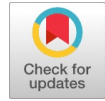


# Medical Image Classification Based On Normalized Coding Network with Multiscale Perception



K. Arun Kumar, P. Rajashekar Reddy, Mahesh Kusuma

**Abstract:** Medical imaging classification is playing a vital role in identifying and diagnoses the diseases, which is very helpful to doctor. Conventional ways classify supported the form, color, and/or texture, most of tiny problematic areas haven't shown in medical images, which meant less efficient classification and that has poor ability to identify disease. Advanced deep learning algorithms provide an efficient way to construct a finished model that can compute final classification labels with the raw pixels of medical images. These conventional algorithms are not sufficient for high resolution images due to small dataset size, advanced deep learning models suffer from very high computational costs and limitations in the channels and multilayers in the channels. To overcome these limitations, we proposed a new algorithm Normalized Coding Network with Multi-scale Perceptron (NCNMP), which combines high-level features and traditional features. The Architecture of the proposed model includes three stages. Training, retrieve, fuse. We examined the proposed algorithm on medical image dataset NIH2626. We got an overall image classification accuracy of 91.35, which are greater than the present methods.

**Keywords:** Normalized Coding Network with Multilayer Perception, Distant Domain Transfer Learning, Deep Learning

## I. INTRODUCTION

Medical image classification is very important process to determine the program recognition area. It will help doctors to identify the small effected areas without human error. Medical image classification is having two stages. In the first stage detecting the features of the medical image. In the next stage, we can build models using those features. In the previous algorithms low level featured images will be classified efficiently. But, in case of high level featured image. Those are sufficient to gain accuracy in case of non-medical images. To improve accuracy in medical image classification, Deep learning algorithms were used. Deep learning models require high range of datasets. We are using NIH2626dataset, which is having nervous tissue images of patient. Deep learning models for small data set, gives very poor performance, accuracy. Training a deep learning model requires high amount of computation and datasets.

So we suggest a different deep model that involves traditional elements. This algorithm used to extract complex features of medical images. In this article, we concentrate on this novel algorithm of learning, multi-dimensional features that includes deep learning model with the original medical image features. This algorithm referred as Normalized Coding Network with multi scale perception (NCNMP).

The main intention of this algorithm is to extract features from medical image automatically from both views, i.e. traditional and deep learning model. This method is used for both high level and low level medical images and useful for multilevel perception of medical images.

In medical image classification, we will face two problems as mentioned below.

1. Feature extraction from small medical image dataset
2. Multi feature extraction from different models

Our new proposed algorithm will overcome these issue stated above.

## II. PROPOSED MODEL

The major points discussed in this article, explained as follows

1. We implemented a deep learning model that integrates high level/complex level features and conventional features to classify images. For this purpose, we trained the deep neural network called the normalized coding network, which uses distant domain transferred convolution neural network. By adding traditional features to deep learning model the efficiency will be very high.
2. To combine traditional features with high level features, we assign a static argument method of proposition to fuse high level & traditional features. Generally traditional feature extraction is a time consuming process. Our new algorithm will reduce these limitations.

We implemented this algorithm on NIH2626 medical image dataset, which is having nervous tissue images of the patient.

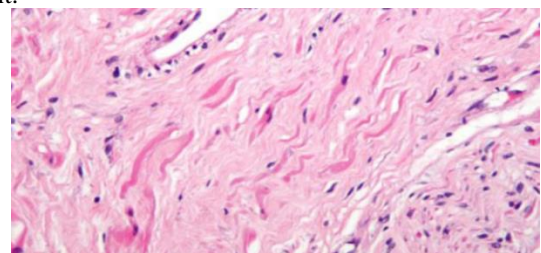


Figure1. Nervous tissue (source from NIH2626)

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## III. METHODOLOGY

Architecture of our proposed algorithm Normalized Coding Network Multilevel Perception (NCNMP) is explained below.

### Normalized Coding Network:

Normalized data means converting data using a z-score or t-score, this is also called standardization. It will rescale

the values from 0 to 1. This process is called feature scaling.

Standardizing residuals: Ratios used in regression analysis can force residuals into the shape of a normal distribution. Normalizing Moments using the formula  $\mu/\sigma$ . Normalizing vectors (in linear algebra) to a norm of one. Normalization in this sense means to transform a vector so that it has a length of one.

