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Segmentation and Abnormality Detection of Cervical Cancer Cells Using Fast Extreme Learning Machine with Particle Swarm Optimization

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Cervical cancer occurs only when the abnormal cells on the cervix will mature and unable to manage clearly in the reformation area. Mostly used technique for detecting the abnormal cervical cells is the routine and there will be no dissimilarity among the normal and abnormal nuclei. The color which is brown is abnormal nuclei and blue is the normal nuclei. Based on the Iterative Decision Based Algorithm, the cells are examined and the denoising of images is performed. Segmentation of the image is the procedure of grouping the digital image into compound sections. The preceding technique namely Support Vector Machine (SVM) will able classify only few nuclei regions but it will take high execution time. So, this research proposed a method called Fast Particle Swarm Optimization with Extreme Learning Machine (Fast PSO-ELM) for classifying all regions of nuclei into touching and non-touching region. This method is more efficient when compared with SVM method.

Key words: Cervical Cancer, Image Denoising, Extreme Learning Machine, White Blood Cells, Particle Swarm Optimization, Fast Extreme Learning Machine.

A Cancer is formed by the assembly of epigenetic and inborn alterations in genes which are generally assisted the function in the cell propagation directive and leads to the development of unrestrained cell (Sukumar and Gnanamurthy, 2015). These cells will pave way to the growth and patience over ordinary a cell which leads to the cancer cell development. Human papilloma viruses (transmitted through sexual contact) occur a pathogenic function in the majority cases of cervical cancer (observe information on cervical cancer in the Pathological Characteristics of Benign and Malignant Neoplasms lab, the Cancer Screening lecture, and the Clinical and Translational Research online module). There are at least 77 subtypes of HPV that are distinguished by variations in their DNA progressions. HPV-16 or HPV-18 DNA is found in 70% of cervical tumors [1]. An additional 20% of tumors contain HPV DNA matching to one of 20 other cancer-correlated subtypes. HPVs have a double-stranded DNA genome. The proper selection of the training algorithms is very significant which facilitates the particular application to avoid the global or local minima problem. To rectify this issue and achieves the better results this work proposed a classifier namely, Fast Particle Swarm Optimization with Extreme Learning Machine (Fast PSO-ELM). White blood cells commonly known as *leukocytes* or *leucocytes* which are protected structure which is

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concerned about the body but not in the unfamiliar resources and contagious infection. These cells will protect the body by attacking the viruses, bacteria and germs which harm the body. From a multi potent cell, all leukocytes are derived and produced and it is called hematopoietic stanch cell. They subsist for concerning 3 or 4 days in the human body. The microscopy images of cells in cervix uteri are marked, so that the abnormal nuclei found are brown in color while normal nuclei are blue in color which is shown in the figure 1.

The image will undertakes the denoising process initially. Generally, in medical images salt and pepper noise is formed. The main goal of an image denoising algorithm is then to reduce the noise level, while preserving the image features (such as edges, textures, etc.).

The rest of this project is structured as follows. Section II provides the related works. Section III explains the proposed method, and Section IV describes the experimental results. Finally, Section V discusses the conclusions of the work.

Background

Jiang et al (2003) article presents White Blood Cell (WBC) segmentation design using scale-Space filtering and watershed clustering is suggested. In their proposal, nucleus and cytoplasm, both of these mechanisms of WBC, are removed correspondingly using dissimilar techniques. An automatic Computer Aided Diagnostic system (CAD) is proposed by Selvaraj and Janakiraman (2013) for detection of liver diseases like hepatoma and hemangioma from abdominal Computed Tomography (CT) images using an evolutionary approach for feature selection. A segmentation system with a modified automatic Seeded Region Growing (SRG) based on Particle Swarm Optimization (PSO) image clustering will be presented by Al-Faris *et al* (2014). An improved Computer Aided Clinical Decision Support System has been developed by Suganthi and Madheswaran (2012) to classify the tumor and identify the stages of the cancer using neural network and presented.

