CLASSIFICATION OF SEVERELY OCCLUDED IMAGE SEQUENCES VIA CONVOLUTIONAL RECURRENT NEURAL NETWORKS

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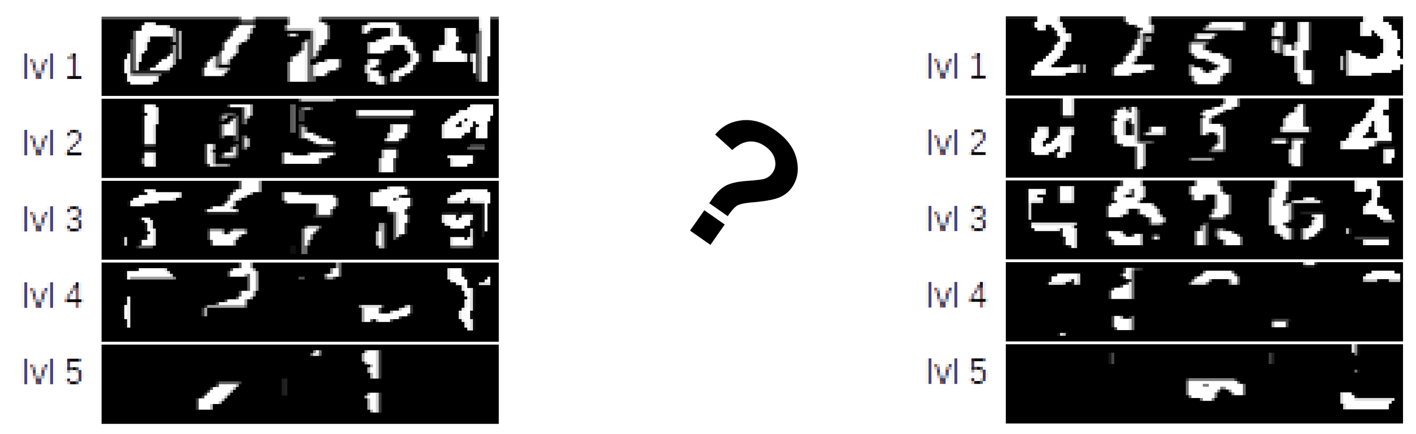


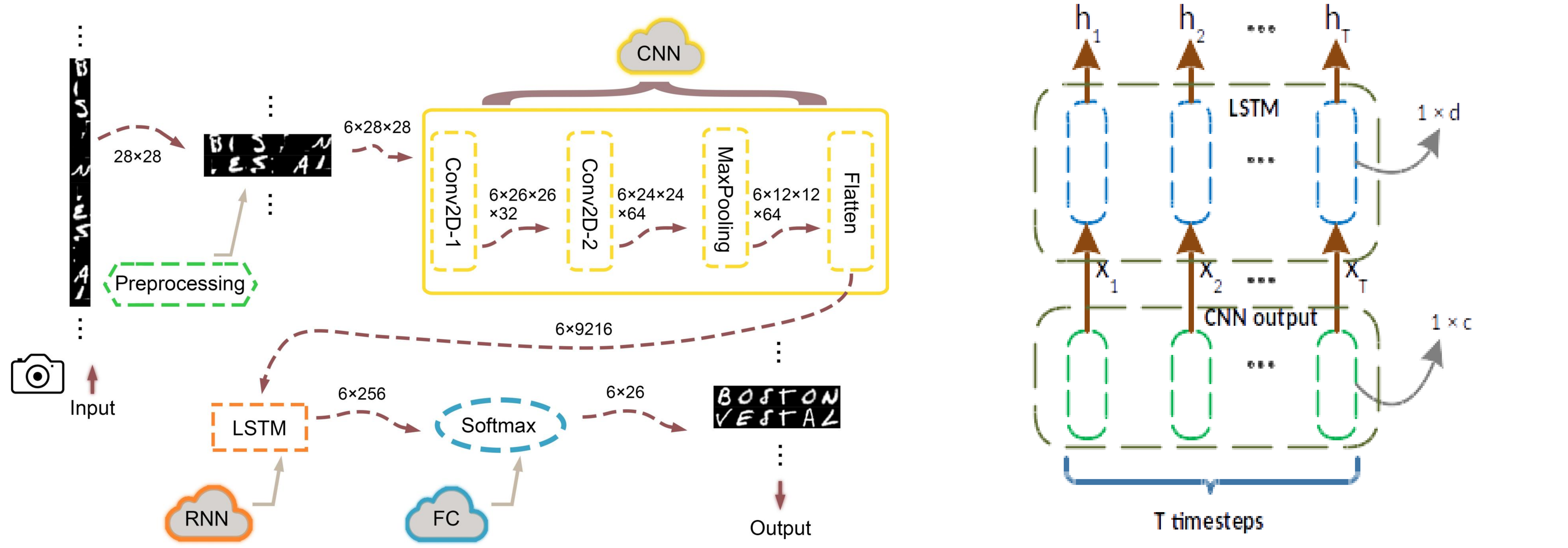
Is the machine able to identify severely occluded images? How?

