Original Article

Cervical Cancer Severity Analysis In Pap Smear Images By Using E-Atcmp, P-Atcmp, R -Atcmp And Jpr Of Cervical Nucleus Texture Features With Ensemble Classification Technique

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Abstract

Cervical cancer is the main essential reason for demise amongst ladies in worldwide. Proper and well-timed analysis can save you the lifestyles to a few level. Owing to its prominence, the intention of the research article is analyzing severity class of Abnormal Cell of the Pap smear photo with the aid of using the use of awesome and joining distinct function extraction technique with the class approach. In this paper 4 function extraction techniques have been used: From that, three were awesome function extraction techniques specifically Extending – Augmented Texton Co-Occurrence Matrix Pattern (E-ATCMP), Potent – Augmented Texton Co-Occurrence Matrix Pattern (P-ATCMP) & Rough - Augmented Texton Co-Occurrence Matrix Pattern (R-ATCMP) and endured one become joining distinct function extraction technique named as Joint Pattern Recognition (JPR). The JPR technique represents all of the distinct feature extraction technique of P-ATCMP&R-ATCMP functions are becoming a member of collectively as one function to evaluate their joint overall performance. Then those 4 function extraction techniques are examined over Naïve bayes, Random Forest, k-nearest neighbour Classifier and ensemble classifier representing Statistical parameters. Henceforth the resulting statistical parameters defined in awesome characteristic mining approach with the magnificence approach, planned R-ATCMP with Ensemble Classifier had given the higher consequences than the opposite awesome functions with Classifier approach. Similarly joining distinct feature extraction technique with the class approach defined, proposed JPR+Ensemble Classifier had given higher consequences than all of different awesome function extraction with classifier strategies.

Keyword: TCMP approach, feature extraction and Ensemble Classification.

1.INTRODUCTION

Generally cancer is incurable disorder all over the world [1-3]. So many researchers, pathologists have located much wide variety of methodologies to remedy the cells which may best by most cancers. In in advance days such a lot of methodologies are to be had to stumble on the signs and symptoms of most cancers [4-6]. All round the sector ladies had been stricken by sorts of most cancers viz., breast and cervical most cancers [7,8]. Unmanaged increase of cells with inside the part of breast is breast most cancers [9].

The cells in a part of the Cancer that paperwork in tissues of the cervix are cervical most cancers [10]. Cervical Cancer cells originate from pre-cancerous, benign lesions with inside the out of control cells that are gift with inside the cervix. The outcomes interpreted with the aid of using World Health Organization (WHO), the preliminary degree for the improvement of cervical most cancers is moderate dysplasia, thereafter its slight dysplasia, excessive dysplasia, sooner or later ends in carcinoma in situ (CIS) in addition to invasive cervical most cancers [11,12].

In order to stumble on cervical most cancers mechanically with the assist of screening tests. Among them one of the maximum crucial technique is the segmentation of cellular nuclei from the stained specimens [13,14]. However, remote nuclei of the cells in fantastic acquisitions offer hard hints with inside the segmentation is extra wide variety of nuclei with diverse traits beneath neat happen in gone-of-a-kind acquisition situations in good-decision scans of the whole microscope slide[15]. Thresholding is the maximum crucial technique for segmentation method[16] and additionally it's far an simple technique to transform grey scale photograph into binary photograph primarily based totally on the worldwide or neighborhood threshold value[17,[18]. Bi-stage thresholding is a way which ought to be classifies the pixels into companies. First one represents wherein the pixels with grey ranges are lie above a sure threshold value, while the alternative wherein the pixels are lie beneath a sure threshold value [19,20]. Binary category is one of the feature technique used to decide if the affected person which has been stricken by the most cancers[21].

2. CERVICAL CANCER SEVERITY CLASSIFICATION SYSTEM

In this studies article, we've got evolved Severity magnificence of cervical most cancers class gadget primarily based totally on distinct and becoming a member of distinct texture functions and ensemble classifier. Two important contribution of the proposed gadget is function extraction and function class. Overall technique of Severity Classification gadget is given in following figure.1

