

# CRN: End-to-end convolutional recurrent network structure applied to vehicle classification

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## 1. Introduction

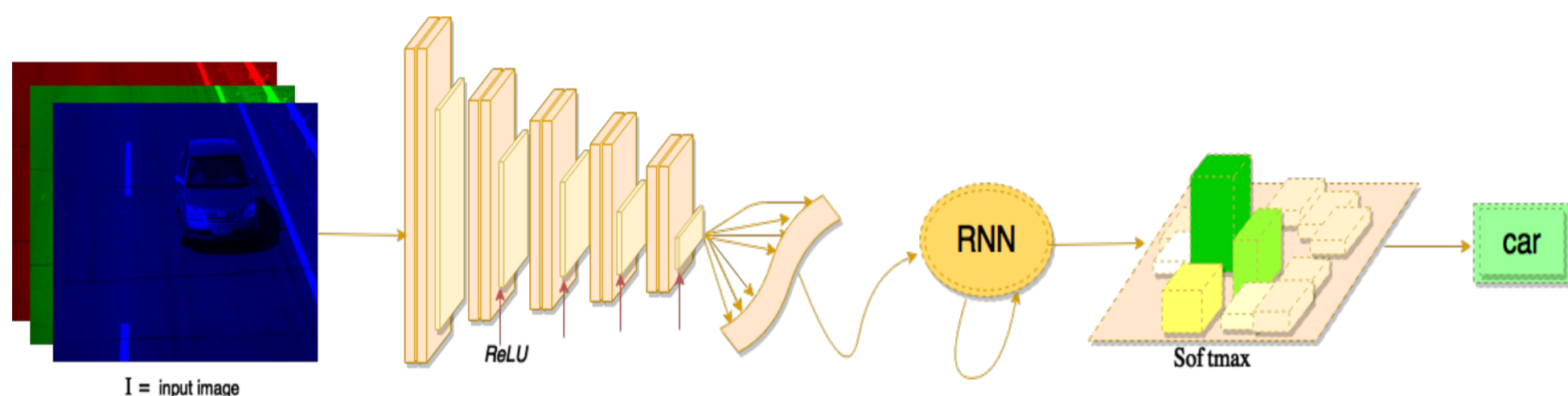
- Traffic Surveillance Cameras (TSC)
  - essential for an Intelligent Traffic System
  - captures images of passing vehicles and other objects [1]
- **Problem statement**
  - classify different types of vehicles from images
- **Challenges**
  - changes in illumination, scale, surface color of vehicles and viewpoint

## 2. Proposed Convolutional Recurrent Network (CRN)

- Takes advantage of the high level feature from CNN and the flexibility of RNN into a joint model
- Merges two deep learning models into a single structure:
  - CNN part learns discriminative features from input data
  - the output of the CNN is directly fed to an RNN that is used as classifier
- End-to-end feature learning model

## 3. Implementation

- ESOGU model
  - Extracts intermediate features from CNN
  - Flattens the CNN features to form a single descriptor
  - RNN is used as a classifier instead of the softmax layer



- Model architecture

Module	Layers	Output Size
CNN	Conv	$224 \times 224$
	Conv	$224 \times 224$
	Pool	$112 \times 112$
	ConvBlock <sub>1</sub>	$56 \times 56$
	ConvBlock <sub>2</sub>	$28 \times 28$
	ConvBlock <sub>3</sub>	$14 \times 14$
	ConvBlock <sub>4</sub>	$7 \times 7$
	FC <sub>1</sub>	[25088]
	FC <sub>2</sub>	[4096]
	FC <sub>3</sub>	[4096]
RNN	LSTM	$nb_{classes}$

## 4. Experimental results

- Datasets

Dataset	Resolution	No-samples	No-classes
Road vehicle [4]	-	2,427	2
BIT-Vehicle [5]	1600x1200 or 1920x1080	900	6
MIO-TCD [6]	-	786,702	11



- Metrics

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision_i = \frac{TP}{TP + FP}$$

