Impact of Image Compression on Classification Performance and Computer Resources in Deep Learning Image Recognition

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Abstract

In this report, we will first study the Portable Network Graphic (PNG) format and its differences from the Joint Photographic Experts Group (JPEG), JPEG2000 (an evolution of the latter), and Better Portable Graphic (BPG) formats. Then we will analyse the impact of PNG compression on the classification accuracy of a Convolutional Neural Network (CNN) for image recognition and its necessary computer resources, specifically storage and calculation resources. To do so, we will perform tests using the framework Caffe and the pre-trained CNN called AlexNet. Finally, we will compare the impact on classification accuracy of the PNG format with existing results for JPEG, JPEG2000, and BPG formats, while adding information about the computer resources.

Contents

List of Acronyms and Abbreviations

BPG Better Portable Graphic

CNN Convolutional Neural Network

CR Compression Ratio

JPEG Joint Photographic Experts Group

PNG Portable Network Graphic

PSNR Peak Signal-To-Noise Ratio

SSIM Structural Similarity Index Measure

1 Introduction

Image recognition is more and more used in many areas such as facial recognition, surveillance, healthcare, and more. After observing that image recognition through deep learning requires a lot of storage space and computer resources, we thought it would be interesting to study the parameters which can be changed to optimize the use of these resources. It was conjectured in [1] that the quality of an image plays a role in how well it can be correctly classified by an image classifying neural network. We, therefore, focused our interest on the impact of image compression on the performance of convolutional neural networks (CNNs) in terms of classification and computer resources. M. Dejean-Servières, et al. [2] already examined the impact of Joint Photographic Experts Groups (JPEG), JPEG2000, and Better Portable Graphics (BPG) image compression, on image classification with a Convolutional Neural Network. We therefore decided to take this paper as a basis and to add another widely used format, Portable Network Graphics (PNG). We chose PNG because it was indicated in [2] that it might be interesting to compare the result of the PNG format with the other already tested formats.

1.1 Aims and Objectives

We aim to optimize CNN's image recognition through image compression. We are going to reproduce the same test tool as in the paper [2]. We are therefore going to take the same dataset of images and use the Caffe framework [3] with the pre-trained network bvlc Alexnet, as described in [4]. Caffe is a deep learning framework mainly used for image classification, we are going to use its python interface. Thanks to this analytical tool, we will classify this dataset compressed in PNG format and compare the accuracy of classification with their work on JPEG, JPEG2000, and BPG. At the same time, we will study the impact of image compression, on the computer resources used in image recognition.

1.2 Goals

The goals are to replicate the analytic model in [2], which shows the impact of image compression on the performances of a CNN for image recognition, and thus to complete their analysis, with the PNG format. We also intend to consider the consumption of computer resources.

1.3 Background and rationale

As our goal is to find a correlation between image compression and the classification performance of a CNN, several notions are important to understand our report.

1.3.1 CNN

Our report talks about image recognition with deep learning, it is therefore essential to have a good understanding of CNNs. Indeed, a CNN is a class of neural networks widely used for image recognition. As its name implies, it uses the mathematical operation called convolution. Its purpose is to classify an image into a category. CNN, is composed of succession of layers. The main layers are:

- The convolutional layers are responsible for extracting information from the image for classification. More precisely it detects patterns in images. For this purpose, more and more precise filters are used. Filters are applied across the image using convolution. The filters of the first layers will for example detect geometric shapes or edges. And the last ones will detect features, such as hair or eyes for example. Up to the point of classifying the image. Applying this filter will produce what is called a feature map.

- A pooling layer is placed after a convolutional layer. Its goal is to reduce the size of the features maps produced by the previous convolutional layer. This work is done because otherwise, any small change in an image would result in different feature maps. So we summarize the areas of the feature map by calculating the average of its values for example.

- The fully connected layer is placed at the end of the network and is responsible for assigning a probability that the image is likely to belong to a given class.

1.3.2 Image formats/compression

Our paper focuses on the impact of PNG on classification and computer resources compared to JPEG, JPEG2000, and BPG. It is therefore important to understand the differences between these formats.

1.3.2.1 PNG

PNG is a lossless raster-graphics file format and was created for replacement of the Graphics Interchange Format (GIF). It supports palette-based images of 24-bit RGB or 32-bit RGBA colours, grayscale images with an optional alpha channel for transparency, and full-colour non-palette-based RGB or RGBA images. The compression offered by this format is a lossless compression 5 to 25% better than GIF compression.

