Detection of Dysplastic Cervical Cells from Pap Smear images using Texture Features of the nucleus

NEW YORK INSTITUTE OF TECHNOLOGY

Mary Margarette Sanchez, Dono Shodieva, Angel Singh, and SimranSanju Kadan

Department of Biological & Chemical Sciences, New York Institute of Technology, New York, NY

Mentor: Prof. N Nath

Introduction

Nearly one in six deaths all over the world are related to cancer, making it the leading cause of death in the Americas, Europe, and Western Pacific regions. It accounted for over 10 million deaths worldwide in 2020. Cervical cancer is the fourth most commonly occurring malignancy among women globally. There were over 604,000 new cases of cervical cancer and nearly 342,000 related deaths in 2020. The Papanicolaou smear staining and microscopy of the cervix cells by cytopathologists can prevent the disease by detecting precancerous nuclear morphological anomalies. However, the whole manual process of this test is time-consuming and prone to human errors, making them inefficient. An untackled issue is that since most cases of cervical cancer are diagnosed in developing and underdeveloped countries, there are just not enough resources to carry out this test in those nations. Therefore, quantitative analysis with a computer-aided approach is extremely significant for it may increase detection efficiency and accuracy while also providing a standard categorization approach. In this study, five nuclear texture features were quantified and used to differentiate the benchmark pap-smear images into various categories, specifically normal cells, and moderate, and severe dysplastic cells. The varying relationship between the data was compared for visual analysis of the cells with the use of graphs. One of the main methods to analyze and classify data is called clustering and is based on the K-means learning algorithm. It can group the data into one or several classes based on its relativity to the mean of that cluster.

Objective

The aim of this study is to investigate and measure five nuclear texture features using the benchmark pap smear images and examine if these features can be used to discriminate between normal cells, moderate, and severe dysplastic cells as well as to examine the accuracy or validation rate of this prediction of classification of these cells into their respective classes.

Materials & Methods

The 300 cervical pap smear images examined were acquired from the Herlev University Norup Benchmark dataset in Denmark. It served as the *Ground Truth,* a set of pap-smear cervical cell images categorized in agreement by several cytopathologists, for analysis of nuclear texture characteristics. Cell Profiler, a free open-source software to analyze cells, was used to pre-process (convert to gray-scale and segment the nucleus) the pap smear images and to quantify the texture features of the nucleus. The quantified data was then input into an excel file to efficiently calculate the mean ± standard deviation of each category and the respective p-values by Student's t-test of each texture feature in normal v moderate, and normal v severe comparison. The visualizations were generated using Tableau by comparing one or more distinctive features and different patterns were observed which supported the hypothesis of differentiating between normal and subclasses of dysplastic cells.

