Cite as:

S. F. dos Santos and J. Almeida, “Less is More: Accelerating Faster Neural Networks Straight from JPEG,” in *2021 25th Iberoamerican Congress on Pattern Recognition (CIARP)*, Porto, Portugal, 2021, pp. 237–247, doi: 10.1007/978-3-030-93420-0_23

BibTeX:

```bibtex
@inproceedings{CIARP_2021_Santos,
    author    = {S. F. {dos Santos} and J. {Almeida}},
    title     = {Less is More: Accelerating Faster Neural Networks Straight from JPEG},
    pages     = {237–247},
    booktitle = {2021 25th Iberoamerican Congress on Pattern Recognition (CIARP)},
    address   = {Porto, Portugal},
    month     = {May 10–13},
    year      = {2021},
    publisher = {{Springer}},
    doi       = {10.1007/978-3-030-93420-0_23},
}
```
Abstract. Most image data available are often stored in a compressed format, from which JPEG is the most widespread. To feed this data on a convolutional neural network (CNN), a preliminary decoding process is required to obtain RGB pixels, demanding a high computational load and memory usage. For this reason, the design of CNNs for processing JPEG compressed data has gained attention in recent years. In most existing works, typical CNN architectures are adapted to facilitate the learning with the DCT coefficients rather than RGB pixels. Although they are effective, their architectural changes either raise the computational costs or neglect relevant information from DCT inputs. In this paper, we examine different ways of speeding up CNNs designed for DCT inputs, exploiting learning strategies to reduce the computational complexity by taking full advantage of DCT inputs. Our experiments were conducted on the ImageNet dataset. Results show that learning how to combine all DCT inputs in a data-driven fashion is better than discarding them by hand, and its combination with a reduction of layers has proven to be effective for reducing the computational costs while retaining accuracy.

Keywords: Deep Learning · Convolutional Neural Networks · JPEG · Discrete Cosine Transform · Frequency Domain

1 Introduction

Convolutional neural networks (CNNs) have achieved state-of-the-art performance in several computer vision tasks, such as, classification, segmentation, object detection, image super resolution, denoising, medical images, autonomous driving, road surveillance, among others [28]. However, in order to achieve this performance, increasingly deeper architectures have been used, making computational cost one of the main problems faced by deep learning models [1].

For storage and transmission purposes, most image data available are often stored in a compressed format, like JPEG, PNG and GIF [2]. To use this data with a typical CNN, it would be required to decode it to obtain RGB images, a task demanding high memory and computational cost [2]. A possible alternative is to design CNNs capable of learning with DCT coefficients rather than RGB
pixels \cite{2,4,5,16}. These coefficients can be easily extracted by partial decoding JPEG compressed data, saving computational cost.

In this paper, we investigate strategies to accelerate CNNs designed for the JPEG compressed domain. The starting point for our study is a state-of-the-art CNN proposed by Gueguen et al. \cite{5}, which is a modified version of the ResNet-50 \cite{6}. However, the changes introduced by Gueguen et al. \cite{5} in the ResNet-50 raised its computational complexity and number of parameters. To alleviate these drawbacks, Santos et al. \cite{16} proposed to feed the network with the lowest frequency DCT coefficients, thus losing image details irretrievably. Here, we explore smart strategies to reduce the network computation complexity without sacrificing rich information provided by the DCT coefficients.

Experiments were conducted on the ImageNet dataset, both in a subset and in the whole. Our reported results indicate that learning how to combine all DCT inputs in a data-driven fashion is better than discarding them by hand. We also found that skipping some stages of the network is beneficial, decreasing its computational costs, while also increasing the performance.

The remainder of this paper is organized as follows. Section 2 briefly reviews the JPEG standard. Section 3 discusses related work. Section 4 describes strategies to speed-up CNNs designed for DCT input. Section 5 presents the experimental setup and reports our results. Finally, Section 6 offers our conclusions.