1.3.2.2 JPEG/JPEG2000/BPG

We are not going to take an in-depth interest in the image formats already described in the paper [2]. We will more focus on the main differences between them and the PNG format.
First of all, none of the three formats support transparency, unlike PNG. Both JPEG2000 and BPG are both lossy and lossless and JPEG is only lossy. We remind that PNG is only lossless. And finally these three formats are often smaller than PNG for the same image. Another important feature of the PNG format is the decoding time, which is faster than other formats as describe in [5].

1.3.2.3 Metrics

We will use the same metrics as described in [2]. The metrics are described below:

- **Compression ratio**: The **Compression Ratio (CR)** of an algorithm, represent the compression efficiency for a given image. $CR = n1/n2$ with n1 the number of bits in the original image, and n2 in the compressed image.
- **Quality metrics**: The **Peak Signal-To-Noise Ratio (PSNR)** is a metric used to compare the quality of a compressed image with an uncompressed one.
  However, it cannot reproduce the quality evaluation of humans. For this reason, we will use also the **Structural Similarity Index Measure (SSIM)** metric that is more accurately reflects the image quality evaluation of humans. SSIM and the purpose of its use are explained by M. Zhou Wang, et al. in the paper [6].
- **Rank difference**: To measure the classification performance, we measure the rank difference obtained by computing the difference between the classification rank result of the original image, and the compressed one.

1.3.3 Computer resources metrics

To calculate the impact of image compression on computer resources when classifying images, we decided to calculate the time required to classify each image. Also, we take into account the impact on storage space, which is an important measure. These measures are very hardware dependent. We have tried to limit the variance of our results as much as possible by using the same configuration for each of our tests. That is why all our tests are running on an Ubuntu virtual machine with 5120 Mo of RAM, an Intel i7-6700HQ processor at 2.60GHz with 4 cores dedicated to the virtual machine. All classifications calculation are running on the CPU.

2 Theoretical framework

To better understand the subject and to be able to find relevant information we need to have a strong theoretical view of the subject. First, we need a better understanding of the different compression formats that are going to be used. We use [7] and [8] for the JPEG formats, [9] for the BPG format and finally [10] for the PNG format. Also, strong knowledge about deep learning technology, and especially CNN is needed and, we, therefore, use papers from Yann LeCun [11], [12], and a very useful one from Saad Albawi and Tareq Abed Mohammed [13]. Finally, to learn and understand the tools that we use, the paper by A. Krizhevsky, I. Sutskever, and G. E. Hinton [4] is very useful concerning ImageNet and [3] for the Caffe framework.

3 Research questions & Hypotheses

The questions this report answers are the following:

- What impact do the different compressions have on the classification performance of the CNN?
- What impact do different compression algorithms have on computer resources?

This study is designed to assess the hypothesis that the PNG format will be less performant regarding classification than JPEG 2000 and BPG for a given image quality since we simulate a lossy PNG format by removing colours, and the paper [2] shows that colours are really important for classification. However, the second hypothesis we want to assess is that we can save a non-negligible amount of computer resources since PNG format is faster to decode than the others, as described in [5].

4 Research Methodology

We use the empirical method. Indeed, we replicate the tests of [2] and perform quantitative observations.

4.1 Procedure, data collection, and analysis

To reproduce the dataset of the paper [2], our data collection will be the same. We have collected the ImageNet dataset of images from ILSVRC2012* and selected the same 55 images as described in the table in Appendix 1: Selected Dataset of [2]. We use a subset of 55 images out of the 50,000 images in the ImageNet dataset, this can be considered small, but these images are chosen to be representative of the accuracy of the dataset as described in [14]. We will therefore use (Python or C script to automatise the tasks), LibJPEG† to perform JPEG compression, OpenJPEG‡ for JPEG2000, and the BPG encoder supplied by F. Bellard § for the BPG compressions. In addition, we use pngquant¶ for the PNG format. We chose this library because it allows us to simulate lossy compression on PNG by removing colours in the image. This method will allow us to make much more interesting comparisons since PNG is a lossless format, it is only possible to reduce the width and height of the image. Other libraries exist but based on these results [15], we chose pngquant, the one we felt was most appropriate for our research. However, we decided to remove the grey-scale images because, as explained in [2], colours are really important for the classification and the results are therefore always better with RGB images.

