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Cervical Cancer Detection Using Gabor Featured Convolutional Neural Networks

Abstract: Cervical cancer is identified as the most killing disease in women patients from past two decades. Even though various medical treatments are available at present, its death rate is not reduced. Hence, various computational and automated methods are proposed to improve the medical treatments as early as possible at an earlier stage. From the past decades, machine and deep learning methods are used for detecting the cervical cancer images. The deep learning algorithms provide superior results for the cervical cancer detection system. Therefore, Gabor Featured Convolutional Neural Networks (GFCNN) is proposed to detect the cancer regions in cervical images. It proposes Cervical Cancer Detection System (CCDS) is significantly analyzed by applying the methodologies on the cervical images which are available in Guanacaste Dataset. The proposed CCDS is constructed with the following modules Gabor transforms, Feature computations, Classification and Segmentation. The Gabor transform transforms the pixel coordinates and then intrinsic variation features are determined. These features are classified by the GFCNN classifier. The GFCNN method is tested on the set of cervical images in Guanacaste Dataset and its performance is analyzed with respect to precision, recall and cancer accuracy rate. The proposed CCDs method achieved 98.42% of PN, 98.54% of RL and 98.45% of AY. The results of GFCNN method for cervical cancer detection and segmentation system are compared with other state-of-the-art methods.

Keywords: *compared, GFCNN, analyzed, segmentation, methodologies*

I. Introduction

Cancer is the abnormal growth of cells in human body due to various genetic disorders and life style changes in patients. The cancer is affected in patient irrespective of the sex. Most affected cancer type in women patient is cervical cancer which originates from the cervix region of the human body and spreads deeply to other nearby regions. The severity levels of this cervical cancer have four stages [1-3]. The cervical cancer is exhibited by its initial symptoms as abdomen pain and vomiting and blood in urinal region. If the patient is initially identified through these symptoms in human body, their survival rate will be improved by various modern and advanced treatments. As per World Health Organization (WHO) survey on cervical cancer throughout the world, it is identified that the cervical cancer is fourth type of crucial cancer in women patients around the world. In 2020, approximately 6,00,000 of women patents were affected by cervical cancer around the world and it is expected to increase 10, 00,000 in the year of 2030. Every year, the death count due to this cervical cancer around the world is approximately 3,00,000. The screening of cervical cancer in women patient may have several levels based on the treatment procedure. The screening methodologies of cervical cancer are HPV, Pap smear testing, colposcopy and biopsy [4]. Mostly Pap smear testing and biopsy testing are now a day used in the world to screen the cervical cancer. In case of Pap smear cell testing method, a small thin and light rod is inserted into the region of the cervix of the women patient and the cells in this cervix area are collected. Most of the clinical evaluation process for cervical cancer detection uses Pap smear testing and the Cervigram analysis methods. Both cervical cancer identification methodologies used image processing techniques to locate the abnormal regions in these captured images. For these experimental process or test, the higher end Charge Coupled Camera (CCD) is presently used by the clinicians to acquire the images in both Pap smear testing and Cervigram. In the Pap smear cell test based cervical cancer detection framework, the entire cell image has not been used. Instead, their nucleolus is only used by the clinicians to detect the cervical cancer. It used various logical based pixel segmentation algorithms to segment the pixels being the abnormal category.

By analyzing their nucleolus of all the obtained Pap smear cells, the cancer is diagnosed in this method. In case of biopsy method, the cervical regions are captured through the certain high resolution tiny camera and it is analyzed through various image processing techniques [5].The colposcopy is otherwise called as Cervigram which required high powered tiny camera units to capture the opening of the vegina region of the women patient. In case of colposcopy, magnifier with strong electric field is used to magnify or enlarge the cells in the

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region of the cervix and they are analyzed or diagnosed.The acquired cervigram regions have been examined by various abnormal pixel detection algorithms such as probability based approach and kernel based approach. Eventhough these pixel detection algorithms are highly powerful technique to detect the cancer in cervical images, the processing cost of this method is high. In oredr to overcome such limitations in the existing study of the cervigram method, the deep learning approaches have been proposed here to detect the pixels regarding with cancer region. There are two treatements available at present as radiotheraphy or surgery. In radiotheraphy based method, a light density radiation is passed in the regions of cancer and these cells are discarded by applying the radiation. Another method surgery removes the cancer affected portion in the cervical regions. Both methods used accurate image processing methods to detect the cancer affected regions.

Fig. 1 shows the cervical image with cancer regions.

Fig. 1.Cervical image with cancer regions

The article is explained with various sections, section 2 elaborates the various existing methods for cervical cancer , section 3 proposes a deep learning model based cervical cancer detection system, section 4 states the results obtained by the proposed method and section 5 concludes this research work.