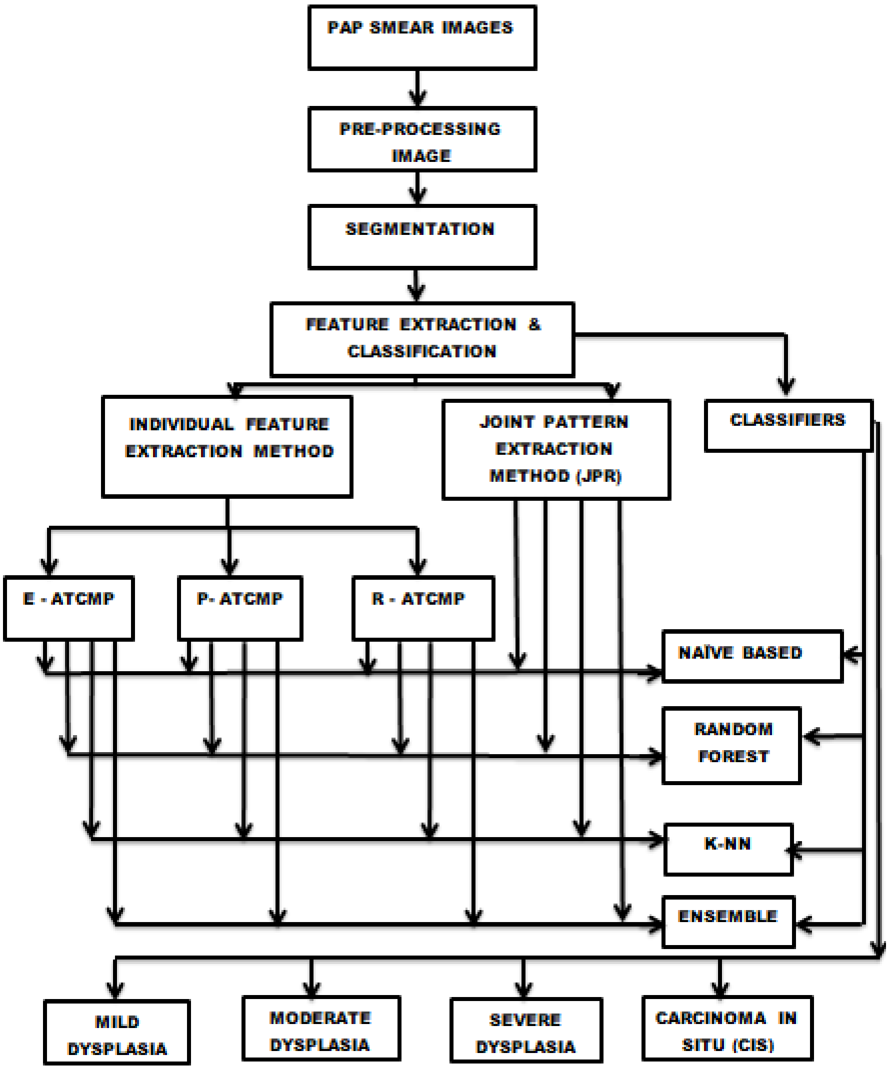


Figure.1 Feature Extraction

The function mining is lessen about unique facts with the aid of using measuring sure houses, or functions, that distinguish one enter sample from any other sample. The extracted function is anticipated to offer the traits of the enter kind to the classifier with the aid of using thinking about the outline of the applicable houses of the photo right into function. This research article proposed 4 new function mining strategies. they're particularly Extending – Augmented Texton Co-Occurrence Matrix Pattern (E-ATCMP), potent – Augmented Texton Co-Occurrence Matrix Pattern (P-ATCMP) & Rough - Augmented Texton Co-Occurrence Matrix Pattern (R-ATCMP) and remained one turned into becoming a member of awesome function extraction approach named as Joint Pattern Recognition (JPR). The JPR approach represents all of the distinct feature extraction strategies of E-ATCMP, P-ATCMP&R-ATCMP functions are becoming a member of collectively to 1functionto evaluate their joint performance. The sorts of distinct and becoming a member of distinct feature extraction functions approach is given here.

Distinct Methods:

- E-ATCMP.
- P-ATCMP.
- R-ATCMP.

Joining Method:

- JPR.

Distinct Methods:

2.1.1 Feature Extraction using E-ATCMP:

The Texton template described in E-ATCMP isn't like TCM. Here 4 unique texton kinds are described. This texton color has represented equal value of two pixel from four pixel. This texton will be applied to the original image as two pixel as step length, we get four different image at last integrate all we get final extracted image. From that we may extract our features like IDM, ASM, Max Probability and entropy) that described in figure 2 and 3.

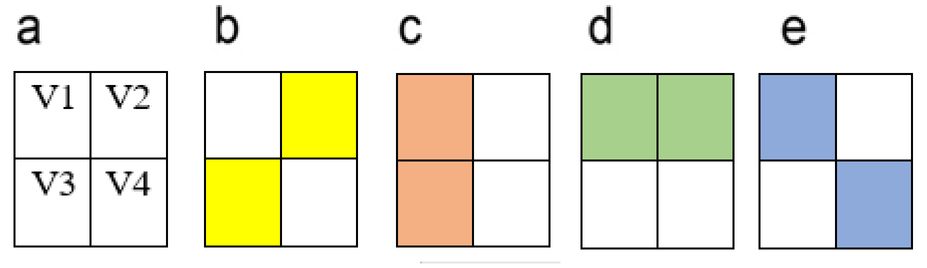


Figure.2. Special texton types of E-ATCMP (a) original 2x2 matrix (b)Texton T1 (c) Texton T2 (d) Texton T3 (e) Texton T4

