A MULTIFACETED TACTIC FOR DETECTION OF CERVICAL CANCER USING EXTREME LEARNING MACHINE WITH CROW SEARCH OPTIMIZATION CLASSIFICATION

Geetha , S.Suganya

Department of computer science Bharathiar university
Ask2geetha@gmail.com
suganya_cs@rvsgroup.com

ABSTRACT:-

Malignancy or carcinoma is the unrestrained development of cells. There are numerous kinds of malignancies. In this, we are concentrating on one of the normal tumor of females is malignant growth of the cervix. Cervical cancer is the second most kind of malignant growth found in females, apart from the breast cancer which is first existence. There are abundant quantities of screening tests for Cervical cancer in which Pap smear has done. Pap smear is a virtuous device for first screening of this cancer yet it has constraints as there are consistently odds of blunder due to human perceptions. The main aim of this research is to preclude failures by utilizing computerized methods for identifying the cervical cell. Here, the image of Pap smear has been improved by utilizing Kaun Filter. The weight factor in kaun filter is resolved using an optimization technique called Bayesian Optimization Algorithm. Thus it tends to be an upgraded KF. The reformed picture has been segmented by Active Contour model. In this, the weight upgrade issue has been rectified using Analytic Hierarchy Process optimization technique. Hereafter, the solid features are eliminated from the segmented region which is most significant for identifying the cancer by utilizing ELM-CSA (Extreme Learning machine with Crow Search optimization) classifier. Experimental results for the cervical cancer identification by the proposed ELM-CSA outperforms 93.5% of accuracy, 88.7% of specificity,79.21% of precision,92.25% of recall and 79.26% of F-measure than the existing classifiers such as ELM, ENN-TLBO, SVM and RBFN.

Keywords: Cervical cancer, Pap smear test, ELM-CSA, UKF, ACM with AHP.

1. INTRODUCTION

Cervical malignant growth has gotten one of the significant reasons for disease passing among ladies around the world. This can be relieved in its previous stage. For a large portion of the cases it shows manifestations just in the serious stages. Cervical disease is a malignant growth emerging from the cervix. Malignancy is because of the irregular development of cells that can attack or spread to different pieces of the body [1]. The cervical malignancy is additionally happened in the women understanding inside and it tends to be recognized by filtering the interior locale of the vagina. Human Papillomavirus (HPV) infection is the primary source of cervical malignant growth development in women patients. This infection at first influences the cells in the cervical area of the ladies patients and spreads over the whole locale of the cervix [2]. There are no precise signs and manifestations of cervix cancer in beginning phases, so standard screening by PAP's smear is done [3]. PAP's smear test is one of the best screening strategies uses to identify cancer cells. In this a clinician gather a model of cells from the ramparts of the cervix, this model is then positioned on a glass slide and marked with a tint. At that point the slide is concentrated under a microscope to discover unusual cells. Screening by PAP's smear help in recognition of malignancy and its fix at beginning phases. Pap smear screening is tedious and in some cases it gives wrong outcomes. Automatic detection and segmentation of Pap smear image is one of the one of the fascinating work of image processing. In the previous work, automated method of segmentation is a challenging task. Morphological operations are used to segment the Pap smear image by the corresponding values of the neighboring pixels. [4] Watershed segmentation [5-6] was applied on the green channel of the RGB images, followed by region merging and elimination to obtain the cell boundaries.

The rest of the paper is organized as follows. Section 2 gives a detailed description about the proposed architecture, section 3 describes the results and discussions have to be carried out for this proposed work, and finally the paper is concluded in section 4.

2. PROPOSED ARCHITECTURE

The proposed approach is to recognize the cervical malignancy utilizing Pap smear images is appeared in Figure 3. The input images utilized in this strategy are normal Pap smear images. In this effort, we considered a distinct cell Pap smear images to assess the cell as regular or unusual. The primary stage is the pre-processing step in which Upgraded Kaun filter has been utilized for improving the image. An Active Contour Method (ACM) has been utilized to portion the recognized cells from the Pap smear image. The weight factor for the energy minimization has been settled by utilizing an advancement method as Analytic hierarchy process (AHP). In light of this, the strong highlights are removed from the sectioned areas. At that point the ELM-CSA has been used for better precision of classification. Figure 1 gives the thorough picture of proposed approach for identifying the cervical cancer.