II. Literature survey

Nur Ain Alias et al. (2023) reviewed many literatures for segmenting the nucleus region using deep learning algorithms. The comparisons between these studies based on the Pap smear cell images were detailed in this work.Shan Fang et al. (2022) developed and proposed Shuffle Net which was initially derived from the existing Convolutional Neural Network (CNN) architecture. The internal layers count and its hardware utilization elements were significantly reduced in this proposed Shuffle Net. The cervical images were enhanced based on the pixel intensity using enhancement algorithm and this enhanced cervical image was classified by the proposed Shuffle Net classification module in this work. The authors attained 95.32% of PN, 94.98% of RL and 94.68% of AY on the cervical images.Li et al. (2022) implemented cervical cancerous pre stage detection system with the aid of the vision transformer. The authors fused the input cervical image data after extracting the features value from the source cervical image. This method was tested by three set of cervical image dataset. The first cervical image dataset obtained 96.1% of detection accuracy and the second cervical image dataset obtained 95.3% of detection accuracy and the third cervical image dataset obtained 94.9% of detection accuracy. All these three dataset experimental results were cross validated by different fusion algorithms in this work. Wan Azani Mustafa et al. (2022) detected the abnormal cancer regions in cervical images using the artificial machine learning algorithm. The segmented regions belonging to abnormal pixels were classified more accuretely with the other regions of pixels. Nur Ain Alias et al. (2022) enhanced their internal region of pixels which are belonging to abnormal category uisng pixel enrichement algorithm. The false positives and negatives were significantly reduced by this enhancement algorithm.Viñals et al. (2021) screened the precancerous cervical images using dynamic feature classification algorithm. The authors applied their proposed dynamic featuring classification algorithm on two set of cervical images. The first sets of cervical images were tested randomly by the proposed feature dynamic algorithm and the second sets of cervical images were tested by cross validation algorithm in this work. The authors attained 94.75% of PN, 94.79% of RL and 94.01% of AYon the cervical images.

Yusufaly et al. (2020) developed and constructed an effective treatment tool for identifying or predicting the cervical cancer in women patient. The authors used knowledge based identification method for identifying or locating the cancer affected patients using various soft computing algorithms. The experimental results of these knowledge based cervical cancer detection methods were analyzed with respect to various computational parameters in this work. Hua et al. (2020) extracted and computed multilevel features from the healthy case cervical image dataset and the cancer case cervical images dataset. The authors used these computed multilevel set of variant features for the input of the classifier in order to produce the classification results. This method was tested by three set of cervical image dataset. The first cervical image dataset obtained 90.5% of detection accuracy and the second cervical image dataset obtained 91.9% of detection accuracy and the third cervical image dataset obtained 93.4% of detection accuracy. All these three dataset experimental results were cross validated by different k-fold combination algorithms in this work. Hu et al. (2019) proposed cervical precancerous detection methodology or framework using observational deep learning algorithm and automated evaluation algorithm. Both algorithms were proposed for the segmentation of precancerous regions. The algorithms were evaluated based on their pixel properties and they were performance evaluated by various fold evaluation metrics in this paper. The authors attained 94.28% of PN, 93.15% of RL and 93.28% of AY on the cervical images. Stübs et al. (2018) detected cervical cancer at an earlier stage using biopsy testing method. This method was entirely based on the linear featuring method which was tested on the real time clinical dataset cervical images. The limitation of this method with other existing methods was also analyzed.

Problem statement

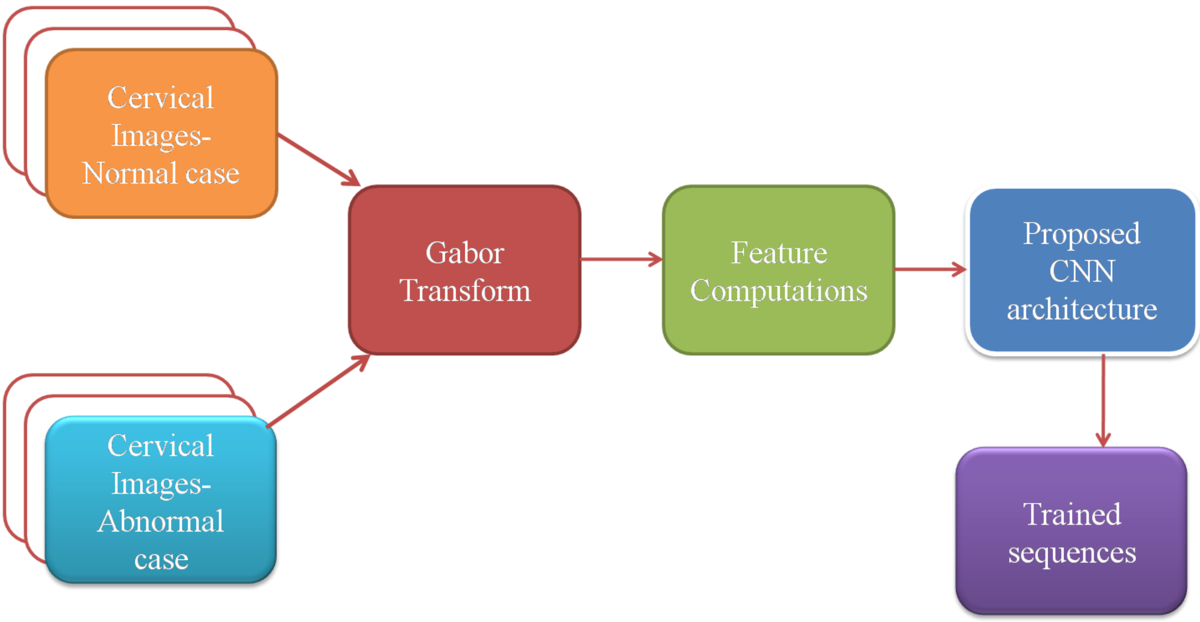
The problems are identified by analyzing the existing methodologies and techniuqes for cervical cancer detection process. Based on these methods, the problem statement is determined and stated below.