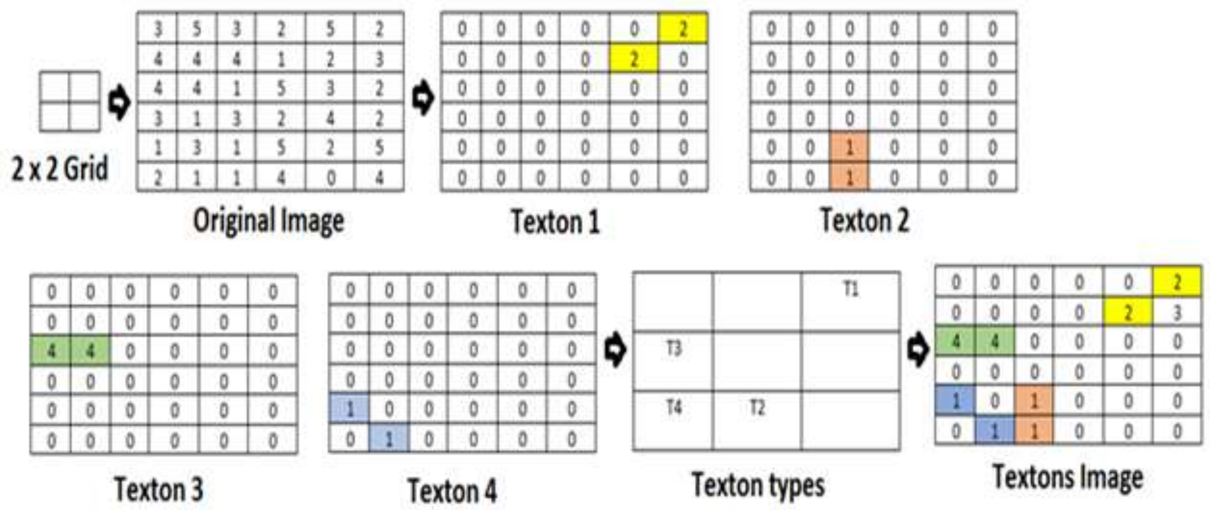


Figure.3: Texton image formation process using E-ATCMP (a) 2x2 Matrix (b) Original image intensity value (c) Texton location of the original image (d) Four texton types (e) Final texton image of E-ATCMP.

2.1.2. Feature Extraction using P-ATCMP:

Texton Detection

The Texton template described in P-ATCMP isn't like TCM. Here 6 unique texton kinds are described. This texton color has represented equal value of two pixel from four pixel. This texton will be applied to the original image as two pixel as step length, we get four different image at last integrate all we get final extracted image. From that we may extract our features like IDM, ASM, Max Probability and entropy) that described in figure 4 and 5.

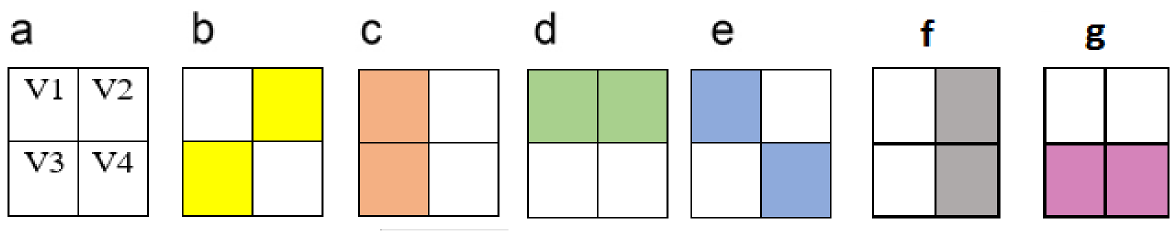


Figure.4. Special texton types of P-ATCMP(a) original 2x2 matrix (b)Texton T1 (c) Texton T2 (d) Texton T3 (e) Texton T4 (f) Texton T5 (g) Texton T6.

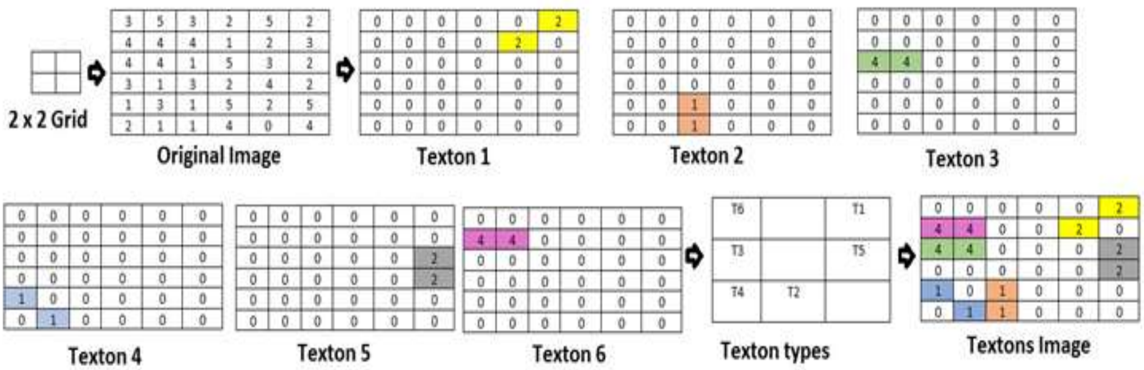


Figure.5: Texton image formation process using P-ATCMP (a) 2x2 Matrix (b) Original image intensity value (c) Texton location of the original image (d) Four texton types (e) Final texton image of P-ATCMP.

