A Convolutional Fuzzy Neural Network for Image Classification

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***Abstract*—A model of Convolutional Fuzzy Neural Network for real world objects and scenes images classification is proposed. The Convolutional Fuzzy Neural Network consists of convolutional, pooling and fully-connected layers and a Fuzzy Self Organization Layer. The model combines the power of convolutional neural networks and fuzzy logic and is capable of handling uncertainty and impreciseness in the input pattern representation. The Training of The Convolutional Fuzzy Neural Network consists of three independent steps for three components of the net.**

Keywords—classification; fuzzy clustering; convolutional neural networks; fuzzy neural networks

I. Introduction

Nowadays Convolutional Neural Networks (CNN) are one of the most powerful approaches to solve image classification problems. The CNN architectures make the explicit assumption that the inputs are images, which allows to encode certain abstract properties into the architecture.

However, it is still diffucult to detect the boundaries between classes in the classification of images of complex objects or complex real-world scenes. These classification objects are often characterized by uncertainty and inaccuracy in its representation and have a complex structure with non-isolated, overlapping classes.

In contrast to classical classification, the fuzzy classification means that neighboring classes have the continuous boundary with overlapping areas. The classified object is characterized by its degree of belonging to different classes. This approach is suitable for many applications and also provides a simple representation of the complex feature space.

To enable a system to deal with cognitive uncertainties in a manner more like humans, one may incorporate the concept of fuzzy logic into the neural networks. The resulting hybrid system is called fuzzy neural, neural fuzzy, neuro-fuzzy or fuzzy-neuro network. The hybrid systems combine the capabilities of neural networks and fuzzy computations [1, 2].

For practical purposes, a fuzzy neural network is often more effective than just a fuzzy network or an ordinary (classical) neural network, as it allows indeterminate and inaccurate information processing.

Fuzzy logic and neural networks are combined in various ways. Fuzziness can be incorporated into different parts of traditional neural networks. One of the main way is to incorporates fuzziness into the structure of networks by additing fuzziness to the values of learning examples, by "blurring" input data and obtaining output information in terms of fuzzy sets theory [2–6].

A model of Convolutional Fuzzy Neural Network (CFNN) for real world objects and scenes images classification is proposed in the paper.

II. The CFNN

A. The typical structure of a CNN

The typical structure of a convolutional neural network ([7–9]) consists of 2 parts:

- a convolutional network (Convolutional and Pooling Layers);
- a classifier(some Fully-Connected Layers).

A convolutional network (part 1) consists of various combinations of convolutional and pooling layers. The stack of these layers convert an input image into a set of high-level features. These features become an input information for a classifier (part 2). It is one or more fully-connected layers (just regular multilayer perceptron). The output of the classifier (and the output of the whole CNN) is class scores for the input object.

B. The structure of a CFNN

The proposed Convolutional Fuzzy Neural Network (CFNN) model's architecture is built up of four types of layers: convolutional layer, pooling layer, Self-Organization (or Fuzzy) Layer, and fully-connected layer. To form a full Convolutional Fuzzy Neural Network architecture we stack three parts:

- a convolutional network (convolutional and pooling Layers);
- The Self-Organization Layer (The Fuzzy Layer);
- a classifier (some fully-connected layers).

The structure of the CFNN is represented in the Figure 1.