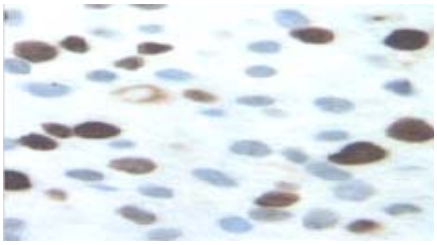


Fig. 1. Input Image

Li *et al* (2012) presents an effectual and proficient Computer Aided Diagnosis (CAD) scheme derived from Principle Component Analysis (PCA) and Extreme Learning Machine (ELM) to support the mission of thyroid disease diagnosis. Huang *et al* (2010) investigates more revises ELM for sorting in the characteristic of the ordinary optimization process and widen ELM to a precise category of "generalized" SLFNs—support vector network. Pimenta *et al* (2013) estimates the proportion of ADC in persistent cervical cancer, the universal number of cases of cervical ADC in 2015, the effect of cervical screening on ADC, the number of ADC cases attributable to high-risk HPV types -16, -18, -45, -31 and -33, and the possible collision of HPV immunization using different data sources counting: GLOBOCAN 2008, Cancer Incidence in Five Continents (CI5) Volume IX, cervical showing information from the World Health Organization/Institut Català d'Oncologia Information Centre on HPV and cervical cancer, and available journalism.

Ravikumar (2015) gives a novel technique for WBC detection based on the fast relevance vector machine (Fast-RVM). The proposed method successfully works for WBC detection, and effectively reduces the effects brought about by illumination and staining. Particle Swarm Optimization (PSO) hybridized with Sequential Forward Selection (SFS) and Sequential Backward Selection (SBS) algorithm is proposed by Gunasundari and Janakiraman (2015) for improving the performance of the classification system. Hassanien *et al* (2014) introduces a hybrid approach that combines the advantages of fuzzy sets, ant-based clustering and multilayer perceptron neural networks (MLPNN) classifier, in conjunction with statistical-based feature extraction technique. 2D Otsu algorithm based on particle swarm optimization (PSO) is proposed by Helen *et al* (2011) to segment CT lung images. Poletti *et al* (2012) implemented eleven thresholding methods, i.e. the ones that appear in the literature as the best performers, and compared their

performance in segmenting chromosomes and chromosome clusters in cytogenetic Q-band images.

Wang *et al* (2013) presented as vary of total HPV, solitary HPV and numerous HPV disease were analogous through the five existence. They suggested that HPV disease is common with HPV16 and HPV 58 as the main subtypes in women in Shenzhen city. Huang *et al* (2005) examined the consequence of eight PSO topologies on presentation of the PSO-ELM. The outcomes showed empirically that the Global topology was additional shows potential than every other topologies in optimizing the PSO-ELM according to the Root Mean Squared Error (RMSE) on the validation set in the majority of the appraised datasets. Saraswathi *et al* (2011) appraises the presentation of ICGA-PSO-ELM and contrast their results with existing techniques in the prose. An exploration into the purposes of the chosen genes, using an organism's biology method, exposed that several of the recognized genes are concerned in cell signaling and propagation. A novel hybrid approach founded on clustering and Particle Swarm Optimization (PSO) is suggested for gene selection and categorization of microarray data by Yang *et al* (2013). In those approaches, PSO merging with clustering technique are used to achieve gene selection to decrease redundancy. Owing to its improved simplification presentation with much faster junction tempo than further learning algorithms for neural networks, Extreme Learning Machine (ELM) is preferred to perform sample classification in the hybrid method.

MATERIALS AND METHODS

In this section, the proposed Fast PSO-ELM method is demonstrated for detecting the defect in cervical cancer cells. The main aspects of the algorithm namely, Extreme Learning Machine, Particle swarm Optimization is discussed as follows.