2.1.3. Feature Extraction using R-ATCMP:

The Texton template described in R-ATCMP isn't like TCM. Here 20 unique texton kinds are described. This texton color has represented equal value of three pixel from nine pixel. This texton will be applied to the original image as three pixel as step length, we get twenty different image at last integrate all we get final extracted image. From that we may extract our features like cluster shade, cluster, contrast, variance, correlation, inverse difference moment that described in figure 6 and 7.

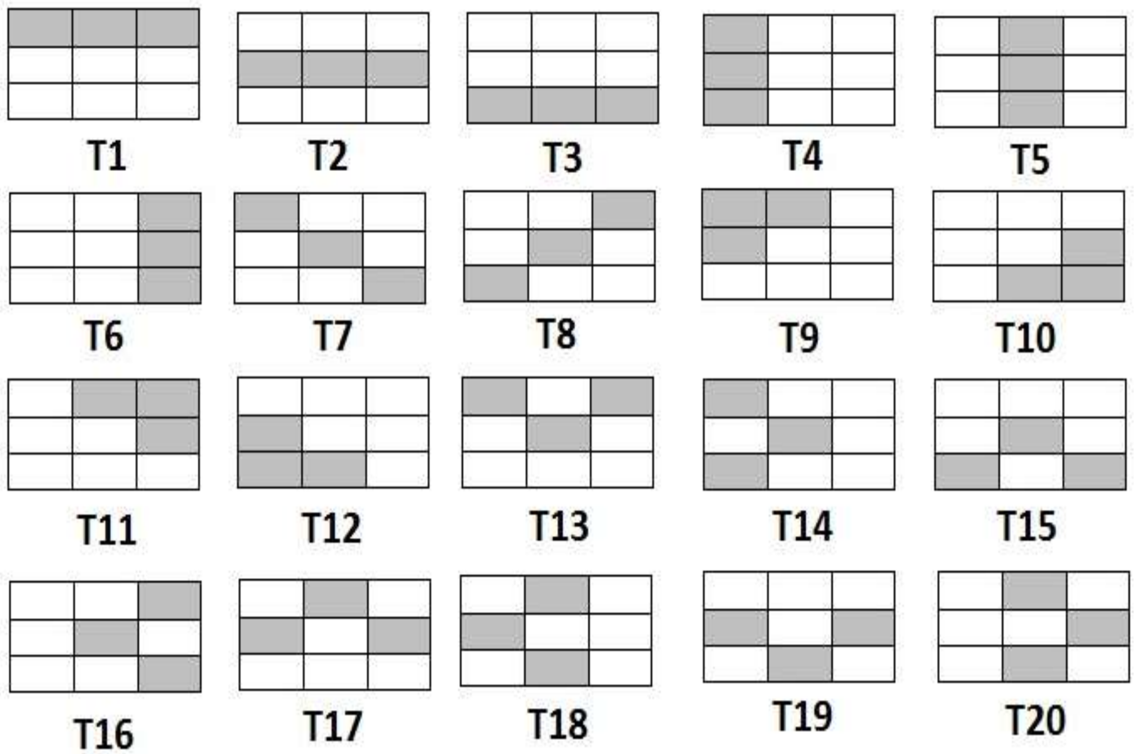


Figure.6 : 20 types of 3 x 3 Textons

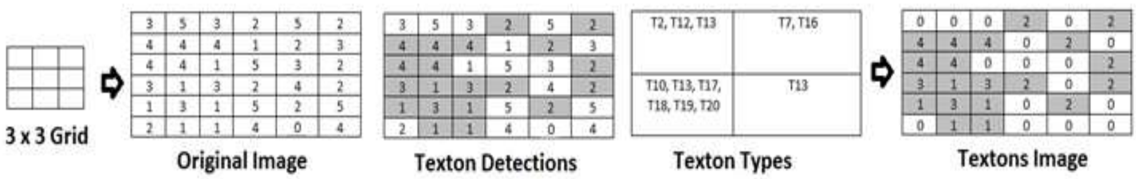


Figure.7 : Texton Detection Process

JOINING DISTINCT FEATURE EXTRACTION FEATURES METHOD:

2.1.4. Feature Extraction using JPR:

The call JPR Stands for Concatenated Feature Extraction. The JPR approach represents all of the wonderful function extraction strategies of E-ATCM,P-ATCMP & R-ATCMP functions are becoming a member of collectively to at least one function to evaluate their joint performance.

3. NUCLEUS FEATURE CLASSIFICATION:

All individual and joint features are examined over Naïve bayes, Random Forest, KNN and ensemble classifier. This test based on the 512 pap smear live images. All of the images are severe cases of cervical images like moderate dysplasia - 107, slight dysplasia - 124, intense dysplasia - 139, & Carcinoma in Situ (CIS) have been 142 images.