Figure 1: Normal Cell

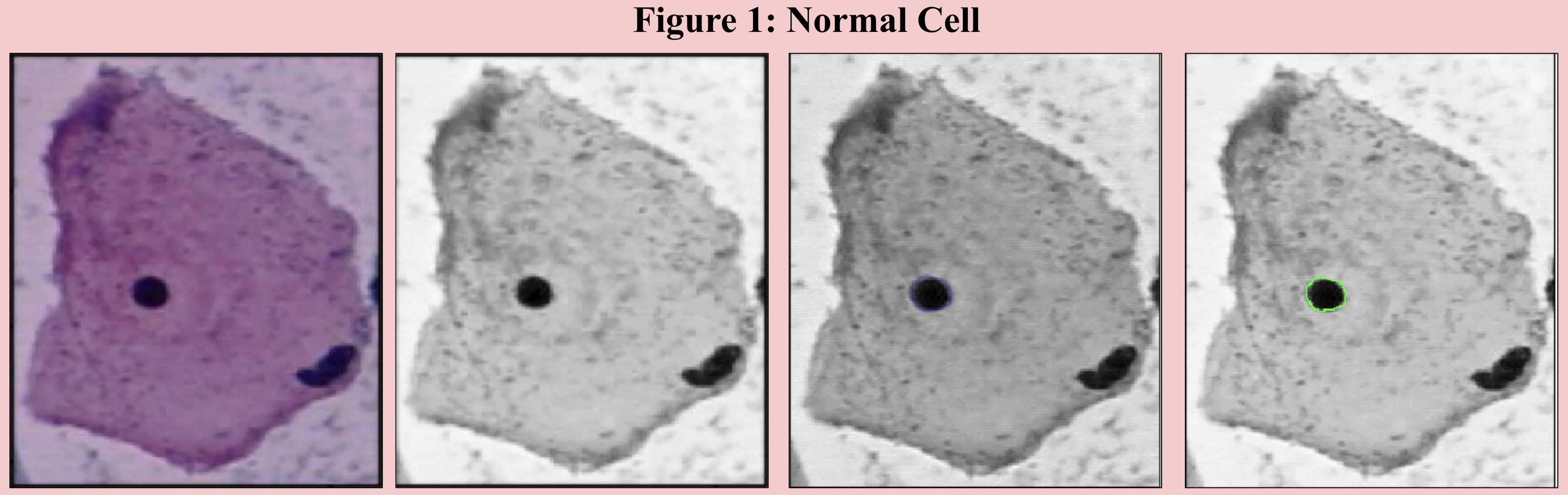
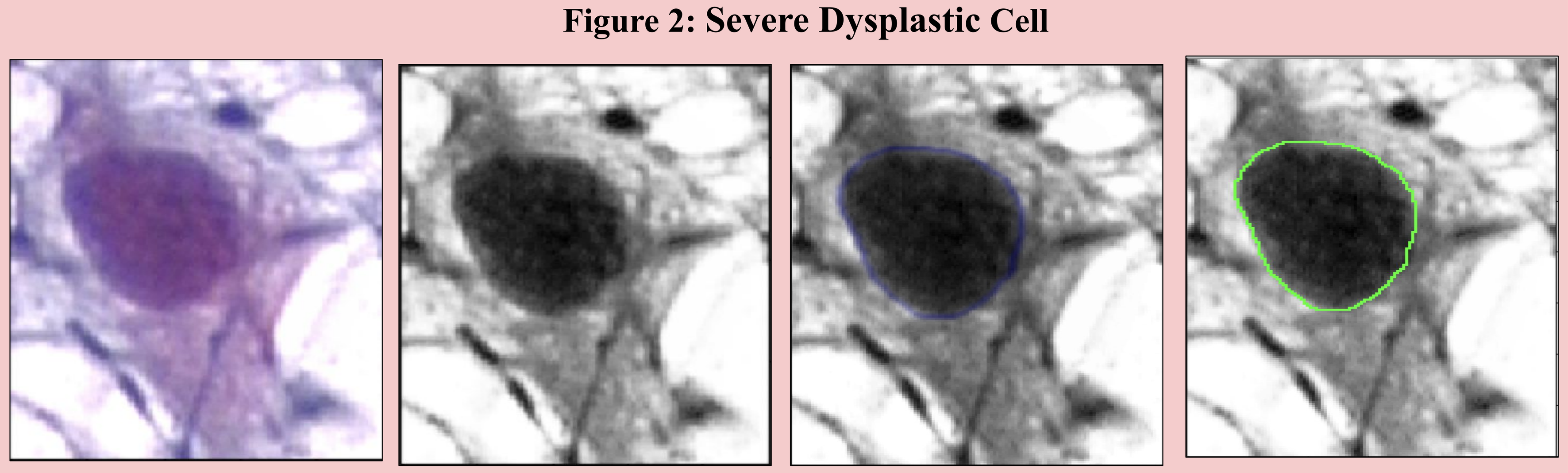


Figure 2: Severe Dysplastic Cell



Original Stained Pap Smear Image → Convert to Gray Scale → Manual Nuclear Segmentation → Segmented Nucleus

5 Nuclear Texture Parameters

- Angular Second Moment
- Contrast
- Correlation
- Inverse Difference Moment
- Entropy

Results

Table 1: Mean ± Standard Deviation of all the 5 texture features examined.

