CNN-BASED DETECTION OF GENERIC CONTRAST ADJUSTMENT WITH JPEG POST-PROCESSING

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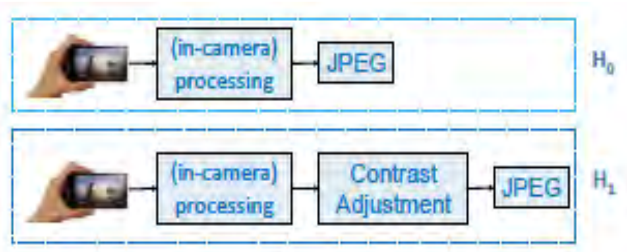
Detection of contrast adjustments in the presence of JPEG post processing is known to be a challenging task. JPEG post processing is often applied innocently, as JPEG is the most common image format, or it may correspond to a laundering attack, when it is purposely applied to erase the traces of manipulation. In this paper, we propose a CNN-based detector for generic contrast adjustment, which is robust to JPEG compression. The proposed system relies on a patch-based Convolutional Neural Network (CNN), trained to distinguish pristine images from contrast adjusted images, for some selected adjustment operators of different nature. Robustness to JPEG compression is achieved by training a JPEG-aware version of the CNN, i.e., feeding the CNN with JPEG examples, compressed over a range of Quality Factors (QFs). Experimental results show that the detector works very well under a wide range of QFs and scales well with respect to the adjustment type, yielding very good performance under a large variety of unseen tonal adjustments.

1 GOAL OF PROPOSED SYSTEM

- **PROBLEM**
  - ✓ Poor resilience to post-processing, in particular to JPEG compression is a problem common to most contrast enhancement detection tools.
  - ✓ Most available tools are thought to detect one very specific kind of manipulation. [1-2]
- **DETECTION TASK**

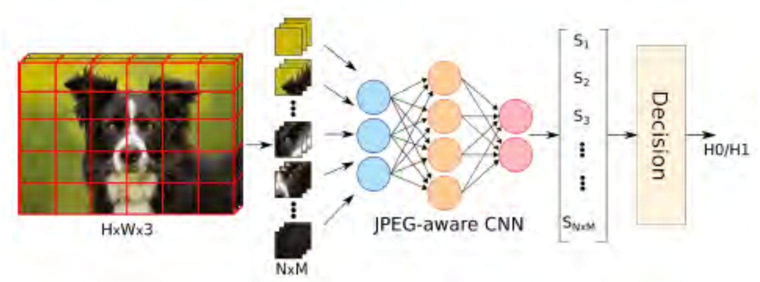


- **GOAL**
  - ✓ We look for a generic detector of contrast adjustment, that is, a detector which generalizes well to a **wide variety of tonal adjustments**.
  - ✓ The detector should survive **weak to moderate JPEG compression**.

[1] Haodong Li, Weiqi Luo, Xiaoqing Qiu, and Jiwu Huang, "Identification of various image operations using residual-based features," IEEE Transactions on Circuits and Systems for Video Technology, 2016.
[2] Neetu Singh and Abhinav Gupta, "Analysis of contrast enhancement forensics in compressed and uncompressed images," in 2016 International Conference on Signal Processing.

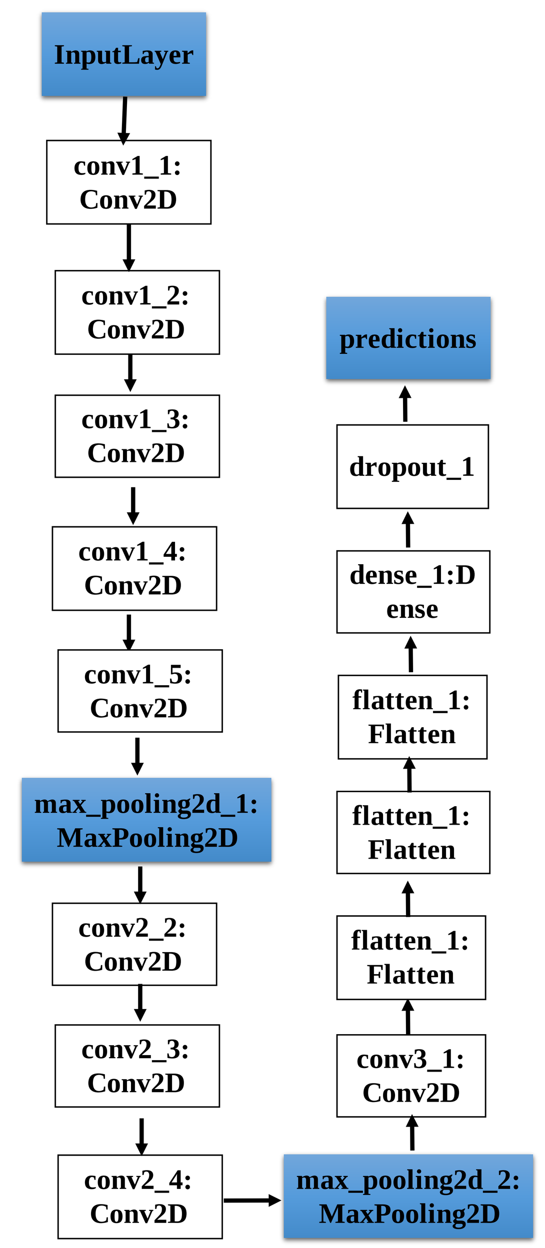
2 CNN ARCHITECTURE

We network works on 64*64*3 patches. Detection is performed by aggregating the soft scores of the image patches and then thresholding.



