

LEARNED PARAMETERIZED CONVOLUTIONAL APPROXIMATION OF IMAGE FILTERS

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KEYWORDS

Convolutional neural networks, grayscale morphology, edge detection, computational efficiency, image processing

ABSTRACT

Multilayer neural networks are considered universal approximators applicable to a wide range of problems. There are quite detailed theoretical and applied studies for fully connected networks, while for convolutional networks the results are more scarce. In this paper, we tested the approximating capability of deep neural networks with typical architectures like ConvNet, ResNet, and UNet as applied to classical image processing algorithms. Canny edge detector and grayscale morphological dilation with the disk structuring element were selected as target algorithms. As we have seen, even relatively lightweight neural models are able to approximate a filter with fixed parameters. Since classical algorithms are parameterized, we considered different approaches to the parameterization of the neural networks and found out that even the simplest of them, adding parameters in the input images channels, works well for low parameter count. Also, we measured an inference time of a neural network approximation and a classical implementation of the grayscale dilation with the disk structuring element. Starting from a certain radius, a neural network works faster than an algorithm even on one core of the CPU without fine-tuning the architecture for performance, thus confirming the viability of ConvNets as a differentiable approximation technique for optimization of classical-based methods.

INTRODUCTION

Nowadays, artificial neural networks (ANNs) are considered universal approximators for analytic functions of any complexity. Theoretical studies have been conducted for feedforward neural networks; in particular, Hornik et al. (1989) proved that standard perceptron with one or more hidden layers is capable of approximating any Borel measurable function from one finite-

dimensional space to another to any desired degree of accuracy. Similar studies for convolutional networks were also conducted by Zhou (2019), who showed that a deep convolutional neural network can approximate any continuous function to an arbitrary accuracy when its depth is large enough. But there is still a lack of studies about the neural networks capability of approximating algorithms, particularly image processing algorithms. Many convolutional network architecture families, such as ConvNet, ResNet, UNet, etc., are successfully used in various image processing tasks (Li et al. 2021; Andreeva et al. 2019), including ones with existing algorithmic solutions (Karnaushkin and Sklyarenko 2022; Panfilova and Kunina 2020). However, it is not obvious that especially for tasks where specialized algorithmic solutions are known, a general-purpose neural network could solve the same task with comparable computational and representational efficiency. To research this aspect, we decided to test the ability of typical NN architectures to approximate individual image processing operations, since difficulties with this simplified problem would indicate deeper issues for use of neural networks as a general-purpose tool for image processing. We chose Canny edge detector and morphological dilation as examples of typical image processing operations since the former is comparatively well-researched from the neural approximation point of view (Fernández et al. 2011), and for the latter there is no exact computationally efficient algorithm anyway.

Approximation of classical image processing algorithms with neural networks is not only interesting from a theoretical point of view but also leads to practical benefits:

(1) a neural network is trainable, and thus can potentially achieve a better solution than the classical filter, which is deterministic and whose parameters must be chosen manually. For example, Jampani et al. (2016) proposed to learn bilateral filters from data and showed that it leads to performance improvements compared to a fixed parametric form.

(2) a neural network model can be implemented both

on CPUs and GPUs, which development is constantly evolving in speed and power consumption, so the inference of neural network can be significantly faster compared to classical algorithm (Di Febbo et al. 2018);

(3) a neural network approximation can replace the classical filter within a more complex system based on ANNs as well, allowing for end-to-end system training (Yi et al. 2016).

The rest of the paper is structured as follows: the following section provides a brief theoretical overview of existing work on approximating classical algorithms with neural networks and approaches to parameterization of the neural networks. The next section includes a description of the experiments and a discussion of the results. Finally, the paper is concluded with a summary and pointers to the possible future work.

RELATED WORK

In this section, we will describe the main existing results on the approximation of classical filters, which can be considered as baselines for further research. Since classical algorithms have the important property of natural parametrization, which means they can be customized for specific requirements, we will also consider approaches to the parametrization of neural networks.

