Cervical Cancer Prediction and Classification using deep learning

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March 3, 2020

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***Abstract*— Cervical cancer is one of the increasing sicknesses among women in India and also around the world. Early analysis is good for better treatment, yet due to vulnerability in detecting cancer cells becoming more complex one. Machine Learning (ML) systems were used to predict the cancer cells in human beings. For this method the cervical cancer datasets were taken from Unique Client Identifier (UCI) store to predict the cancer cells . But this approach failed to provide better accuracy. In this paper, we propose a cervical cancer cell prediction and classification system based on deep learning techniques . Convolutional neural network (CNN) model is used for prediction and classification.To extract deep-learned features, the cell images were fed into a CNNs model. Further, the input images were classified using an extreme learning machine (ELM)-based classifier. CNNs model is uses the methods namely, transfer learning and fine tuning for providing better accuracy. The experiment was done by collecting the cervical cancer dataset from pap smear Herlev database. Alternatives to the ELM, multi-layer perceptron (MLP) and autoencoder (AE)-based classifiers are also examined. The proposed CNN-ELM-based system achieved high accuracy in the prediction problem (2-class) and classification problem (4-class).**

Keywords- Convolutional neural network (CNN), Extreme learning machine (ELM), Autoencoder (AE)

1. Introduction

Cervical cancer become fourth most common type of cancer among women around the world [1], which causes loss of their lives. Cervical cancer can be cured with early analysis and diagnosis . According to a study conducted by World Health Organization (WHO), the cervical cancer become second most common type of in women living in rural areas in 2012. Roughly 4,45,000 people have been suffered with this disease, and 2,70,000 people have died because of this disease.

The early stage symptoms of cervical cancer are usually not distinguishable, but the major symptom is the vaginal bleeding. This cervical cancer can be treated , only if it is detected at an starting stage.

The diagnosis of cancer is done by a screening process and a biopsy. Image processing techniques also used for finding spread of the cancer in human. These techniques are become cost effective but time consumption was less.

Machine learning techniques and wireless communication technologies allow us to create a medical diagnosis system which can be operated in real-time accurately and also without human interaction. But, there are many difficulties like packet loss during transmission, for medical video data transfer high bandwidth is required, and to deal with variations in data a robust algorithm is needed. To resolve these issues, the efficient techniques is needed.

Currently, deep learning is a emerging one that is used in many application especially in medical application. It provides greater accuracy in medical field. According to the survey, deep learning provides better result in cancer cell detection[2].

Due to the success of deep learning in many medical applications, In this paper, deep learning-based system is developed to predict and classify cervical cancerous cells. In specific, convolutional neural networks (CNNs) followed by an extreme learning machine (ELM)-based classifier is developed. Different models of CNNs are investigated via transfer learning. A general database, the Herlev database [12], has been used .

The modules of the work are (i) introducing CNNs in cervical cancer cell prediction and classification, (ii) introducing ELM-based classifier, and (iii) introducing AE-based classifier. The CNN is used extracts deep learned features from the input images. After extraction , these features are fed into ELM based classifier or AE based classifier. The paper is arranged as follows. The proposed system is dicussed in Section 3. Experiments and results are discussed in Section 4. The conclusion and future work in Section 5.

2. Previous works

There are various method to predict and classify cervical cancer . In existing method, most of the works carried out in Machine Learning. In machine learning , algorithms used for prediction and classification of cervical cancer are support vector machine (SVM), logistic regression , random forest method, decision tree classifiers and k means (K-NNs). Here some of the existing methods were discussed in the following paragraphs.

In existing work, SVM-based cervical cancer prediction and classification system in [13] used a subset of Herlev database [12], and the subset consisted of less than 150 images of which 108 were normal and 41 were abnormal cells (cancer affected). The system achieved an accuracy less than 90% . The small subset had been taken for experiments, so there was issue in providing the accuracy of the system.

Cervical cell images segmentation was performed using a hierarchical segmentation algorithm in [14].The segmentation accuracy was not that much accurate. The accuracy get reduced due to noisy texture, the nucleus extraction from some cells had been failed. The Herlev database had been used for this work. Hierarchical clustering algorithm was used in [15],for classification. The issues involved in this approach was overlapping of cytoplasm.

Various machine learning methodologies were analyzed[16] for cervical cancer prediction and classification. The methods comprised of classification and regression tree, and random forest tree with k-means learning. An accuracy obtained by this system was only 67.5% . The database used in this method was not public, and it is small.

KNNs and ANNs-based classification system was proposed in [17]. The database used in this experiments were Herlev database. The accuracy obtained by k-NNs based system was only 88% , on other hand ANN based system obtained 54% accuracy. Various back propagation NN-based system was designed [18]. A private database used for experimentation and also the images where of poor quality. So the accuracy got reduced due to this issue. Table 1 summarizes the previous algorithm used with estimated accuracy.

