Employing Neocognitron Neural Network Base Ensemble Classifiers To Enhance Efficiency Of Classification In Handwritten Digit Datasets

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ABSTRACT

This paper presents an ensemble of neo-cognitron neural network base classifiers to enhance the accuracy of the system, along the experimental results. The method offers lesser computational preprocessing in comparison to other ensemble techniques as it ex-preempts feature extraction process before feeding the data into base classifiers. This is achieved by the basic nature of neo-cognitron, it is a multilayer feed-forward neural network. Ensemble of such base classifiers gives class labels for each pattern that in turn is combined to give the final class label for that pattern. The purpose of this paper is not only to exemplify learning behaviour of neo-cognitron as base classifiers, but also to purport better fashion to combine neural network based ensemble classifiers.

KEYWORDS

Classifier ensemble, Error Back-Propagation, Multiple Classifier Combination, Neocognitron, Neural Networks, Pattern Recognition.

1. INTRODUCTION

Artificial Neural Network ensemble system is a learning paradigm i.e. an assembly of base neural networks ; all are trained for the same task. In general, an artificial neural networks ensemble is built in two steps, i.e., training of component base neural networks, and then assembling the posted predictions .It originates from Hansen & Salamon's work, which showed the generalization ability of artificial neural networks, that is to train base neural networks and then combining their prediction.

An ensemble can be made by multiple network architectures or may be same architecture trained with different algorithms or may be different initial random weights, or even different classifiers

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[4]. The constituting networks can be developed by training with sampled datasets such as the strategy of resampling data.

Hansen & Salamon showed in paper presented in 1990 an important result that the generalization ability of a neural network may be improved using an ensemble of similarly assembled neural networks [1].

The motivation of using ensemble of neural network base classifiers is to improve the performance of classification over that of individual classifiers. Theoretically it has been shown that the performance of the ensemble cannot be worse than any single component used separately if the predictions of individual classifier are unbiased and/ or uncorrelated [2].

The base classifiers are multilayered feed forward neural networks; neogonitron. The neocognitron is a hierarchical neural network, whose architecture has been suggested on the basis of visual system of mammals. It can acquire the capability of recognizing by learning [3].

2. DATASET DESCRIPTION

2.1 Handwritten Digit Dataset

Handwritten digits dataset have 18,000 samples of the digits ranging from 0 to 9, collected from postcodes on letters from Germany. These handwritten examples were digitized onto images with 16x16 pixels between 256 grey levels.

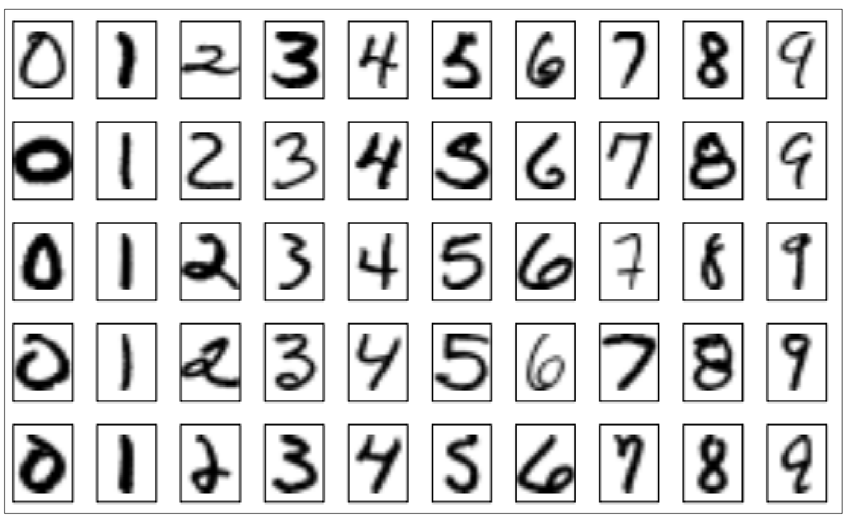


Fig. 1: Each block is a 16 × 16 representation of a handwritten digit.

The dataset was divided into a training set with 1000 examples per digit and a test set with 600 examples per digit. The sampled images are normalized resulting in the similar size and positional shift. The concern is to predict, the identity of each image (0, 1... 9) from 16x16 intensity values, accurately.

The error rate is to be very small in order to avoid misdirection of mails. Some of other application of Handwritten digit dataset is bank checking process and reading different forms .

3. METHODOLOGY

Classically one can guess intelligently for the appropriate size of base neural network, in this case digitized handwritten digits to convergence. In principle, it is quite possible for a classifier to learn input patterns of any complexity provided that training database is quite adequately large enough.

