

RECENT ADVANCES IN MACHINE LEARNING - SS2022

Detecting Real and Generated Images

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July 14, 2022

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Outline

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Task Description

1. To classify the real and fake images, where the fake images have been generated using SNGAN using different upsampling techniques:
 - ▶ Bilinear interpolation
 - ▶ Bicubic interpolation
 - ▶ Pixelshuffle
2. Is the model working for other upsampling techniques?
3. Can we get better results by using vertical and horizontal projections instead of radial ones, when images are transformed in frequency domain?
4. Can we get better results by using a convolution neural network (CNN) for the detection?

Methodology

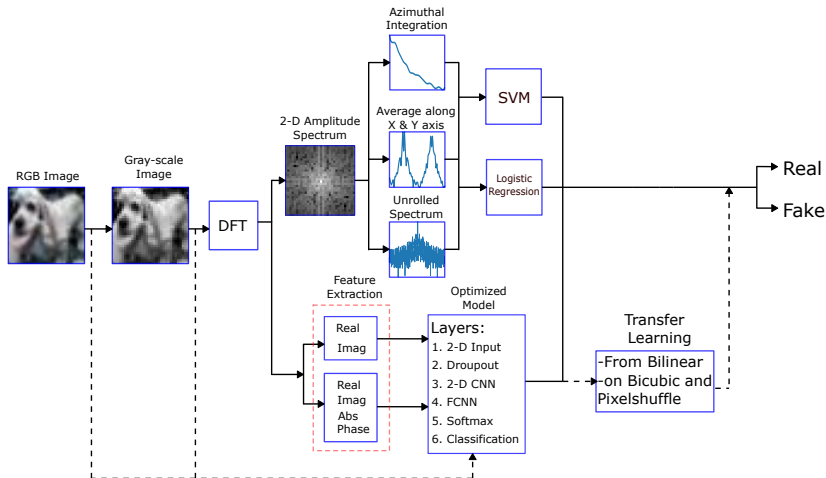
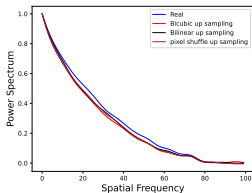


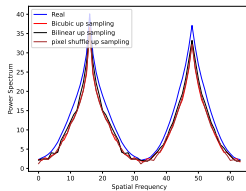
Figure: An illustration of our proposed methods

- ▶ Watch your Up-Convolution: CNN Based Generative Deep Neural Networks are Failing to Reproduce Spectral Distributions [1]
- ▶ Unmasking DeepFakes with simple Features [2]
- ▶ A Material-Sensing Time-of-Flight Camera [3]

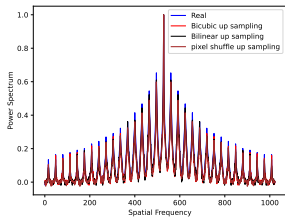
Methodology



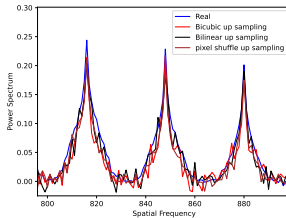
(a) Azimuthal Integration



(b) Average along X & Y axis



(c) Unrolled Amplitude Spectrum



(d) Zoomed view of Unrolled Amplitude Spectrum

Figure: Mean plots of extracted features

Experimental Results

Azimuthal Integration

Table: Support Vector Machine

		Testing		
		Bilinear	Bicubic	Pixelshuffle
Training	Bilinear	0.7525	0.6475	0.645
	Bicubic	0.66	0.67	0.6325
	Pixelshuffle	0.635	0.685	0.675

Table: Logistic Regression

		Testing		
		Bilinear	Bicubic	Pixelshuffle
Training	Bilinear	0.72	0.635	0.62
	Bicubic	0.6825	0.6725	0.6225
	Pixelshuffle	0.6475	0.695	0.67

Experimental Results

Average along X & Y axis

Table: Support Vector Machine

		Testing		
		Bilinear	Bicubic	Pixelshuffle
Training	Bilinear	0.8125	0.755	0.74
	Bicubic	0.6775	0.80	0.7225
	Pixelshuffle	0.6775	0.72	0.785

Table: Logistic Regression

		Testing		
		Bilinear	Bicubic	Pixelshuffle
Training	Bilinear	0.7725	0.725	0.685
	Bicubic	0.6875	0.7875	0.6725
	Pixelshuffle	0.68	0.725	0.7875

Experimental Results

Unrolled Amplitude Spectrum

Table: Support Vector Machine

		Testing		
		Bilinear	Bicubic	Pixelshuffle
Training	Bilinear	0.8725	0.6675	0.665
	Bicubic	0.6275	0.8125	0.66
	Pixelshuffle	0.6375	0.6825	0.8075

Table: Logistic Regression

		Testing		
		Bilinear	Bicubic	Pixelshuffle
Training	Bilinear	0.8675	0.655	0.6275
	Bicubic	0.605	0.8025	0.585
	Pixelshuffle	0.625	0.6475	0.81

Table: Result based on Deep Learning Techniques

Upsampling Techniques	Validation accuracy using developed deep learning model in %							
	RGB		Gray-scale		DFT: $[R,I]$		DFT: $[R,I,abs,Phase]$	
Bilinear	85	<i>T.L.</i>	82	<i>T.L.</i>	84	<i>T.L.</i>	95	<i>T.L.</i>
Bicubic	76	78	78	77	82	84	93	93
Pixelshuffle	67	68	73	72	84	84	92	89

- ▶ *T.L.* = Transfer Learning
- ▶ Our developed model works for other upsampling techniques.

Conclusion

In this work we have exploited several state-of-the-art machine learning and deep learning techniques. Our results have depicted that the spatial low resolution deepfake generated using SNGAN based on different upsampling techniques can be classified using our developed methods with a maximum accuracy of 95%. The future work can be analysis of our developed models on images that are wavelet based transformed.

References



R. Durall López, M. Keuper, and J. Keuper, “Watch your up-convolution: Cnn based generative deep neural networks are failing to reproduce spectral distributions,” 03 2020.



R. Durall, M. Keuper, F.-J. Pfreundt, and J. Keuper, “Unmasking deepfakes with simple features,” *ArXiv*, vol. abs/1911.00686, 2019.



M. Heredia Conde, “A material-sensing time-of-flight camera,” *IEEE Sensors Letters*, vol. 4, no. 7, pp. 1–4, 2020.