For each image format, we create 288 variations since we delete the grey images used in the paper [2], and add the PNG variations. This leads to a total of 15840 images to analyse. Using Caffe, all these 55 originals images and the 15785 compressed ones will be classified one by one with the pre-trained CNN bvlc Alexnet to be able to compute the rank differences between the original images with the compressed ones. The rank refers to the place of the correct class of the image classified by the CNN, in the list, sorted

* http://www.image-net.org/challenges/LSVRC/2012/ † http://libjpeg.sourceforge.net
‡ http://www.openjpeg.org § https://bellard.org/bpg ¶ https://pngquant.org

in descending order, of the probabilities of each class deduced by the CNN. For example, if a cat image, with the original image, is ranked 'cat' at the 1st rank, and ranked 'cat' at the 4th rank with the compressed image, then this corresponds to a rank difference of -3. In addition to the rank, we compute metrics such as SSIM, PSNR, and Compression Ratio in order to find correlation between them.

5 Results and analysis

In this section, we present our results and their analysis.

5.1 Data

This section presents our data and analyse each format independently of the others. For each of the bellow formats, we encoded 3960 images. Also, they share the same scale parameters and the RGB color mode. The scale parameter controls the resolution of the compressed image. A scale of 1/2 means that the height and the width of the original image are divided by 2.

5.1.1 JPEG

JPEG images have been encoded with LibJPEG encoder. As parameters we use the quality parameter which is a percentage controlling the quantization process. The best image quality is reached with a Quantization Parameter (QP) of 100 and the most compressed image a QP set to 1.

Table 1: JPEG encoding parameter

Scale	Color	Quality
1,1/2,1/4,1/8	RGB	1, 2, 3, 4, 5, 6, 7, 8, 10, 12, 14, 16, 18, 20, 25, 30, 40, 50

Table 2: JPEG rank difference and compression ratio according to parameters

Compression Parameters			Rank differences			Compression Ratio		
Scale	Color	Quality	Mean	Median	std dev	Mean	Median	Std dev
1/1	RGB	30	1.42	0	10.39	6.65	7.5	2.94
1/2	RGB	40	3.43	0	30.92	18.76	20.13	8.63
1/2	RGB	10	- 1.51	0	50.42	41.07	42.48	20.24
1/4	RGB	50	- 5.27	0	49.37	46.69	49.22	22.88
1/4	RGB	20	- 16.76	-1	83.96	70.35	70.73	35.43
1/8	RGB	50	- 58.56	-4	130.3	99.39	102.37	50.14

5.1.2 JPEG2000

JPEG2000 images have been encoded with OpenJPEG encoder. As parameters, we use the quality layers parameter which describes the compression ratio of each layer. For example, "[200,40,20]" means that the compressed image has three quality layers, with a compression ratio of 200 for the first layer, 40 for the second and 20 for the third. The more layers with a small number of compression ratio there are, the better the quality of the compressed picture is.

Table 3: JPEG2000 encoding parameter

Scale	Color	Quality Layers
1,1/2,1/4,1/8	RGB	[200,40,20],[200,40],[200],[100,20,10],[100,20],[100],[50,40,20],[50,40],[50],[25,20,10],[25,20],[25] [15,10,1],[15,10],[15],[10,5,1],[10,5],[10]

Table 4: JPEG2000 rank difference and compression ratio according to parameters

Compression Parameters			Rank differences			Compression Ratio		
Scale	Color	Quality	Mean	Median	std dev	Mean	Median	Std dev
1/1	RGB	200,40	- 2.36	0	20.35	8.13	8.29	4.31
1/1	RGB	50	- 2.69	0	19.24	10.16	10.4	5.38
1/2	RGB	100,20,10	- 1.34	0	28.11	8.11	8.37	4.3
1/2	RGB	100,20	- 3.78	0	34.31	16.23	16.63	8.61
1/2	RGB	200,40,20	- 3.73	0	34.14	16.26	16.62	8.63
1/4	RGB	15,10,1	- 11.05	0	66.92	6.99	7.6	3.42
1/8	RGB	10,5,1	- 56.15	-5	134.26	23.02	24.14	12.01

5.1.3 BPG

Unfortunately, the paper describes a tool to manipulate the BPG format that is not compatible with caffe, our classification tool. The authors therefore had to find a method to classify these images that they have not written in their work. This is why for the rest of our work, we were able to extract less data on the BPG format. We intend to find a method to be able to classify this format as well as to calculate its SSIM and PSNR.

