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Segmentation Of Cervical Cancer Lesions: A Comparative Analysis Of Image Processing Algorithms

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Abstract

The most prevalent type of cancer in women worldwide is uterine cervical cancer. The majority of cervical cancer (CC) cases can be avoided by participating in screening programmes that look for precancerous lesions. Colposcopic cervigrams or images from digital colposcopy have been acquired in raw form. This study presents a novel framework that combines image enhancement, pre-processing, and image segmentation to identify cervical cancer. Three phases make up this framework: the Dual Tree Discrete Wavelet Transform (DTDWT) for pre-processing, the Curvelet transform and Contour Transform (CC) for image improvement, and the K-means clustering for segmentation.

Keywords: Image Processing, Cervical cancer, Dual-Tree Discrete Wavelet Transform (DTDWT), Curvelet Transform, Contour Transform, K-Means clustering.

1. Introduction

The lower uterus's linear section is called the cervix. That is why the uterus' neck has been described. According to the cancer community in the USA, there are 12,800 new cases of cervical cancer (CC), which result in 4000 fatalities each year, making it the leading cause of death for women [1]. Most documented examples of CC involve people under the age of 50. The unchecked growth of the cervical cells leads to CC. Each cell has a specific lifespan. While they are dying, fresh cells are produced. Cancer cells, on the other hand, continue to grow and divide. Cancer is the result of this ceaseless division. Some factors, including smoking, a weakened immune system, and the Human Papillomavirus (HPV) virus, reduce the risk of cancer. There are more than 100 human papillomaviruses, of which 85 are benign and just 15 cause cancer in humans. The valuable screening test pap smear test, which was defined as cancer if found at an early stage can be controlled successfully [2], has resulted in a decrease in the number of reported cases of CC during the past 20 years. As doctors advise that the pap smear test and human papillomavirus test be done at the same time, women who are now aware of cancer usually undergo this procedure.

Cervical screening not only detects cancer but also keeps an eye out for cell abnormalities, such as enlargement of the nucleus. Unnatural cells can turn into cancerous cells if they are not treated properly. The pap smear tests are not always accurate due to human error and a lack of time to receive the results. As a result, a quick, precise, and simple electrical method must be developed to reveal atypical cells.

2. Related Works

Table 1 gives the related work done on the detection of cervical cancer by using Image Processing techniques.

Table 1: Related work on the detection of cervical cancer by Image Processing techniques

Author name	Description	Methods used
Xu, Tao, et al [3]	For the purpose of testing image-based cervical disease classification algorithms, this paper offered a brand-new picture dataset coupled with expert-annotated diagnoses.	Histogram of Local Binary Pattern, Convolutional Neural Network
Taneja, Arti, Priya Ranjan, and Amit Ujlayan [4]	In order to improve the prediction of the abnormality level, this article improves single-cell segmentation performance using integrated geometrical feature vectors and Gray Level Co-occurrence Matrix (GLCM) (area, cell size, cell intensity, and maximum intensity).	Gray level co-occurrence matrix, Neighborhood-Concentric filtering, Neural network-relevance vector Machine
Selvathi, D., W. Rehan Sharmila, and P. Shenbaga Sankari [5]	The suggested approach employed the deep learning technique for two levels of classification, then a support vector machine (SVM) to address the overlapping cell concerns.	Deep learning, Support Vector Machine, Convolutional Neural Network (CNN)
Bora, Kangkana, et al [6]	For the purpose of obtaining shape features, a brand-new segmentation method has also been put out in this study. Color and texture features have been analysed using the Ripplet Type I transform, Histogram first order statistics, and Gray Level Co-occurrence Matrix, respectively.	Ripplet Type I transform, Histogram first order statistics and Gray Level Co-occurrence Matrix