Where as in case in which network size is less than optimum, it is poorly trained. Several techniques have been to improvise the generalization ability of artificial neural networks.

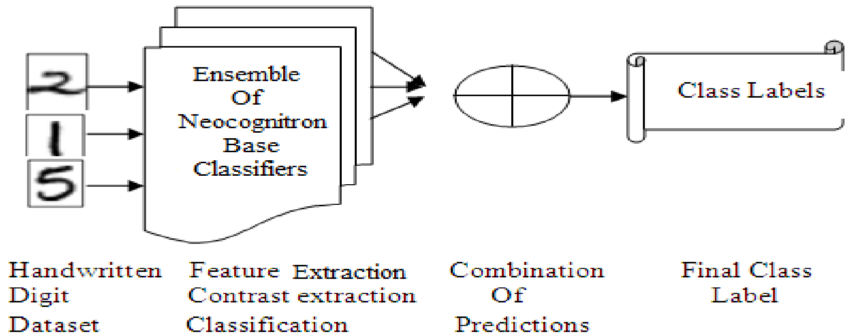


Figure 2: Block diagram of methodology used in handwritten digit recognition.

We propose schemes based upon contributed decision posted by combining multiple base ensemble neocognitron neural network classifiers for Handwritten digit dataset. Figure 2. Shows the methodology used in proposed work, that is, to employ neocognitron as neural network base classifier for the ensemble.

4. BASE CLASSIFIER : NEOCONGNITRON

The neocognitron proposed by Prof. Kunihiko Fukushima[3],[5],[6], is a hierarchical multilayered artificial neural network. It is made up of two types of cells: S-cell and C-cell; S-cells extract the local features and C-cells tolerate features deformation, like local shifts, and slants. Local features are integrated gradually in the input layer by layer . Classification is done at highest layer.

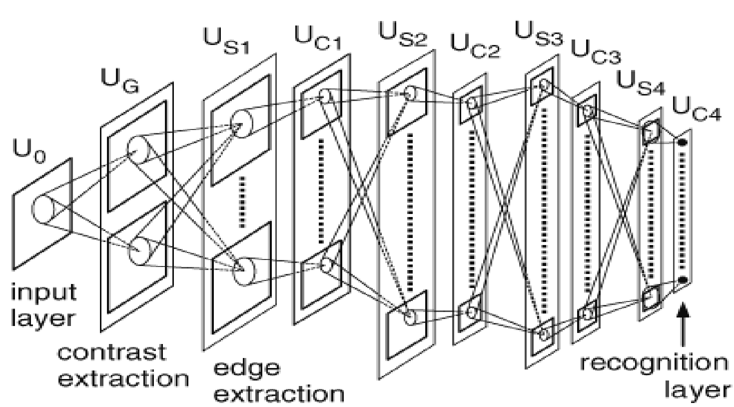


Figure 3: Shows a typical architecture of neo-cognitron neural network. The lowest stage is the input layer which correspond to photoreceptors.

From the Figure 3, the neo-cognitron network used in the approach has following four stages of layers S-cell and C-cell: U0 → UG → (US1 and UC1) → (US2 and UC2) → (US3 and UC3) → (US4 and UC4.) The output of layer USi is fed to layer UCi, there it generates a smoothed version of the response of layer USi.

4.1 Working Of Neocognitron

The input connections of C ith-cells, which come from S ith- cells of the preceding layer, are fixed. Each C ith-cell receives input connections from a group of S ith-cells those who extract same feature. The C ith-cell responds if, single S ith-cells results an output.

The C-cell's output is less sensitive to positional shift of the input handwritten data pattern. C-cells performs like a smoothing function, as the output of a layer of preceding S-cells is spatially smoothed in the response of the higher layer of C-cells. Each layer is further divided into sub-layers, "cell-planes", depending upon the features that these cells responds.