3.1. Feature Classification using Naive Bayes Classification:

After completely extracted all the features from the pap smear images. we've evolved Naive Bayes is a maximum famous and handiest probabilistic set of rules in class. It has capacity to deal with lacking fee and imbalance data. It defines all of the attributes are independence or no dependency among all of the attributes besides the attributes that turn out to be the goal class. Thus, it overlook the impact of correlation of different attributes and totally dependence to the goal class.

3.2. Feature Classification using Random Forest Classification:

After the cervical nucleus functions are extracted, In this random wood land strategies random samples are decided on and all this functions are prepare to shape the schooling pattern. Subset samples is returned sampling from the schooling pattern set.

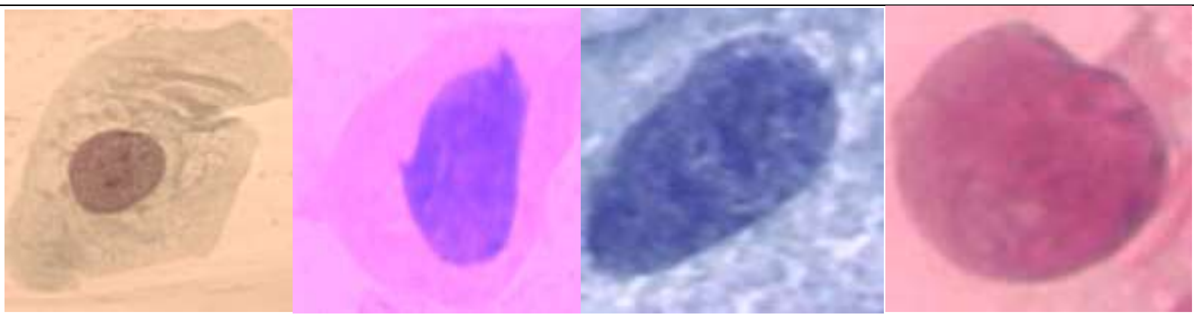
3.3. Feature Classification using K-NN Classification:

K-Nearest Neighbor is a non-parametric classifier this is used for regression and classification. The word parametric manner that we can't make assumptions at the statistics distribution. In KNN classifier, there may be no want of express schooling phase. Centroid is only a middle of unique cluster. In KNN the statistics is split into check set and schooling set. For each row of check set nearest neighbor okay primarily based totally on Euclidean distance of schooling set factor are observed.

4. RESULTS AND DISCUSSION

4.1 Image Data set.

• The database contained 512 images the distribution discussed in previous section 3 will become a dataset for this work. The Sample images from each criteria given in figure.8.



(A) (B) (C) (D)

Figure.8. Some of the cells found in cervix: (A-C) mild, moderate and severe dysplasia,(D) Carcinoma in situ

4.2. Results and Analysis

The Experimental results was analyzed by the basic parameters of all the classifiers. That was given in equation 1-3.

$$Sensitivity = TP/(TP + FN) \quad \text{-----------(1)}$$

$$Specificity = TN/(TN + FP) \quad \text{-----------(2)}$$

$$Accuracy = (TN + TP)/(TN + TP + FN + FP) \quad \text{-------- (3)}$$

Table. 1. image dataset

Cancer	Testing	Training data	Total no of images
Mild	57	50	107
Moderate	74	50	124
Severe	89	50	139
carcinoma in situ	92	50	142
Total	**312**	**200**	**512**

4.2.1. Distinct feature Extraction and Classification

As per the implemented results individual feature extraction method with Ensemble classification provided the good result. So that the all method based ensemble classification confusion is illustrated in Table.2.

Table.2 2.a. Confusion matrix (E-ATCMP+Ensemble)

Class predicted	Ground Truth			
	Mild	**Moderate**	**Severe**	**Carcinoma in situ**
Mild dysplasia	27	9	10	11
Moderate dysplasia	12	42	9	11
Severe dysplasia	10	12	56	11
Carcinoma in situ	11	9	12	60

2.b. Confusion matrix (P-ATCMP+Ensemble)

Class predicted	Ground Truth			
	Mild	**Moderate**	**Severe**	**Carcinoma in situ**
Mild dysplasia	36	8	9	4
Moderate dysplasia	8	51	7	8
Severe dysplasia	4	13	65	7
Carcinoma in situ	13	8	9	62

2.c Confusion matrix (R-ATCMP+Ensemble)

Class predicted	Ground Truth			
	Mild	**Moderate**	**Severe**	**Carcinoma in situ**
Mild dysplasia	46	3	4	4
Moderate dysplasia	5	61	3	5
Severe dysplasia	5	5	75	4
Carcinoma in situ	5	4	5	78

In Table 2 (a,b,c) & 3 represents the results of E-ATCMP, P-ATCMP and R-ATCMP with Ensemble classification