BPG images have been encoded with the BPG encoder supplied by F. Bellard encoder *. As parameters, we use the Quantization Parameter (QP) which controls the image quality. The best image quality is reached with a QP set to 1, and the most compressed image with a QP set 51.

Table 5: BPG encoding parameter

Scale	Color	Quantization Parameter (QP)
1,1/2,1/4,1/8	RGB	30, 35, 36, 37, 38, 39, 40, 41, 42 ,43, 44, 45, 46, 47 48, 49, 50, 51

Table 6: BPG rank difference and compression ratio according to parameters

Compression Parameters			Compression Ratio		
Scale	Color	Quality	Mean	Median	Std dev
1/1	RGB	35	8.32	8.33	4.76
1/1	RGB	39	13.87	12.97	9.56
1/1	RGB	41	18.8	17.	13.8
1/2	RGB	30	17.9	17.89	9.78
1/2	RGB	35	28.06	26.78	16.87
1/2	RGB	38	39.2	37.52	23.52
1/2	RGB	40	51.02	50.22	29.87
1/4	RGB	35	89.55	86.71	47.47
1/4	RGB	40	159.45	155.13	85.25
1/8	RGB	30	176.16	174.43	91.17

* https://bellard.org/bpg

5.1.4 PNG

PNG images have been encoded using the pngquant library and we use as parameters the Color Quality parameter which control the image quality that actually decreases the number of colours used in the image. The best image quality is reached when the parameter is set to 100 and the worst image quality when the parameter is set to 0.

Table 7: PNG encoding parameter

Scale	Color	Color Quality
1,1/2,1/4,1/8	RGB	1, 2, 3, 4, 5, 6, 7, 8, 10, 12, 14, 16, 18, 20, 25, 30, 40, 50

Table 8: PNG rank difference and compression ratio according to parameters

Compression Parameters			Rank differences			Compression Ratio		
Scale	Color	Quality	Mean	Median	std dev	Mean	Median	Std dev
1/1	RGB	30	- 1.03	0	10.13	1,86	1,95	0,88
1/2	RGB	40	1.13	0	23.96	6,53	1,86	3,25
1/2	RGB	10	- .43	0	22.49	8.78	8.82	4.66
1/4	RGB	50	- .6	0	40.57	21,45	21,26	11,91
1/4	RGB	20	- 2.89	0	45.07	27.62	27.01	15.69
1/8	RGB	50	- 32.	-1	86.23	66,98	67,57	37,97

5.2 Results

After analysing the formats independently, in this section we compare the formats with each other.

5.2.1 Size Comparison

We compared the average sizes and compression ratios of the 4 image formats. The results are presented as a plot and their associated value. Figure 1 shows the mean sizes of each format. We can see that the JPEG2000 is the heaviest format with 35205 Bytes, followed closely by PNG with 32237 Bytes on average. These two formats are a lot heavier than JPEG and BGP with respectively 6693 and 4439 Bytes. Clearly, BPG is the lightest format.

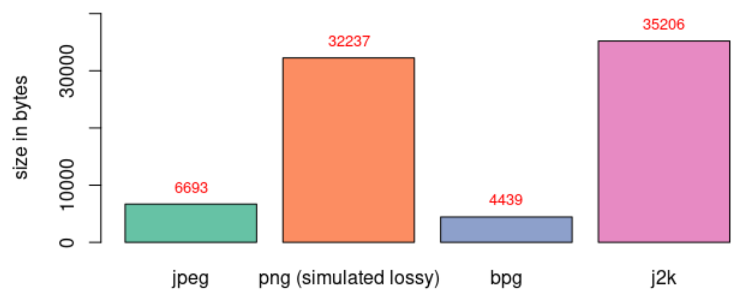

Figure 1: Mean Sizes Comparison

The second plot, Figure 2, shows the mean compression rations of each format. We can say, again that BPG achieves of the highest compression ratio with a mean compression ratio of 272.5. PNG is the worst in compressing images here with a mean of only 38, because it is a lossless image format, and we simply simulate a lossy format by removing colours. Respectively, JPEG and JPEG2000 have a mean compression ratio of 72.5 and 105.10.