Iliyasu, Abdullah M., and Chastine Fatichah [7]	For effective feature selection and classification of cells in cervical smeared (CS) images, a quantum hybrid (QH) intelligent approach is proposed. This approach combines the adaptive search capability of the quantum-behaved particle swarm optimization (QPSO) method with the intuitionistic rationality of the traditional fuzzy k-nearest neighbours (Fuzzy k-NN) algorithm.	quantum machine learning, Fuzzy k-NN, quantum-behaved PSO
Singh, Sanjay Kumar, and Anjali Goyal [8]	This research described a method for segmenting the nuclei of pap smear cells from the uterine cervix utilising watershed segmentation.	Watershed segmentation, Morphological operations, Thresholding
William, Wasswa, et al [9]	The survey examines 15 years' worth of articles on automated cervical cancer diagnosis and classification using pap-smear images using image analysis and machine learning. Using three sets of keywords—segmentation, classification, cervical cancer; medical imaging, machine learning, pap-smear; and automated system, classification, pap-smear—the survey examines 30 journal papers that were electronically obtained from four scientific databases (Google Scholar, Scopus, IEEE, and Science Direct).	K-Nearest-Neighbors, Support Vector Machine
Sornapudi, Sudhir, et al [10]	This study investigates a deep learning (DL)-based nucleus segmentation method that gathers localised data by creating superpixels utilising a straightforward linear iterative clustering algorithm and convolutional neural network training.	convolutional neural network, Deep Learning
Zhao, Lili, et al [11]	This study proposed a multi-instance extreme learning machine-based approach for accurately detecting aberrant cervical cells.	multi-instance extreme learning machine
Manogaran, Gunasekaran, et al [12]	The variation in DNA copy number across the genome is modelled using a Bayesian hidden Markov model (HMM) with a Gaussian Mixture (GM) Clustering method.	Bayesian hidden Markov model, Gaussian mixture clustering

Bhargava, Ashmita, et al [13]	In this study, a strategy for detecting and categorising cancer utilising HOG feature extraction and classification using support vector machines (SVM), k-nearest neighbours (KNN), and artificial neural networks (ANNs) is proposed.	Artificial Neural Network, Support Vector Machine, KNN
Hemalatha, K., and K. Usha Rani [14]	This study proposes an enhanced edge detection method using a fuzzy approach to separate the nucleus and cytoplasm from cervical pap smear images.	Fuzzy Approach, Edge Detection Fuzzy Inference System
Zhao, Lili, et al [15]	This research proposed a novel unsupervised segmentation method for overlapping cervical smear images without the need for training data.	K-Means, Max-flow/min cut algorithm, Voronoi –based dump division

3. Proposed Framework for Detection of Cervical Cancer by using Image Processing

Three crucial stages make up the innovative framework for the image-based detection of cervical cancer. Pre-processing comes first, followed by image enhancement and segmentation, in that order.

- **Stage 1:** Pre-processing: Dual Tree Discrete Wavelet Transform approach
- **Stage 2:** Image Enhancement: Curvelet and Contour Transformation approaches
- **Stage 3:** Segmentation: K-Means clustering method

3.1 Pre-Processing Stage by DT-DWT

The Discrete Wavelet Transform (DWT) features excellent signal energy compression, flawless reconstruction with short support filters, little redundancy, and very little computational overhead. The fuzzy denoising approach known as Dual Tree Discrete Wavelet Transform (DT-DWT) offers shiftable sub-bands, strong directional selectivity, and low redundancy. Two critically-sampled separable 2D DWT can be used in tandem to perform a 2D Dual-Tree Discrete Wavelet Transform (DT-DWT) on an image. The ability to use 2D wavelet transforms that are more selective in terms of orientation makes the Dual-Tree DWT (DT-DWT) superior to separable 2D DWT.

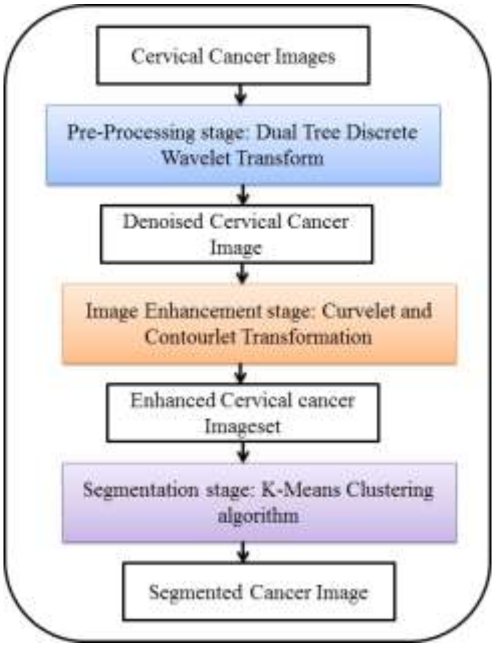

Figure 1: A Novel Framework for Detection of Cervical cancer by using Image Processing