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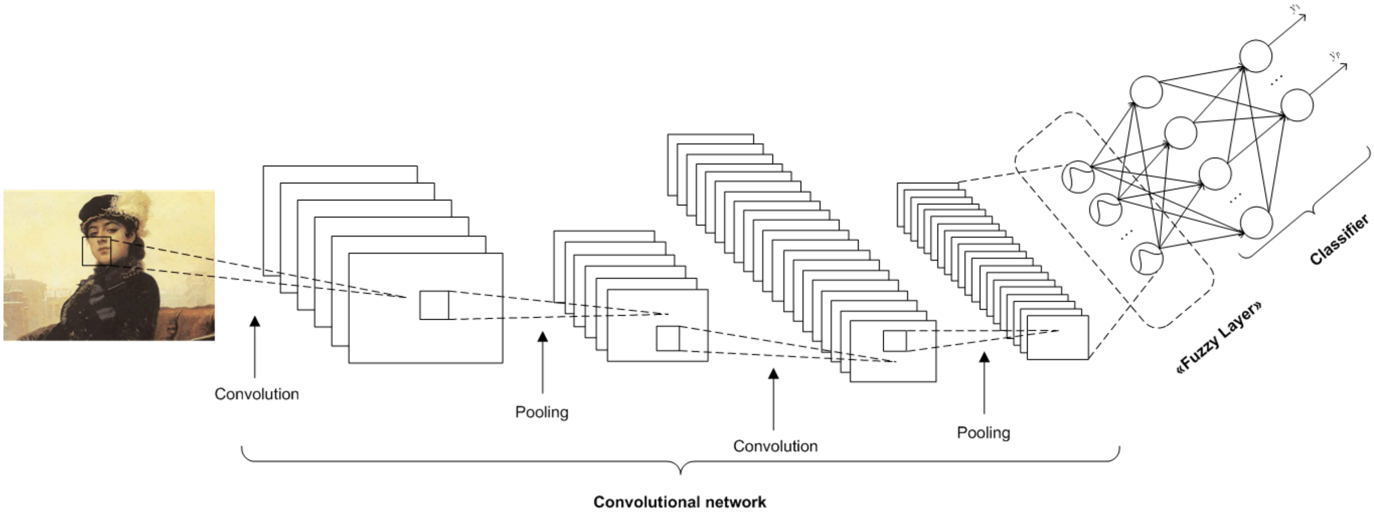

Fig. 1. The structure of CFNN.

In contrast to regular Convolutional Neural Network, the CFNN includes The Self-Organization Layer (The Fuzzy Layer) that is a kind of preprocessor. It is situated between the convolutional network and the classifier (a kind of postprocessor).

The convolutional network (part 1) takes an input images and form some abstract high-level properties of it by series of convolutional and pooling layers interchange.

The structure of The Fuzzy Layer and the classifier is represented in the Figure 2.

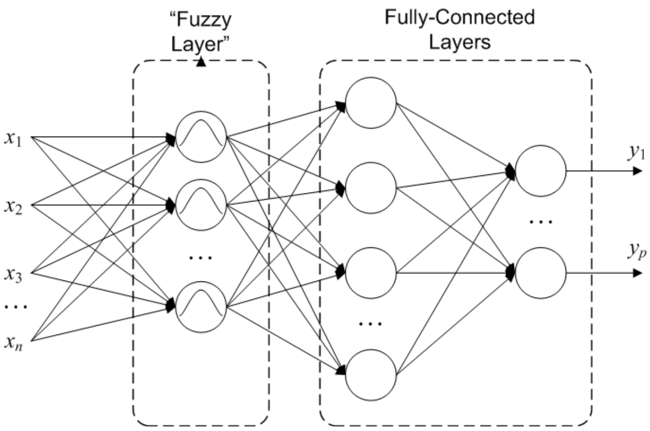

Fig. 2. The structure of the last CFNN layers.

The Fuzzy Layer performs a preliminary input data distribution into a predetermined number of clusters. Note that these clusters are not equivalent to output classes and the number of clusters and target classes can differ. The outputs of the Fuzzy Layer (part 2) neurons represents the values of the membership functions for the fuzzy clusters of input data. These membership grades indicate the degree to which data points belong to each cluster. These values goes to the input of a classifier (part 3). Its output is the full CFNN output (the class scores).

Let L be the number of neurons of the fuzzy layer (the number of clusters). The neurons of the "fuzzy layer" activation functions are radial basis functions (usually in the form of a Gaussian function) modeling the membership of the input vector $\boldsymbol{x}$ to each of the L clusters.

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-m)^2}{2\sigma^2}} \tag{1}$$

Parameter m is the centroid of a cluster, parameter σ – "blurring" of cluster boundaries level (both are real values).

If the vector $\boldsymbol{x} = [x_1, x_2, ..., x_j, ..., x_n]$ is fed to the input of the network, the "fuzzy layer" formed a vector consisting of the degrees of belonging $\boldsymbol{x}$ to the specific cluster centers: $[\mu_1(\boldsymbol{x}), \mu_2(\boldsymbol{x}), ..., \mu_L(\boldsymbol{x})]$. The components $\mu_l(\boldsymbol{x})$ are calculated (2) to satisfy the normalization condition (3) for each training sample vector $\boldsymbol{x}^{(k)}$, $k = 1, ..., K$, where K – is the number of vectors in the training set.

$$\mu_l\left(\boldsymbol{x}^{(k)}\right) = f(S) = f\left(\sum_{j=1}^{n} x_j^{(k)}\right) \tag{2}$$

$$\sum_{l=1}^{L} \mu_l\left(\boldsymbol{x}^{(k)}\right) = 1 \tag{3}$$

The outputs of neurons of the "fuzzy layer" are used as inputs of the classifier.