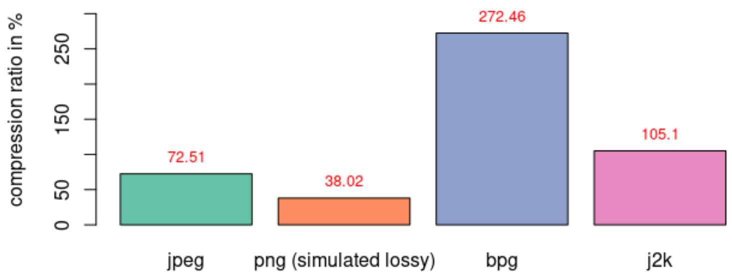

Figure 2: Mean Compression Ratios Comparison

5.2.2 Time comparison

Then we analyse the classification time for each image, so we can compare the influence that the image format has on the classification time.

The time difference may seem really small, but on huge datasets, it can be very significant. Indeed the classification time of PNG is 2% smaller than the JPEG and 7% smaller than JPEG2000 according to our tests.

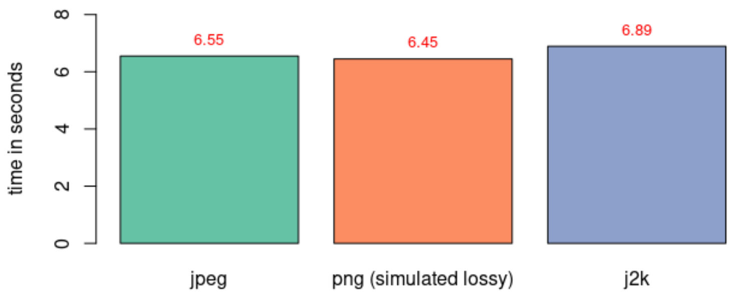

Figure 3: Mean Time Comparison

Moreover, we can observe a slightly lower standard deviation (shown in Figure4) than the others for PNG, which means that the image size has very little impact on the decoding time of PNG images.

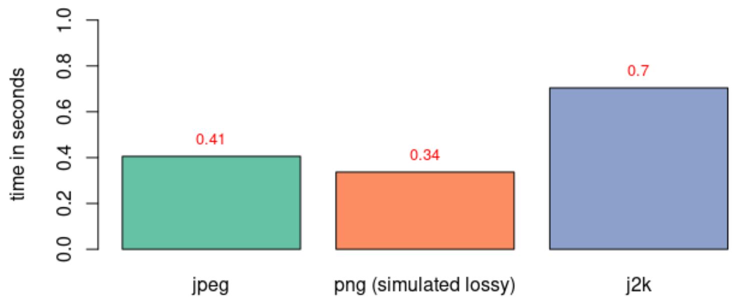

Figure 4: Standart deviation Time Comparison

5.2.3 Compression Ratio influence

Figure 5 shows the influence of compression rate on a subset of images that had their original image well ranked (average original classification rank: 0). We can see that the compression rate has a much greater impact on JPEG than on the others. JPEG2000 and PNG formats can compress more without losing as much in rank difference.