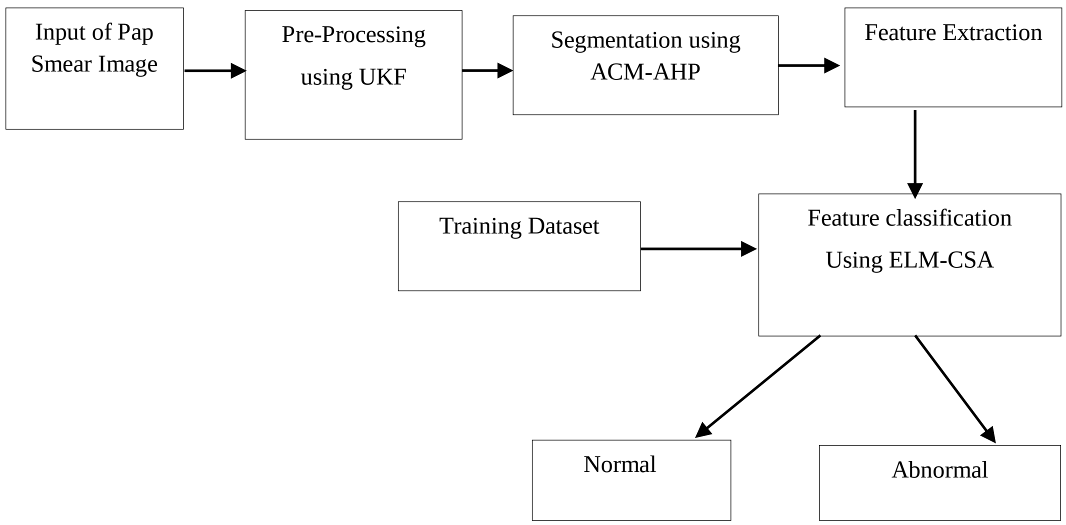


Figure 1 System Architecture for cervical cancer Detection

2.1 Dataset Description

The dataset of DICOM image of Pap smear cancer is gathered from the kaggle website. There are above 250 images of various ages are utilized for assessing the cervical cancer identification. In this dataset, there are various types of cervical cancer have been identified such as 1) Superficial squamous (74 cells), 2) Intermediate squamous (70 cells) 3) Columnar (98 cells), 4) Severe Dysplastic (197 cells), 5) Moderate Dysplastic (196 cells) 6) Light dysplastic (187 cells) and 7) Carcinoma in situ (150 cells)

2.2 Preprocessing of the Image

In pre-processing, at first, the contribution as Pap smear picture has been prepared by Contrast Limited Adaptive Histogram Equalization (CLAHE) to upgrade by eliminating the difference enhancement in a picture. At that point, Updated Kaun channel (UKF) has been used for lessening the commotion without eliminating the critical substance in a Pap smear picture.

The Kaun filter has been calculated using

$$\tilde{R}(t) = I(t).W(t) + \bar{I}(t).[1 - W(t)], \quad (1)$$

$\tilde{R}(t)$→De-noised image,

I (t) →image corrupted with noise

Ī (t) →mean image intensity within the filter window.

W (t) → weighted coefficient of Kaun filter determined as:

$$W(t) = \frac{1-\frac{c_u^2}{c_I^2(t)}}{1+c_u^2}, \quad (2)$$

Wherec_u and c_I (t) are variation coefficients of speckle u (t) and image I (t) respectively. Based on the weight factor, the accomplishment of noise decrease has been anticipated.

In this, the weight factor has been advanced by applying Bayesian Optimization Algorithm (BOA) to upgrade the image quality and reduce the commotion.

Bayesian Optimization Algorithm is utilized to locate the global optimum in a least number of steps. It consolidates earlier conviction about f which is an assessment work inspected at a pixel point x and updates the earlier with tests attracted from f to improve approximates f.

Algorithm: Upgraded Kuan filter
Input: *Weight factor of Kaun Filter*
Output: *Optimized Weight factor of Kaun Filter*
Method

1. *Choose the weight coefficient of Kaun filter from the eqn. (2)*
2. *Choose the surrogate model based on Gaussian Process (GP) is* $p(f|W)=N(f|\mu,X)$ *and define its Prior using the function* $p(f_{new}|W_{new},X,y)=\int p(f_{new}|W_{new},f)p(f|W,y)\,df=N(f_{new}|\mu_{new},\Sigma_{new})$
3. *Find the next weight values* x_t *by optimizing the acquisition function over the GP*
4. *Obtain a possible sample* $y_t = f(x_t) + \epsilon_t$ *from the objective function f.*
5. *Add the sample to previous samples* $D1{:}\ t=\{D1{:}t-1,\ (x_t, y_t)\}$ *and update the GP.*
6. *Choose the updated GP and apply it into the kaun filter eqn (1)*
   Thus the kaun filter (KF) named as Upgraded KF

