

IEEE International Conference on Image Processing 25-28 October 2020, United Arab Emirates



Kernelized dense layers for facial expression recognition

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(Machine Learning for Recognition in Images and Videos II)

Outline

- Facial expression recognition
- Fine-grained recognition
- Improving convolutional neural networks
- Kernelized dense layers
- Experiments and results
- Conclusion and perspectives

Facial expression recognition

Objective •

Classifying human emotions given facial images as one of ٠ seven basic emotions: happy, sad, fear, disgust, anger, surprise and neutral.





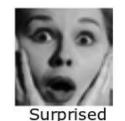


Fear



Happy

Sad





Neutra

Anger

- Challenge
- Small inter-class differences; ٠
- Large intra-class differences; •

Fine-grained recognition

• Going beyond classical image classification.

• It consist of discriminating categories with only small subtle visual differences.

• Many fine-grained datasets emerged for this purpose (e.g. CUB Bird, Stanford Car...etc)

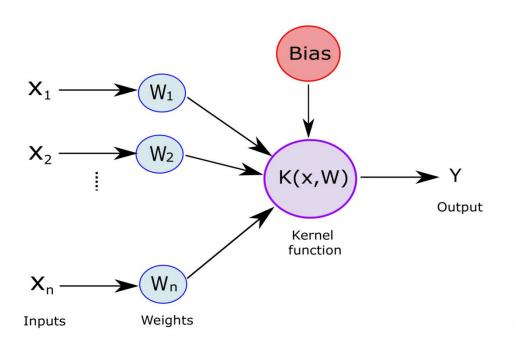
Improving convolutional neural networks (1/2)

- Many researchers tried to improve different levels of CNNs by:
- Replacing convolution (e.g. Kervolutional neural networks, Wang et al, 2019);
- Enhancing pooling (e.g. Universal Pooling, Hyun et al, 2019);
- Dimensionality expansion (e.g. Bilinear pooling, Kernel pooling)

Improving convolutional neural networks (2/2)

- The majority of these works uses kernel functions.
- Their focus is more on improving the process of fully connected layers.
- We build upon that and propose to use kernel functions on fully connected layers.

Kernelized dense layers



- It is similar to a classical neuron.
- It applies higher degree kernel function.

Datasets (1/3)

• FER2013



- ICML 2013 Challenges in Representation Learning.
- 28.709 images for training.
- 3.589 images for validation.
- 3.589 images for test.

Datasets (2/3)

• RAF-DB



- Real-world Affective Face DataBase.
- It contains 29.672 images.

Datasets (3/3)

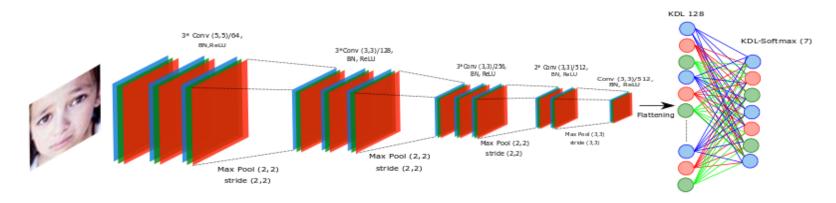
• ExpW



- EXPression in-the-Wild dataset.
- It contains 91.793 images.

Experiments and results (1/4)

• We built a CNN with two Kernelized dense layers.



- We used three kernel functions for our experiments:
 - A linear kernel = fully connected layers.
 - Polynomial kernel of second and third degree.
- Many other kernels can be used (e.g. L1 norm, L2 norm, Gaussian RBF, Laplacian, Abel...etc.)

Experiments and results (2/4)

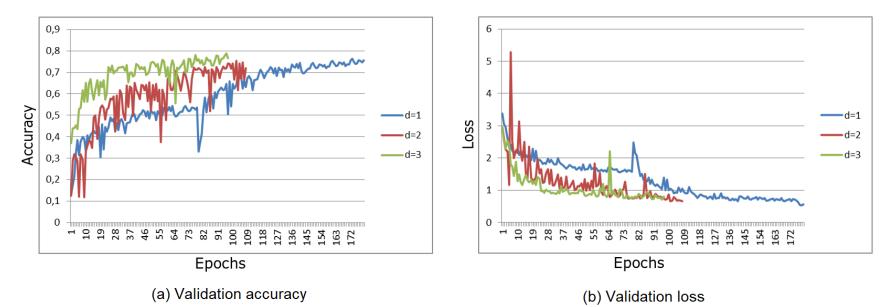
- Second-order polynomial kernel increases for about 0.7% for FER2013, 0.25% for ExpW and 0.6% for RAF-DB.
- Third-order polynomial kernel increases further the overall accuracy for about 1.15% for FER2013, 0.75% for ExpW and 1% for RAF-DB.

	Dataset		
Models	FER2013	Exp W	RAF-DB
Base-Model-FC	70.13%	75.91%	87.05%
(Base-Model-KDL, n=1)			
Base-Model-KDL (n=2)	70.85%	76.13%	87.64%
Base-Model-KDL (n=3)	71.28%	76.64%	88.02%

Table 1: Accuracy rates of the proposed approach with different kernel functions.

Experiments and results (3/4)

- Due to the use of early stopping, the learning process is interrupted as soon as the model reaches its max capacity.
- The higher degree is the kernel function, the fast it converge.



Validation accuracy and validation loss on ExpW with the three kernel configurations.

Experiments and results (4/4)

	Dataset		
Models	FER2013	ExpW	RAF-DB
Base-Model-FC	70.13%	75.91%	87.05%
(Base-Model-KDL, n=1)			
Base-Model-KDL (n=2)	70.85%	76.13%	87.64%
Base-Model-KDL (n=3)	71.28%	76.64 %	88.02%
Tang et al. [12]	71.16%	_	_
Guo et al. [13]	71.33%	_	_
Kim et al. [1]	73.73%	_	_
Bishay et al. [14]	_	73.1%	—
Lian et al. [15]	_	71.9 %	_
Acharya et al. [7]	_	_	87%
S Li et al. [16]	_	_	74.2%
Z.Liu et al. [17]	_	_	73.19%

Table 2: Accuracy rate of the proposed approach and state-of-the-art approach

Conclusion and perspectives

- Using higher order kernel function for FC layer enhances the discriminative power of CNN.
- It also improves the convergence speed of the network.
- The ability of capturing high order information that are crucial for fine-grained classification tasks such as the FER.
- As future work, other kernel functions will be considered, compared and combined



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