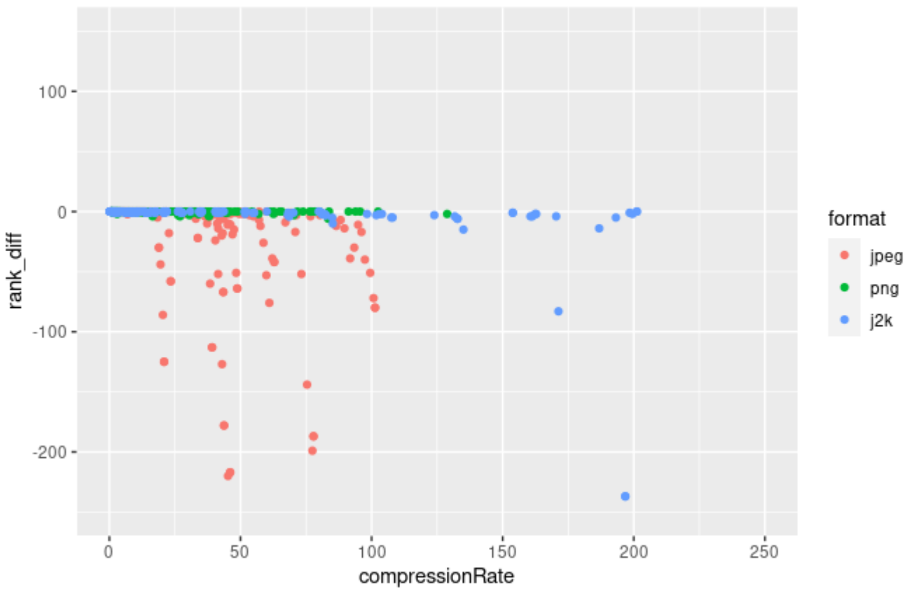

Figure 5: Granny Smith Rank difference according to compression ratio

Figure 6 shows the same analysis but on a subset of images that had their original image badly ranked (average original classification rank: 67.25).
In this set of image, we can see that compression quickly has a negative impact on the rank difference of the PNG images.

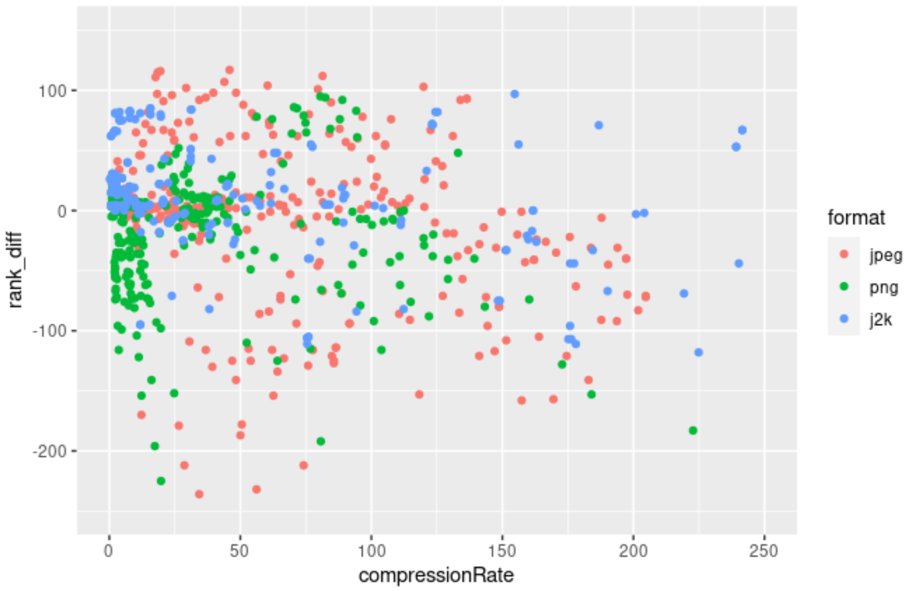

Figure 6: Cleaver, meat cleaver, chopper Rank difference according to compression ratio

Figure 7 shows that PNG preserves SSIM more than others with the compression ratio.

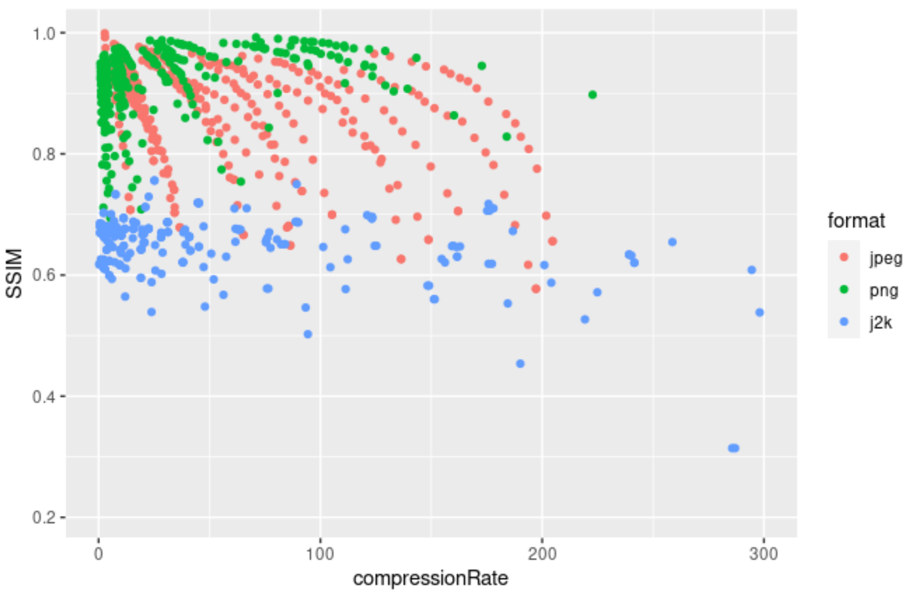

Figure 7: Impact of compression rate on SSIM

5.2.4 SSIM influence

We want to know on which format the SSIM has the most impact Figure 8 shows that SSIM has a much greater impact on JPEG and PNG than on JPEG2000.

