

**HEP-2 CELL IMAGES FEATURE EXTRACTION BASED ON TEXTURAL
AND STATISTICAL ANALYSIS**

By

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FINAL PROJECT REPORT

Submitted to the Department of Electrical & Electronic Engineering
in Partial Fulfillment of the Requirements
for the Degree
Bachelor of Engineering (Hons)
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CERTIFICATION OF APPROVAL

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CERTIFICATION OF ORIGINALITY

This to certify that I am responsible for the work submitted in this project, that the original work is my own except as specified in the references and acknowledgements, and that the original work contained herein have not been undertaken or done by unspecified sources or persons.

NURUL SYAMIMI BINTI A.AZIZ

ABSTRACT

This project is about Human Epithelial type 2 (HEp-2) Cell Images Feature Extraction Based on Textural and Statistical Analysis. The medical industries have yet to found any reliable solution in differentiating the Anti-Nuclear Antibodies disease according to its cell pattern. Current practice, subject to physician's expertise, is not very reliable and cannot be reproduced. The main objective of this project is to provide significant differentiable features based on textural and statistical features of the HEp-2 cell images. The textural features are basically based on the surface of the cells which are analyzed from the grayscale images of the cells. The features are later classified to test its reliability. In this project the images will be analyzed in grayscale mode and processes using two different order of statistical analysis. The second order statistical analysis contains the textural features representation. It was found out that homogeneity and correlation of patterns are the same. Hence, avoid using this feature in order not to have wrong classification information. Also not all Gray-Level Co-occurrence Matrices (GLCM) properties features can be used to differentiate HEp-2 cell patterns. At the end of this project, the results shows that the use of textural (second order statistical) analysis is beneficial to get better accuracy of classification, though it still depends on the type of classifier used.

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LIST OF ABBREVIATIONS

HEp-2	Human Epithelial type 2
ANA	Anti-Nuclear Antibodies
IIF	Indirect Immunofluorescence
CAD	Computer Aided Diagram
SURF	Speeded-up Robust Features
EER	Equal Error Rate
ROI	Region of Interest
GLCM	Gray-Level Co-occurrence Matrices
NHOG	Normalized Histogram of Oriented Gradient
H	Homogeneous
F/FS	Fine-Speckled
S/CS	Coarse-Speckled
N	Nucleolar
C	Centromere
KNN	k -NN Classifier
ADA	ADABOOSTM2 Classifier
FOS	1 st Order Statistics
SOS	2 nd Order Statistics
BOS	1 st and 2 nd Order Statistics

CHAPTER 1

INTRODUCTION

1.1. Background of Study

Human Epithelial type 2 (HEp-2) cells are the additional substance that have been used in order to act as the binder for the anti-nuclear antibody (ANA) in which the ANA will bind to the nucleus of the HEp-2 cell [1]. HEp-2 cells are used in analyzing ANA disease as it can detect a large range of antigens and has a high sensitivity towards the presence of the antigens [2]. Indirect Immunofluorescence (IIF) with HEp-2 cells has been used to detect antinuclear auto-antibodies for diagnosing systemic auto-immune diseases. The IIF will appear in different fluorescence patterns to determine different types of auto-immune diseases.

Based on current practices, these patterns are differentiated manually by specialists and basically took a long time to obtain the result [3]. In addition, the result might vary since it depends on the experience of the specialist which can affect the reliability of the result and the reading cannot be reproduced officially for future reference [4]. Therefore, in order to ensure that the result for pattern classification of this HEp-2 cells is reliable and standardized according to its patterns' features, there have been studies on developing a Computer-Aided Diagnosis (CAD) systems that can automatically classify the pattern according to a standard algorithm [4].

To complete the classification process, it must be aided with supporting information regarding the pattern itself. These can be done by extracting the features of each pattern and the data can be used for classification. According to [5], there are five(5) features that can be extracted from an image. The features are; averaging, edges, simple neighborhoods, motion, and texture. Each feature has different method to extract and to use in different applications.

Basically the process covers three main parts that is pre-processing of the originally captured images, region of interest analysis, and finally the features extraction based on textural and statistical evaluation. Four (4) main patterns that are significant to HEp-2 cells are (a)homogeneous, (b)speckled, (c)nucleolar, and (d)centromere accordingly as shown in Figure1.