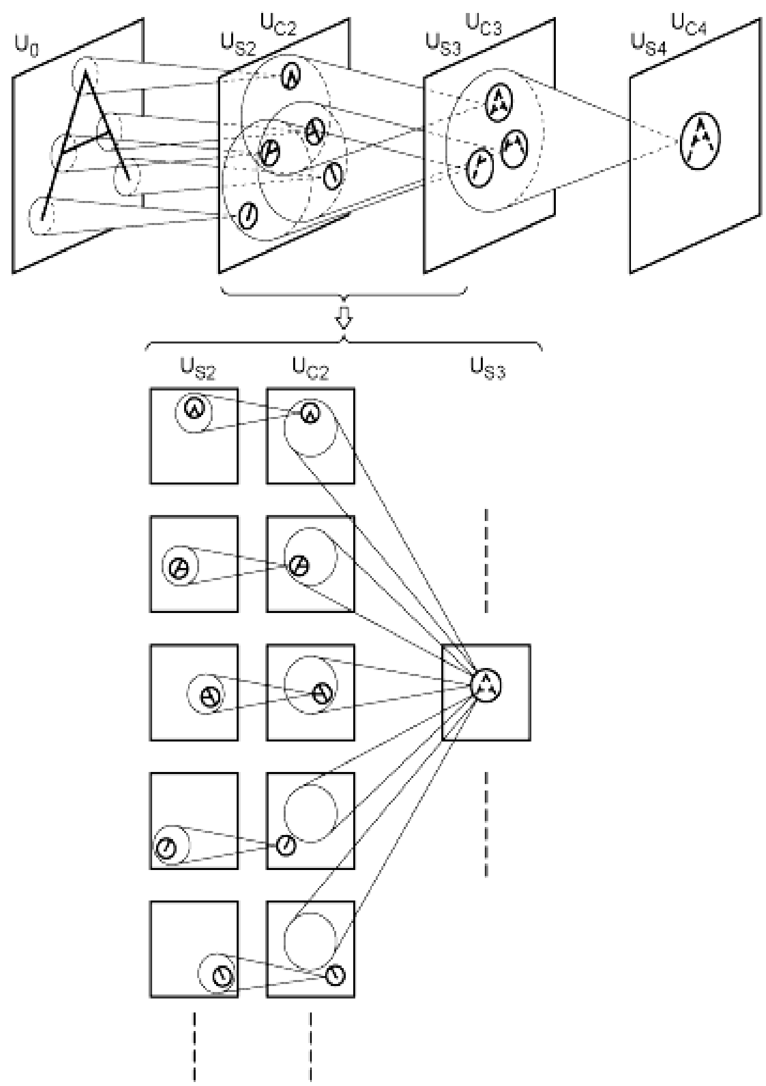


Figure 4: The process of pattern recognition in the neocognitron. The lower half of the figure is an enlarged illustration of a part of the network.

Working Of Layers:

- UG Layer (Contrast Extraction): Layer UG consists of on-center cells, and one off-center cells. The output from layer UG depends upon spatial orientation of the input connections and is equal to zero in the area of flat intensity.
- US1 Layer (Edge Extraction): Layer US1 is an edge-extracting layer. The S-cells is trained using supervised learning. Due to supervised learning for the feature's location. The cell with coinciding receptive field center with that of that specific feature, takes the place of seed cell of that cell-plane, and it reinforces the output automatically.
- Intermediate Layers (Competitive Learning): The S-cells of stages second and third that is, US2 and US3, are automatically self-organized by using unsupervised competitive learning technique as in original work [3].Winner-take-all technique detects the seed cell.
- Highest Layer (Supervised Learning): The highest stage S-cells (US4), are trained by a supervised competitive learning technique. The learning rule we used here is same as the competitive learning that is being used for the training of US2 and US3. At this stage the given class labels of the digitized handwritten digit training patterns also used for the same purpose. In the case of many deformed digitized handwritten digit training patterns more than one cell-plane is generated to take care of the deformed handwritten digit pattern for one class, in US4. Therefore, the class name of digitized training pattern is allocated to the cell-plane during learning. Thus, each cell-plane of highest stage has ten labels.

4.2 Self Organization Of The Network

- Winner Take All Technique: Amongst the cells present in the vicinity, which is called a hyper column, those cells that respond prominently becomes the winner. The input links of the winner is amplified. And the amount of amplification of every input link connecting to the winner is proportional to intensity of the resultant of that cell.
- Translational Symmetry: The connections that are amplified are to preserving translational symmetry. The maximum-output cell controls the growth of neighboring cells in the vicinity along with it's own, just as the growth around seed in the crystal.

5. Method Of Training & Combining Ensemble Of Base Classifiers

The ensemble of neural network can be produced by training each constituting network with a different learning-set [8]. In this paper the base neo-cognitron neural network classifiers are trained over different learning sets, achieved by sampling whole training data into overlapping sets.