Though many existing methods available for cervical cancer detection process, the level of cancer segmentation accuracy and its classification accuracy is not optimum for further diagnosis process. Moreover, the existing methods were used for classifying the higher resolution cervical images and they were not tested with low resolution cervical images. Therefore, GFCNN method is proposed for overcoming the issues in existing methods.

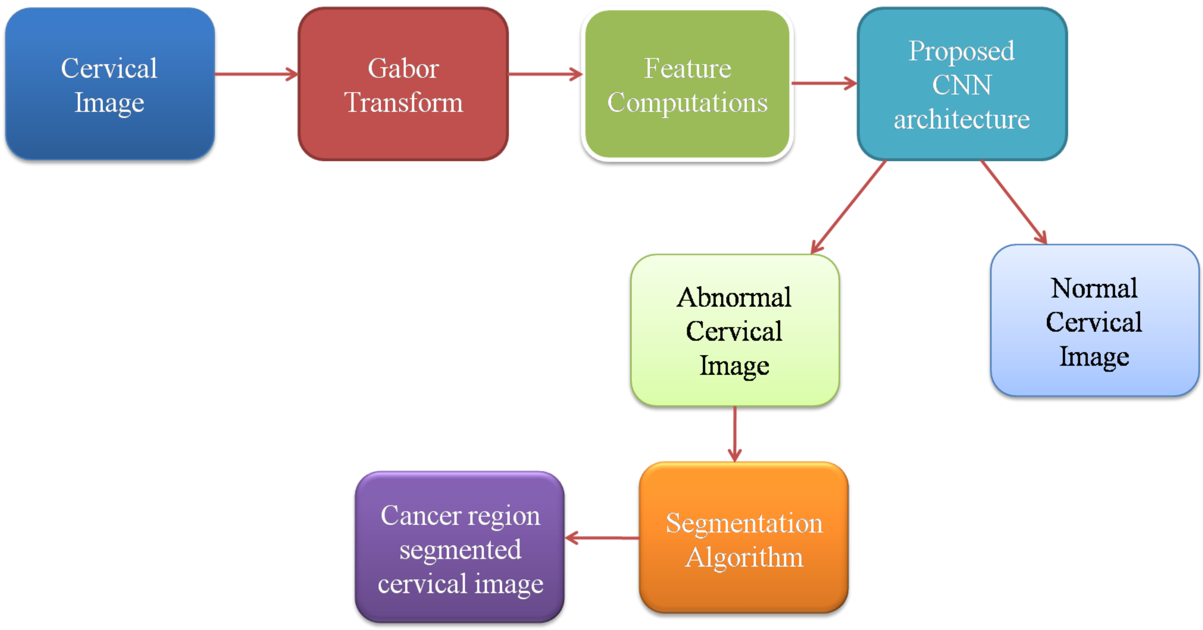
III. Proposed Methodologies

This work proposes Cervical Cancer Detection System (CCDS) is significantly analyzed by applying the methodologies on the cervical images which are available in Guanacaste Dataset.This proposed CCDS is constructed with the following modules.

- Gabor transform;
- Feature computations;
- Classification;
- Segmentation;



(a)



(b)

Fig. 2.(a) CCDS-training mode (b) CCDS-testing mode

3.1 Gabor transform

The transform plays an essential role for decomposing the source image in order to produce significant number of sub band images or coefficients. Most of the conventional transforms such as Discrete Wavelet Transform (DWT), Non-Sub sampled Contourlet Transform (NSCT) decomposed the source image into set of sub band coefficients and they have reverse functionality to reconstruct the original image after processing with the decomposed coefficients. These conventional transforms exhibits or produces significant errors or losses during the decomposition of the source image. This is main limitation of these kinds of conventional transforms. This limitation is overcome by using Gabor transform in this paper. This transform do not decompose the source image. Instead, it performs the conversion process of each pixel in the source cervical image into multi orientation pixel format. During the transformation process of all the pixels in the source cervical image, the losses or errors produced is very less when comparing with other similar transforms. Moreover, the Gabor transform is basically derived from the Fourier Transform (FT). This FT transforms all the pixels in source cervical image into frequency where the spatial properties of the pixel are absent. Hence, the coordination property is unstable between the spatial and frequency. Therefore, the stabilization is required between the spatial and frequency for each pixel in transformed cervical image. So that, any feature will not be loss. By considering these properties, the Gabor transform is derived from the FT and it provides complete stability between spatial and frequency for each pixel in the transformed cervical image.

Fig.3. is the Gabor interfacing with the cervical image, where the input of this module is cervical image and the output from this module is Gabor image.