### 2 JPEG compression

The JPEG standard (ISO/IEC 10918) was created in 1992 and is currently the most widely-used image coding technology for lossy compression of digital images. The basic steps of the JPEG compression algorithm are described as follows. Initially, the representation of the colors in the image is converted from RGB to YCbCr, which is composed of one luminance component (Y), representing the brightness, and two chrominance components, Cb and Cr, representing the color. Also, the Cb and Cr components are down-sampled horizontally and vertically by a factor of 2, for human vision is more sensitive to brightness details than to color details. Then, each of the three components is partitioned into blocks of 8x8 pixels and 128 is subtracted from all the pixel values. Next, each block is converted to a frequency domain representation by the forward discrete cosine transform (DCT). The result is an 8x8 block of frequency coefficients, each corresponding to the respective DCT basis functions, with the zero-frequency coefficient (DC term) in the upper left and increasing in frequency to the right and down. The amplitudes of the frequency coefficients are quantized by dividing each coefficient by a respective quantization value defined in quantization tables, followed by rounding the result to the nearest integer. High-frequency coefficients are approximated more coarsely than low-frequency coefficients, for human vision is fairly good at seeing small variations in color or brightness over large areas, but fails to distinguish the exact strength of high-frequency brightness variations. The quality setting of the encoder affects the extent to which the resolution of each frequency component is reduced. If an excessively low-quality setting is used, most high-frequency coefficients are reduced to zero and thus discarded altogether. To improve the compression ratio,
the quantized blocks are arranged into a zig-zag order and then coded by the
run-length encoding (RLE) algorithm. Finally, the resulting data for all 8x8
blocks are further compressed with a lossless algorithm, a variant of Huffman
coding. For decompression, inverse transforms of the same steps are applied
in reverse order. If the DCT computation is performed with sufficiently high
precision, quantization and subsampling are the only lossy operations whereas
the others are lossless, so they are reversible.

3 Related work

The processing of JPEG compressed data has been widely-explored by many
conventional image processing techniques as an alternative to speed up the com-
putation performance in a variety of applications, such as face recognition [3],
image indexing and retrieval [12], and many others. In deep learning era, the po-
tential of the JPEG compressed domain for neural networks has received limited
attention and a few works have emerged in the literature only recently.

To accelerate the training and inference speed, Ehrlich and Davis [4] refor-
mulated the ResNet architecture to perform its operations directly on the JPEG
compressed domain. Since the lossless operations used by the JPEG compression
algorithm are linear, they can be composed along with other linear operations
and then applied to the network weights. In this way, the basic operations used in
the ResNet architecture, like convolution, batch normalization, etc, were adapted
to operate in the JPEG compressed domain. For the ReLU activation, which is
non-linear, an approximation function was developed.

In a different direction, Deguerre et al. [2] proposed a fast object detection
method which takes advantage of the JPEG compressed domain. For this, the
Single Shot multibox Detector (SSD) [10] architecture was adapted to accommo-
date block-wise DCT coefficients as input. To preserve the spatial information
of the original image, the first three blocks of the SSD network were replaced by
a convolutional layer with a filter size of 8x8 and a stride of 8. In this way, each
8x8 block from JPEG compressed data is mapped into a single position in the
feature maps used as input for the next layer.

Similarly, the neural network introduced by Gueguen et al. [5] is a modified
version of the ResNet-50 [6] capable of operating directly on DCT coefficients
rather than RGB pixels. After the DCT coefficients are obtained by partial
decoding JPEG compressed data, their Cb and Cr components are up-sampled
to match the resolution of the Y component. Next, the Y, Cb, and Cr components
are concatenated channel-wise, passed through a batch normalization layer, and
fed to the convolution block of the second stage of the ResNet-50. Due to the
smaller spatial resolution of the DCT inputs, the strides of the early blocks of
the second stage were decreased, mimicking the increase in size of the receptive
fields in the original ResNet-50. Also, the second and third stages were changed
to accommodate the amount of input channels and to ensure that, at their end,
they have the same number of output channels as the original ResNet-50.

However, these changes led to a significant increase in the computational
complexity of the ResNet-50 network. To alleviate its network computation costs
and number of parameters, Santos et al. extended the modified ResNet-50 network of Gueguen et al. to include a Frequency Band Selection (FBS) technique for selecting the most relevant DCT coefficients before feeding them to the network. The FBS technique relies on the idea that higher frequency information have little visual effect on the image, retaining the lowest frequency coefficients. Although this approach is efficient, image details are completely lost by discarding high frequency information, which may drop the model accuracy.

4 Speeding up CNN models designed for DCT input

In this paper, we extend the work of Santos et al., investigating smarter strategies to reduce the computational complexity and number of parameters of the ResNet-50 network proposed by Gueguen et al. In Section 4.1, we examine learning strategies to reduce the number of channels in the early stages of the ResNet-50 network but without sacrificing any information provided by the DCT coefficients. In a different direction, Section 4.2 investigates the possibility of reducing the computational complexity by decreasing the number of layers of the network, while attempting to keep the model accuracy.