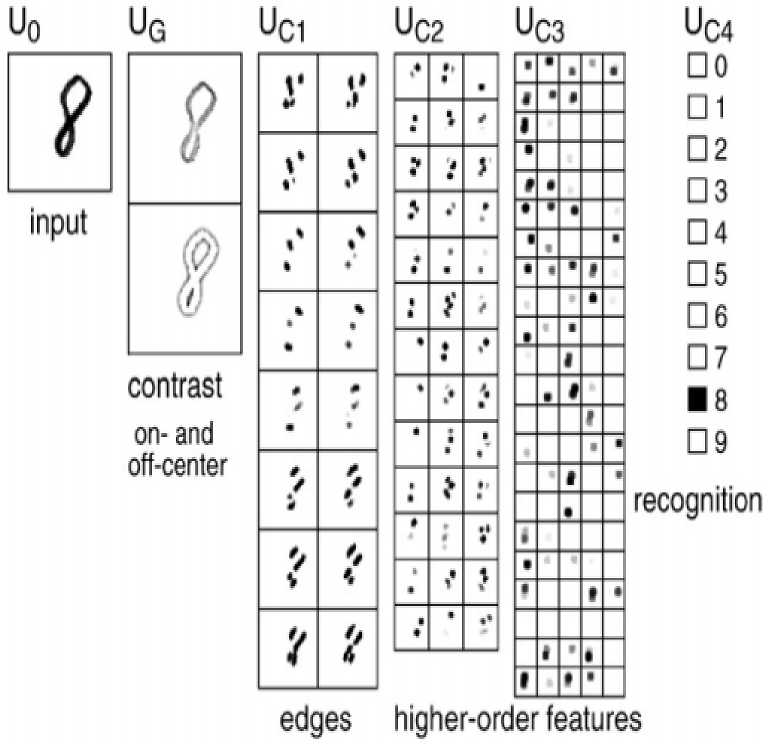


Figure 5. Shows recognition Of digit using individual neocognitron classifier.

For a classification problem the base classifiers result in similar of disagreeing discrete class label [8]. Among the labels predicted by each of the base classifier of the ensemble the final class label is to be chosen for that particular digitized handwritten digit input pattern. For this a combination scheme is to be employed for the purpose that is described as follows.

5.1 Combination Scheme

C-cells are Let us consider the decision of the t^{th} classifier as d_t, $j \in \{0, 1\}$, $t = 1 \ldots, T$ and $j = 1, \ldots C$, where T is number of base neocognitron neural network classifiers; C is total number of classes. If t^{th} classifier chooses class ω_j, then d_t, $j = 1$, and 0, otherwise.

In above described majority voting results in the ensemble that choose that class label as final, for which base classifiers gets the highest number of votes, despite the sum of votes exceeds 50 percent.

6. IMPLEMENTATION & RESULTS

Table 1. shows the parameters used for neo-cognitron base classifiers.
Combining results of classifiers, recognition rate and generalization ability can be improved used to recognize handwritten digit. Combine classifiers have better results when basic classifiers have small error rate and they are different.

Table 2. Shows the Experimental results of using ensemble of neo-cognitron over single neo-cognitron classifer.

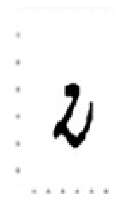
Table 1. Parameters used for training each layer

Parameters	Uo	Separation	UG	S	UC1	S	UC2	S	UC3	S	UCl
Number of horizontal and vertical cells in the plane	65	-	71	-	37	-	21	-	13	-	10
Number of planes in a layer, to be redefined later	1	-	2	-	16	-	-	-	-	-	-
Number of planes in a column	1	-	2	-	8	-	13	-	22	-	10
Size of pat without frame	65	-	71	-	37	-	21	-	13	-	20
Horizontal Separation between layers	-	10	-	10	-	10	-	10	-	40	-

Table 2. Experimental results of using ensemble of neo-cognitron over single neo-cognitron classifer.

Classifier Used	**Recognition Rate**		**Time(sec)**		**Space Used**
	Train.	**Test**	**Train.**	**Test**	
Single Neo-cognitron Classifier	100 %	99%	1342	123	1211
Ensemble of 5 Neo-cognitron Classifiers	100%	99.4%	1955	235	1531

Table 3. Some instances for which the single neo-cognitron neural network predicted wrong class labels.

						
Instance No. 1	Instance No. 2	Instance No. 3	Instance No. 4	Instance No. 5	Instance No. 6	Instance No. 7
Final Class 9	Final Class 0	Final Class 2	Final Class 6	Final Class 8	Final Class 8	Final Class 3
Correctly Classified	Not Correctly Classified	Correctly Classified	Correctly Classified	Not Correctly Classified	Not Correctly Classified	Correctly Classified

7. CONCLUSIONS

It has been concluded that best recognition rate for Handwritten digits Dataset is 99.4%. Errors that limits recognition rate are because of uncorrected shape of digits. As the minimal data required to train the ensemble is significantly large, a parallel computing algorithm for training of base neo-cognitron classifiers will provide significant decrease in time complexity.

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