Motivations

- Most deep learning tasks are conducted with high quality data sources;
- Their performance may not be reliable in noisy or occluded data sets;
- Distortions such as blur, noise, occlusion, etc., will degrade image classification performance;
- Severe occlusions, which block major or key areas of the images, are especially detrimental;
- Classification of severely occluded images is highly needed in many real applications such as self-driving.

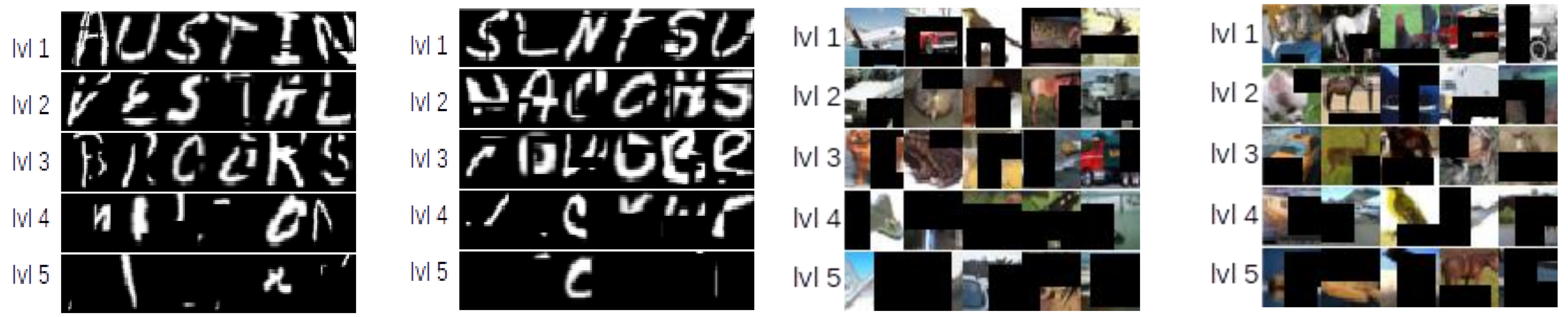
Contributions

- We propose to apply convolutional recurrent neural network (CRNN) for classifying severely occluded image sequences;
- We create three occluded image datasets based on MNIST [1], EMNIST [2] and CIFAR-10 [3], with which we conduct both machine learning experiments and human learning experiments;
- Experiment results show that the proposed CRNN outperforms both conventional methods and most human experimenters.



1. *Data preprocessing*: convert input images into image sequences with fixed length *T*;
2. *Image embedding:* learn image representations for each input image and combine the feature maps of the *T* images;
3. *LSTM for image sequences:* model the spatial contextual dependency among image sequences;
4. *Classification:* classify image sequences based on the output of LSTM unit.

Examples of occluded image sequences



(a) City names (b) Random character sequences (c) CIFAR-10 image sequences with regular patterns (d) Random CIFAR-10 image sequences

References

[1] Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner, "Gradient-based learning applied to document recognition," *Proceedings of the IEEE*, vol. 86, no. 11, pp. 2278–2324, 1998.
[2] Gregory Cohen, Saeed Afshar, Jonathan Tapson, and Andr e´ van Schaik, "Emnist: an extension of mnist to handwritten letters," arXiv preprint arXiv:1702.05373, 2017.
[3] L. Wan, M. Zeiler, S. Zhang, Y. LeCun, and R. Fergus, "Regularization of neural networks using dropconnect," *Proceedings of the 30th International Conference on Machine Learning (ICML-13)*, 2013, pp. 1058–1066.