The network consists of,

- **5 convolutional layers** followed by a **max-pooling** layer. In the first convolutional layer 32 filters are applied. Then the number of filters increases by 32 at each leayer. For all filters, the kernel size is 3*3, stride 1.
- **3 convolutional layers** followed by a **max-pooling**. The number of filters of size 3*3 (applied with a stride 1) increases by 32 at each layer. The pooling is the same as before.
- **A final convolutional layer** with 128 1 x 1 filters
- **A fully-connected layer** with 250 input neurons, **dropout** 0.5, and 2 output neurons, followed by a **softmax layer**.



3 JPEG-AWARE TRAINING FOR GENERIC CE DETECTION

We propose a JPEG-aware CNN-based approach to detect contrast adjusted images in the presence of JPEG-post processing.

JPEG-aware CNN training is achieved in two steps:

- **Unaware case,** the network is trained to distinguish recognize between patches coming from pristine and contrast-adjusted images.
- **Aware case,** the aware model is obtained by fine-tuning the unaware network, by feeding CNN with JPEG compressed examples (QF >=80)

Rationale behind GENERIC training approach,

It is not viable to consider all possible kinds of tonal adjustments for training, so we propose to train the CNN by using three algorithms belonging to 3 different classes: i) **CLAHE**, ii) **Gamma Correction** and iii) **HS,** which we think are sufficient to generalize to other CE operators.

4 METHODOLOGY

- **Algorithms used for training,**
  Adjustment operators work on the luminance channel only
  - ✓ RGB to HSV
  - ✓ Applied enhancement to the luminance channel (V-channel)
  - ✓ HSV to RGB
- **Algorithms used for testing,** i) Parameter matching and mismatching, ii) software mismatch
- **Asses the performance under software mismatch,**

  i) **AutoContrast**, **AutoColor** and **Auto Tone**; algorithms which operate differently on the three color channels

  ii) **Curves_S;** a (hand-crafted) smooth S-curve is applied to enhance the contrast in the midtones.

  iii) **Brightness** and **Contrast;** generic tools of Photoshop for enhancing and reducing brightness and contrast.

  iv) **Histogram Equalization (HistEq)**

5 RESULTS (I)

- **Dataset,** uncompressed, camera-native, images are taken from the RAISE8K dataset (of size 4288*2848).
- **The images are divided into 64*64 patches**
  - ✓ 2*10^6 patches per class were selected to train the CNN, 2*10^5 patches were used for testing

The overall performance of the detector on full images are reported in following table in terms of AUC, for both matched and mismatched processing parameters.

- ✓ AUC for CLAHE manipulation is always above 98% (easiest to detect)
- ✓ Gamma Correction AUC below 90% for QF<=95 (difficult case)
- ✓ Good performance in the absence of JPEG.

		QF							
		No JPEG	**100**	**98**	**95**	**90**	**85**	**80**	**75**
CLAHE	0.003	100	99.9	99.8	98.9	97.6	97.6	96.8	96
	0.005	100	99.9	99.9	99.4	98.9	98.8	98.5	98
	0.007	100	99.9	100	99.6	99.1	98.9	98.7	98.5
Gamma Corr	**1.5**	98..8	98.5	94.2	89.2	87	84	81.2	81
	1.7	99.4	98.9	95.7	91.8	90.4	89.7	89.2	88.1
	0.7	99.1	97.1	92.3	87.3	85.6	81	78	69
	0.6	99.7	99.5	97.3	91.6	86.7	83.7	80.1	77.3
HS (%)	3	99.6	98.1	95.8	91.4	87.8	85.7	83.5	83
	5	99.5	98.9	97.6	93.7	92.6	91.5	90.3	89.4
	7	100	99.3	98.3	95.5	94	93.7	93.6	93

AUC under matched processing. Matched parameters are in bold.

6 RESULTS (II)

- **Software Mismatch**
  For generating mismatched test images, we considered different operators by processing the images with adjustment tools provided by Photoshop.

	QF						
	No JPEG	**100**	**98**	**95**	**90**	**85**	**80**
HistEq	100	99.9	99.9	99.5	98.3	96.9	94.8
Brightness +	97.5	97.7	95.2	93.6	91.2	87.8	85.6
Contrast +	99.1	100	99.6	97.9	94.7	91.9	87.1
Brightness -	96.7	97.3	93.3	90.1	84.2	78.8	75.6
Contrast -	98.8	99.6	96.4	91.2	87	82	80
Curve_S	99.6	99.8	99.8	99.1	97.7	96	93.6
AutoContrast	95.9	94.7	93	91.9	90.2	89	86.5
AutoColor	98.2	98.6	96.8	95.3	93.7	91.8	89.1
AutoTone	99.5	99.5	99	98.2	97.2	96.1	94.5

Performance (AUC) of the detector for different tonal adjustments

7 EXAMPLES OF TRAINING IMAGES

Pristine, Gamma Corr 1.5, Gamma Corr 0.7, CLAHE 0.005, HS (5%)

8 EXAMPLES OF TESTING IMAGES – SOFTWARE MISMATCH

AutoContrast Ps, Contrast (-50) Ps, Contrast (+70) Ps, Brightness (-50) Ps, Brightness (+50) Ps, Curve_S Ps

9 CONCLUSIONS

We proposed a JPEG-aware CNN-based approach for the detection of contrast adjusted images in the presence of JPEG post-processing. To accomplish this task, and build a detector which works well for generic contrast adjustment, we trained the CNN with a three classed of tonal adjustments of different nature. Results show that our detector achieves good performance over a wide range of QFs and generalizes well to unseen tonal adjustments.

As further research, it would be interesting to see if the performance with respect to the most difficult cases can be improved by refining the composition of the training, i.e., the types of contrast adjustments considered and their proportions, and also the strategy adopted to fuse the results obtained on the 64x64 patches.