4.1 Reducing the number of channels

To start, we evaluate the simple idea of reducing the number of channels in the early stages of the modified ResNet-50 of Gueguen et al., which has been proven to be effective in reducing the computational costs of the network. First, we reduce the number of input channels of the second stage to 64 but we kept the decreased strides at its early blocks, as proposed by Gueguen et al. To accommodate this amount of input channels, we change number of output channels of the second and third stages are changed to be the same as the original ResNet-50. Then, we evaluate different strategies to reduce the number of DCT inputs from 192 (i.e., 3 color components × 64 DCT coefficients) to 64.

Unlike the FBS of Santos et al., where the DCT inputs are discarded by hand potentially losing image information, we take advantage of all DCT inputs and learn how to combine them in a data-driven fashion. For this, we evaluate three different approaches: (1) a linear projection (LP) of the DCT inputs (Section 4.1), (2) a local attention (LA) mechanism (Section 4.1), and (3) a cross channel parametric pooling (CCPP) (Section 4.3).

Linear projection (LP) The ResNet-50 network have residual learning applied to every block of few stacked layers, given by Equation 1, where $F()$ is the residual mapping to be learned by the $i$-th block of stacked layers, $W_i$ are its parameters, $x$ are the input data, and $y$ are the output feature maps.

$$y = F(x,W_i) + x$$ (1)

The $F() + x$ operation is executed by a shortcut connection and a element-wise addition, but their dimensions must be equal. When they are not, a $W_s$
linear projection can be applied in order to match the dimension. As can be seen in Equation 2 assuming that \( x \) have \( n \) input features maps and \( W_s \) is a weight matrix of size \( m \times n \), the product \( W_s \cdot x \) will output in \( m \) feature maps, where each one is a linear combination of all the \( n \) inputs from \( x \).

\[
y = F(x, W_i) + W_s \cdot x \tag{2}
\]

We apply this linear projection to reduce the number of channels from 192 of the DCT inputs to 64 of the convolution block of the second stage. In this way, we consider the DCT inputs as a whole regardless the importance of each of their frequencies to the image content. Also, the skewness or kurtosis (shape) of their distribution is preserved by the linear transformation.

**Local attention (LA)** The local attention proposed by Luong et al. [11] is a soft attention mechanism used on the machine translation task to analyze a word with a small context window of adjacent words, learning attention maps which focus on relevant parts of the input information.

We adapt this mechanism to be used in the DCT inputs in order to reduce the number of channels from 192 to 64. This is performed according to Equation 3, where \( x \) is an input with \( n \) features maps, \( r \) is its reshaped version partitioning it into \( m \) groups of \( \frac{n}{m} \) channels, \( W \) is a weight matrix of size \( m \times (\frac{n}{m}) \), \( y \) is an output with \( m \) feature maps, and \( \odot \) is the Hadamard product.

\[
r = \text{reshape} \left( x, \left[ m, \frac{n}{m} \right] \right) \tag{3}
\]

\[
s = W \odot r
\]

\[
a_i = \text{softmax}(s_i), \forall i \in \{1 \ldots m\}
\]

\[
y_i = a_i \cdot r_i, \forall i \in \{1 \ldots m\}
\]

First, the input \( x \) is split into \( m \) partitions \( r = \{r_1, \ldots, r_m\} \) with \( \frac{n}{m} \) features maps. Then, alignment scores \( s \) are obtained by computing the Hadamard product between \( W \) and \( r \). For each partition \( i \in \{1 \ldots m\} \), alignment scores \( s_i \) are normalized by applying the softmax function, producing attention maps \( a_i \) which are used to amplify or attenuate the focus of the distribution of the input data \( r_i \). Therefore, the feature map \( y_i \) outputted for the \( i \)-th partition is a linear combination of adjacent channels. In this way, we preserve information of the DCT spectrum for the entire range of frequencies.