Extreme Learning Machine

Extreme Learning Machine (ELM) is a layer of single hidden feed forward networks (SLFNs) which randomly chosen the input influences and decides the output influence systematically of SLFNs. The ELM rule for the input is that one can randomly decide and append the parameters of hidden module. After random selection of the hidden modules parameter, SLFNs ensembles the linear system where the output influences of the network can be established technically by simplified inverse process of the hidden layer output matrices. For an surveillance data set with N nodes in the hidden layer and the excitation utility G, the extreme learning machine model can be expressed as

$$f(x) = \sum_{i=1}^{N} \boldsymbol{\beta}_i G(a_i, b_i, x_i) = \boldsymbol{\beta}.\boldsymbol{h}(x) \quad ...(1)$$

Where b_i is the output weight of the ith hidden layer node and the output neuron, a_i is the input weight of the input neuron and the ith hidden layer node, and b_i is the offset of the ith hidden layer node. Consider $h(x)= [G(a1,b1,x1,),..,G(aN,bN,xN)]$ denotes the output matrix of hidden layer. a_i and b_i are randomly selected before training and remain the same in the training procedure. The output weights b_i can be obtained by solving the least-squares solutions of the following linear equation:

$$min \sum_{i=1}^{N} \|\boldsymbol{\beta}_i.\boldsymbol{h}(x_i) - y_i\| \quad ...(2)$$

The best solution is obtained by ELM and applied in several applications such as Bioinformatics, Biometrics, Image processing, Signal processing, etc. It is a three step simple training algorithm. The machine learning in ELM is very speed. But the standard algorithm will face the issues like over fitting, minima, etc. for several establishment functions.

Given a training set $\aleph$ = {(xi,ti)|xi ∈R^n,ti∈R^m,I = 1,…,N}, activation function g(x), and hidden node number N,

Step 1: Randomly assign input weight w_i and bias b_i, I = 1,…N.

Step 2: Calculate the hidden layer output matrix H.

Step 3: Calculate the output weight β

(b = H+T)

Where T =[t1,…,tN]^T.

The ELM algorithm is very simple and provides the results accurately when compared with other standard algorithms. ELM provides capable solution with tunable parameters. ELM has unique features for dealing with classification and regression tasks and it is very easy to implement.

Standard Particle Swarm Optimization

PSO algorithm is inspired by the social behaviour of biological organisms and has the ability of groups of animal some species to work in the desirable position in particular area, e.g. birds flocking to a food source. PSO works on the flock of birds initializing randomly over the penetrating space, where the each bird is called as a "particle". These "particles" fly through a convinced pace and locate the large-scale best position after various iteration. At every iteration, every particle adjusts its pace vector, founded on its impetus and the influence of its top position (P_b) with the finest position of its neighbors (P_g), and then a new position the "particle" to fly is obtained. Guessing the element of searching space is D, the whole number of particles is n, the position of the i-th particle can be stated as vector $X_i = (x_1, x_2,\ldots, x_{iD})$; the best position of the i-th particle penetrating in anticipation of presently is indicated as $P_{ib} = (p_{i1}, p_{i2},\ldots, p_{iD})$ and the best position of all particles penetrating awaiting at present is denoted as vector as $P_g = (p_{g1}, p_{g2},\ldots, p_{gD})$;the velocity of the i-th particle is indicated as vector as $V_i = (v_{i1}, v_{i2},\ldots, v_{iD})$. Then the original PSO is illustrated as:

$$V_{id}(t+1) = V_{id}(t) + C_1^* rand()^* [p_{id}(t) + x_{id}(t)]$$

$$+C_2^* rand()^* [p_{gd}(t) + x_{id}(t)] X_{id}(t+1) = X_{id}(t) + V_{id}(t+1)1$$

$$\leq i \leq n, \quad 1 \leq d \leq D$$

...(3)

Then, the parameters (all weights and biases) are restructured with the help of Extreme Learning Machine algorithm. In Figure 2 illustrates that the proposed methodological process is used to detect the cervical cancer cells.