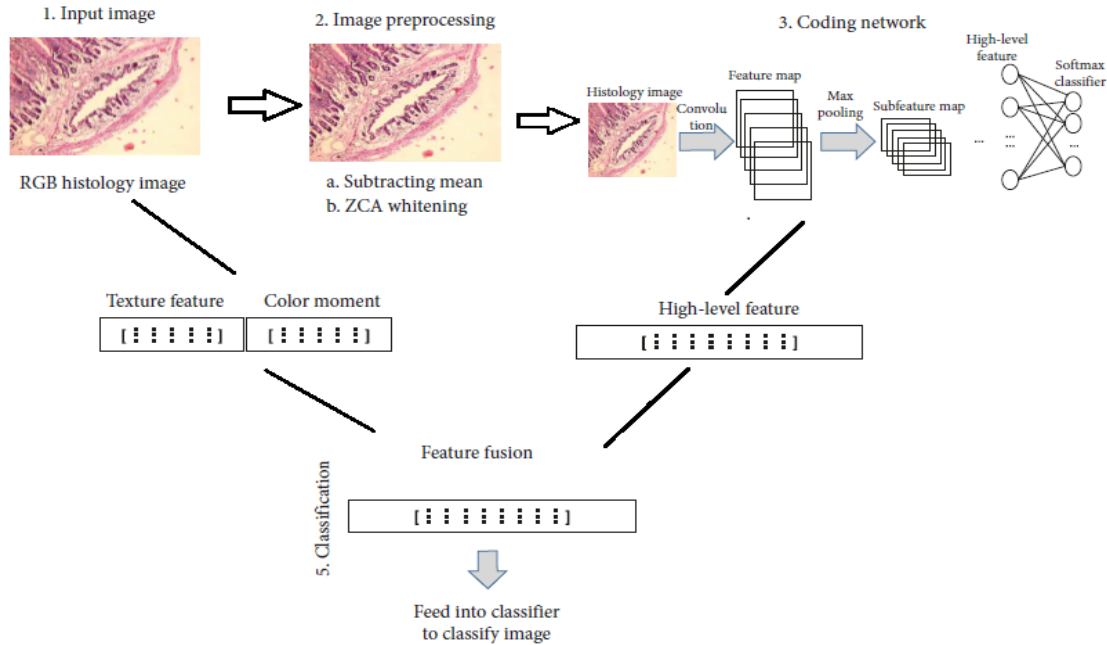


Figure 2: NCNMP Architecture

### Pooling function:

In the proposed algorithm we use pooling function

$$y_{j,k}^i = \max_{0 \leq p,q \leq 9} (x_{j.9+p,k.9+q}^i) \quad \text{--- (1)}$$

Where

$y_{j,k}^i$  is the output feature ,

$x_j^i$  is the input feature map

Input region ->  $4 \times 4$  overlapping local region.

### Activation function:

We use Exponential Linear Unit (ELU) as activation function in the proposed model. ELU is very important activation function due to, they have positive activation so their mean value is positive value. So this problem makes bias shift for units in other layer. Most of the advanced machine learning algorithms uses this zero-centered, normalized ELU.

$$f(t) = \begin{cases} t & \text{if } t > 0 \\ \alpha (\exp(t) - 1) & \text{if } t \leq 0 \end{cases} \quad \text{----- (2)}$$

$$f'(t) = \begin{cases} 1 & \text{if } t > 0 \\ f(t) + \alpha & \text{if } t \leq 0 \end{cases} \quad \text{----- (3)}$$

## IV. EXPERIMENT AND RESULTS

We implemented the Normalizedcoding network to extract the complex-level characteristics in Pytorch, which is a Tensor flow tool that apply convolutional neural networks, and extracted the traditional features based on color moment and texture. We verified the accuracy of our method on single benchmark medical image datasets. We conducted all of our experiments on a computer with i7-processor 3.2 GHz CPU, 32G main memory, and GTX1080 GPU.

### The NIH2626 Dataset

The NIH2626 dataset consists of four categories of basic tissue pictures that area unit representative of various tissue varieties. It is explained in table1. This medical image (RGB) having size 720 X480. NIH2626 is a medical dataset. It have 2626 images, which includes1026 nervous tissue images, 484 connective tissue images, 602 epithelial tissue images, and 514 muscular tissue images. Inorder to evaluate our experiments, each dataset was classified into three stages, a training set, a validation set, and a test set with the ratio 4:2:1. The images are cropped from the original dataset in order to obtain fixed-size 180×180 images for applying the Normalized coding network algorithm. For NIH2626, each image was randomly cropped to 420× 420 and then resized to the constant 180×180 image.

Along with that, we flipped the image in both directions to further modification of the image datasets. While simulation the network gives assumptions about each patch, and the average will be considered by softmax layer, if the patches belongs to the same image. The influence of image augmentation on the efficiency and run time will be explained in the following experiments.

The network schema of our deep learning model framework is presented detail in Table 1. ReLus as an activation function is applied for each convolutional layer, Batch normalization procedure will help in order to improve the efficiency of our deep algorithm training.