3.2 Image Enhancement Stage

3.2.1 Curvelet Transform

The intriguing phenomena that appear along curved edges in a 2D image are the focus of image enhancing techniques based on curvelet transforms. The Curvelet transform works well for enhancing edges since it is appropriate for images with edges. The scaling rule, or more specifically, the spatial domain related to scale by parabolic curving, is one of the novel aspects of the curvelet transform. It also has a brand-new pyramid.

3.2.2 Contour Transform

The Laplacian Pyramid (LP) and a Directional Filter Bank are combined in the contour transform, which is an extension of the wavelet transform in two dimensions (DFB). A directional filter bank is used to connect point discontinuities into linear structures when the Laplacian pyramid is used to record point discontinuities. An picture is divided into a number of radial subbands using the Laplacian Pyramid (LP), and then each LP detail subband is divided into any power of two's number of directional subbands using Directional Filter Banks (DFB). A quad-tree structure can be used to represent the contour coefficient. A quadtree will form because each coefficient at the coarsest level has four children in the sub band above it, and each of those children also has four children.

3.2 Image Segmentation Stage by K-Means Clustering algorithm

The experimental data are divided into K mutually exclusive clusters using the K-Means clustering algorithm. An algorithm called K-Means clustering is used to categories or group items based on their features or attributes into K number of groups. K is a positive integer in this case. By reducing the sum of squares of distances between the data and the matching cluster centroid, groups are formed. K-Means clustering is used to categorized the data. Large volumes of data can be clustered with this approach. In contrast to the hierarchical clustering method's tree structure layout, it produces clusters at a single level. Each observation in the data is viewed as an item with a location in space, and a partition is discovered where objects inside each cluster are as likely to be close to one another and as far away from objects in other clusters as possible. The process of clustering includes a crucial stage called distance measure selection. The distance between two items determines how similar they are. Due to the fact that some parts may be closer together at one distance and farther apart at another, it significantly affects the shape of the clusters. In order to provide the correlation between different data features, the correlation distance metric is chosen.

4. Result and Discussion

4.1 Evaluation Metrics

The performance of the proposed framework can be evaluated by using the metrics like Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR) and Execution Time.

Table 1: Comparison of the Mean Squared Error (MSE) values for the transformation approached in the proposed framework

Transformation Techniques	Mean Squared Error (MSE)			
	Image 1	Image 2	Image 3	Image 4
Dual Tree Discrete Wavelet Transform	16.521	16.412	16.501	16.536
Curvelet Transform	15.642	15.521	15.589	15.601
Contour Transform	14.214	14.222	14.362	14.251

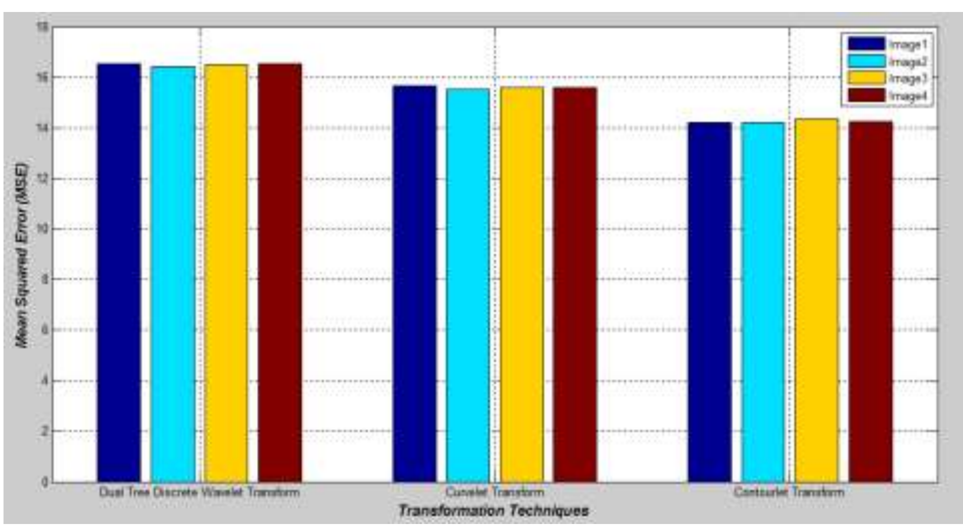

Figure 2: Performance analysis of the transformation techniques like Dual Tree Discrete Wavelet Transform, Curvelet Transform, and Contour Transform against Mean Squared Error (MSE)