Neural network approximation of classical algorithms

The first works on the research topic appeared even in the 20th century. For example, De Ridder et al. (1999) investigated the application of neural networks to nonlinear image processing using Kuwahara filter for image smoothing as a target. The authors experimented with several architectures of a network, including single- and double-layer perceptrons with different sizes of the hidden layers and a specially designed modular neural network. Although the authors managed to train the model to smooth the images, the result was still too far from true Kuwahara filter smoothing. The reason for this could be due to unsuitable model architecture and loss function.

Fernández et al. (2011) attempted to approximate the Canny and Sobel edge detectors with single-layer perceptron. To take into account the spatial dependence in the images, a pixel and its eight adjacent pixels were fed to the input of the model, which almost corresponds to a convolution with a kernel size of 3x3. The authors didn't manage to achieve a good quality of the approximation, which can probably be explained by the inability of the single-layer model to learn complex dependencies in the data. However, these studies can be taken as a baseline for subsequent experiments.

Fernández et al. (2011); De Ridder et al. (1999) used neural networks with typical architecture: just a multi-layer perceptron. A totally different approach was proposed by Zhukovskiy et al. (2018). The authors developed a complete reproduction of the Canny, Niblack, and Harris filters using only neural network operations: convolution, pulling, concatenation, etc., so the algorithm's parameters do not need to be selected manually

because their optimal values will be determined during training. But this approach has its disadvantage since it requires creating a new architecture for each filter, which is very time-consuming and requires a deep understanding of the algorithm's inner workings. It also does not correlate with the aim of our study.

Parameterization approaches

In the previous works, the ability of neural networks to approximate a particular filter with fixed parameters was investigated, and those researches are of more theoretical interest. Even though in real-world applications this approach is acceptable, because a filter with specified parameters is often used, it is necessary to be able to customize the filter parameters when creating and optimizing prototypes of the final system. For example, Karnaushkin and Sklyarenko (2022) used Canny edge detector to develop a computer vision-based method of pre-alignment of a channel optical waveguide and a lensed fiber, and the values of the algorithm parameters were being tuned while the development stage. Sometimes it is necessary to give a user the ability to specify the system parameters, as in the case of an ANN-based image pre-compensation system, which must adjust to the parameters of a particular person's eye (Yu et al. 2021) and thus cannot be retrained for each possible set of parameters.

Model parameterization can be achieved in several ways:

(1) by adding parameters values as metadata to the input image channels. This approach was used by Tziolas et al. (2020). In order to enrich the data and improve the quality of the model predicting the clay content of the soil, not only remotely sensed values, which constitute the spectral input channel, but also geographic coordinates, which constitute the auxiliary input channels, are fed as an input. This is the simplest way to provide dependence of the model on auxiliary parameters, which does not entail a significant increase in the size of the model, but in some cases, it might be not enough to learn more complex dependencies between parameters and expected output.

(2) by parameterizing the convolution kernel. Traditional convolutional kernels are shared for all examples in a dataset, which can significantly decrease the quality of the model in case the data are characterized by a large variability. Conditional Convolutions (CondConv), proposed by Yang et al. (2020), and Dynamic Convolutions (DynamicConv), proposed by Chen et al. (2020)), share a common idea: instead of using a single convolution kernel per layer, which is the same for any input, these types of convolutions aggregates multiple convolution kernels, which are input dependent. DynamicConv aggregates several kernels based upon their attentions while CondConv parameterizes the convolutional kernels as a linear combination with example-dependent scalar weights computed using a routing function with learned parameters. Another example of this approach is the Adaptive convolutional neural network (ACNN), presented in Kang et al. (2017). In

ACNN the filter weights are generated with a learned sub-network, which is just a multilayer perceptron and whose input is the side information or metadata. Replacing traditional convolution layers by convolutions with adaptive weights can disentangle the variations related to the side information and extract discriminative features related to the current context, but it can significantly increase the size of the model and slow down its inference time.