To find accuracy we conducted a couple of investigations on the accuracy and run time of code on NIH2626. The efficiency here is defined as the accuracy percentage of classified medical images without error. To give the clarification about accuracy, we compare confusion matrix of both algorithms. It is a table layout that can show the number of false negative, true positive, true negative, and false negative in an evaluation of a multistage image classification program.

**Table 1: Contents of the NIH2626 dataset.**

Image tissue type	Number of samples	Label
Nervous	512	1
Connective	284	2
Epithelial	604	3
Muscular	406	4

**Table 2: performance of different algorithms**

Algorithm	HIS2828 (efficiency)
SVM (traditional feature)	69.26%
SVM (traditional and deep feature)	91.1%
Coding network	80.2%
Coding Network with multi scale perception	91.2%
Normalized Coding Network with multi scale perception	91.35%

Positive rate (TPR) against the false positive rate (FPR) by setting different thresholds, where the definition of TPR and FPR are as follows:

$$TPR = \frac{TPV}{TPV + FNV}$$

$$FPR = \frac{FPV}{FPV + TNV}$$

Where FNV, TPV, FPV and TNV are false negative, true positive value, false positive value, and true negative value respectively. Before the entry of the deep learning model, the support vector machine (SVM) is resolute as a universal classifier in machine learning methods.so here we compared our NCNMP algorithm with the SVM (traditional feature) and SVM (traditional and deep feature).

The results on the NIH2626 dataset, i.e. accuracy is shown in Table 2. Our approach got the best accuracy rate, which is 91.35%. Based on above observation, we can conclude that the accuracy of CNMP, SVM (traditional feature) is the lowest compare to our model NCNMP.

Confusion matrix

Out put clas s	247 14.6%	11 0.6%	7 0.4%	12 0.7%	89.2% 10.8%
	19 1.1%	408 24.1%	5 0.3%	26 1.5%	89.1% 10.9%
	13 0.8%	11 0.6%	284 16.7%	12 0.7%	88.8% 11.2%
	11 0.6%	28 1.7%	12 0.7%	590 34.8%	92.0% 8.0%
	85.2% 14.8%	89.1% 10.9%	92.2% 7.8%	92.2% 7.8%	90.2% 9.8%

Target class

(a)

Confusion matrix

Out put clas s	243 14.6%	11 0.6%	7 0.7%	11 0.8%	90.2% 10.9%
	18 1.5%	408 28.1%	5 0.6%	24 1.5%	90.1% 11.9%
	13 1.8%	11 0.6%	284 19.7%	12 0.7%	90.8% 11.7%
	11 1.6%	28 1.9%	12 1.7%	590 37.8%	92.2% 9.0%
	85.25% 14.8%	89.5% 10.9%	92.25% 7.8%	92.25% 7.8%	90.35% 9.8%

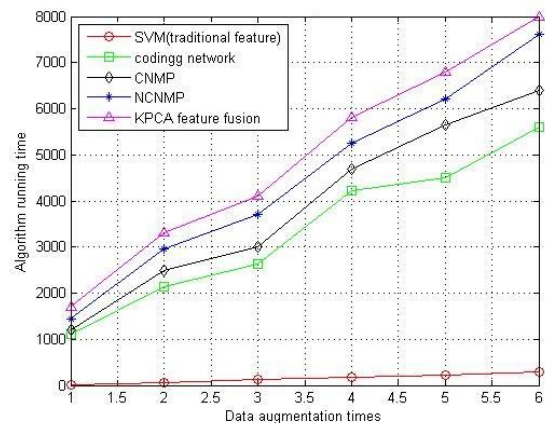
Target class

(b)

**Figure 2: Confusion matrix on the NIH2626 dataset.**

(a) Confusion matrix of CNMP. (b) Confusion matrix of NCNMP.

We will discuss the simulation time of the five algorithms. Comparison can be seen in Figure 3. In the result, we can observe that the coding network can run the fastest. It has several disadvantages in medical classification. Next our proposed algorithm NCNMP got running very fast.



**Figure 3: running time comparison of all algorithms**

## V. CONCLUSION

In this article, we proposed a new medical image classification algorithm that concatenated high-level features from a Normalized coding network with traditional image features, and we call it NCNMP. We assure that, first time deep learning model has concatenated traditional image features to classification of medical images. Experimental results show that this method can achieve an accuracy of 91.35% on the NIH2626 image datasets, which outperforms SVM (traditional features), coding network, and python feature fusion by considerable margins. In future, we can implement efficient pruning strategy to greatly reduce the parameters. In case of feature fusion strategies, we are planning to develop more methods like multistage feature fusion deep neural networks (MFFDNN), based on denoising method and autoencoder, or metaspace fusion to combine heterogeneous representations.

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