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Classification of Cervical MR Images using ResNet101

Shetgaonkar Sitaram (Gauresh)[1], Amita Dessai[2]
[1]*M.E. Student, Dept. of Electronics and Telecommunication Engg., Goa College of Engineering, Goa, India*
[2]*Assistant Professor, Dept. of Electronics and Telecommunication Engg., Goa College of Engg., Goa, India*

***Abstract*: In recent years deep learning has attracted many researchers in the field of computer aided classification of medical images. Adding to it the Convolutional Neural Networks (CNN) are widely used in computer vision problems. Due to lack of availability of medical images it is very difficult to train CNN; therefore, a Pre-trained CNN model (RESNET101) is used in this study to classify cervical MR images in to two classes as normal and abnormal. Study is carried out on authentic database provided by The Cancer Imaging Archive (TCIA) and the classification accuracy was achieved to be 97.27%.**

***Keywords*: Cervical cancer, CNN, Deep Learning, Magnetic Resonance Imaging, Pre-trained model, Resnet101, Transfer learning.**

1. Introduction

Uterine cervical cancer is one of the major cause of women mortality worldwide. This cancer can be treated at early stages but symptoms shown are in advance stages. Human papilloma virus (HPV) is the major cause of cervical cancer. Traditionally Pap Smear test is use to detect cervical cancer wherein cells from cervix are taken and examined under the microscope. The accuracy of such procedure depends on the proficiency of pathologist and have sensitivity of about 53.4 to 64.2% [13]. MR imaging is widely used modality for detection of cervical cancer as it eliminates use of invasive examinations such as cystoscopy and proctoscopy and also has superior soft tissue resolution.

The first important step before detection of cervical cancer is to classify MR images of cervix as normal and abnormal automatically. Deep learning is becoming a key factor of artificial intelligence applications and it is widely used for object categories classification. Automatic classification of cervical MRI using deep learning is very challenging because of lack of availability of images. In this paper we present a method to classify MR images of cervix using pretrained CNN model RESNET101. CNN are existing from long time but their use was restricted due to limited size of accessible data. From a concept of deep learning the image classification problem can be resolved using transfer learning. CNNs are trained on huge collection of data. From these collections it learns number of features which are superior to HOG, LBP, or SURF. Best way to increase power of CNNs without wasting time is use pretrained CNN as a feature extractor.

2. Related work

Deep learning has been used widely in computer vision applications. Pretrained models of ImageNet are getting more popular in recent years. The advantage of using pretrained CNN is that no need to train the CNN model from scratch instead use the pretrained model to classify images through the concept of transfer learning.

Hyeon et al. [1] classified the cervical Pap smear images using Vgg-16 pretrained CNN model. They divided the available datasets in to 80% images for training set and 20% images as test set, they achieved the accuracy of 78%.

Taha et al. [2] used low level and high level features from different layers of CNN and evaluated the performance of CNN as a classifier. The pretrained model used was AlexNet and achieved the accuracy of 98.37%. AlexNet is a CNN model trained on huge ImageNet database for classifying color images of natural objects and scenes.

Bora et al. [3] achieved the accuracy of 95% by using pre trained AlexNet model to classify Pap smear images of cervix. The experiment was conducted on 1611 images.

The study conducted by Gyanendra et al. [4] used Cervical MR images provided by TCIA and features are extracted using VGG-F and classified the images as positive and negative using Matconv-Net based VGG-f pretrained model and achieved the accuracy of 98.9%. They used three different classifiers to classify namely SVM, ensemble tree, and K-nearest neighbors (KNN). And achieved highest accuracy using KNN.

Spanhol et al. [5] conducted a study with BreaKHis dataset using pre-trained model based on AlexNet architecture. The authors used above model to classify histopathological breast cancer images. The authors fine-tuned the AlexNet architecture and its layers of classification while leaving feature layer unchanged. They achieved good accuracy with BreaKHis dataset if compared to the existing methods reported in the literature.

Xu et al. [6] proposed a multimodal deep neural network for cervical dysplasia diagnosis. They collected highly heterogeneous data from the patients screening visit and expand conventional CNN architecture to fully connected layers. Here, multimodal framework is an end-to-end deep network which extracts features from images and non-image modalities and sensitivity for the cervical dysplasia diagnosis is 87.33–90%

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specificity on large dataset which is a very good result on limited information or dataset.

Soumya et al. [7] proposed a frame work for detection and classification of cervical cancer using Texture analysis. They constructed Nonlinear SVM model based on second order and texture features and transform features of the tumour.

Bethanney et al. [8] proposed a methodology to classify cervical cancer using multiclass SVM classifier. The method extracts region of interest using Region growing methods and the texture features are extracted using GLCM. The proposed methodology was used to classify non-cancerous, benign and malignant.

3. Proposed methodology

Since very large data set is required it is tedious to train CNN from scratch therefore pretrained models such as Resnet, VGG, AlexNet, etc. are used widely in recent years of growing deep learning technology. And the concept of transfer learning is attracting many researcher in recent years. These models which are trained on ImageNet datasets are used for the automatic feature extraction and classification of the medical images. These models trained on ImageNet datasets have 1000 categories and around 1.2 million training images. Resnet-101 is a pretrained model which can be loaded using resnet101 function from neural network toolbox. The proposed methodology is depicted in figure 1.