Table 1 gives the MSE values obtained by three transform techniques like DT-DWT, Curvelet transforms, Contour transforms for given four cervical cancer images. Figure 2 depicts the graphical representation of the transform techniques for given four images.

Table 2: Comparison of the Peak Signal to Noise Ratio (PSNR) values for the transformation approached in the proposed framework

Transformation Techniques	**Peak Signal to Noise Ratio**			
	Image 1	**Image 2**	**Image 3**	**Image 4**
Dual Tree Discrete Wavelet Transform	27.6843	28.7932	28.8821	28.7713
Curvelet Transform	35.7952	35.6784	35.8863	35.7772
Contour Transform	37.8743	37.5873	37.9772	37.8661

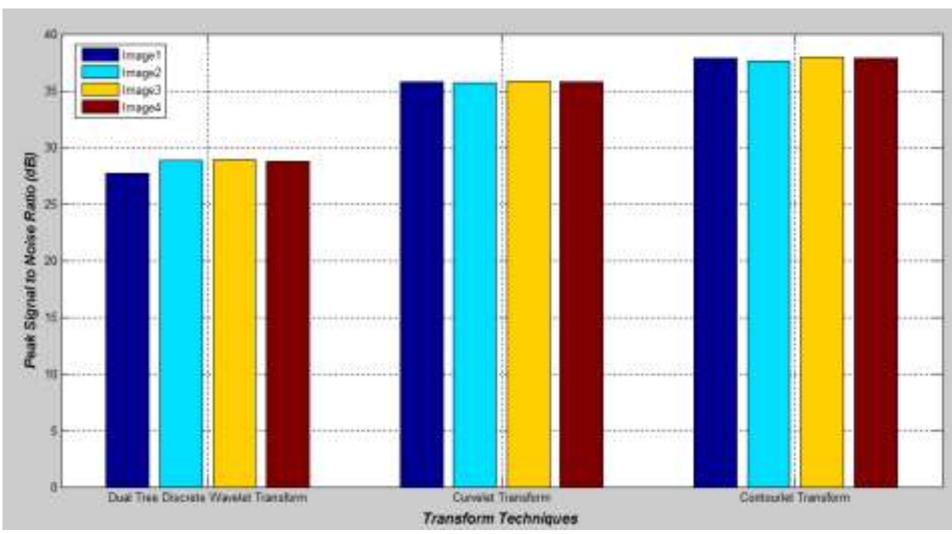

Figure 3: Performance analysis of the transformation techniques like Dual Tree Discrete Wavelet Transform, Curvelet Transform, and Contour Transform against Peak Signal to Noise Ratio (PSNR) value

Table 2 gives the PSNR values obtained by three transform techniques like DT-DWT, Curvelet transforms, Contour transforms for given four cervical cancer images. Figure 2 depicts the graphical representation of the transform techniques for given four images against PSNR values.

Table 3a: Comparison of the Execution time for the transformation approached in the proposed framework

Transformation Techniques	K-Means clustering			
	Image 1	**Image 2**	**Image 3**	**Image 4**
Dual Tree Discrete Wavelet Transform	15.254	15.365	15.478	15.632
Curvelet Transform	14.362	14.852	14.745	14.698
Contour Transform	14.147	14.789	14.689	14.986