The work of the CFNN is divided into three stages: the input pattern (image) comes through a series of transformations, as a result a vector of high-level characteristics is formed; further, Fuzzy Layer performs a preliminary distribution of the input data into fuzzy clusters; the last fully connected layers perform the classification, assigning the result class label to each group of clusters.

III. THE TRAINING OF THE CFNN

The Training of The Convolutional Fuzzy Neural Network consists of three independent steps for three components of the net.

First of all we train the convolutional network (a regular CNN corresponding to the determinate CFNN) to form some abstract properties of the input image by backpropagation [9, 10]. Nowadays there are a lot of "pretrained" models that have been already trained on a large data sets from a related domain [11]. So we can skip this step of CFNN training.

The second part is the tuning of the fuzzy layer parameters that is called self-organization. The Fuzzy Layer is self-organizing. It is trained in an unsupervised way using a competitive learning scheme. Self-organization of the "fuzzy layer" means choosing the positions of the clusters centers (choosing the parameters of the membership functions of (1)). Various fuzzy clustering algorithms can be applied (C-means algorithm, Gustafson-Kessel algorithm [12]).

The third part is the classifier training. The parameters of the convolutional and fuzzy layers are stable. Only fully-connected layers weights are tuning. The classifier is trained by a standard backpropagation algorithm.

After completing the three parts of training, the CFNN becomes ready for work, when an image pixel array is fed to the CFNN input. The output of a network is a vector $\boldsymbol{y} = [y_1, y_2, ..., y_p]$ with components that characterize the belonging of the input image to each of the p classes (class scores). The image is assigned to the class with the max score value.

IV. EXPERIMENTS

Some experiments with CFNN were performed. The model were made to classify whether images contain either a dog or a cat. We use the 'Dogs vs Cats' dataset from Kaggle competition [13]. There are 25,000 labeled dog and cat photos available for training, and 12,500 in the test set.

Some sample images from the 'Dogs vs Cats' dataset are represented in the Figure 3.

Fig. 3. Sample images from 'Dogs vs Cats' dataset.

Our startpoint is using a pretrained model which can recognize a wide variety (1,000 categories) of images and finetuning it for binary classification. We have chosen the VGG model [14] pretrained on ImageNet dataset[15] (which won the 2014 ImageNet competition) as simple but powerful neural network architecture.

We have had three independent steps to train the CFNN model:

1. Finetuning the VGG net to classify cats/dogs images (method for stochastic optimization: Adam). The CNN training takes a lot of resources, so we could have only 2, 5 and 7 epochs.

2. Self-organization of the Fuzzy Layer (fuzzy c-means clustering [16]). We have clustered the set of data several times, with different numbers of clusters. Then we have chosen the number of clusters when the Fuzzy Partition Coefficient [17] is maximized (The FPC is defined on the range from 0 to 1, with 1 being best. It is a metric which tells us how cleanly our data is described by a certain clustering model).

3. The classifier training (method for stochastic optimization: Adam). Only fully-connected layers weights were tuning while the parameters of the convolutional and fuzzy layers were stable, so we could have 100 epochs.

The results of the experiments are presented in the Table 1.

TABLE I. THE RESULTS OF EXPERIMENTS

VGG finetuning epochs	The regular VGG net accuracy, %	The Fuzzy Net accuracy, %
2	44.1	58.3
5	53.3	62.5
7	55.6	70.8

Experimental results show that incorporation the Fuzzy Layer into the CNN allows the quality of classification problem solution (accuracy) increase even when the corresponding regular CNN doesn't show high accuracy. After only 7 epochs of regular CNN training we add some epochs of c-means clustering and the classifier training (that takes much less time than 1 regular CNN training epoch) and can achieve 70% accuracy instead of 55%.

V. CONCLUSION

So, the model of Convolutional Fuzzy Neural Network (CFNN) for image classification is presented in the paper. Fuzziness is incorporated into the structure of network in terms of fuzzy sets theory. The proposed model combines the power

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of convolutional neural networks and fuzzy logic and is capable of handling uncertainty and impreciseness.

Some experimental work to measure the effectiveness of CFNN has been performed and show that the CFNN could provide better accuracy in less training time.

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