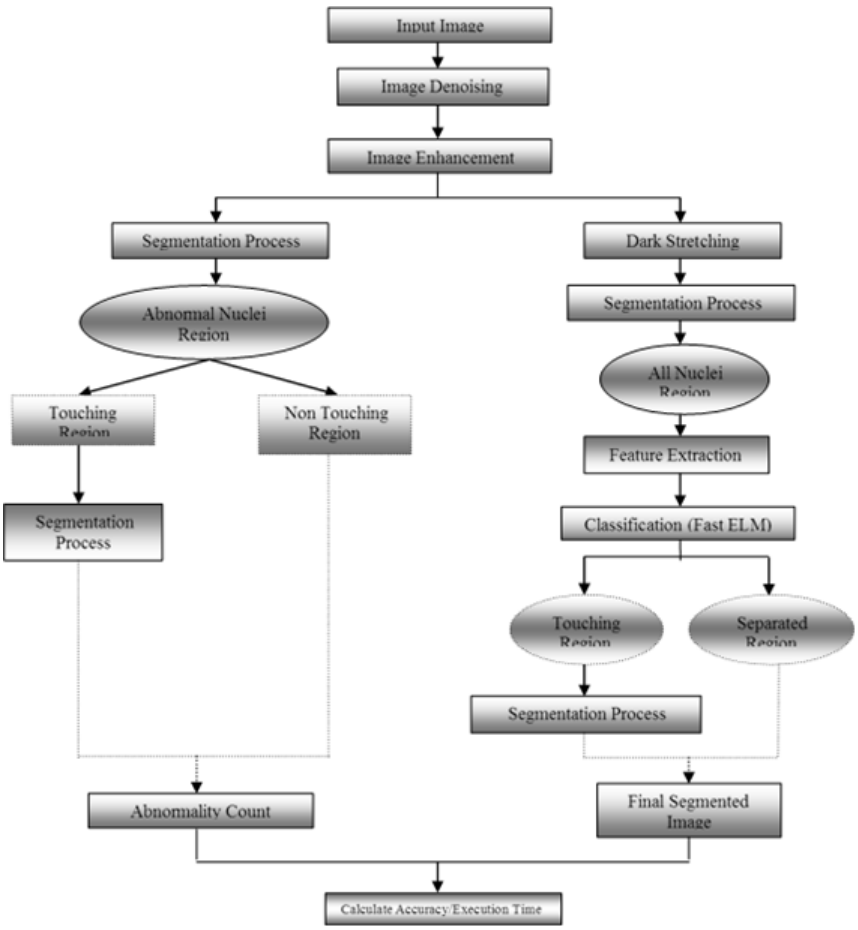


Fig. 2. Methodology Used To Detect Cervical Cancer Cells

Fast Particle Swarm Optimization with ELM Method

This research work integrates to progress Fast PSO-ELM by combining an improved PSO with ELM. The Fast PSO-ELM to select the input influences to boost the generalization presentation and the provisioning of the SLFN. The details of the proposed method are as follows:

Step 1: Initialize a population array of swarm particles with of a set of input influences and secreted favoritisms: $Pi = [W_{11}, W_{12}, \ldots, W_{1n}, \ldots, W_{21}, W_{22}, \ldots, W_{2n}, \ldots; W_{H1}, W_{H2}, \ldots, W_{Hn}, b_1, b_2, \ldots, b_H]$ with random initialized within the range of [-1, 1] on *D* dimensions in the search space.

Step 2: for every group particle, the matching harvest weights are calculated according to ELM as in Equation (1).

Step 3: Then the fitness of each particle $f(x)$ is evaluated. In order to avoid over fitting of the SLFN, the fitness of every particle is accepted as the Root Mean Squared Error (RMSE) on the validation locate only in preference to the complete training set.

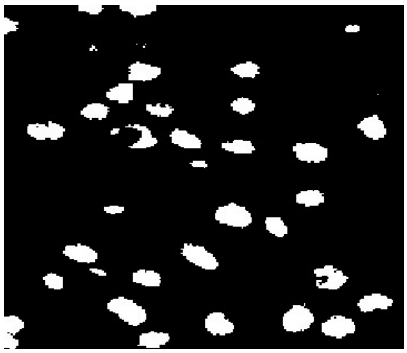
$$p_{i,best} = p_i \left(f(p_{i,best}) - \left(f(p_i) > \eta f(p_{i,best})\right)\right) or \left(f(p_{i,best}) - f(p_i) < \eta f(p_{i,best})\right) and \| wo_{p_i}| < |wo_{p_i,best} \| p_{i,best} \; else \quad ...(4)$$

$$g_{i,best} = p_i \left(f(g_{i,best}) - \left(f(p_i) > \eta f(g_{i,best})\right)\right) or \left(f(g_{i,best}) - f(p_i) < \eta f(g_{i,best})\right) and \| wo_{p_i}| < |wo_{g_i,best} \| g_{i,best} \; else \quad ...(5)$$