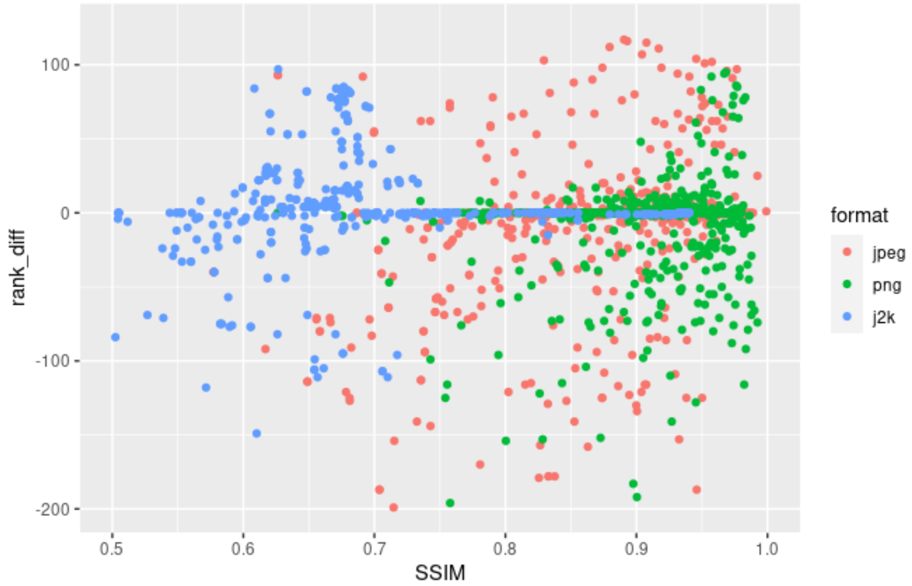

Figure 8: Impact of SSIM on rank difference

6 Discussion

First of all, the most interesting results are the size of each image when coded in a given format. We have seen that the BPG format is the lightest and therefore if space is an important factor, it would be better to choose the BPG formats. However, as explained above, the BPG format is not yet compatible with a large number of applications or systems. For this reason, it may be preferable to choose another format to maximise compatibility. We also showed that the image format has little influence on the classification time, with PNG format being only 7% faster than the JPEG2000 format. However, this small difference can have a significant impact on the classification of very large databases. However, JPEG2000 outperforms PNG in term of the space occupied on the disk.
In terms of performance classification, both formats are better than JPEG, but JPEG2000 is still better when it comes to classifying images that already have a poor classification rank. However, we have some limitations on our findings given our inability to classify the BPG format. The classification performance of BPG will certainly be superior to the others, but we lack the classification time of BPG images that could outperform PNG. This lack of data is due to the fact that BPG is not compatible with our testing tool.

Our study compares the main image formats used. However, other studies show the impressive performance of other formats such as FLIF [16]. This format is also a lossless format but like PNG, we can simulate lossy compression. Furthermore, FLIF is 43% lighter on average than PNG. It might therefore be interesting to compare the classification performance of this format.

7 Conclusion

We can now identify what impacts JPEG, JPEG2000, PNG, and BPG compression algorithms have on computer resources for image recognition. Indeed, BPG is capable of the highest compression ratio that saves more space, while PNG takes the most space. Also, regarding classification time, we show that PNG takes less time to be classified than the other formats. Finally, the classification performance is also impacted by these different formats. JPEG has a huge dependency on compression rate, while PNG is less affected by this and J2K seems to loose in rank difference slowly compared to other formats.

We can therefore conclude that our hypotheses have been confirmed, as PNG saves classification time and is less efficient than BPG and JPEG2000 in terms of classification accuracy. The choice of a perfect format is still not possible, it is a matter of priority.

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