Table 1 Algorithm and accuracy(%)

S.no	Algorithm	Accuracy (%)
1	Logistic regression	79.1
2	Random Forest	73.3
3	Decision tree classifier	74.2
4	KNN	67.5

3.Proposed system

The CNN models have been successful in several image process applications together with medical image analysis. Inspired by this, we tend to propose a CNNs-based cervical cancer detection and classification system. The CNNs-based systems need vast information for training, and it's very tough to get a large database of medical images. Therefore, transfer learning and fine tuning are popular when the database size is small.

A deep CNN model can be trained using a large amount of data, and the trained model can be used as a pretrained model. The pretrained model parameters are finetuned using a training set of a targeted database. This fine-tuned model is employed for the testing. A general block diagram of the proposed system is shown in Fig.1. In the proposed system, we investigate three CNN models, one among them has a shallow architecture and two others have a deep architecture. The shallow model has two convolutional layer and two max-pooling layers. The input is the RGB image of size 224 × 224. There are 64 filters of size 5×5 in the initial convolutional layer, and 128 filters of size 5×5 within the second convolutional layer. The stride of the filters is 2 pixels.The mask size of the max-pooling filters is 2×2. The rectified linear unit is employed for the non-linear activation. After the second max-pooling layer, the features are flattened, and fed into a fully connected layer. There are two fully connected layers followed by a SoftMax layer. Once the training was finished, it was fine-tuned by a training set of the intended database.

A minibatch Stochastic Gradient Descent (SGD) algorithm has been used to optimize the parameters of the model. The batch size is 20, the learning rate is 0.01, and therefore the epoch size is 50. In the proposed system, we investigate two deep CNN models in the form of the VGG-16 Net and the Caffe Net[20]. These two models were trained using millions of images. They are also used in many applications including for Epilepsy Seizure Detection. In the proposed system, we tend to use an ELM-based classifier. The ELM is a shallow network and has several benefits like fast learning, easy convergence, and fewer randomized.

In the proposed system, there are two ELMs after the last fully connected layer of the CNN model[21]. The output of the first ELM is about to provide normal or abnormal cells, while the output of the second ELM is about to provide categories of normal and abnormal cases. Once the first ELM training is finished, the output is removed, and therefore the hidden layer is fed to the second ELM. The amount of neurons within the hidden layer is fixed to 2048, which means the ELM refers to a sparse representation. The SGD algorithm is employed to optimize the weights of the ELM. Suppose that there are Nh neurons within the hidden layer of the ELM. The row-wise output vector of the layer has the scale of 1×Nh and is denoted as h(xi), where xi is that the input vector. The output weight vector that connects the hidden layer to the output layer is denoted as α and has the scale of the Nh × No, where No is that the number of output categories. The output of the ELM is as follows:

$$f(x_i) = h(x_i)\alpha,\ i \in \{1: N_h\}.$$

The objective function is defined as

$$\min_{\alpha} \| \alpha \|_F^2 + \rho \sum_{i=1}^{N_h} \| e_i \| ^2$$

where $\|\boldsymbol{\alpha}\|_F$ is the Frobenius norm of the weight vector, ρ is the penalty parameter, and e is the training error vector.

Alternative to the ELM-based classifier, we have a tendency to investigate AE based classifier. The AE has the facility to get rid of noise and it's good for extracting generic options of a category. There's one hidden layer within the AE. The amount of neurons within the hidden layer is empirically fastened to 128. The SGD rule is employed to optimize the weights of the AE.

4. Results and Discussion

We used the Herlev database in our experiments. The database was developed in Herlev University Hospital (Denmark). There are total 917 cells and 7 categories, 3 categories belong to normal and 4 categories belong to abnormal. There are 242 images for normal and 675 images for abnormal. We used a 5-fold cross validation approach. For fine tuning, we used 80% of the data in iteration. The remainder 20% was used for testing. After five iterations, all the data were tested. The final accuracy was obtained by averaging accuracies of five iterations. The Herlev dataset was used for each the training and therefore the testing the shallow CNN model using the 5-fold cross-validation approach. There was no fine tuning the model.

The Table 2 shows the accuracy of the negative rates and the positive rates. All of the three models have two fully connected layers and a Softmax layer. The VGG-16 Net and the Caffe Net have a equal performance, and also the shallow model has approximate performance. The performance of the shallow model specify that for a low size database a shallow CNN model will also perform well. If there's a constraint of time, we may use the shallow model without abundant loss in accuracy.

The performance of the system using the ELM-based classifier and AE-based classifier are described in the Table 3 and Table 4. The high accuracy have obtained by using ELM compared all other algorithms Table 5. The AE-based classifier also given the better performance Table 5. The proposed architecture is given in Fig.1. The Convolutional neural network architecture was described in Fig.2.