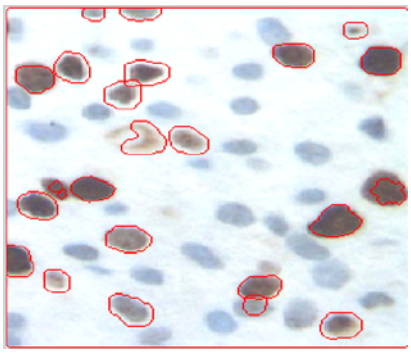
where $f(P_i)$, $f(P_{i,best})$ and $f(g_{i,best})$ are the corresponding fitness for the *i*-th particle, the best position of the *i*-th particle and global best position of all particles, respectively. woP_i, $woP_{i,best}$ and

(a) Abnormal Nuclei Region

(b) Non Touching Nuclei Region



(c) Touching Nuclei Region



(d) Detected Abnormal Nuclei

Fig. 3. Abnormal Nuclei Region

$wog_{i,best}$ are the corresponding output weights obtained by MP generalized inverse when the input weights are set as the *i*-th particle, the best position of the *i*-th particle and global best position of all particles, respectively. The parameter $h > 0$ is tolerance rate.

Step 4: Velocity update - Update the velocities of all particles at time *k* (current iteration) using the particles objective or fitness values which are functions of the particles current positions in the design space at time *k*. At each iterations, the rapidity of the entire particles is rationalized as:

$$v_i(k+1) = \beta[v_i(k) + c_1\gamma_1 (p_{i,best} - p_i) + c_2\gamma_2(g_{i,best} - p_i)] \quad ...(6)$$

Step 5: Position update-The position of each particle is updated using velocity vector as follows:

$$p_i(k+1) = x_i + v_i(k+1) \quad ...(7)$$

Step 6: Memory update -Update $p_{i,best}$ and $g_{i,best}$ when circumstance is convened and new-fangled population is generated.

Step 7: Stopping Criteria - The algorithm repeats steps 3 to 6 until certain criteria are met, along with hard threshold value as maximum number of iterations. Once stopped, the algorithm descriptions values of g_{best} and $f(g_{best})$ as its resolution.

The improved PSO with ELM will provides the best optimal weights *W* and bias *b* so that the fitness will achieves the minimum for getting better generalization performance with minimum number of hidden neurons. It makes advantage of both ELM and PSO. The procedure describing proposed Fast PSO-ELM approach is as follows.

1. Initializing FPSO with population size, inertia weight and creations without improvable.
2. Estimating the robustness of each particle.
3. Comparing the robustness values and establishes the restricted best and inclusive best particle.
4. Updating the velocity and position of each particle till value of the robustness function touches.
5. After touching, the large-scale best particle in the swarm is fed to ELM classifier for training.
6. Training the ELM classifier.

The Fast PSO-ELM algorithm will provide the advantage of minimizing the structural risk of ELM, where Structure Risk Minimization (SRM) is defined as the inductive principle in machine learning use and quickly will optimize the global ability of FPSO.

Table 1. Confusion matrix

	Positive	Negative
Positive	TP	FP
Negative	FN	TN

RESULTS AND DISCUSSION

The experimental results are performed on various blood cell images using MATLAB. Since that the WBC are only segmented and its number of WBC noticed through several techniques is estimated with essentially present in the image which is physically gained. Collected 50 images from pathologist and 40 used for training data and remaining 10 for testing data. To classify abnormal nuclei regions and all nuclei regions, fast PSO-ELM technique is used in 'a*b*' regions based on the color information. By using appropriate n-values (Assume n=6), it is possible to separate abnormal nuclei regions and all nuclei regions respectively with the help of proposed technique. It is shown in the figure 3(a).