2.3 Segmentation using ACM with AHP:

ACM:

The ultimate goal of Pap smear segmentation is to give the improved sectioned picture by utilizing Active Contour method. Inspite of shape, ACM (Snakes) is utilized to find the skeleton of the object layer and furthermore it is utilized in numerous methodologies, i.e., by recognizing the edge portions at that point which equally relates to one another. The snake decides the decreasing of both inner and the outer energy happen dependent on the development of control points which achieves the exact restrictions of object. The utilization of energy can be composed as:

$$E_{snake} = \int_0^1 E_{int}\big(v(s)\big) + E_{ext}\big(v(s)\big)ds \quad (3)$$

At the point, when the outer energy of the snake approach object limit position, to compute the slope of the picture as

$$E_{external} = E_{Image} + E_{con} \quad (4)$$

The Inner Energy is computed using equation (5).

$$E_{internal} = E_{cont} + E_{curv} \quad (5)$$

Where E_{cont} represents the snake's stability and E_{curv} represents the snake's elastic degree and the equation are given below:

$$E_{cont} = \alpha(s)|v_s(s)|^2 \quad (6)$$

$$E_{curv} = \beta(s)|v_{ss}(s)|^2 \quad (7)$$

$$E_{internal} = (\alpha(s)|v_s(s)|^2 + \beta(s)|v_{ss}(s)|^2)/2 \quad (8)$$

Sensitivity to the contour's primary locus inside the confined minima is among the issues needed on the active contour models. On the off chance that the difficult size augments, causes gigantic computational endeavors. This is to be settled by utilizing the AHP optimization algorithm.

AHP:

In ACM, reducing the energy capacity will make the silhouette impervious toward the Snake. It is a multi-model program which is utilized for dynamic cycle in extremely complex situation. The factors are viewed as dependent on prioritization. Epitome weight values are determined dependent on the confined energy. It changes over observational information into numerical model. The mathematical likelihood is process expected and satisfies the anticipated objective. In this way, it is applied in ACM for partitioning the locale for calculation that makes to anticipate the efficient features for recognizing the cervical disease.

Algorithm: Segmentation using ACM with AHP

Input: *P(s, t), Ein, Eext, t*

Output: *Segmented region of Pap Smear cell region*

Method:

1. *To estimate the desired contour position and shape as a curve in the given image pixels.*
2. *Initialize the E_{in} (Elasticity and stiffness of the contour)*
3. *Initialize the E_{ext} (Weighted combination of image and constraints)*
4. *The energy function is calculated as follows*
   - *(a) The optimal weight value from the energy of the contour is calculated by using AHP optimization algorithm.*
   - *(b) Compute the weight for different energy values by a Pairwise comparison matrix A*
   - *(c) Calculate the normalized weight using normalized comparison Matrix A_{norm}*
   - *(d) Calculate the option score matrix by averaging the entries rows and columns in matrix*
   - *(e) Rank the options are computed using the weight vector and the score matrix.*

(f) Find the best global score of the weight

5. *Total energy is calculated*
6. *The pixels are modified to minimize the total energy*
7. *The segmentation of ACM has been improved using the weight minimized in the energy function*
8. *Segmented region of Pap smear cell region image is displayed.*

2.4 Feature Extraction:

The features of Pap smear pictures are extricated thusly of identifying the malignancy part of the cervix locale. A portion of the highlights from the Pap smear pictures are Nucleus perimeter Maxima and Minima in nucleus, Nucleus solidity, Nucleus mean and Nucleus entropy. And also some of the texture features such as GLCM, Haralick Features, size, shape of Pap smear image, and geometric features like mean, median, entropy, irregularity, concavity, convexity, area and perimeter have been haul out. The above taken out features are utilized for effectual feature classification method utilizing ELM-CSA**.**

2.4 Feature Classification using ELM-CSA:

Extreme Learning Machine calculation can be utilized to prepare Single Layer Feed forward Network (SLFN) was proposed by Huang et al. 2006. In ELM, the primary thought includes the hidden layer weights. Besides, the predispositions are haphazardly created and the output weight calculation is prepared by utilizing the least-squares arrangement. Moreover, they have been characterized by the yields of the targets and the concealed layer [9].