**Cross Channel Parametric Pooling (CCPP)** In a cross channel parametric pooling layer, a weighted linear recombination of the input features maps is performed and then passed though a rectifier linear unit (ReLu) [9]. Min Lin et al. [9] proposed to use a cascade of such layers to replace the usual convolution layer of a CNN, since they have enhanced local modeling and the capability of being stacked over each other. Formally, a cascaded cross channel parametric pooling is performed according to Equation 4 [9], where \( f_{l,i,j,k} \) stands for the output of the \( l \)-th layer, \( x_{i,j} \) is the input patch centered at the pixel \((i,j)\), \( k \) is used to
index the feature maps, $W_{l,k}$ and $b_{l,k}$ are, respectively, weights and biases of the $l$-th layer for the $k$-th filter, and $N$ is the number of layers.

$$f_{i,j,k}^1 = \max(0, W_{1,k}^T \cdot x_{i,j} + b_{1,k})$$

\vdots

$$f_{i,j,k}^N = \max(0, W_{N,k}^T \cdot f_{i,j}^{N-1} + b_{N,k})$$

The cross channel parametric pooling is equivalent to a convolutional layer with a kernel size of $1 \times 1$ [9], which is also known as a pointwise convolution [1], being capable of projecting the input feature maps into a new channel space, increasing or decreasing the amount of channels.

We used a cross channel parametric pooling layer to reduce the number of channels from 192 to 64. Similar to the linear projection, the individual importance of each DCT coefficient for the image content is also not taken into account. On the other hand, the non-linear properties of the ReLU activation encourage the model to learn sparse feature maps, making it less prone to overfitting.

### 4.2 Reducing the number of layers

The modified version of the ResNet-50 introduced by Gueguen et al. [5] skips first stage of the original ResNet-50, feeding the DCT coefficients to the second stage, which is modified to accommodate the amount of input channels. In order to reduce the complexity of the network even further, we analyze the effects of skipping the second, third, and fourth stages of the original ResNet-50, but maintaining the stride reduction proposed by Gueguen et al. [5] at the early blocks of the initial stage in which the DCT coefficients are provided as input.

Different from Gueguen et al. [5], we do not increase the number of input channels at the initial stages, since it would lead to a great increase on the computational complexity of the network. Instead, we keep them the same as the original ResNet-50, whose the number of input channels in the second, third, fourth, and fifth stages are 64, 128, 256, and 512, respectively.

To accommodate such amount of channels, the strategies presented in the previous section were used to decrease or increase the DCT inputs from 192 (i.e., 3 color components $\times$ 64 DCT coefficients) to the amount of input channels of the initial stage in which they are provided as input. Notice that the number of DCT coefficients is close to the number of input channels of the third stage, requiring a less drastic reduction than the one needed to feed them on the second stage. On the other hand, the expected inputs for the fourth and fifth stages have a greater amount of channels than the DCT inputs and, for this reason, they need to be scaled up, however preserving the salient features as the original data.

### 5 Experiments and results

Experiments were conducted on the ILSVRC12 [13] dataset, commonly known as ImageNet, and on a subset of it used by Santos et al. [10]. The ImageNet
dataset has 1000 classes and is divided into a training set of 1,281,167 images and a test set of 50,000 images. The ImageNet subset has 211 of the 1000 classes, totaling 268,773 images that were split into a training set with 215,018 images and a test set of 53,755 images. Image classification tasks at two difficulty levels were considered for this subset: in the coarse granularity, the 211 classes were grouped according to their semantics into 12 categories, namely: ball, bear, bike, bird, bottle, cat, dog, fish, fruit, turtle, vehicle and sign; whereas in the fine granularity, all the 211 classes were used.

All the images were resized to 256 pixels on their shortest side and the crop size for all experiments was 224 × 224. In the experiments, the evaluated networks were trained for 120 epochs with batch size of 128, initial learning rate of 0.05 reduced by a factor of 10 every 30 epochs, and momentum of 0.9. Data augmentation with random crop and horizontal flipping was applied on training phase, while on test, only center crop was used.

The experiments were implemented in PyTorch (version 1.2.0) and performed on a machine equipped with two 10-core Intel Xeon E5-2630v4 2.2 GHz processors, 64 GBytes of DDR4-memory, and 1 NVIDIA Titan Xp GPU. The machine runs Linux Mint 18.1 (kernel 4.4.0) and the ext4 file system.

Section 5.1 compares the performance of the different strategies used to reduce the number of channels from 192 to 64 before feeding them to the network. Section 5.2 shows the effects of reducing the number of layers of the network.

5.1 Effects of reducing the number of channels

Table 1 presents a comparison of the computational costs and the accuracy for the coarse and fine granularity task for the ImageNet subset, and for the entire ImageNet. The computation complexity was measured by the amount of floating point operations (FLOPs) required for passing one image already loaded into the memory through the network and by its number of parameters. The value inside parentheses is the number of input channels at the initial stage of each network.