Experiments

1. Baseline models

- CNN only:
  - CNN
  - CNN-2-S
  - CNN-4-S
- CNN + LSTM:
  - CRNN
  - CRNN-2-S
  - CRNN-4-S

S: replace max pooling with stride of 2
2/4: # of CNN layers

2. Experiment results

Table 1: Performances (%) with regular patterns

Dataset	MNIST	EMNIST	CIFAR10
CNN-2-S	86.22	86.01	44.39
CNN-4-S	88.02	87.26	42.12
CNN	89.44	88.90	54.99
CRNN-2-S	98.27	97.95	89.11
CRNN-4-S	98.15	97.90	90.18
CRNN	98.33	98.14	90.36

Table 2: Performances (%) without regular patterns

Dataset	MNIST	EMNIST	CIFAR10
CNN-2-S	86.37	86.10	44.21
CNN-4-S	88.28	87.81	41.40
CNN	89.37	89.22	53.88
CRNN-2-S	86.68	86.66	45.64
CRNN-4-S	88.15	88.16	48.21
CRNN	87.89	87.81	50.62

Table 3: CRNN performance with regular patterns

Seq len	$T = 5$	$T = 10$	$T = 15$	$T = 20$	$T = 25$
MNIST	98.33	98.11	98.23	98.10	98.06
CIFAR	98.36	88.29	88.11	88.19	87.93
Seq len	$T = 6$	$T = 12$	$T = 18$	$T = 24$	$T = 30$
EMNIST	98.14	97.83	97.76	97.78	97.62

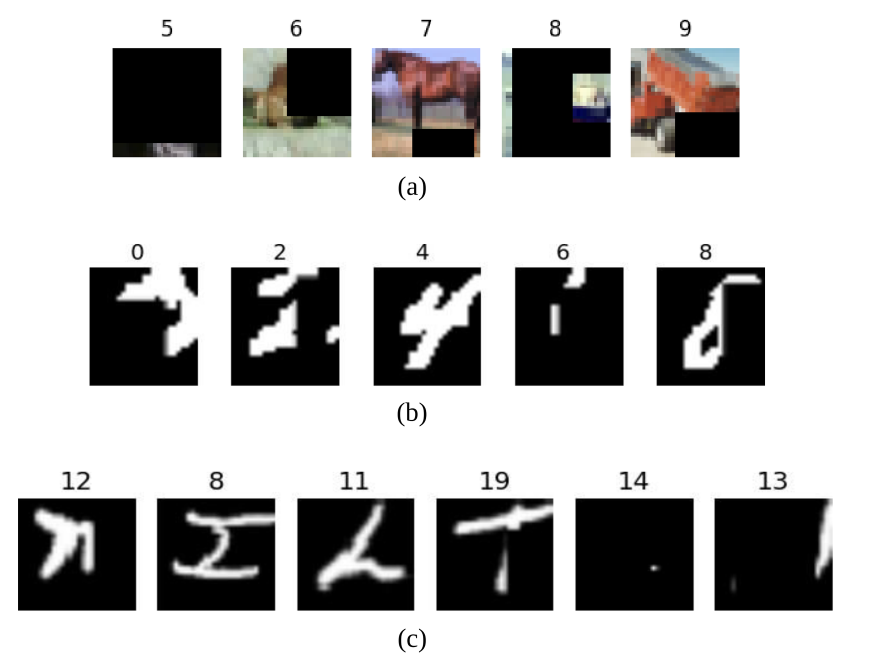
Table 4: CRNN versus human with regular patterns

Dataset	MNIST	EMNIST	CIFAR10
Non-Expert	93.96	92.52	71.11
Expert	100.00	99.26	97.78
CRNN	98.33	98.14	90.36

Table 5: CRNN versus human without regular patterns

Dataset	MNIST	EMNIST	CIFAR10
Non-Expert	75.56	71.79	50.19
Expert	81.00	78.89	71.67
CRNN	87.89	87.81	50.62

3. Three examples of CRNN classification results



(a) Correct classification of the image sequence: 5-6-7-8-9. (b) Correct classification of the digit sequence: 0-2-4-6-8. (c) Correct classification of the city name: M-I-L-T-O-N.