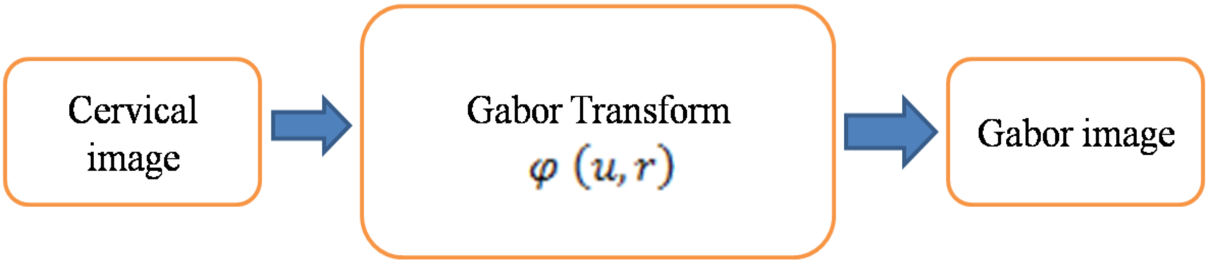


Fig.3. Gabor interfacing with the cervical image

In this paper, two dimensional Gabor transform is used based on their two dimensional kernel as illustrated in the following equation.

$$\varphi\ (u,r) = \exp(-\pi^2(\frac{\gamma^2}{f^2}(u_r - f)^2 + \frac{\rho^2}{f^2}v_r) \quad (1)$$

Where, u_r and v_r are the polar coordinates and they are depicted in the following equations.

$$u_r = u\ cos\theta + v\ sin\theta \tag{2}$$

$$v_r = -u\ sin\theta + v\ cos\theta \tag{3}$$

Where, θ is the orientation of each pixel which varies between 0 degree and 360 degree with respect to the tuning parameters γ and ρ and the tuning frequency f.

This two dimensional Gabor kernel is multiplied with the source cervical image using linear Convolution principle which significantly produces the multi orientation cervical image.

3.2 Feature Extraction

It is the process of reducing the redundant data from the image and it helps to transform the raw value of each pixel into numerical values which are used to identify the specific property of the pixel in the image. The feature computation is necessary for extracting the specific property of each individual pixel in cervical image which helps to differentiate the two images which are belonging to both normal and cancer cervical image. Hence, its process is important for the further classification work. Further, GLCM and binary index features are used which are derived from the Gabor image and they are explained below.

3.2.1 Grey Level Co-occurence Matrix (GLCM)

This co-occurrence feature correlates each pixel property in Gabor cervical image and its surrounding pixel property. The texture pattern of the pixel is used to differentiate the other pixels with the center pixel in an image. This feature computation is based on the phase of each pixel which is to be extracted features from the Gabor cervical image. The features belonging to 45 degree and the features belonging to 90 degree of each pixel in cervical Gabor image are extracted and the matrix is constructed based on this degree of orientation of pixels. The following mathematical equations help to compute the GLCM features from the Gabor cervical image.

$$Row\ Mean\ (RM) = \mu_i = \sum_{i,j=0}^{M-1} i * p(i,j) \tag{4}$$

Whereas, each index value of the GLCM matrix is denoted by $p(i,j)$ and M is the number of rows. The GLCM matrix is constructed with equals row and column.

$$Column\ Mean\ (CM) = \mu_i = \sum_{i,j=0}^{M-1} j * p(i,j) \tag{5}$$

$$Row\ Variance\ (RV) = {\sigma_i}^2 = \sum_{i,j=0}^{M-1} p(i,j) * (i - \mu_i)^2 \tag{6}$$

$$Column\ Variance\ (CV) = {\sigma_j}^2 = \sum_{i,j=0}^{M-1} p(i,j) * (j - \mu_j)^2 \tag{7}$$

$$Energy = \sum_{i,j=0}^{M-1} p(i,j)^2 \tag{8}$$

$$Dissimilarity = \sum_{i,j=0}^{M-1} p(i,j) * |i - j| \tag{9}$$

$$Contrast = \sum_{i,j=0}^{M-1} p(i,j) * (i - j)^2 \tag{10}$$

3.2.2 Binary features

The binary feature derives the feature property for each pixel in the cervical Gabor image. It is otherwise called as Local Binary Features (LBF). The number of feature property derived by binary features is equals to the number of pixels in the cervical Gabor image. In this feature extraction procedure, the 3*3 odd numbered sub window is placed on the first position center in the cervical Gabor image. The index binary value of the center pixel is compared with the other index values in the same sub window. The following equation is used to compute the binary feature of each pixel value in the cervical Gabor image.

$$Binary\ feature\ (pc) = \sum_{i=1}^{I-1} 2^i * F(pc - p_i) \tag{11}$$

Whereas, I is the total number of surrounding values in sub window and pc is the center pixel value and p_i is the surrounding pixel value.

The functionality of binary feature is computed using the following equation.

$$F\ (pc) = \begin{cases} 1;\ if\ pc > p_i \\ \quad 0;\ else \end{cases} \tag{12}$$

Finally, the feature matrix is computed by integrating the GLCM features and LBF and this final matrix is given to the classification module.