Consider M set of training dataset such that $(m_i, n_i) \in A^a, i = 1,2, \ldots, N$ with N samples and a features. The ELM output can be calculated using

$$n = f(x) = \sum_{i=1}^{L} \beta_i g(m_i) \tag{9}$$

$$= \sum_{i=1}^{L} \beta_i g(w_i * m_j + b_i), j = 1,2, \ldots, N \tag{10}$$

Where L denotes the hidden nodes,

b_i denotes the bias vector

g denotes the activation function

β_i denotes the weight vector between the hidden node and output node.

The equation (9) can be rewritten as

$$H\beta = B \qquad (11)$$

Based on the equation (11), the network cost function has been minimized so that the output weight β can be defined by calculating the least square solution as

$$\hat{\beta} = H^{\dagger}T \qquad (12)$$

Where $H^{\dagger}$ denotes Moore–Penrose generalized inverse matrix of hidden layer output H

The weight factor for the hidden nodes in ELM can be optimized using Crow search optimization (CSA).

Crow search optimization (CSA)

CSA is a bio inspired algorithm which was proposed by A.Askarzadeh in 2016 which recreates the stowing away of food conduct of crow [8]. Crow is a keen fledgling that can recall faces and caution its species at serious risk. One of the most proofs of their astuteness is concealing food and recalls its area.

Algorithm for Feature Classification using ELM-CSA

Inputs: *A training set of* n *classes* $(m_i, n_i) \in A^a, i = 1,2,\dots,N$, *a test sample* T, *hidden feature number* H,*activation function g(x),hidden node number N*
Output: *Cervical Cancer identification*
Method:

1. *Randomly assign the input weight and the bias vector for hidden parameters as(* w_i , b_i*)*
2. *Compute the hidden layer output matrix H using the equation (10)*
3. *Initialize the population size, crow position* C_p*, crow's memory* m_i*,* $Count_{max}$ *Maximum number of iterations.*
4. *While count < $count_{max}$ do*
5. *For* $crow_i$ $\mathcal{E}$ *crows do*
   i) *Updates crow position by selecting random value of another crow position xj*
   ii) *If this value is greater than Awareness Probability 'AP',then crow xi will follow xj by mj*
   iii) *Update new crow position using*

$$x_{i,count+1} = \begin{cases} x_{i,count} + rand_i * f_{i,count} * \\ (m_{j,count} - x_{i,count}) \;, rand_j \geq AP_{j,count} \\ rand\ position, \quad otherwise \end{cases}$$

where $AP_{j,count}$ → *crow j awareness probability, count* → *iteration number,* $rand_i, rand_j$ → *random numbers,* $f_{i,count}$ → *the crow i flight length to denote crow j memory.*

End for

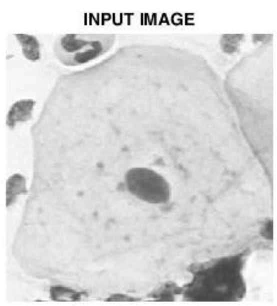
a) *Check the boundary solutions*
b) *Calculate the fitness value for each crow*
c) *Update crow's memory using*

$$m_{i,count+1} = \begin{cases} x_{i,count+1} \\ , f(x_{i,count+1}) \leq f(m_{i,count}) \\ m_{i,count}, \quad otherwise \end{cases}$$

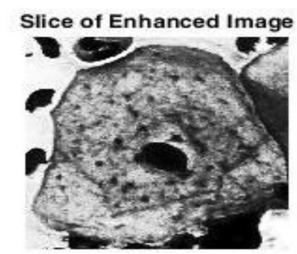
End while.