Table 1. Comparison of computational complexity (GFLOPS), number of parameters, and accuracy for the original ResNet-50 with RGB inputs and networks using DCT with different strategies to reduce number of input channels.
For both tasks on the ImageNet subset, the RGB-based network performed better than the DCT-based ones. In the fine-grained task, the network of Guéguen et al. [5] achieved the highest accuracy among the DCT-based networks, but also have the highest number of parameters and computational complexity, even compared to the RGB-based network. Similar results were obtained by the networks of Santos et al. [16] and ours in terms of accuracy however greatly reducing the computational complexity and number of parameters. In the coarse-grained task, our LA and CCPP networks yielded better results than that of Guéguen et al. [5] and a similar performance to the DCT + FBS (3x32) of Santos et al. [16].

On the full ImageNet dataset, the network of Guéguen et al. [5] also achieved the highest accuracy, whereas the results obtained for those of Santos et al. [16] and ours were similar, with the advantage of reducing the network computation complexity. Among the strategies we proposed, LA performed slightly better than LP and CCPP. Compared to the networks of Santos et al. [16], our strategies yielded a similar accuracy to DCT + FBS (3x32), while having a computational complexity similar to DCT + FBS (3x16), showing that the use of smarter strategies to learn how to reduce the number of input channels is promising.

The computational complexity and number of parameters of all our strategies (LP, LA, and CCPP) are identical and better than the original ResNet-50, proving to be effective for accelerating computation without sacrificing accuracy.

5.2 Effects of reducing the number of layers

When stages of the network are skipped, we need to decrease or increase the DCT inputs in order to match the amount of channels expected at the initial stage in which they are provided as input. For this, we use the CCPP method, since the results for all the strategies presented in Section 4.1 were similar. This strategy was chosen because it is commonly applied in CNNs in order to obtain channel-wise projections of the feature maps, like in depthwise separable convolutions [1]. Table 2 presents the computational complexity and number of parameters of our ResNet-50 using DCT as input when skipping different stages.

| Approach                        | GFLOPs | Params |
|---------------------------------|--------|--------|
| Skip the first stage            | 3.20   | 25.6M  |
| Skip the first and second stages| 2.86   | 25.1M  |
| Skip the first, second, and third stages | 8.26   | 23.9M  |
| Skip the first, second, third, and fourth stages | 10.76  | 15.8M  |

As it can be seen, skipping the first and second stages was beneficial, reducing the computational complexity and number of parameters of the network. However, as more stages were skipped, although the number of parameters is decreased, the computational complexity is greatly increased. This is due to the
decreased strides at the early blocks of the initial stage. For this reason, the skipping of the first and second stages is the only setting considered in the next experiments, since only it saves the computational costs of the network.

Table 3 compares the computational complexity, number of parameters, and accuracy between state-of-the-art methods and our proposed strategy, which skips the first and second stages and uses CCPP to accommodate DCT inputs. Skipping the first and second stages benefited not only computational costs of the network, but also its accuracy. In both tasks on the ImageNet subset, this modification led to the best performance among the DCT-based networks. On the full ImageNet dataset, it achieved the second best accuracy among the DCT-based networks, behind only the modified ResNet-50 of Gueguen et al. [5], whose computational complexity and number of parameters are considerable bigger.

Table 3. Comparison of computational complexity (GFLOPS), number of parameters, and accuracy for the original ResNet-50 with RGB, state-of-the-art networks designed for DCT, and our strategy for reducing the number of input channels and layers.

| Approach                                       | ImageNet Subset | ImageNet     |
|-----------------------------------------------|-----------------|--------------|
|                                              | Fine | Coarse |          |          |
| RGB (3x1) [6]                                | 76.28 | 96.49 | 73.46 |          |
| DCT (3x64) [5]                               | 70.28 | 94.15 | 72.33 |          |
| DCT + FBS (3x32) [16]                        | 69.79 | 94.53 | 70.22 |          |
| DCT + FBS (3x16) [16]                        | 68.12 | 93.92 | 67.03 |          |
| DCT + CCPP (1x64)                            | 70.09 | 94.85 | 69.73 |          |
| DCT + CCPP + skipping 1st and 2nd stages (1x128) | 71.21 | 94.84 | 70.49 |          |

6 Conclusion

In this paper, we addressed the efficiency issues of CNNs designed for the JPEG compressed domain. More specifically, we speeded-up a modified version of the ResNet-50 proposed by Gueguen et al. [5] and improved by Santos et al. [16]. Although these proposals are effective, they introduced changes in the ResNet-50 [6] that either raised the computational costs or lost relevant information from the input. In contrast, we explored smart strategies to reduce the computational complexity without discarding useful information.