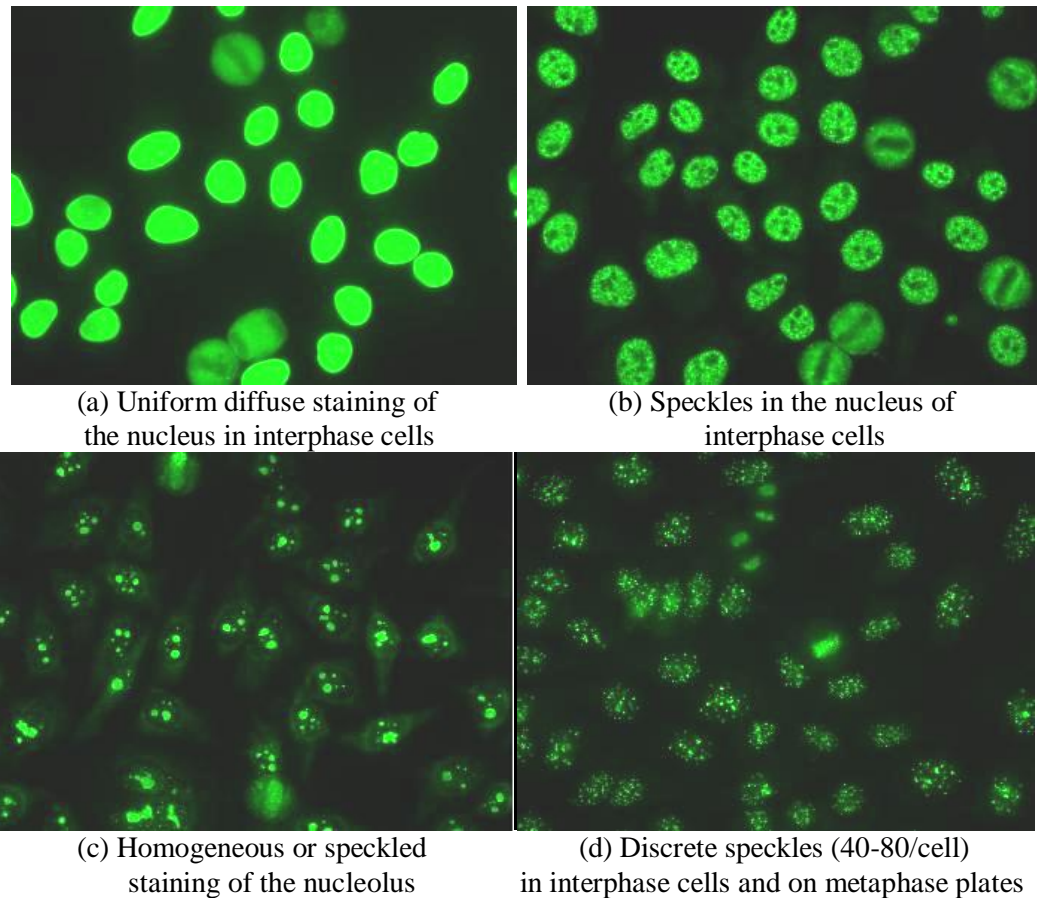


Figure 1: Four Different Types of HEp-2 Cell Images (a) Homogeneous (b) Speckled (c) Nucleolar (d) Centromere [6]

1.2. Problem Statement

Current techniques of pattern classification available in literature have some limitations in terms of performance and accuracy in determining the main patterns namely homogeneous, speckles (fine and coarse), centromere, and nucleolar. Correct identification of features is necessary in producing accurate information that is essential in developing automated classification system that can identify patterns accurately and reduce the time required for diagnosis.

1.3. Significance of the Project

- To improve the current practice used in the medical institution, by developing standard method for classification purposes
- To apply the best image processing techniques for feature extraction and statistical representative of cell patterns

1.4. Objectives

This project will be focusing on extracting the image textural and statistical features for five (5) major patterns; homogeneous, fine-speckled, coarse-speckled, nucleolar, and centromere. Below are the objectives of this project:

- To identify textural and statistical features to be utilized to differentiate each pattern
- To measure the texture difference between the patterns
- To assess the reliability of each textural representation by distinguishing one from the other
- To test the accuracy of classification using the extracted features

1.5. Scope of Study

Overall, this project covers five main types of HEP-2 cell patterns which are; homogeneous, fine-speckled, coarse-speckled, nucleolar, and centromere.

1.6. Feasibility of the Project

From the literature done, it was found that some parts of the project were already done by some researchers on other types of images. Some of the researches are focusing on HEP-2 cell images but among those researches none of it summarized the texture of the cells for each pattern types. Therefore using current available application, Matlab, the project will utilize its image processing tools to implement the functions in aiding the medical industries with specific data range representing the textural and statistical information of each pattern. Finally, after summarizing the processes to be done, this

project is possible to be completed within the time range specified for Final Year Project I (FYP I) and Final Year Project II (FYP II).