	Normal	Moderate	Severe
Angular Second Moment	0.0037± 0.0023	0.0025±0.0019	0.0033±0.0044
Contrast	176.49 ±119.02	73.53 ± 52.40	84.35±76.03
Correlation	0.65 ± 0.18	0.75 ± 0.10	0.79 ± 0.12
Inverse Difference Moment	0.195 ± 0.048	0.200 ± 0.0576	0.217 ± 0.268
Entropy	8.869 ± 1.066	9.348 ± 1.267	9.244 ± 1.100

Table 2: Calculated p-values by student t-test for normal v moderate cells, and normal v severe cells respectively.

Parameters with p-values < 0.05 are statistically significant. This was used to determine the discriminatory features (purple and green-colored rows) for each comparison.

	Normal v Moderate
Angular Second Moment	0.0003157323357
Contrast	0.00000000000017052
Correlation	0.00001113256263
Inverse Diffrence Moment	0.5756369969
Entropy	0.004258444641

	Normal v Severe
Angular Second Moment	0.4690779519
Contrast	0.00000003236632254
Correlation	0.00000001436562459
Inverse Difference Moment	0.008762637612
Entropy	0.01527216987

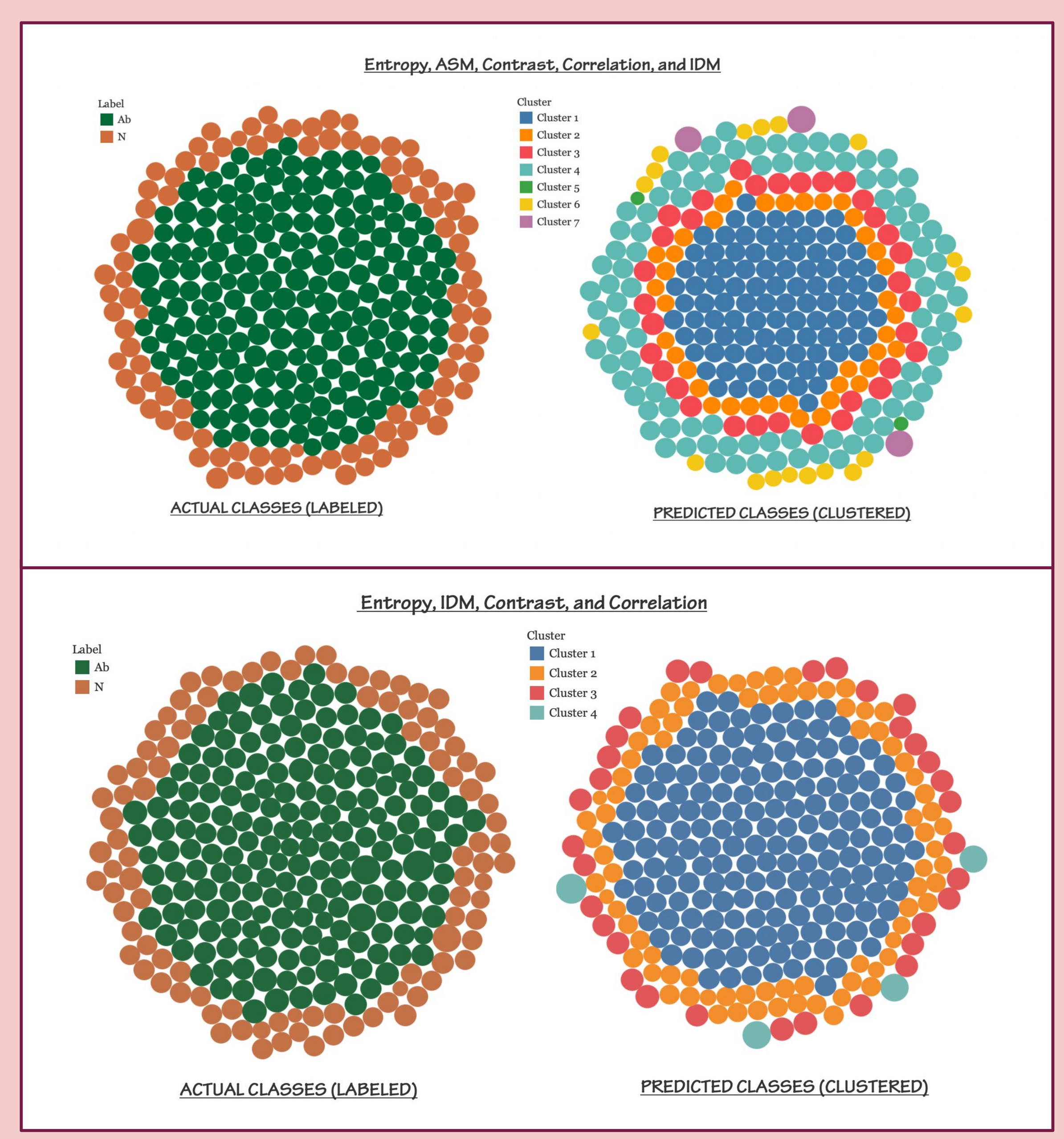


Figure 3: Bubble Graphs - Two Class (Normal v Abnormal)

The unsupervised K-means clustering method in Tableau identified multiple classes upon examining all the normal and dysplastic cells measurements. A total of 4-7 different clusters were formed representing several possibilities of groupings. It can be concluded that these multiple classes identified are different variations of abnormal (AB) cells.