Table 3 3.a. Performance measure of E-ATCMP with Ensemble

Class predicted	Sensitivity (%)	Specificity (%)	Accuracy (%)
Mild dysplasia	47.37	87.06	79.81
Moderate dysplasia	56.76	87.39	80.13
Severe dysplasia	62.92	86.10	79.49
carcinoma in situ	65.22	85.00	79.17
Overall Sensitivity, Specificity & Accuracy Results	58.07	86.39	79.65

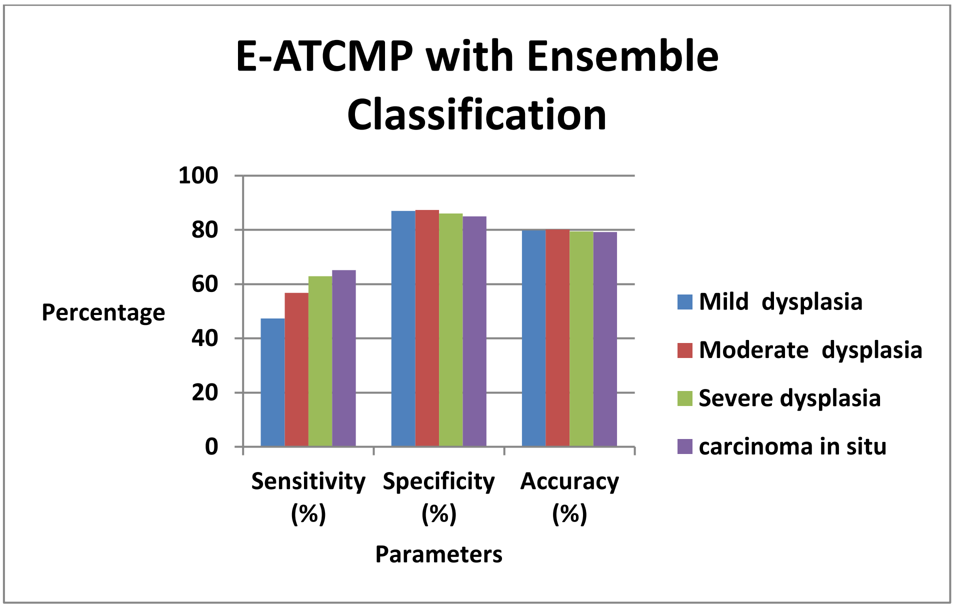
3.b Performance measure of P-ATCMP with Ensemble

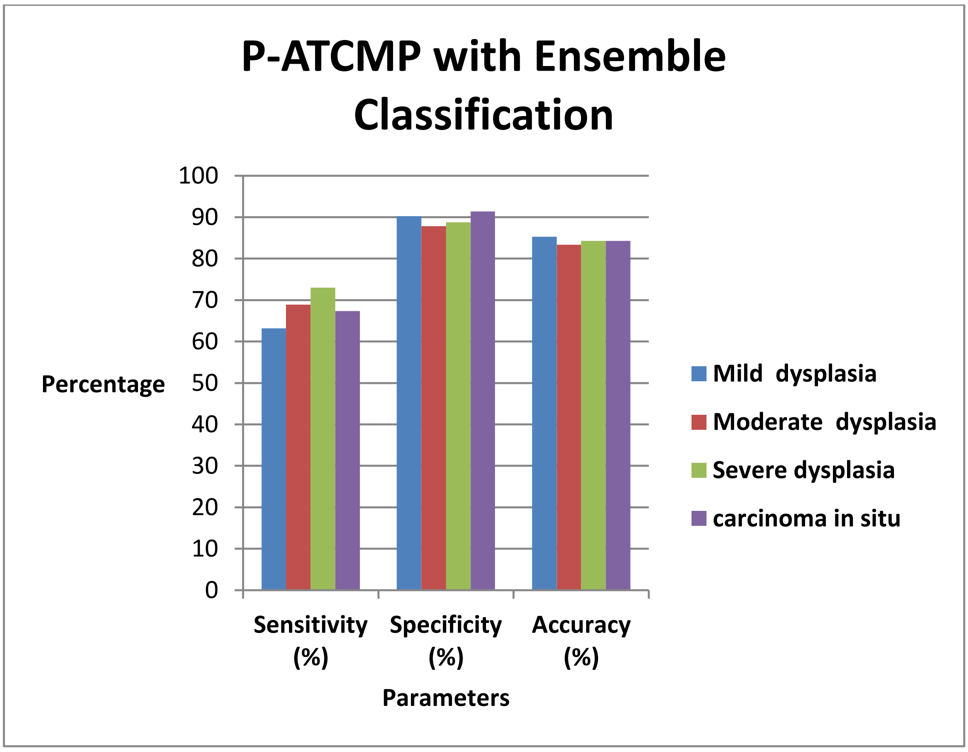
Class predicted	Sensitivity (%)	Specificity (%)	Accuracy (%)
Mild dysplasia	63.16	90.20	85.26
Moderate dysplasia	68.92	87.82	83.33
Severe dysplasia	73.03	88.79	84.29
carcinoma in situ	67.39	91.36	84.29
Overall Sensitivity, Specificity & Accuracy Results	68.13	89.54	84.29