We conducted experiments on the ImageNet dataset, both in a subset and in the whole. Our results on both datasets showed that learning how to combine all DCT inputs in a data-driven fashion performs better than the FBS technique of Santos et al. [16], where the DCT inputs are discarded by hand. Also, we found that skipping some stages of the network is beneficial, proving to be effective for reducing the computational complexity while retaining accuracy.

As future work, we intend to evaluate other learning strategies for accelerating computation without sacrificing accuracy. Also, we want to evaluate the use of our strategies with other network architectures, like EfficientNet [17] and MobileNet [7]. In addition, we also plan to extend the ideas applied on networks designed for JPEG images to those devised for MPEG videos [15,14].
Acknowledgment

This research was supported by the FAPESP-Microsoft Research Virtual Institute (grant 2017/25908-6) and the Brazilian National Council for Scientific and Technological Development - CNPq (grant 314868/2020-8).

References

1. Chollet, F.: Xception: Deep learning with depthwise separable convolutions. In: CVPR. pp. 1251–1258 (2017)
2. Deguerre, B., Chatelain, C., Gasso, G.: Fast object detection in compressed JPEG images. In: IEEE Intelligent Transportation Systems Conference (ITSC’19). pp. 333–338 (2019)
3. Delac, K., Grgic, M., Grgic, S.: Face recognition in JPEG and JPEG2000 compressed domain. Image Vision Computing 27(8), 1108–1120 (2009)
4. Ehrlich, M., Davis, L.S.: Deep residual learning in the JPEG transform domain. In: ICCV. pp. 3484–3493 (2019)
5. Gueguen, L., Sergeev, A., Kadlec, B., Liu, R., Yosinski, J.: Faster neural networks straight from JPEG. In: NIPS. pp. 3937–3948 (2018)
6. He, K., Zhang, X., Ren, S., Sun, J.: Deep residual learning for image recognition. In: CVPR. pp. 770–778 (2016)
7. Howard, A.G., Zhu, M., Chen, B., Kalenichenko, D., Wang, W., Weyand, T., Andreetto, M., Adam, H.: Mobilenets: Efficient convolutional neural networks for mobile vision applications. arXiv preprint arXiv:1704.04861 (2017)
8. Li, Y., Gu, S., Gool, L.V., Timofte, R.: Learning filter basis for convolutional neural network compression. In: ICCV. pp. 5623–5632 (2019)
9. Lin, M., Chen, Q., Yan, S.: Network in network. arXiv preprint arXiv:1312.4400 (2013)
10. Liu, W., Anguelov, D., Erhan, D., Szegedy, C., Reed, S.E., Fu, C.Y., Berg, A.C.: SSD: single shot multibox detector. In: ECCV. pp. 21–37 (2016)
11. Luong, M.T., Pham, H., Manning, C.D.: Effective approaches to attention-based neural machine translation. In: Conference on Empirical Methods in Natural Language Processing (EMNLP’15). pp. 1412–1421 (2015)
12. Poursistani, P., Nezamabadi-pour, H., Moghadam, R.A., Saeed, M.: Image indexing and retrieval in JPEG compressed domain based on vector quantization. Mathematical and Computer Modelling 57(5-6), 1005–1017 (2013)
13. Russakovsky, O., Deng, J., Su, H., Krause, J., Satheesh, S., Ma, S., Huang, Z., Karpathy, A., Khosla, A., Bernstein, M.S., Berg, A.C., Li, F.F.: Imagenet large scale visual recognition challenge. Intl. J. Computer Vision 115(3), 211–252 (2015)
14. Santos, S.F., Almeida, J.: Faster and accurate compressed video action recognition straight from the frequency domain. In: SIBGRAPI – Conference on Graphics, Patterns and Images (SIBGRAPI’20). pp. 62–68 (2020)
15. Santos, S.F., Sebe, N., Almeida, J.: CV-C3D: action recognition on compressed videos with convolutional 3d networks. In: SIBGRAPI – Conference on Graphics, Patterns and Images (SIBGRAPI’19). pp. 24–30 (2019)
16. Santos, S.F., Sebe, N., Almeida, J.: The good, the bad, and the ugly: Neural networks straight from jpeg. In: ICIP. pp. 1896–1900 (2020)
17. Tan, M., Le, Q.V.: Efficientnet: Rethinking model scaling for convolutional neural networks. In: ICML. pp. 6105–6114 (2019)