The main aim of Fast PSO-ELM is to predict the boundary locations which are more distant from the nearest vectors of both categories. The touching region and separated region are classified accurately by using the proposed Fast PSO-ELM and represented below in figure 3(b) and 3(c).

Table 2. shows the accuracy and execution time for Proposed Fast PSO-ELM technique

Techniques	Accuracy (%)	Execution Time (Seconds)
kNN	65.87	54
SVM	68.21	42
ELM	71.56	35
PSO-ELM	75.12	29
Fast PSO-ELM	96.84	18

The accuracy is evaluated by integrating the final segmented image which are extracted from all nuclei region and the enhanced image nuclei are indicates the abnormality count which are detected in the abnormal nuclei region as given in figure 3(d) below.

Testing Precision and Recall

A perfect diagnostic procedure has the potential to completely discriminate subjects with and without disease. Values of a perfect test which are above the cut-off are always indicating the disease, while the values below the cut-off are always excluding the disease. Values above the cut-off are not always indicative of a disease since subjects without disease can also sometimes have elevated values. Such elevated values of certain parameter of interest are called false positive values (FP). On the other hand, values below the cut-off are mainly found in subjects without disease. However, some subjects with the disease can have them too. Those values are false negative values (FN). Therefore, the cut-off divides the population of examined subjects with and without disease in four subgroups considering parameter values of interest. Abnormality is defined as the ratio of abnormal nuclei regions to that of all nuclei regions. The accuracy calculations for abnormal and normal nuclei to provide prevalence are as follow.

Accuracy= (sensitivity) (prevalence) + (specificity) (1-prevalence)

- True Positive (TP) –subjects with the disease with the value of a parameter of interest above the cut-off
- False Positive (FP) –subjects without the disease with the value of a parameter of interest above the cut-off
- True Negative (TN) –subjects without the disease with the value of a parameter of interest below the cut-off
- False Negative (FN) –subjects with the disease with the value of a parameter of interest below the cut-off

The first step in the calculation of sensitivity and specificity is to make a 2x2 table with groups of subjects divided according to a gold standard or (reference method) in columns, and categories according to test in rows

Sensitivity is expressed in percentage and defines the proportion of true positive subjects with the disease in a total group of subjects with the disease (TP/TP+FN). Actually, sensitivity is defined as the probability of getting a positive test result in subjects with the disease (T+|B+). Hence, it relates to the potential of a test to recognize subjects with the disease.

Specificity is a measure of diagnostic test accuracy, complementary to sensitivity. It is defined as a proportion of subjects without the disease with negative test result in total of subjects without disease (TN/TN+FP). In other words, specificity represents the probability of a negative test result in a subject without the disease (T-|B-). Therefore, we can assume that specificity relates to the aspect of diagnostic accuracy that describes the test ability to recognize subjects without the disease, i.e. to exclude the condition of interest.

The Table 2 gives the accuracy and execution time comparison of the proposed method of abnormality detection using Fast PSO-ELM. That the abnormality detection for cancer cells through touching and non touching nuclei for enhancing the process using Fast PSO-ELM gives 96.84% accuracy and less execution time for proposed method of Fast PSO-ELM

CONCLUSION

In the world, second common cancer is the cervical cancer. Numerous images of the cells are with the noise and which is complicate to detect the abnormal nuclei accurately. The proposed FAST PSO-ELM method will able to diagnosis the cancer cells early for treatment. And also, this work will provide the information to detect the abnormal cells using various algorithms. The image with noise is detected easily using this technique and eliminate by using the denoising process. The proposed method will accurately classify the touching and non-touching image form all normal and abnormal nuclei. The experimental evaluation for the proposed method is carried out and from the results it is proved that the proposed method achieved the classification accuracy of 97%. The main benefit is that the proposed method is that it suitable for high degree of noise image and it can effectively isolate the abnormal and all nuclei regions. In future Fast PSO-ELM technique can be executed in numerous cells for identifying better accuracy. The minute cell extraction can be done with the assist of this technique.

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