Classifications

The main work proposes a novel CNN architecture which is depicted in Fig.3, which is the extension of the AlexNet conventional CNN architecture. This classification module produces the results of the classification process based on the internally generated features by each internal layers of the proposed CNN architecture [16-19]. The five Convolutional layers and five pooling layers are used to generate the internal features from the externally generated feature set. The specifications in terms of the number of filters used and its size are clearly depicted in Table 1.The externally generated features are fed into Con_Layer1 which performs th convolution process and its output is fed into two layers Con_layer 3 and P_layer1. Here, P_layer is used to reduce the input feature size using Max-pooling algorithm. This max-pool algorithm uses 2*2 sub window mask to suppress the input data based on the window size. This layer output is sent to Con_layer2 and its output is fed into P_layer2. The output of Con_layer3 is fed into P_layer3 for data suppression process and to Con_layer4. The output of P_layer4 and P_layer5 are merged along with the output of P_layer2 and the merged data is named as Internal Feature Integrator (IFI) [20]. This IFI is further fed into dense layers to produce the output as either normal or abnormal, as illustrated in Fig.3.

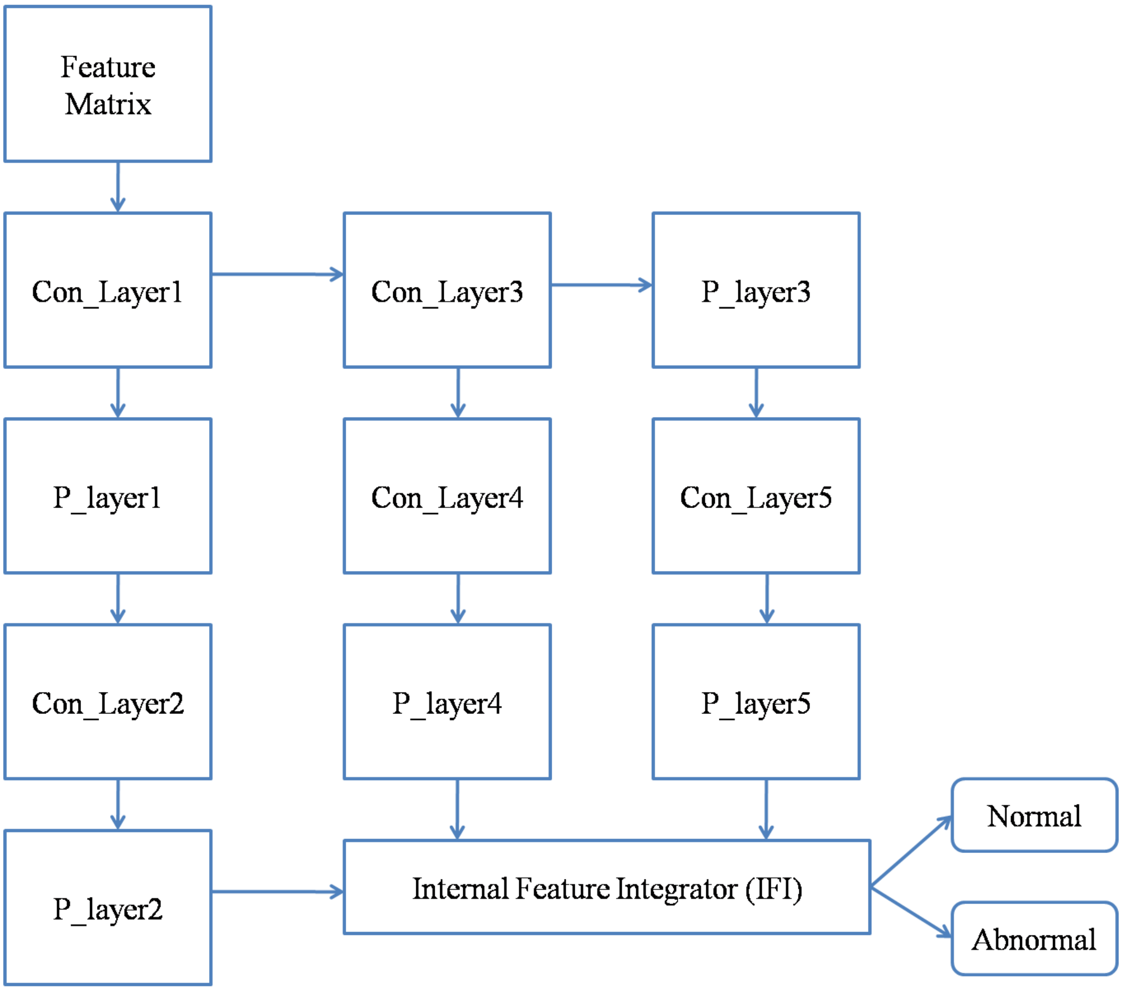


Fig. 3 Proposed CNN for CCDS

Table 1 CNN specifications

Layer name	Layer specifications
Con_layer1	32 filters by 3*3
Con_layer2	64 filters by 7*7
Con_layer3	512 filters by 5*5
Con_layer4	1024 filters by 7*7
Con_layer5	512 filters by 5*5
P_layer1	Max-pooling by 2*2
P_layer2	Max-pooling by 2*2
P_layer3	Max-pooling by 2*2
P_layer4	Max-pooling by 2*2
P_layer5	Max-pooling by 2*2

From the classified abnormal cervical image, the cancer regions are segmented using morphological processing algorithm [13-14].