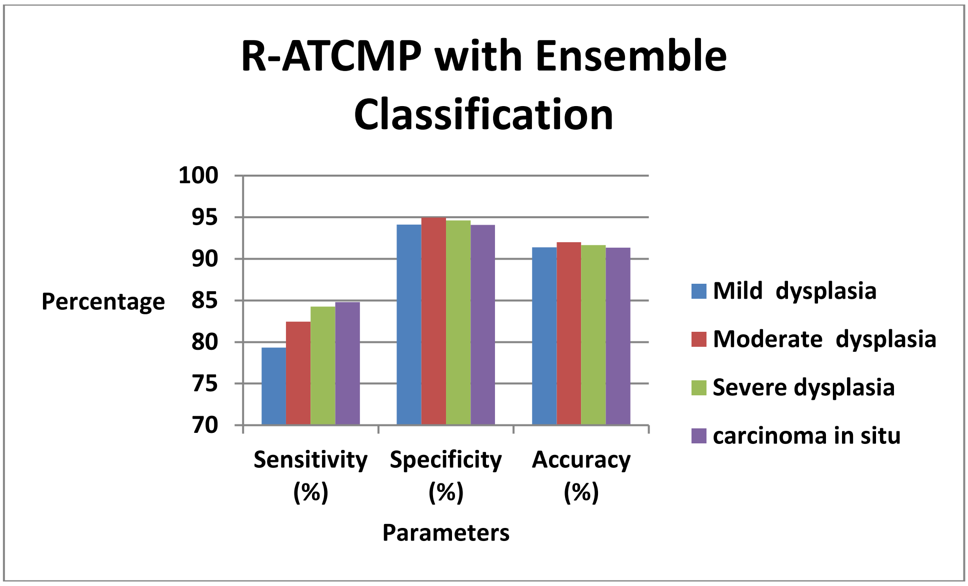
3.c Performance measure of R-ATCMP with Ensemble

Class predicted	Sensitivity (%)	Specificity (%)	Accuracy (%)
Mild dysplasia	79.31	94.12	91.37
Moderate dysplasia	82.43	94.96	91.99
Severe dysplasia	84.27	94.62	91.67
carcinoma in situ	84.78	94.09	91.35
Overall Sensitivity, Specificity & Accuracy Results	82.70	94.45	91.59

For relative analysis, the proposed system (R-ATCMP + Ensemble) provides better results in terms of the parameters such as sensitivity, specificity & accuracy. The details are given in figure.9







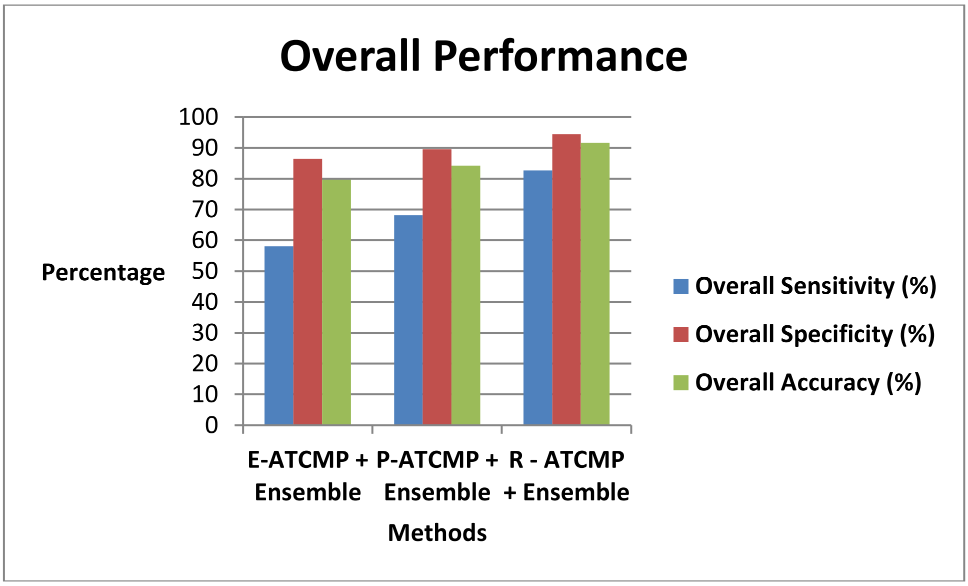


Figure.9. Comparison Results Distinct feature Extraction methods with EnsembleClassification Technique.

4.2.2. Distinctand Joining distinctfeatures& Classification combination comparison:

The confusion matrix of the JPR+Ensemble method is given in table.