(3) by adding extra input layers for metadata to the neural network. Wei (2020) and Gessert et al. (2020) used a multiple-input neural network, which consists of two branches: the first one is a single- or multilayer perceptron that process a vector of metadata and the second one is a convolutional neural network that process an input image. The outputs of these sub-networks are then concatenated and processed with the common part of the network. Ellen et al. (2019) developed this idea and proposed several schemes for metadata incorporation. While in the previous three works metadata was added to a convolutional neural network, Mudiyanse-lage et al. (2021) demonstrated how to add metadata to a graph neural network.

METHODS AND RESULTS

For our experiments, we have chosen two classical algorithms: Canny edge detector and grayscale morphology, namely, dilation with the disk structuring element. Both of them are often used in industrial recognition systems (e.g. Panfilova and Kunina (2020), Panfilova et al. (2021), Erlygin and Teplyakov (2021)). There is a baseline on an approximation of Canny operator (Fernández et al. 2011), but there was a feedforward neural network used, while research for convolutional neural networks was not conducted. And, as far as we are concerned, there are no published studies for approximation of morphological dilatation. Moreover, there is no computationally efficient implementation of dilation with the disk structuring element compared, at least, to the rectangular structuring element, for which fast window size-independent algorithm (vHGW) is available (Limonova et al. 2020).

Furthermore, we want to investigate two different approaches to approximating filters: regression and classification. As long as Canny detects edges on the image, it might be considered as a classification of each pixel whether it is a part of an edge or not. On the other hand, morphological filters do not „classify“ each pixel; instead, they process an input image to another one, which might be considered as a regression.

Approximation with fixed parameters

At first, we wanted to test the ability of the neural networks to approximate a particular filter with specified parameters. There are three key parameters of Canny edge detector (Canny 1986): standard deviation for Gaussian kernel σ , lower bound for hysteresis thresholding (low threshold), and upper bound for hysteresis thresholding (high threshold). We specified these parameters as $\sigma = 1$, low threshold = 0.1, high

threshold = 0.2. For morphological dilation, we approximated the filter with two sizes of the radius: $R_1 = 5$ as a baseline and $R_2 = 20$ to be sure that the receptive field of the network is large enough to approximate dilation with a big radius.

We tried three architectures: ConvNet, which is a stack of convolutional layers with ReLU as activation function, ResNet, and UNet. These architectures might be considered as the gold standard of convolutional networks because they are well-known and often used in many cases of image processing and computer vision (Li et al. 2021). We considered only the most typical neural network architectures without optimizing them for a particular filter. The reason is that our study aims to investigate the universality of standard neural network models for solving classical image processing problems for which there already exists a well-working analytical algorithm.

As we mentioned earlier, the problem of Canny edge detector approximation can be formulated in terms of a pixel-by-pixel classification, thus we used the binary cross-entropy loss function. The metrics are Matthew’s correlation coefficient, or MCC, (Cheng et al. 2021), and Intersection over Union, or IoU, (Zheng et al. 2019). For morphological dilation approximation, we used the mean squared error loss function and mean absolute error as a metric. Also, we compared different models using the loss function value on the test dataset.

For each filter, all three networks were trained with the same hyperparameters. Particularly, we used Adam optimizer with learning rate 0.001 and parameters $\beta_1 = 0.9, \beta_2 = 0.999$; cosine annealing scheduler with warm restarts with a period of 8 epochs; 50 epochs for training. As the dataset, we used Linnaeus5 with images of size 128x128 pixels split into training, validation, and test sets with 6000, 1000, and 1000 images, respectively.

All three models showed comparable results for morphology approximation, but for Canny detector approximation, the best quality was achieved with ResNet (table 1), that is why in the following experiments we used only this architecture. Our implementation of ResNet reproduces the classic implementation and differs only in the number of layers and the number of filters in convolutional layers. It consists of 7 residual blocks, each of them containing 2 convolutional layers with 12 filters. A visualization of the ResNet work is shown in the fig. 1 and fig. 2 for Canny edge detector and grayscale morphology with the disk structuring element, respectively.

