generated. For CIFAR10 dataset, images of (32×32, 24×24, 16×16, 8×8) resolution are generated. Figure 3 shows one sample image with its generated low resolution images from both dataset.

Here, for the sake of computing power and training time constraint, trained model of these dataset is used for feature extraction. Layer-wise architecture details of CNN feature extractor for both dataset are tabulated in Table 1. Proposed cascade CNN framework is implemented in Python library Keras and TensorFlow. This framework is trained with each generated low resolution image dataset of MNIST and CIFAR10.

RESULTS AND DISCUSSION
The proposed framework is evaluated on each generated low resolution image dataset of MNIST and CIFAR10, over performance metric accuracy. The performance of this framework is also compared with the performance of simple CNN model over the same dataset. The details of performance comparison of simple CNN framework and cascade CNN framework over both dataset are tabulated in Tables 2 and 3 respectively.

Now, comparison graph between simple CNN and proposed cascade CNN are generated for both datasets which is shown in Figure 4. This graph clearly shows that the proposed cascade CNN framework outperforms over simple CNN. The proposed framework successfully classifies lower resolution images with high accuracy rates.

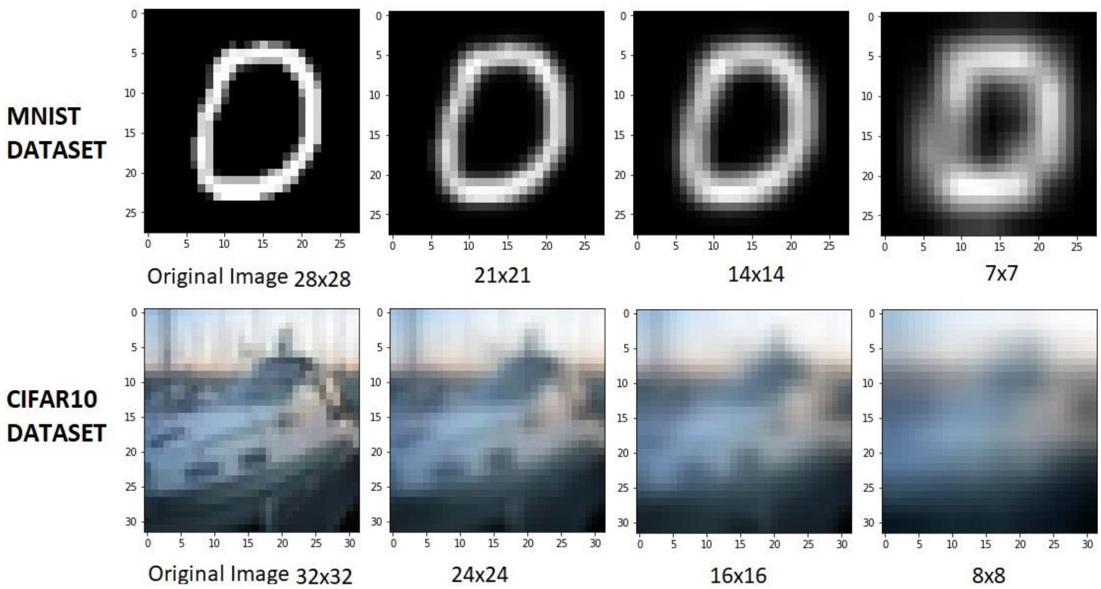

Fig. 3: *Original Image with Their Low Resolution Image of MNIST [10] and CIFAR10 [11].*

Table 1: *Layer-wise Architectural Details of CNN for MNIST and CIFAR10 Dataset.*

CNN Architecture for MNIST			CNN Architecture for CIFAR10		
Layers	**Layers Parameter**	**Activation Function**	**Layers**	**Layers Parameter**	**Activation Function**
Conv2D Conv2D Maxpooling2D	32, size=(3, 3) 32, size=(3, 3) Size=(2, 2)	Relu Relu	Conv2D Conv2D Conv2D Maxpooling2D Dropout	32, size=(3, 3) 32, size=(3, 3) 32, size=(3, 3) Size=(2, 2) 0.25	Relu Relu Relu
Conv2D Conv2D Maxpooling2D	64, size=(3, 3) 64, size=(3, 3) Size=(2, 2)	Relu Relu	Conv2D Conv2D Conv2D Maxpooling2D Dropout	64, size=(3, 3) 64, size=(3, 3) 64, size=(3, 3) Size=(2, 2) 0.25	Relu Relu Relu
Dense	512	Relu	Dense	512	Relu

Table 2: *Performance Comparison of Simple CNN Framework and Proposed Cascade CNN Framework over MNIST Dataset.*

Image Resolution	Accuracy	
	Simple CNN Framework	Proposed Cascade CNN Framework
28×28	0.9952	0.9954
21×21	0.9938	0.9950
14×14	0.9920	0.9939
7×7	0.9687	0.9915

Table 3: *Performance Comparison of Simple CNN Framework and Proposed Cascade CNN Framework over CIFAR10 Dataset.*

Image Resolution	Accuracy	
	Simple CNN Framework	Proposed Cascade CNN Framework
32×32	0.7686	0.7712
24×24	0.7247	0.7697
16×16	0.6678	0.7263
8×8	0.5796	0.6771

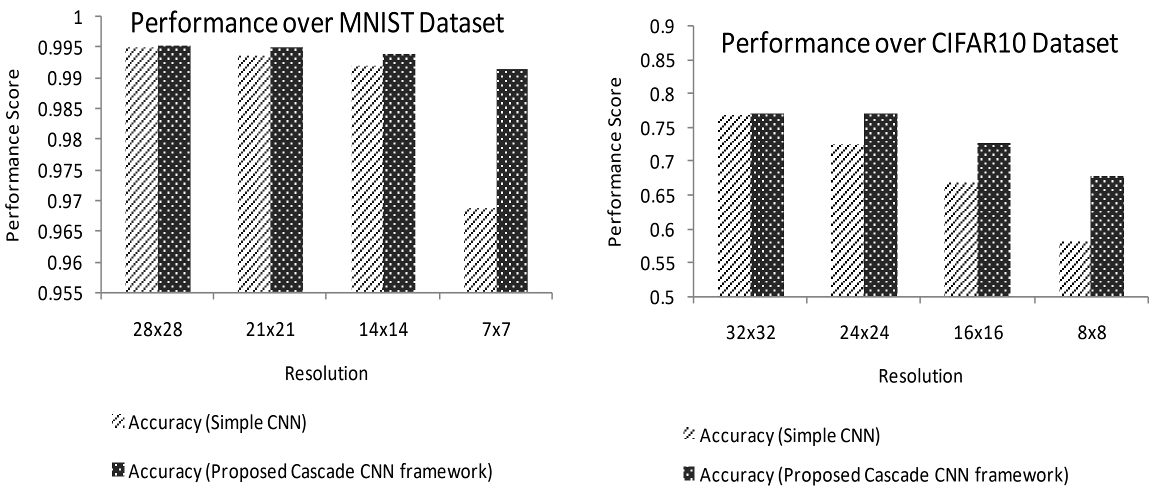

Fig. 4: *Comparison Graph between the Simple CNN and Proposed Cascade CNN Framework over MNIST and CIFAR10 Dataset.*

CONCLUSION

Proposed cascade framework is implemented and evaluated on MNIST and CIFAR10 dataset with their lower resolution dataset. This framework successfully classifies lower resolution images with high accuracy rates. Experimental results show that this framework performs better than the classification of low resolution images over simple CNN based image classifier.

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