CHAPTER 2

LITERATURE REVIEW

2.1. Critical Analysis

2.1.1. Textural Feature Extraction

Recently, there has been a lot of studies on the classification of HEp-2 cell images in conjunction towards developing a reliable and standardize system to analyze and classify different types of ANA. According to Ghosh & Chaudhary [4], four types of feature extraction have been done towards the same data set in order to compare the successfulness. The first feature is by using Speeded-up Robust Features (SURF) that function by detecting the key-points of an image and store it in a vocabulary for further classification. SURF technique is used for static signature (image of the signature) verification with range of equal error rate (EER) between 14.5% - 19% [7].

The second feature extraction technique is based on Region of Interest (ROI) that focuses on the cell nuclei or clusters of cell nuclei which later can be classified according to its sub-feature [8]. For HEp-2 cell images, the sub-features used include the standard deviation of the gray values, the 30th (P_{30}) and 60th (P_{60}) percentiles of the gray values in the ROI, the percentile range ($P_{range} = P_{60} - P_{30}$), and the roundness of the ROI [4]. For the third feature, textural, the cell images will be evaluated in its gray-scale. Disregard its original colors, by using Grey-Level Co-occurrence Matrix (GLCM) where the intensity of the gray level will be taken into account. The main criteria involves in this extraction type is the texture and tone of the image which is closely related together and its presence are inversely proportionate between each other [9].

Lastly is the Normalized Histogram of Oriented Gradient (NHOG) feature. This feature extracting method has been used in pedestrian detection by camera sensor in intelligent vehicle where the statistic of the gradient map of target image will be extracted in histogram manners [10]. Referring to Ghosh & Chaudhary [4], who had

done the feature extraction using all four (4) features, the successful rate is listed in Table 1. Moreover, Tsu-Yi *et. al* [11] in their paper discovered the average accuracy of using textural feature analysis to differentiate the patterns is 80.3%. Therefore for this paper, the textural features of the HEp-2 cell images will be used in the feature extraction stage.

Table 1: Intensity-wise, class-wise, and overall accuracy (in percentage) for each feature [4]

Feature Type	Percentage of Accuracy								Overall
	Intensity-wise		Class-wise						
	Positive	Inter	HO	FS	CS	NU	CY	CE	
HOG	83.84	80.31	82.67	64.89	93.58	70.59	82.76	89.42	82.25
Texture	90.40	81.54	87.33	68.09	96.33	86.27	68.97	93.75	86.39
ROI	80.56	50.78	87.33	0	88.99	58.82	86.21	70.19	67.13
SURF	77.53	57.85	68.67	44.68	59.63	76.47	84.48	75.96	68.67

2.1.2. Statistical Feature Extraction

The statistical features of an image is important in automatic image processing by computers as it is the only way that the computer could recognize and identify the image features. It differs with human that can recognize an image from natural and geometric language [12]. Computer can only recognize information that is transferred using its language.

Therefore, prior to classifying HEp-2 cell images, the statistical features must be extracted to obtain the required data. These data is calculated based on statistical formulas such as; mean standard deviation, and variance [13]. The formula is calculated from the gray intensity level obtained from the gray-scale images. Athilakshmi *et. al* in [13] used the statistical feature to identify the quality of lumber and use the correlation coefficient to justify the pass level for the lumber quality. Lumber is wood material that has been manufactured into boards. The quality level of lumber is important to produce good quality furniture and structures.

In 2010, Vasconcelos *et. al* [14] used statistical method to represent the textural features of lung to identify if the lung is emphysema or not. To represent these features, several descriptors are used. Table 2 shows the list of statistical measures and its corresponding textural measures used in [14].

Table 2: Statistical Measures and Corresponding Textural Representation

Statistical Measures	Textural Measures
Angular Second Moment (ASM)	Degree of uniformity, energy
Entropy (ENT)	Randomness
Inverse Difference Moment (IDM)	Local homogeneity
Correlation (COR)	Linear dependency of gray levels
Contrast (CON)	Intensity variation between a pixel and its neighbor, over the region

2.2. Framework of the Study

Based on the literature review and critical analysis done, none of the researches have specified which of the textural representation is valid, in terms of statistical representation, to be used as the indicator of the pattern characteristic. Therefore, this project will focus on extracting the textural features together with the use of statistical representation. Eventually, this project will highlight the reliable textural measures that can be used in identifying the patterns. These measures must have significant difference between each pattern before it can be finalized as the best data to be extracted for classification purposes.