Model	Num. of parameters	Metrics		
		MCC	IoU	Test BCE
ConvNet	25.8k	0.9185	0.9230	0.0462
ResNet	29.1k	0.9286	0.9322	0.0425
UNet	28.7k	0.8291	0.8481	0.1020

TABLE 1: Metrics for Canny edge detector approximation

Moreover, we compared inference times of the ResNet (fig. 3) with the skimage.morphology (v.0.17.2) implementation and noticed that starting from a cer-

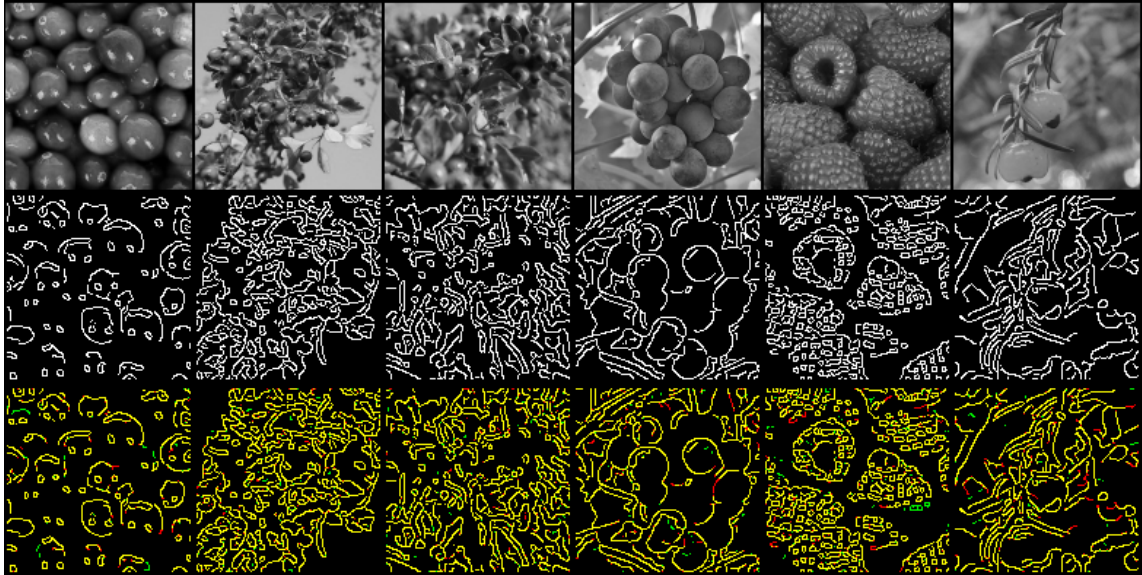


Fig. 1: Approximation of Canny edge detector with fixed parameters (1-st row: original images, 2-st row: Canny edge detector, 3-st row: pixel difference with the neural network output, where black, yellow, green, and red colours stand for true negative, true positive, false positive, and false negative pixels, respectively).