IV. RESULTS AND DISCUSSIONS

The proposed Cervical Cancer Detection System (CCDS) is significantly analyzed by applying the methodologies on the cervical images which are available in Guanacaste Dataset. This dataset is chosen for the following reasons.

- It contains high number of cervical images and all are annotated with experts.
- It has both low contrast and high contrast cervigram images.
- The accuracy and prediction results of the previous methods which used same set of cervical images are available in this dataset.
- License free utilization and reproductiability of the images from this dataset.

This dataset was initially constructed in the year of 1993 and updated by every year with new set of cervical images in order to make this dataset active. This dataset was maintained technically by the Guanacaste organization. The total 1045 cervigram images are available in this dataset and these images are accessible by various research community groups based on request only and the images in this dataset was not strictly used by any commercial purposes. In this dataset, there are 850 cervigram images which are belonging to normal category and 195 cervigram images which are belonging to abnormal category. The MATLAB 2021 version simulation software has been used for simulating the proposed CCDS methodology. The harware and softwares used for experiemental setup is illustarted in Table 2.

Table 2 Experimental setup

Source or Equipement name	Requirements
Hadware	Intel core i7 processor
	16 GB RAM memory unit
	1 TB SSD drive
	Optical keyboard and mouse
Software	MATLAB
	2021 version

The performance of CCDS methodology has been significantly analyzed using the parameter Normal Detection Rate (NDR) and the Abnormal Detection Rate (ADR). The NDR is defined as the ratio between the detected normal image count and the total normal images in this dataset and it is measured by percentage. Hence, the value of NDR is lie between 0 and 100. The NDR value below 70% is considered as there is no proper training of the images from the dataset. The NDR value greater than 90% is considered as there is a proper training of the images in the dataset. It is also stated by the following equation.

$$NDR = \frac{\text{Detected normal image count}}{\text{Total normal images}} * 100\% \quad (13)$$

The ADR is defined as the ratio between the detected abnormal image count and the total abnormal images in this dataset and it is measured by percentage. Hence, the value of ADR is lie between 0 and 100. The NDR value below 70% is considered as there is no proper training of the images from the dataset for the category of abnormal. The NDR value greater than 90% is considered as there is a proper training of the images in the dataset for the category of abnormal. It is also stated by the following equation.

$$ADR = \frac{\text{Detected abnormal image count}}{\text{Total abnormal images}} * 100\% \quad (14)$$

Table 2 is the estimation of detection rate value of the proposed CCDS.

The proposed CCDS method achieved 99% of NDR by detecting 842 normal images over 850 normal images. The proposed CCDS method achieved 99% of ADR by detecting 190 abnormal images over 195 abnormal images. Therefore, the Average Detection Rate (AVDR) is the average value between the obtained NDR and ADR in percentage, as illustrated in Table 2.

Table 2 Estimation of detection rate value of the proposed CCDS

Parameters	Values
Total cervical images	1045
Cervical images belonging to normal category	850
Cervical images belonging to abnormal category	195
Detected normal images count	842
Detected abnormal images count	190
NDR	99%
ADR	97.4%
Average Detection Rate (AVDR)	98.2%

Further, the proposed CCDS method is evaluated and compared significantly against various existing deep learning algorithms in terms of AVDR in percentage. The proposed CCDS achieved 98.2% of AVDR, where as Inception CNN achieved 95.1% of AVDR, Google Net CNN achieved 94.8% of AVDR, REsNET CNN achieved 94.8% of AVDR and GAN achieved 97.7% of AVDR, as illustrated in Fig. 4.

Fig. 4 is the pictorial view of performance comparison of CCDS based on deep learning algorithms.

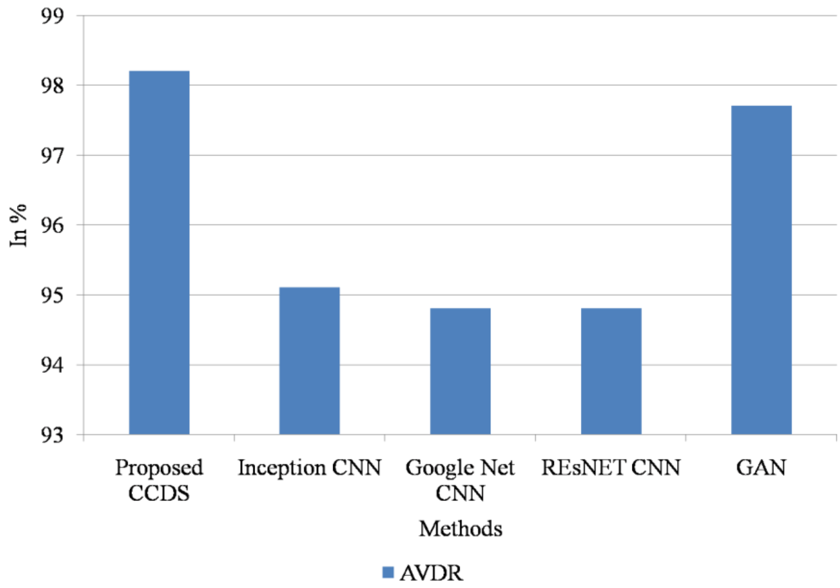


Fig. 4 Pictorial view of performance comparison of CCDS based on deep learning algorithms

