Development and Application of Convolutional Neural Network for the Recognition of Objects in the Scheme of Electric Grid

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Abstract. One of the current design problems in the electric power industry is the labor intensity of synthesizing mathematical models to calculate the electrical modes of the network. It takes a lot of time to compose a detailed model of a large power system based on circuit diagram data. To simplify, speed up, and automate the data input, a convolutional neural network is proposed. In this paper the definition of convolutional neural network is given, its elements are described, the architecture of neural network is developed, the accuracy of its work on the schematic diagrams of various power systems is 0.84.

1. Introduction
A neural network is a sequence of neurons connected by synapses. Convergent neural networks are the most effective in visual pattern recognition. They provide partial robustness to various distortions in images (changes in scale, displacements, rotations, etc.).

1.1. The architecture of the convolutional neural network
A convolutional neural network consists of several layers:

- Padding layer. In the convolutional sliding process, the edges of the input image are cropped, converting the 5x5 matrix into a 3x3 matrix. In this case, the outermost pixels are not in the center of the kernel. The Padding technique converts the matrix by adding pixels, usually of zero value, to the edges. The extra pixels allow you to create an output matrix the same size as the input matrix.

- Pooling layer. This layer reduces the size of the collapsed feature, simplifying data processing and supporting efficient learning. It is also necessary for extracting dominant features.

Types of Pooling layer:
1. Max Pooling returns the maximum value of the part of the image covered by the kernel, it excludes noise signals;
2. Average Pooling returns the average of all values of the part of the image covered by the kernel, using dimensionality reduction as a method to suppress noise.

The input layer is supplied with an image of size NxM, which the program sees as an array of pixels of size NxMx3. It is necessary for the neural network to be able to distinguish all image inputs and recognize features specific to a particular schema element. In the convolution layer the filter, which is a matrix of size from 3x3 to 7x7, finds certain features of objects.
As a result, an output feature matrix is formed, which has the form \((h,w,N)\), where \(h\) and \(w\) are the length and width obtained as a result of clipping, and \(N\) is the number of filters. The more convolution layers the image passes through, the more complex characteristics are output in the activation images.

Figure 1 shows the convolution principle. An image of size 32x32x3 is given. In Convolution Layer 1, using filter 5x5 and step 1, a matrix of size 28x28x6 is obtained (1). In the Subsample layer, applying a 2 x 2\((f=2)\) filter, and step 2 \((s=2)\), the image height and width are reduced by a factor of 2. Therefore, 28x28x6 now becomes 14x14x6.

Furthermore, considering the 14x14x6 volume, applying another convolutional layer with a 5x5 filter and step 1, we get a 10x10x16 matrix, and then in this network in the sub-sample layer 2 we again reduce the height and width by half, obtaining a 5x5x16 volume.

2. Data set for training
As we know, to avoid overtraining the neural network, we need a sufficiently large data set (>10,000 images), and the entire set must be partitioned. The schematic schemes of power systems consist of pictograms (Figure 2), which are based on graphical primitives: circles, rectangles and lines. To get rid of manual data markup, the authors used computer graphics algorithms (Bresenham algorithm, Bezier curve algorithm, and others) to automatically obtain a marked data set.
Figure 2. Pictograms used on circuit diagrams of power systems.

The result was a set for 14000 images, divided into 28 classes (transformers, autotransformers, power lines, busbars, circuit breakers of all voltage classes 6-1150 kV). Objects of random size and orientation (vertical or horizontal) were placed in a random area of a 70*70 pixel frame, therefore giving a meaningful sample of data.

3. The architecture of the convolutional neural network
During the search for the optimal architecture of convolutional neural network, which would satisfy the accuracy of object recognition on the schematic circuit equal to 85-92%, a number of options presented in Table 1 have been considered.

Table 1. The Architecture of the Convolutional Neural Network

| Variant number | Layers | Type of layer | Filter size | Number of filters | Number of neurons | Activation function | Training data | Validation data |
|----------------|--------|---------------|-------------|------------------|------------------|--------------------|---------------|-----------------|
| 1              | Con    | 3*3           | 64          | -                | Re               | Lu                 | 86            | 84              |
| 2              | Max pool | 2*2          | -           | -                | -                | -                  | -             | -               |
| 3              | Con    | 3*3           | 128         | -                | Re               | Lu                 | -             | -               |
| 4              | Max pool | 2*2          | -           | -                | -                | -                  | -             | -               |
| 5              | Con    | 3*3           | 256         | -                | Re               | Lu                 | -             | -               |
| 6              | Max pool | 2*2          | -           | -                | -                | -                  | -             | -               |
| 7              | Dense  | -             | -           | 128              | Re               | Lu                 | -             | -               |
| 8              | Den    | -             | 200         | Re               | -                | -                  | -             | -               |
For all variants in the output layer the Softmax activation function was used, which allows to determine the probability of the picture belonging to one or another class. Also for all architectures of convolutional neural networks the quality of the loss function was chosen Categorical cross-entropy, and the optimization was performed by the RMSprop algorithm. On average, it took 6 minutes (50 epochs) to train the neural networks on a system with a GPU. The third architecture showed the highest accuracy, and it was used to identify objects in the schematic

4. **Object detection algorithm in the scheme of electric grid**

Developed convolutional neural network can distinguish one object from another, but cannot determine its place in the image where there are several objects. This classification problem with localization and currently there are several methods to solve it: floating window, YOLO-algorithm, convolutional neural network based on regions (R-CNN).
The authors have settled on a floating window method with a fixed window size of 70*70 pixels. The image of the circuit is divided into k-windows, and the resulting data set is loaded into a trained R-CNN, which predicts the presence of certain objects. If there is an object inside the window, the process of its localization begins. To do this, the image inside the window is divided into 49 parts of size 10*10 pixels, each part is reconstructed to a 70*70 image by adding a white background. The resulting dataset is again fed to the input of the neural network, and the output will be obtained in which parts the object is located.

Figure 3. Element detection.

5. Results
To test the developed neural network and the image recognition algorithm, a fragment of the circuit diagram of the Krasnoyarsk power system was taken. The neural network was able to "see" all the objects in the diagram and indicate their location. The average recognition accuracy was 92%, which is considered an excellent result in computer vision.

The developed neural network makes it possible to recognize various electrical devices on power system circuit diagrams. This is the first step toward creating a digital complex for automatic construction of computational models of power systems. Further work will be focused on converting the neural network data into a graph of an electrical network, the branches of which will be either power lines or transformers, and the nodes will be power plant buses or substation buses.

Figure 4. Element detection.
6. Conclusion
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