6. *Optimal weights for the output matrix of the hidden layer H of ELM is obtained.*
7. *Calculate the output weight using the equation (12)*
8. *Pap smear cancer is classified and accuracy is calculated.*

3. OUTCOMES AND DISCLOSURE

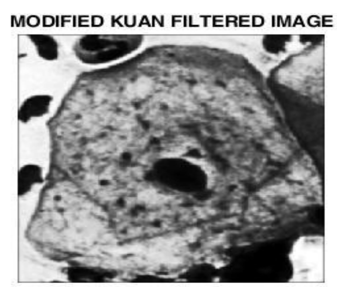


Input Image

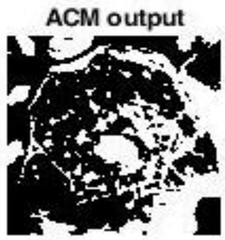


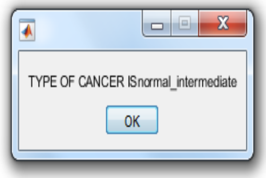
Filtered Image

Kaun Filter Image



Upgraded Kaun Filter





Detection of Type of Cancer

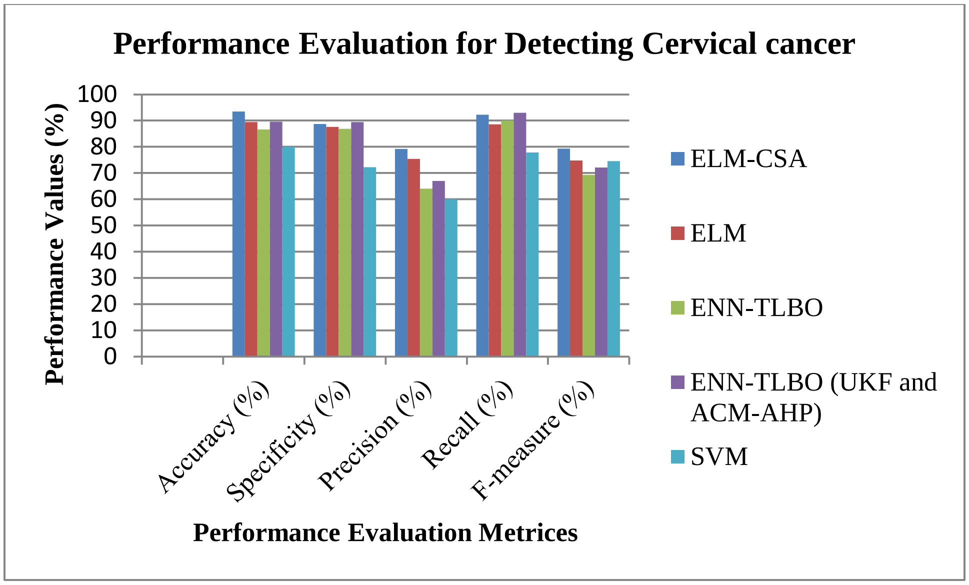
Segmented Image Using ACM-AHP

Figure 2 UKF and ACM-AHP results of Input Pap smear Image

Figure 2 shows the UKF and ACM-AHP results of Input Pap smear Image. Table 2 gives the ELM-CSA cervical cancer cells classification when modification is applied in Kaun Filtering and ACM with AHP. It illustrates that the predicted ELM-CSA with UKF and ACM-AHP has attained the better performance with 93.5 % accuracy, 88.7 % of specificity, 79.21% of precision, 92.25% of recall and 79.26% of f-measure than ELM, ENN-TLBO, ENN-TLBO (UKF and ACM-AHP) [] and SVM [7] and [10]

Table 2: Numerical Evaluation of Cervix cancer detection

Performance Metrics	**ELM-CSA**	**ELM**	**ENN-TLBO**	**ENN-TLBO (UKF and ACM-AHP)**	**SVM**
Accuracy (%)	93.5	89.5	86.67	89.6	80
Specificity (%)	88.7	87.62	86.83	89.41	72.24
Precision (%)	79.21	75.4	64	67	60
Recall (%)	92.25	88.6	90	93	77.8
F-measure (%)	79.26	74.81	69.33	72.11	74.5



4. CONCLUSION:

Here, an Upgraded Kaun-Filter (UKF) is utilized for reducing the commotion without eliminating the edges. The output produced by this filtering is upgraded for calculating the effectual partition of the segmentation. ACM is utilized for portioning the malignant growth part. So as to limit the nearby energy in the ACM, the weights have been enhanced by meta-heuristic optimization method called AHP is utilized. Therefore, better outcomes have been accomplished by sectioning the specific area from filtering image. Highlights are removed from the portioned picture and ELM is exploited for classifying the cervical cancer. CSA technique has been utilized for resolving the weight parameter issue in the ELM. The result of the proposed ELM-CSA classification has become high exactness of 93.5% than existing classifiers such as ELM, ENN-TLBO, ENN-TLBO (UKF and ACM-AHP) and SVM. In future, a large number of datasets will be used for finding the accuracy and also novel algorithms will be utilized for classifying the cervical cancer within less time constraint.