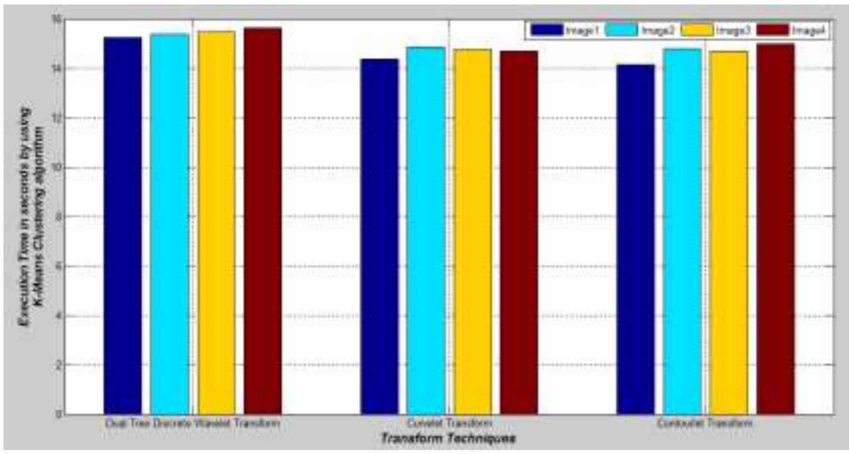

Figure 4a: Performance analysis of the K-means segmentation algorithm by using different transform techniques against execution time

Table 3a gives the comparison of the three different transform techniques by using K-Means clustering algorithm has used in the segmentation process against execution time. Figure 4a gives the graphical representation of the K-Means segmentation algorithm by using different transform techniques against execution time.

Table 3b: Comparison of the Execution time for the transformation approached in the proposed framework

Transformation Techniques	EM (Expectation-Maximization) clustering			
	Image 1	**Image 2**	**Image 3**	**Image 4**
Dual Tree Discrete Wavelet Transform	111.788	112.852	112.763	111.884
Curvelet Transform	112.897	112.542	111.563	111.323
Contour Transform	110.986	110.745	110.632	110.521

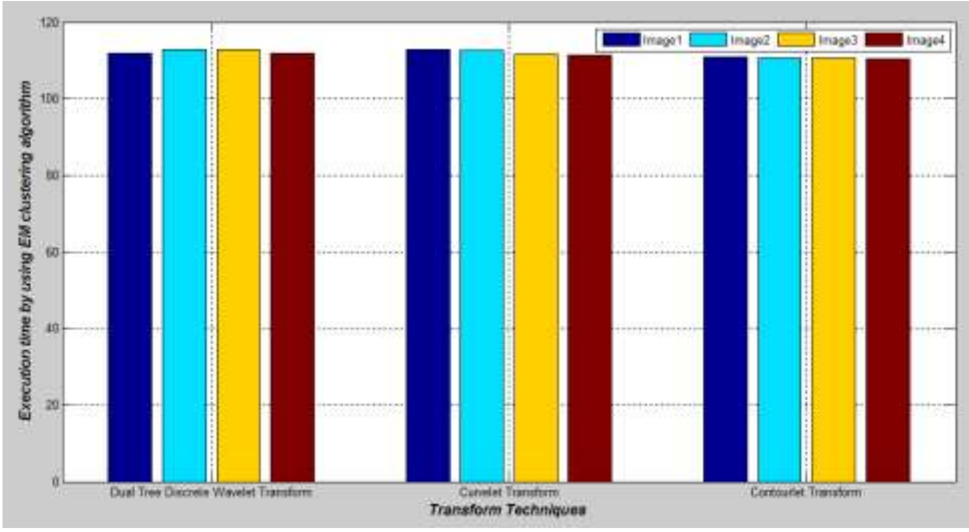

Figure 4b: Performance analysis of the EM Clustering segmentation algorithm by using different transform techniques against execution time

Table 3b gives the comparison of the three different transform techniques by using Expectation-Maximization (EM) clustering algorithm has used in the segmentation process against execution time. Figure 4a gives the graphical representation of the EM clustering segmentation algorithm by using different transform techniques against execution time.

5. Conclusion

In this paper, a novel paradigm for the use of image processing techniques in the disclosure of Cervical Cancer (CC) has been described. In the pre-processing stage and picture augmentation phases, wavelet transforms such as Dual Tree Discrete Wavelet (DT-DWT), Contour Transform, and Curvelet Transform are used. Image segmentation has used K-Means clustering. It is evident from the experimental result obtained in three steps that K-Means produces the result more quickly than EM clustering is used in the segmentation process.

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