Further, the proposed CCDS method is evaluated and compared significantly against various existing machine learning algorithms in terms of AVDR in percentage. The proposed CCDS achieved 98.2% of AVDR, where asAdaboost classifier achieved 93.1% of AVDR, Random Forest classifier achieved 93.7% of AVDR, K-Nearest Neighbour (KNN) Classifier achieved 92.8% of AVDR and Adaptive Neuro Fuzzy Inference System (ANFIS) classifier achieved 94.5% of AVDR, as illustrated in Fig.5.

Fig. 5 is the pictorial view of performance comparison of CCDS based on machine learning algorithms.

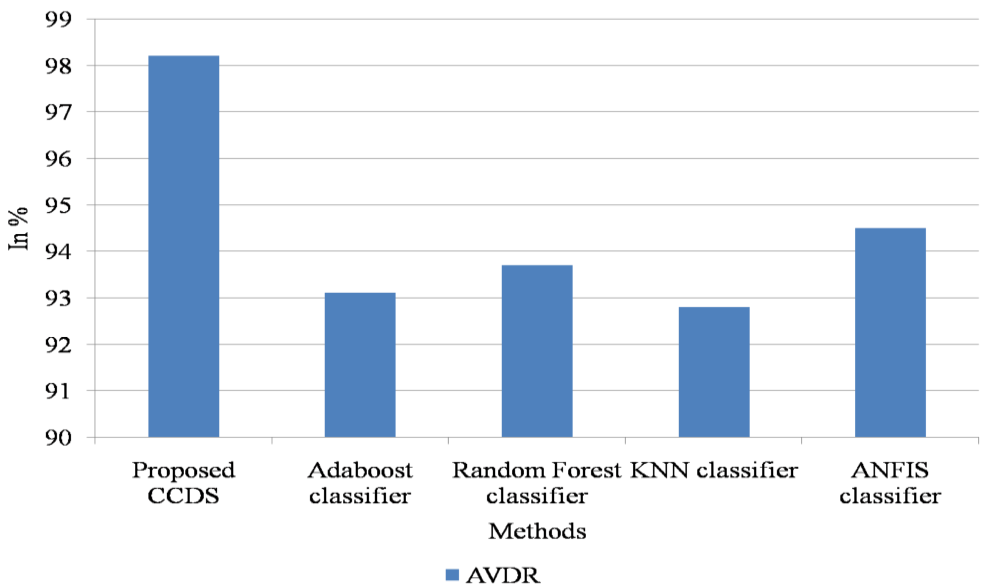


Fig. 5 Pictorial view of performance comparison of CCDS based on machine learning algorithms

Moreover, in conjunction with the previous performance metrics, the proposed CCDS method is further significantly analyzed by the following equations.

$$Precision(PN) = \frac{TP}{TP+FP} * 100\% \quad (15)$$

$$Recall\ (RL) = \frac{TP}{TP+FN} * 100\% \tag{16}$$

$$Accuracy\ (AY) = \frac{TP+TN}{TP+TN+FP+FN} * 100\% \tag{17}$$

Whereas, TP and TN are belonging to pixel being correctly identified as cancer and FP and FN are belonging to pixel incorrectly identified as cancer.

These performance metrics are chosen in this paper that they are reconfigured and interfaced with the true and false positive and negative pixels in the final image. Moreover, these are the key factors to compatre the efficacy of the proposed method with other state of the art methods.

Fig.6 is the performance metrics for the proposed CCDS methodology with respect to PN, RL and AY on open access cervigram images. The proposed CCDs method achieved 98.42% of PN, 98.54% of RL and 98.45% of AY.

Fig. 6 is the pictorial performance metrics analysis or the proposed CCDS methodology.