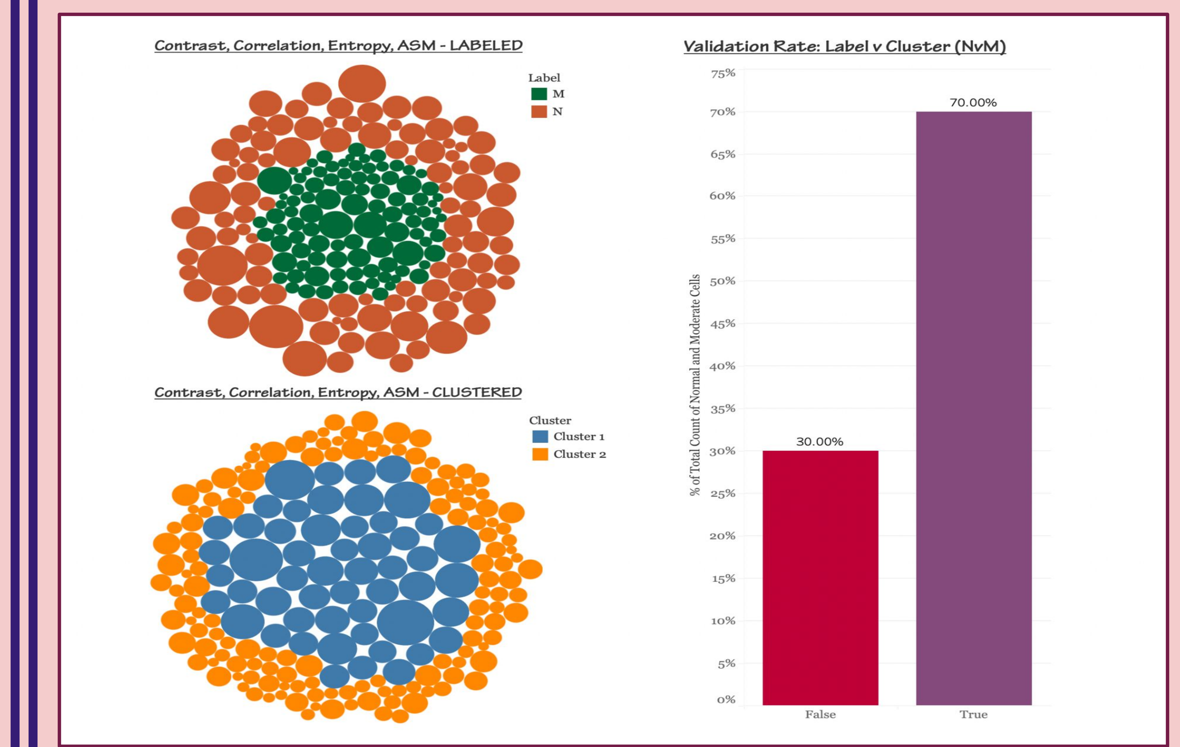


Figure 4: Bubble Graph - Two Class (Normal v Moderate)
When comparing the unsupervised clustered packed bubble graphs to the known Ground Truth data of Normal cells and Moderate dysplastic cells, the clustered bubble graphs showed that 70.00% of the total cell images were accurately classified using the discriminatory features. By using a different method of visualization: a packed bubble graph, we can visualize how the normal (N) and moderate (M) cells are differentiated without labels using the K-means algorithm.