References

1. Soumya M. K, Sneha K and Arunvinodh C, 'Cervical Cancer Detection and Classification using Texture Analysis ', Biomed Pharmacol J 2016; 9(2).
2. Robbins CSC, Pang C, Leask J. Australian newspaper coverage of human papillomavirus vaccination, October 2006–December 2009. J Health Commun. 2011;17:149–59
3. G. N. Papanicolaou, "A new procedure for staining vaginal smears," Science, vol. 95, no. 2469, pp. 438-439, 1942.
4. Mithlesh Arya, Namita Mittal, Girdhari Singh,' Cervical Cancer Detection Using Segmentation on Pap smear Images', ICIA-16, August25-26,2016,Pondicherry,India ©2016ACM.ISBN978-1-4503-4756-3/16/08.

5. Vincent L, Soille P: Watersheds in digital spaces: An efficient algorithm based on immersion simulations. IEEE Transactions on Pattern Analysis and Machine Intelligence 1991,13(6):583–598. 10.1109/34.87344
6. T. Chankong, N. Theera-Umpon, and S. Auephanwiriyakul, "Automatic cervical cell segmentation and classification in Pap smears," Computer methods and programs in biomedicine, vol. 113, no. 2, pp. 539-556, 2014
7. William W, Ware A, Basaza-Ejiri AH, Obungoloch J. A review of image analysis and machine learning techniques for automated cervical cancer screening from Pap smear images. Comput Methods Progr Biomed 2018;164:15–22. https://doi.org/10. 1016/J.CMPB.2018.05.034.
8. Abdelazim G. Hussien, Mohamed Amin, Mingjing Wang, Guoxi Liang, Ahmed Alsanad, Abdu Gumaei and Huiling Chen,' Crow Search Algorithm: Theory, Recent Advances, and Applications' IEEE Transactions and Journals, Vol. 4, 2016
9. Shifei Ding • Xinzheng Xu • Ru Nie,' Extreme learning machine and its applications ', Neural Comput & Applic (2014) 25:549–556, DOI 10.1007/s00521-013-1522-8.
10. Xue Y, Chen S, Qin J, Liu Y, Huang B, Chen H. Application of deep learning in automated analysis of molecular images in cancer: a survey. Contrast Media Mol Imaging 2017. https://doi.org/10.1155/2017/9512370.
11. Geetha, S.Suganya,' Automatic Detection of Cervical Cancer Using UKF and ACM-AHP ',International Journal of Advanced Research in Engineering and Technology (IJARET),Volume 11, Issue 8, August 2020, pp. 285-295
12. Tareef A, Song Y, Huang H, Wang Y, Feng D, Chen M, Cai W. Optimizing the cervix cytological examination based on deep learning and dynamic shape modeling. Neurocomputing 2017. https://doi.org/10.1016/j.neucom.2017.01.093.
13. Geetha, S.Suganya , Enhancing the Classification of Pap Smear Images using ENN – TLBO classification Method, International Journal of Innovative Technology and Exploring Engineering (IJITEE), ISSN: 2278-3075, Volume-9 Issue-6, April 2020
14. Chen YF, Huang PC, Lin KC, Lin HH, Wang LE, Cheng CC, Chen TP, Chan YK, Chiang JY. Semi-automatic segmentation and classification of pap smear cells. IEEE J Biomed Health Inf 2014;18. https://doi.org/10.1109/JBHI.2013.2250984.
15. Sukumar P, Gnanamurthy RK. Computer aided detection of cervical cancer using Pap smear images based on adaptive neuro fuzzy inference system classifier. J Med Image Health Inf 2016. https://doi.org/10.1166/jmihi.2016.1690.
16. Dewi YN, Riana D, Mantoro T. Improving Naive Bayes performance in single image Pap smear using weighted principal component analysis (WPCA). 3rd int. Conf. Comput. Eng. Des. ICCED 2017 2018. https://doi.org/10.1109/CED.2017. 8308130.
17. Sun G, Li S, Cao Y, Lang F. Cervical cancer diagnosis based on random forest. Int J Perform Eng 2017. https://doi.org/10.23940/ijpe.17.04.p12.446457
18. Becker RL. Applications of neural networks in histopathology. 1995. Pathologica.
19. Martin E, Jantzen J. Pap-smear classification Master's Thesis Tech Univ. Denmark Oersted- DTU.; 2003.