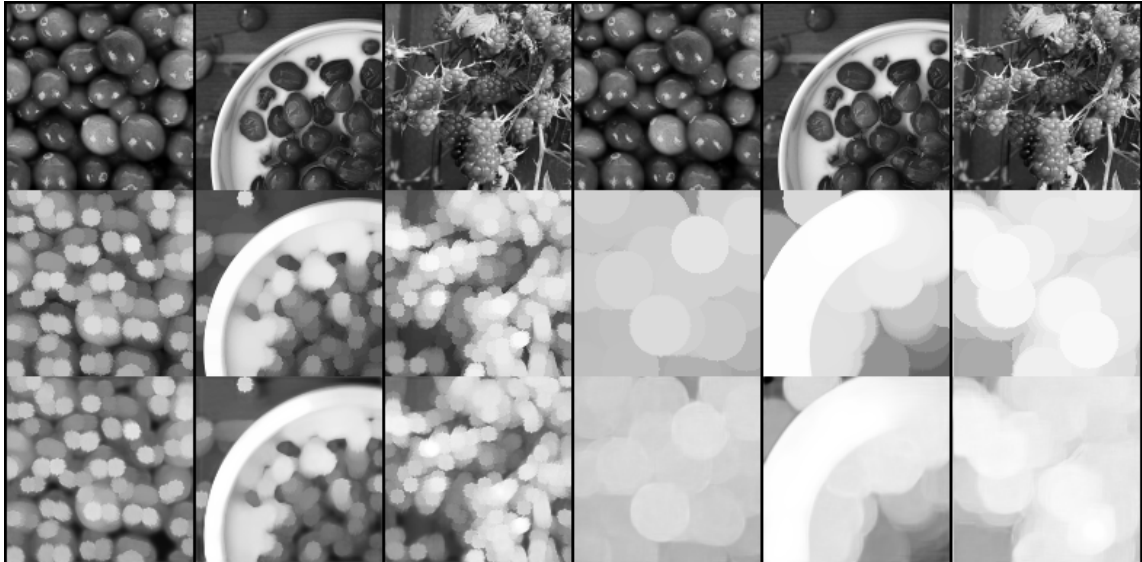


Fig. 2: Approximation of grayscale morphology with the disk structuring element and fixed parameters (1-st row: original images, 2-st row: morphological dilation, 3-st row: neural network). The first three images correspond to dilation with a radius of 5, while the second three correspond to dilation with a radius of 20. Two networks were trained to approximate the morphological dilation with different radii independently.

tain radius, neural network approximation works faster than the classical algorithm even in single-threaded inference mode. In fully parallel GPU inference, the ResNet is faster than the CPU implementation in all cases, and while such performance comparison is unfair, it illustrates one of the benefits of NN approximations, which is the availability of highly parallelized implementations. It is worth mentioning that we did not apply any optimization techniques to speed up inference of the ResNet, while there is a more computational efficient implementation of it (e.g. Lobanov and Sholomov (2019), which provides a threefold increase in the inference performance). The parameters of the testing system are: Intel(R) Xeon(R) W-2133 CPU @ 3.60GHz, 6 cores, 12 threads; GeForce RTX 2080 Ti 11

Gb GPU.

Thus, we found that typical neural network architectures are able to approximate at least some of the typical image processing algorithms, while having few enough weights to be computationally competitive with purpose-built algorithms.

Parameterized approximation

An important property of classical image processing algorithms is parameterization, therefore they can be customized for a particular task while neural networks usually implement a fixed operation. In real-world applications, it is often necessary for a developer or a user to be able to tune the parameters. That is why another aim of our research is to consider the approaches to the

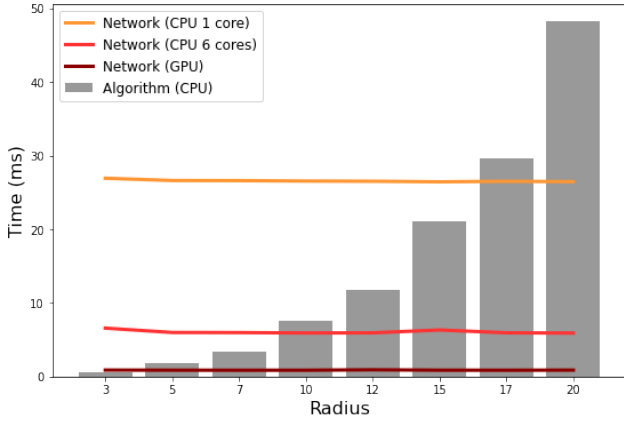


Fig. 3: Inference time of classical algorithm (disk-structured morphological dilation) and its neural approximation with (unparameterized) ResNet. The CPU algorithm implementation is single-threaded.

parameterization of neural networks. We decided to start with the simplest approach, which is adding filter parameters as auxiliary channels of an input image.

Canny detector has three key parameters: sigma, low threshold, and high threshold. The high threshold was parameterized via the low threshold multiplied by a coefficient k . We consider these parameters as independent uniformly distributed in the interval $[0; 3]$ for sigma, $[0.1; 0.2]$ for low threshold, and $[1.05; 2]$ for k , random variables.