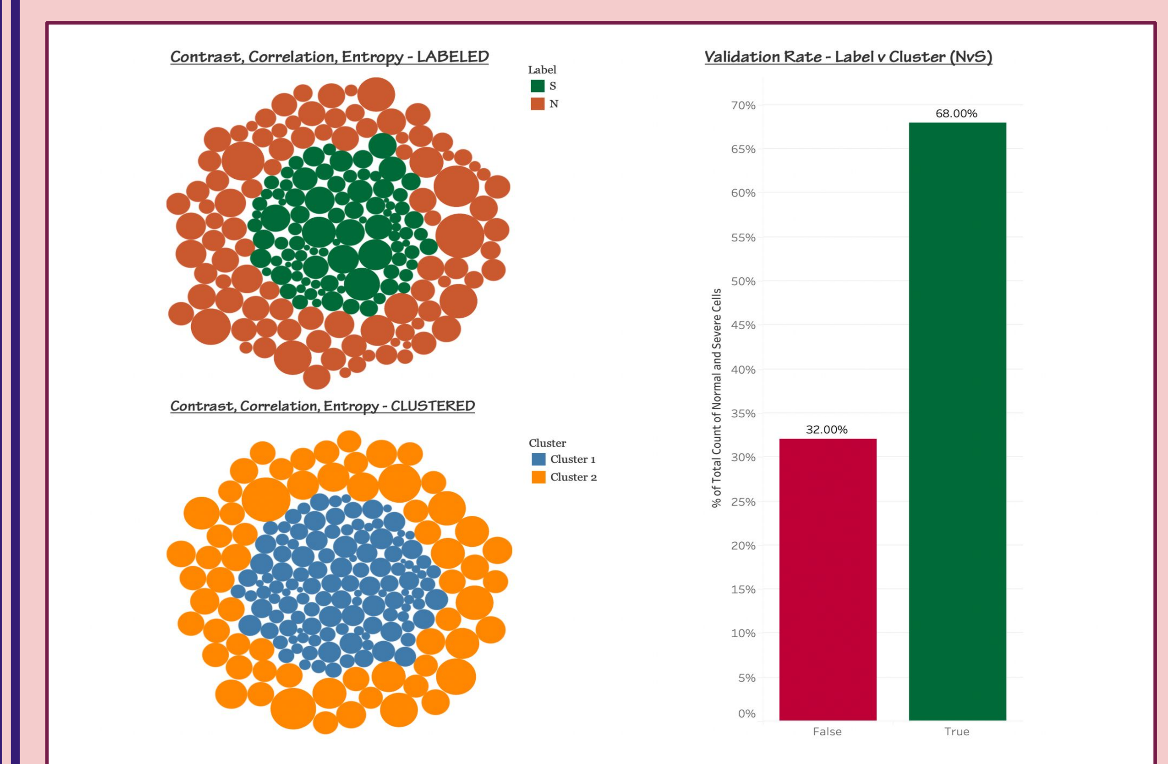


Figure 5: Bubble Graph - Two Class (Normal v Severe)
All normal(N) cells and severe (S) dysplastic cells were also examined using unsupervised K-means clustering comparing it to the known/labeled Ground Truth data. The clustered bubble graph result showed 68.00% accuracy in correctly classifying normal and severe dysplastic cells by using 3 discriminant texture features.

Discussion & Conclusion

- Out of the five measured parameters, **Contrast, Correlation, and Entropy** may consistently be used as discriminatory texture features in all categories examined. Interestingly, ***Angular Second Moment*** can be used as a discriminatory feature for *normal vs moderate* while ***Inverse Difference Moment*** can be used as a discriminatory feature for *normal vs severe.*
- Through K-means clustering in Tableau, the dataset was successfully distinguished between normal vs severe, normal vs moderate, and normal vs abnormal cells. For *normal vs severe* **cells**, there was a **68% success rate** and for *normal vs moderate* cells, there was a **70% success rate.**
- The data visualization software was also able to identify numerous classes within the non-labeled dataset when comparing the normal vs abnormal cells indicating the possibility of more dysplastic subclasses which could be identified in future studies.
- Other research used nuclear textural feature extractions like GLCM and LBP to classify two-class (Normal v Abnormal) pap smear images, with SVM classification obtaining 95-99% accuracy [3]. Although our study did not achieve this optimal accuracy rate, it was unique in terms of analyzing and classifying three different categories while also showing clear visualization of the clustering results. In future, we plan to improve the accuracy results by examining a larger quantity of cervix cells.