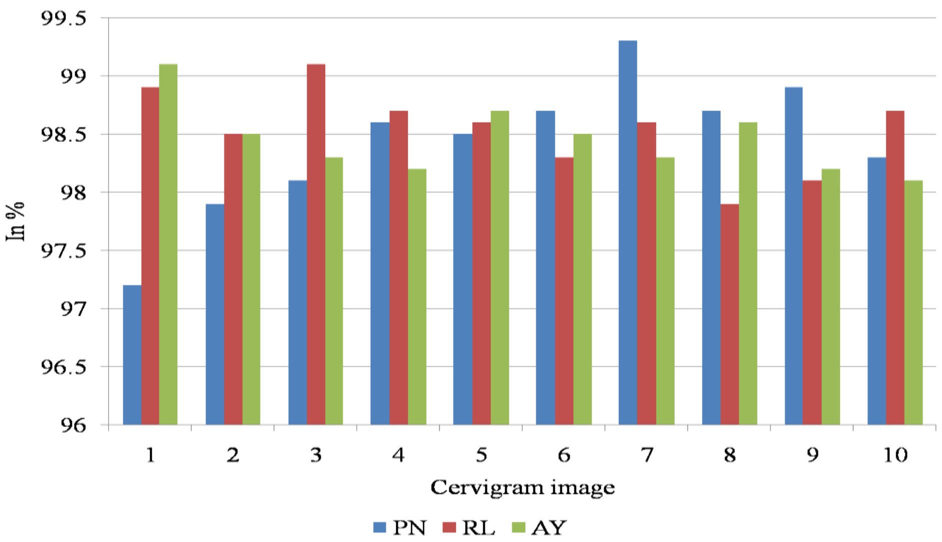


Fig. 6 Pictorial performance metrics analysis or the proposed CCDS methodology

Fig.7 is the comparison analysis of CCDS methodology with other methods Shan Fang et al. (2022), Li et al. (2022), Viñals et al. (2021) and Hu et al. (2019).Shan Fang et al. (2022) attained 95.32% of PN, 94.98% of RL and 94.68% of AY, Li et al. (2022)attained 95.67% of PN, 95.19% of RL and 94.61% of AY, Viñals et al. (2021)attained 94.75% of PN, 94.79% of RL and 94.01% of AY and Hu et al. (2019)attained 94.28% of PN, 93.15% of RL and 93.28% of AY.

Fig. 7 is the pictorial comparison analysis of CCDS methodology with other methods.

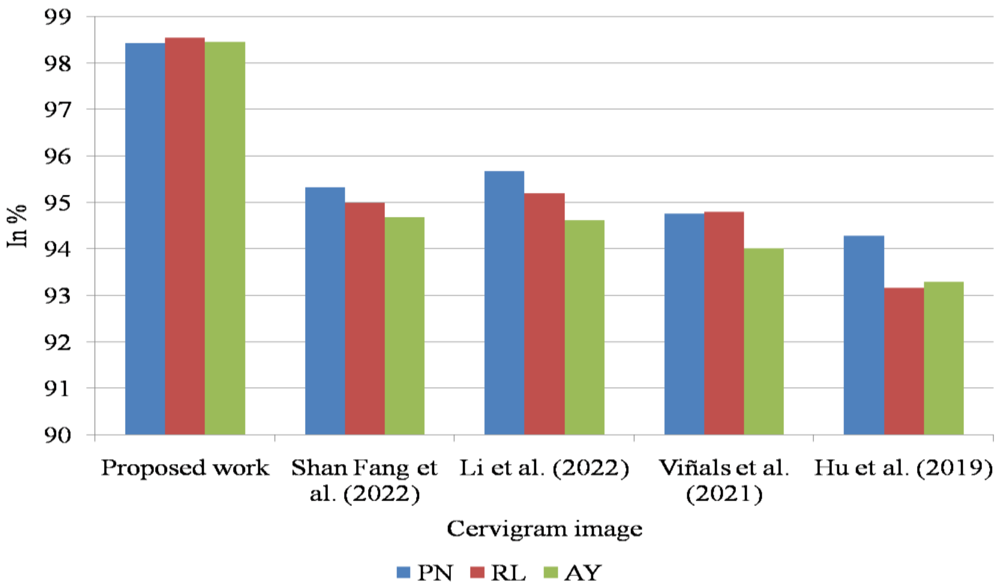


Fig. 7 Pictorial comparison analysis of CCDS methodology with other methods

This proposed work for cervical cancer detection uses K-fold validation algorithm to validate the robustness of the methoologies stated in this research. In addition to the specific, 10 fold validation algorithm has been employed to validate the experiememntal results.

V. Conclusions

An effective CCDS is proposed using GFCNN classification approach for the classifications of cervical images. The methodology consists of Gabor filter with the feature extraction module and the classification module. The Gabor filter and the proposed classification module are integrated to obtain the higher cervical cancer detection or classification rate. To evaluate the un-bias performance of the developed GFCNN module, it is tested on the larger cervical image database in order to validate the proposed system. Hence, this proposed GFCNN method is tested on the set of cervical images in Guanacaste Dataset and its performance is analyzed with respect to precision, recall and cancer accuracy rate. The proposed CCDS method achieved 99% of NDR by detecting 842 normal images over 850 normal images. The proposed CCDS method also achieved 99% of ADR by detecting 190 abnormal images over 195 abnormal images. The proposed CCDs method achieved 98.42% of PN, 98.54% of RL and 98.45% of AY. The experimental results of this proposed GFCNN system is significantly compared with respect to various conventional cervical cancer detection system. The main relevance and suitability of this proposed method stated in this research work are that the developed methods for cervical cancer detection are suitable for both low and high contrast images. Moreover, the proposed methods are helpful to the physcians or radiologist to detect the cervical cancer in women patient with out any complex process or algorithms.

The limitation intends is that it detects the cancer cervical images only and not able to further evaluate the severity stages such as mild stage, Intermediate stage and final stage. Hence, the future direction of this research work is to extend this method to diagnose the cervical cancer into these three stages.

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