Table 2. Accuracy of the system (using CNN)

Classification	Model	Accuracy (%)
Normal	CNN	81.3
Abnormal	CNN	79.4

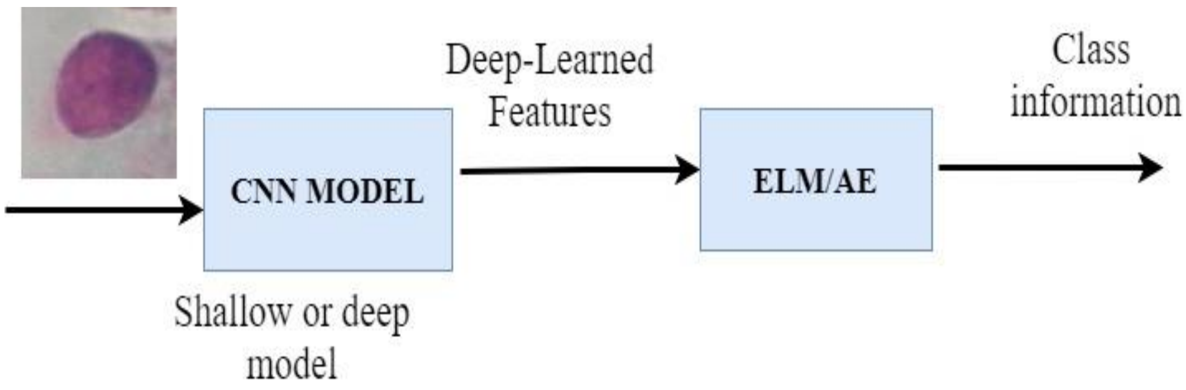

Fig. 1. Architecture of the proposed system

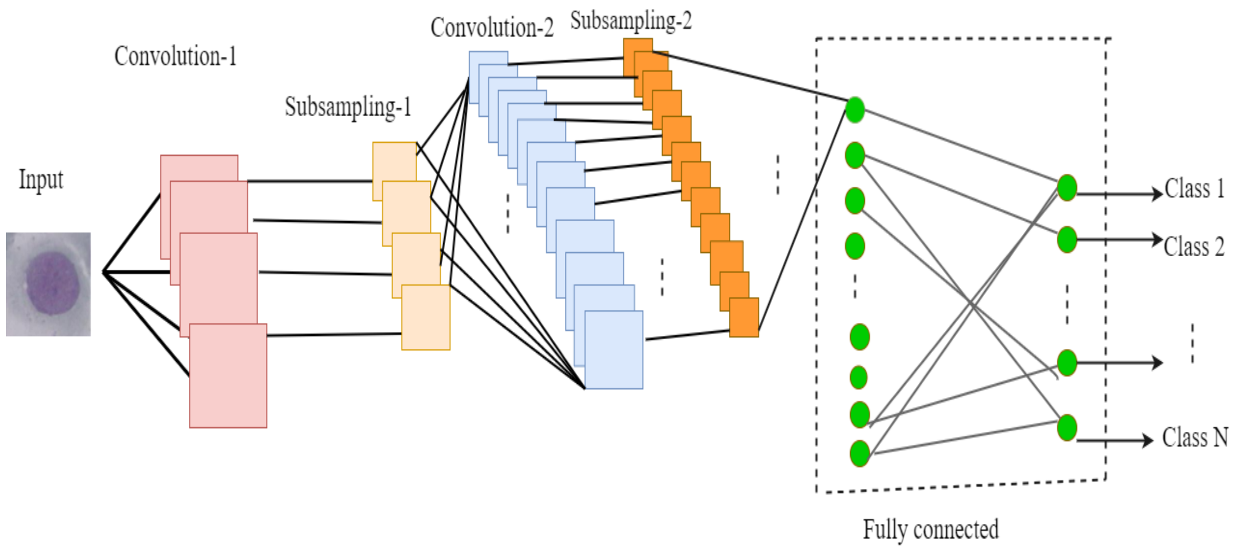

Fig. 2. CNN model architecture

Table 3. Accuracy of the system (using ELM)

Classification	**Model**	**Accuracy (%)**
Normal	ELM	85.2
Abnormal	ELM	86.3

Table 4. Accuracy of the system (using ELM and AE)

Classification	**Model**	**Accuracy (%)**
Normal	ELM+AE	88.2
Abnormal	ELM+AE	89.4

Table 5. Accuracy of the system with different model (4 class problem)

Model	Without ELM & AE	With ELM & AE
Shallow	73.1	87.2
Deep model	75.4	86.4

5.Conclusion

The detection and classification of cervical cancer using CNN was proposed. The ELM-based classifier or the AE-based classifier is used once the CNN model was integrated into the system. The shallow CNN model and deep CNN models were investigated. Both shallow CNN model and deep CNN models were investigated.

The ELM-based classifier achieved accuracy of 88.2% in the 2-class problem and accuracy of 86.4% in the 4-class problem by using herlev database. These accuracies were far better than previous accuracies. In a future work, the proposed system will be evaluated using other databases. Currently, new deep architectures such as ResNet, Inception and tree-based models [22] are providing better results in many applications. So it can be investigated for the cervical cancer detection system.

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