$$MeanPrecision = \sum_{i=1}^C Precision_i$$

$$\kappa = (p_o - p_e) / (1 - p_e)$$

$$Recall_i = \frac{TP}{TP + FN}$$

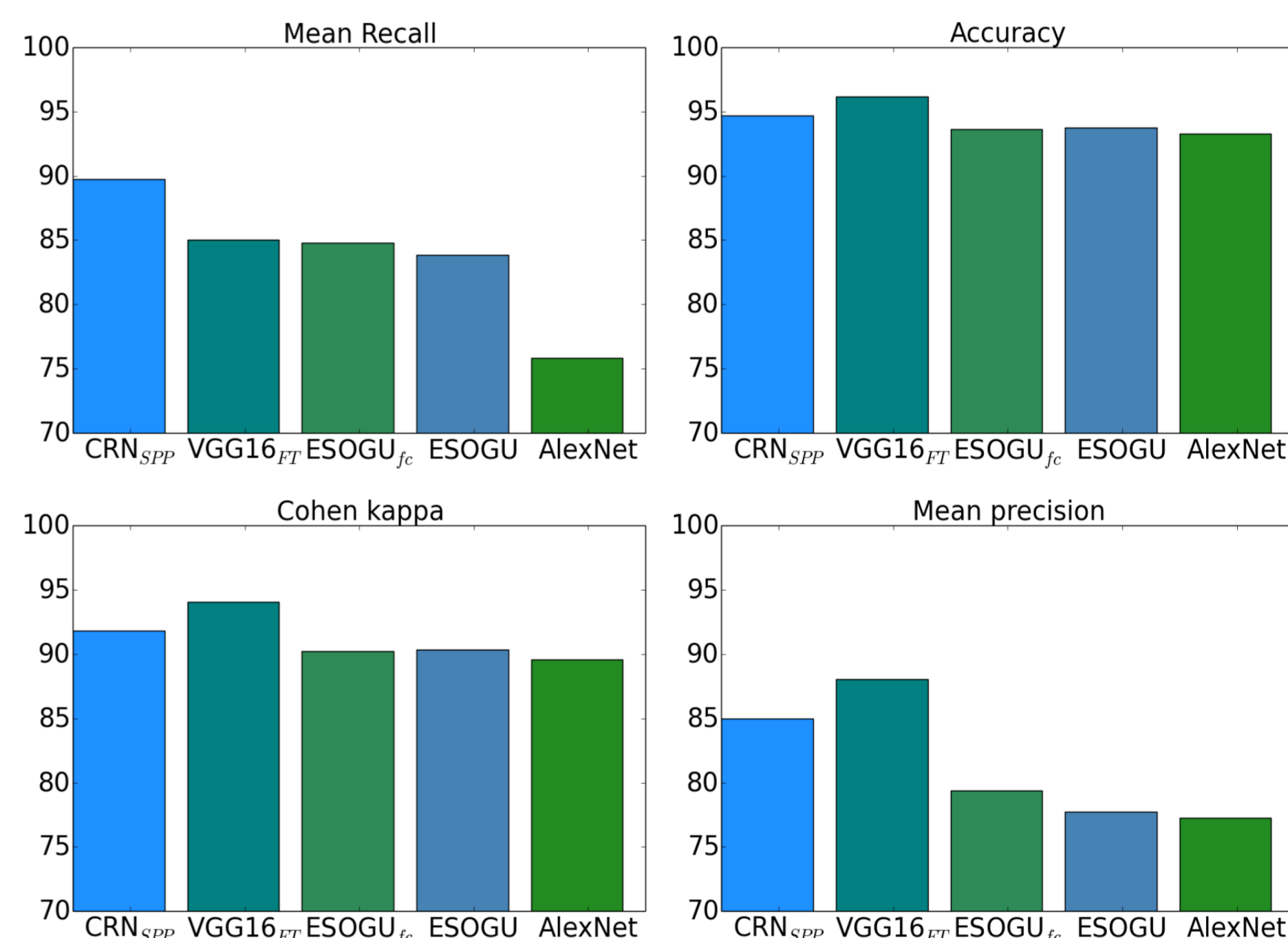
$$MeanRecall = \sum_{i=1}^C Recall_i$$

$p_o$ : Empirical probability agreement,  $p_e$ : Expected agreement

TP: True positives, FP: False positives, TN: True negatives, FN: False negatives

- Comparison with other state-of-the-art

- VGG16 [2]
- AlexNet [3]
- CRN\_spp (ours) [follow-up work]
- ESOGU\_fc (ours)
- ESOGU (ours)



Test Results on MIO-TCD dataset

## 5. Conclusion

- Feature learning part is done using CNN
- Recurrent neural network is used as a classifier
- Model trainable in an end-to-end fashion
- Adaptable to other scenarios like multi-label image classification

## References

- [1] Yong Tang, Congzhe Zhang, Renshu Gu, Peng Li, and Bin Yang. Vehicle detection and recognition for intelligent traffic surveillance system. Multimedia Tools and Applications, 2017.
- [2] K. Simonyan and A. Zisserman. Very deep convolutional networks for large-scale image recognition. ICLR, 2015.
- [3] Krizhevsky, I. Sutskever, and G. E. Hinton. Imagenet classification with deep convolutional neural networks. Advances in Neural Information Processing Systems, 2012.
- [4] Y. Zhou, H. Nejati, T. T. Do, N. M. Cheung, and L. Cheah. Image-based vehicle analysis using deep neural network: A systematic study. IEEE DSP, 2016.
- [5] Z. Dong, M. Pei, Y. He, T. Liu, Y. Dong, and Y. Jia. Vehicle type classification using unsupervised convolutional neural network. ICPR 2014.
- [6] <http://tcd.miovision.com/challenge/dataset/>

## Acknowledgment

This work has been partially supported by the Spanish project TIN2016-74946-P (MINECO/FEDER, UE) and CERCA Programme / Generalitat de Catalunya.