Since the distribution is multidimensional and its components are independent, it is crucial to sample from it with as maximum coverage of the probability space as possible. Latin hypercube sampling (LHS), proposed by McKay et al. (1979), ensures that the set of samples is a very good representative of the real variability. That is why we used it for sampling the set of parameters during training phase.

The training was organised as follows: at each epoch, we sampled 1000 sets of parameters with LHS. For each image from the training set, we randomly chose a set of parameters and added its values to the channels of the image. Since there are 6000 images in the training set, each set of parameters was applied to roughly six images. In the case of continuous random variables, the number of possible sets of parameters is infinite, that is why it makes sense to increase the number of epochs so that the network "see" as many sets of parameters as possible and learn how to approximate them. We trained our model for 200 epochs, which means there were 200000 sets of parameters. Also, we had to increase the number of convolutional kernels in the hidden layers from 12 to 16 compared to the unparameterized version. A visualization of the ResNet work is shown in the fig. 4. A dependence on the parameters is pronounced, but the quality of the approximation is slightly reduced compared to the approximation with fixed parameters. The Matthew's correlation coefficient is 0.8917 and IoU is 0.9021.

Disk-structured morphological dilation has one parameter, which is the radius of the disk. As long as

the radius must be a positive integer, we consider it a discrete random variable, uniformly distributed in the interval $[1; 20]$. The model was trained in the same way as the Canny approximation network, but we did not use LHS because it is not necessary in case of one-dimensional discrete probability space. A visualization of the ResNet work is shown in the fig. 5.

Approximation of Canny edge detector and morphological dilation showed that the simplest parameterization approach via channels of input image works well enough for some applications.

CONCLUSIONS

In this paper, we tested the hypothesis that neural networks can be effectively used to approximate and replace classical image processing operations. We chose two typical image filters, Canny edge detector and grayscale morphological dilation with the disk structuring element. This choice of algorithms allowed us to compare two different approaches to the approximation: classification and regression. As we have seen, neural networks are equally good at both tasks, one only needs to choose the appropriate loss function.

We use typical convolutional networks architectures like ConvNet, ResNet, and UNet with the standard loss functions (binary cross-entropy and mean squared error), not trying to optimize the architecture for a particular filter. As we have seen, even a small model of a neural network is able to approximate a filter with fixed parameters. The only requirement is the large enough number of hidden layers, which determine the size of the model's receptive field. These results might be considered as an argument in favour of the tested hypothesis, obtained experimentally.

Since in real-world applications adjustability of filters might be crucial, our next step was to test is it possible to approximate chosen filters with different parameters but using a single model. We considered different approaches to parameterization of the neural networks, but even the simplest of them, adding parameters in the input images channels, works well. There are still some artifacts, so for the better quality of the approximation, it might need to apply more complex approaches like adding extra layers for parameters only, creating special network blocks, etc. This is the direction of further research.

Using a neural network approximation instead of the classical algorithm has its benefits listed in the introduction. In addition to those, we have found one more advantage of a neural model over the classical implementation of the grayscale morphology. Starting from the specified size of the radius, a neural network works faster than the algorithm (fig. 3) even on one core of the CPU without applying any optimization techniques.

ACKNOWLEDGMENT

This work is partially financially supported by Russian Foundation for Basic Research (project 18-29-26037).