Table 4 Confusion matrix of proposed method (JPR+Ensemble)

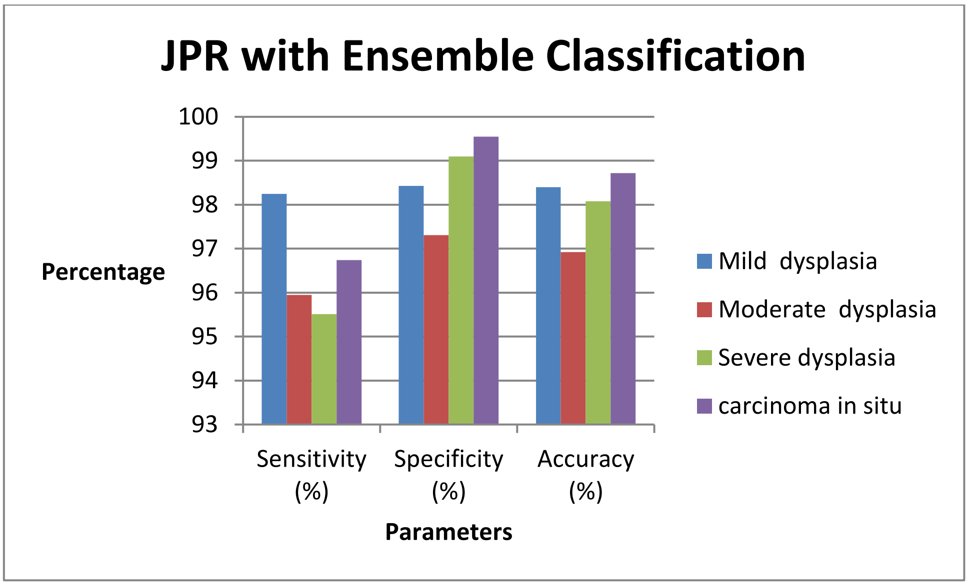
Class predicted	**Ground Truth**			
	Mild	**Moderate**	**Severe**	**Carcinoma in situ**
Mild	56	1	0	0
Moderate	2	71	1	0
Severe	1	2	85	1
Carcinoma in situ	1	1	1	89

In the Table 5, represents parameters TP, TN, FP and FN. In the Table 8, the classification accuracy of JPR with HKSVM in class 1(Mild dysplasia) type cancer is 97.44%, class 2(Moderate dysplasia) is 97.12%, class 3(Severe dysplasia) is 96.47% and class 4(carcinoma in situ) is 97.44%.

Table 5 Performance measure of JPR with Ensemble

Class predicted	Sensitivity (%)	Specificity (%)	Accuracy (%)
Mild	98.25	98.43	98.40
Moderate	95.95	97.31	96.92
Severe	95.51	99.10	98.08
carcinoma in situ	96.74	99.55	98.72
Overall Sensitivity, Specificity & Accuracy Results	96.61	98.60	98.03

The overall classification results shown in Figure 10.



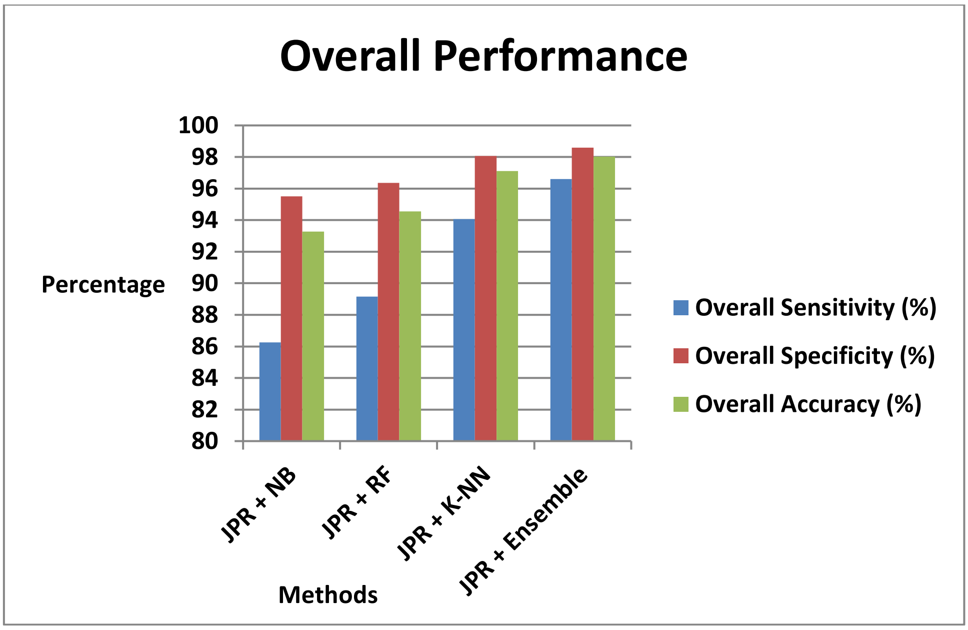


Figure.10. Comparison Results of JPR with all Classification Technique.

CONCLUSION

In this paper, distinct feature based R- ATCMP with ensemble provide better results than the all other distinct techniques and similarly JPR based Ensemble provide better result than the all the distinct methods. Classifier Results calculated based on the basic statistical Parameters of SN(Sensitivity)-SP(Specificity)-AC(Accuracy). Hence, eventually our proposed distinct and becoming a member of distinct method are proved suitable at detecting the severity elegance of the cervical most cancers with inside the pap smear image.

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