- Algorithm of proposed frame work
- Load the dataset
- Adjust the number of training sets
- Load pretrained network Resnet101
- Prepare training images and test images sets
- Pre-process images for CNN
- Extract training features using CNN
- Train a multiclass SVM classifier using CNN features
- Evaluate classifier
- Apply the trained classifier on test images

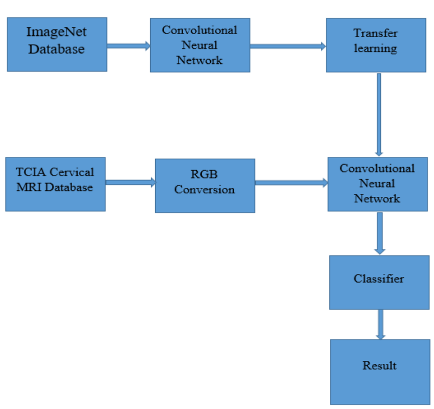


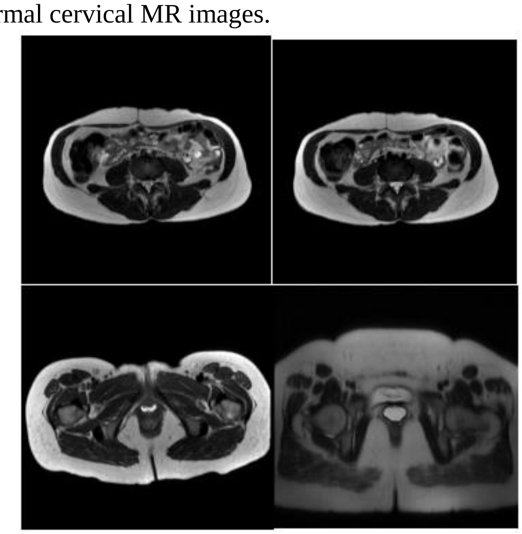
Fig. 1. Proposed block diagram

Resnet-101 is a pretrained model which can classify 1000 classes but for our requirements we restricted the use up to two classes. The dataset was split into testing set and training set. Since net can only process RGB images the images are converted to RGB and resized to 224x224 as required by the CNN. The CNN layer ‘fc1000’ is used to extract features. Further the extracted CNN features are used to train linear SVM. The accuracy of trained classifier is computed based on confusion matrix. In the proposed methodology we classified the cervical MR images provided by TCIA into two categories as normal and abnormal using multiclass linear SVM. The performance of classifier is tested on the images obtained from local hospital.

4. Experimental setup and Implementation

A. Database

In this paper we used uterine Cervical MR image database provided by TCIA which has around 19,193 MRI obtained from 54 patients. It is an open access database freely available to download for educational purpose. Figure 2 shows Normal and Abnormal cervical MR images.


(a) Normal cervical MR images

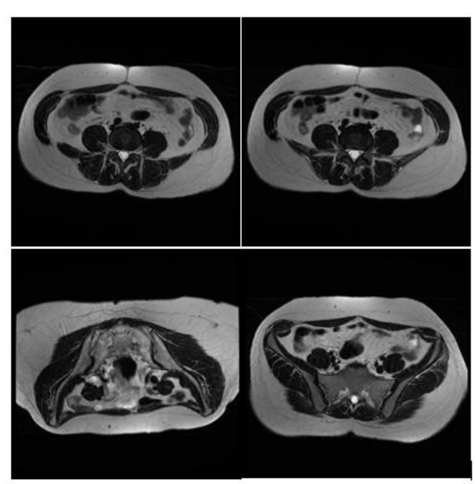

(b) Abnormal cervical MR images

Fig. 2. (a) Normal Cervical MR Images (b) Abnormal Cervical MR Images

B. Implementation

We implemented the proposed frame work using MATLAB 2018a with hardware plan Intel® Core™ i5-5200U CPU @ 2.20 GHz 64 bit operating system. We used MATLAB image processing toolbox using RESNET-101 which can perform image analysis.

C. Evaluation parameters

We evaluated following parameters to test our classifier based on confusion matrix.

1. ERROR RATE: It is calculated as number of all incorrect predictions divided by total dataset.

$$ERR = \frac{FP + FN}{TP + TN + FP + FN}$$

2. ACCURACY: It is the ratio of all correct predictions to the entire dataset

$$ACC = \frac{TP + TN}{TP + TN + FP + FN}$$

3. SENSITIVITY: It is calculated as number of correct positive predictions divided by total number of positives.

$$SN = \frac{TP}{TP + FN}$$

4. SPECIFICITY: It is the ration of number of correct negative predicted to number of negatives.

$$SP = \frac{TN}{TN + FP}$$

5. PRECISION: It is calculated as number of correct positive predictions divided by total number of positive predictions.

$$PREC = \frac{TP}{TP + FP}$$

5. Results and discussions

The classification accuracy is found to be 97.27%, the error rate is 2.73%, and the sensitivity, specificity and precision of the classifier are found to be 96.36%, 98.18%, 98.15% respectively.

A. Results of testing images

The testing images are obtained from local hospital and the proposed methodology was able to accurately classify the images as normal and abnormal. Following tables gives some of the hospital images which are tested using the proposed framework the system classified the images and the result is verified with the radiologist and compared with the medical reports.

B. Input test image

Fig. 3. Input test image

Medical Reports	Proposed Methodology Results
NORMAL	NORMAL

C. Input test image

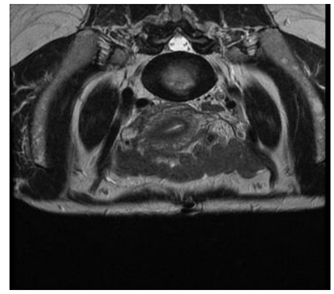


Fig. 4. Input test image

Medical Report	Proposed Methodology Results
ABNORMAL	ABNORMAL

6. Conclusion

This paper presented classification of cervical MRI using RESNET-101 pretrained model. The features are extracted using the concept of transfer learning and the proposed method achieved very good results. The same methodology can be used to classify different medical images which will help radiologist to easily classify normal and abnormal images.

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