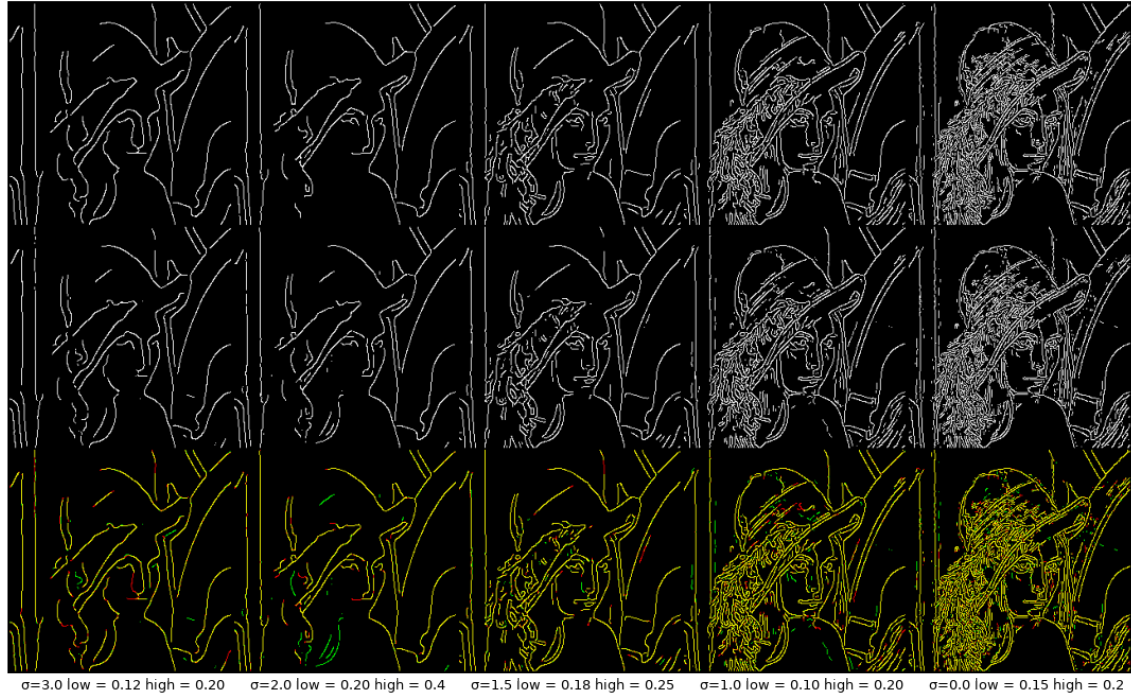


Fig. 4: Parameterized approximation of Canny edge detector (1-st row: Canny edge detector, 2-st row: neural network, 3-st row: pixel difference, where black, yellow, green, and red colours stand for true negative, true positive, false positive, and false negative pixels, respectively).

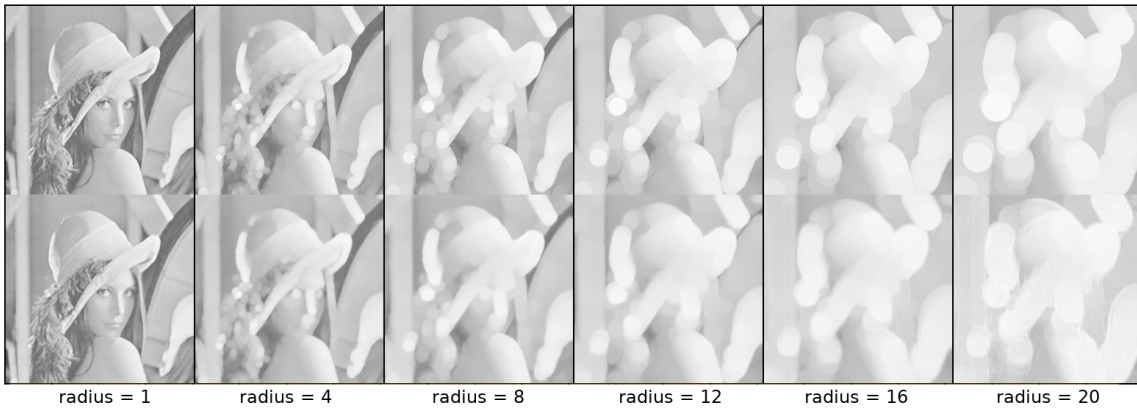


Fig. 5: Parameterized approximation of grayscale morphology with the disk structuring element (1-st row: morphological dilation, 2-st row: neural network).

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