- Another extension of this research is to analyze texture features with shape features, specifically Major and Minor Axis Length, to improve the accuracy of nuclear feature analysis in diagnosing cervical cancer. Other studies [5 & 6] found that shape features were effective in differentiating dysplastic cervical cells.
- The long-term goal of this research is to develop a fully automated system that screens cells using various shape and texture features that a human eye cannot easily detect, under the supervision of a pathologist who will analyze the speed and efficiency. It will allow hospitals or remote areas without enough professional power to diagnose cancer once pap smear slides have been obtained.

References

(1) World Health Organization. (n.d.). *Cervical cancer*. World Health Organization. Retrieved April 24, 2022, from https://www.who.int/news-room/fact-sheets/detail/cervical-cancer
(2) Schilling, T., Miroslaw, L., Glab, G., & Smereka, M. Towards rapid cervical cancer diagnosis: Automated detection and classification of pathologic cells in phase-contrast images. *International Journal of Gynecological Cancer* 17(1), p. 118-126, 2007
(3) Arya, M., Mittal, N.., & Singh, G. (2018, May 31). *Texture-based feature extraction of smear images for the detection of cervical cancer*. IET Computer Vision. Retrieved April 20, 2022, from https://ietresearch.onlinelibrary.wiley.com/doi/10.1049/iet-cvi.2018.5349
(4) 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 Programs Biomed. 2018 Oct;164:15-22. doi: 10.1016/j.cmpb.2018.05.034. Epub 2018 Jun 26. PMID: 30195423.
(5) T. A Sajeena, A. S Jereesh, "Automated cervical cancer detection through RGVF segmentation and SVM classification," 2015 International Conference on Computing and Network Communications (CoCoNet), 2015.
(6) K. Bora, M. Chowdhury, L. B. Mahanta, M. K. Kundu, and A. K. Das, "Automated classification of pap smear images to detect cervical dysplasia," Comput. Method Programs Biomed., vol. 138, pp. 31–47, Jan. 2017.