CHAPTER 3

METHODOLOGY

3.1. Image Acquisition

All images used in this project are acquired from MIVIA Data Set for 21th International Conference for Pattern Recognition. The images were taken by a fluorescence microscope (40-fold magnification) coupled with a 50Wmercury vapor lamp and with a digital camera (SLIM system by Das srl). The original size of the images is 1388x1038 pixels, with 24bits color depth [15].

3.2. Techniques Involved

3.2.1. Pre-Processing

Every image processing must start with a pre-processing stage to obtain a clearer image and to suppress the background noise. For this project, the pre-processing will include transforming the original cell images into grayscale image. Other steps may include photometric or colorimetric processes, noise suppression, adaptive filters, and image re-sampling [12].

Basic image processing will be implemented such as segmentation and noise filtering to enhance the image quality before extracting the features.

3.2.2. Feature Extraction

Since this project will be using textural based feature extraction, all the texture information will be analyzed using particular statistical measures to extract the image features. The statistical measures will then be gathered to analyze the textural features represented. From Figure 1, it is significant that the four patterns have different uniformity level. Therefore, the angular second moment in statistical method can measure the closeness of the element distribution which represents the homogeneity characteristics.

Other textural features can be calculated using other statistical representation that will be explored further in order to find suitable measures that can distinguish the

difference between each pattern. The GLCM is basically a method that transforms the image layout into intensity grid where each of gray level intensity will be represented by numbers according to its intensity level. The numbers will later be calculated according to the specific formula to describe the texture.

3.2.3. Data Acquisition

From the extracted information of the textural features, the data will be compiled together and analyzed accordingly. The data will be used to compare the patterns' difference. The texture of the patterns can be analyzed from the range of values extracted. All data obtained was cross validated between each textural representation and to conclude which of the representation is reliable to be used in extracting HEP-2 cell images in order to provide pre-information for classification process.

3.2.4. Pattern Classification

The acquired data is used as a training input to the classifier to check the features' reliability to differentiate the pattern accordingly. This project is using three (3) and five (5) points k -NN and ADABOOSTM2 as the classifier.

3.3.Flow Chart

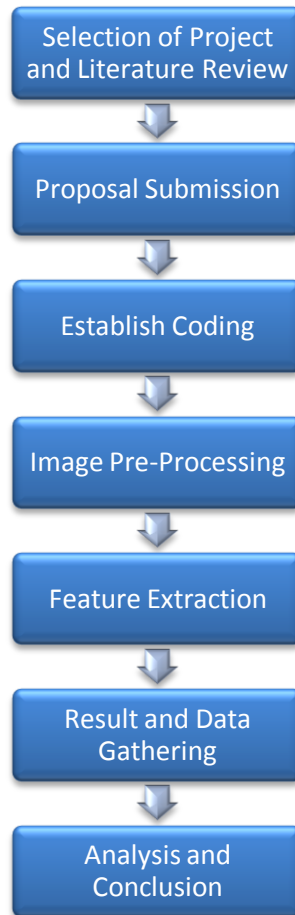


Figure 2: Project Flow Chart

3.4.Project Activities

The author attended a short course on image pre-processing technique and learnt the standard pre-processing procedures and how to simulate it using MATLAB application. Below is part of the available commands in MATLAB image processing toolbox that can be used directly by calling the function:

1. Read image

```
% Declare a figure to display images  
figure(1);  
% Read and image named Koala with JPEG extension and put it in  
a variable  
% named 'Image'  
Image = imread('Koala.jpeg');
```

2. Show image

```
% display the image and give it a title
imshow(Image), title('Original image');
```

3. Convert original image to gray-scale

```
% convert the image to grayscale and put it in a variable
named 'ImageGray'
ImageGray = rgb2gray(Image);
```

4. Convert gray-scale image to negative image

```
% Compute Image negative
NegativeImage = 255-ImageGray;
% display negative image in the third quadrant
```

5. Compute log image

```
% Compute log image
LogImage = log(1+double(ImageGray));
```

Weekly meeting with supervisor and co-supervisor are held to update the progress of the project and to discuss if there are any changes needed.

3.5. Tools and Equipments Required

This project mainly used three applications as listed in Table 3.

Table 3: Applications Required for the Project

Application	Version	Description
MATLAB R2013a - Image Processing Toolbox	8.1	To use the image processing toolbox in processing the images and retrieving the data
Microsoft Office Excel 2010	14.0	For data gathering and analysis
Microsoft Office Word 2010	14.0	Documentation purpose

CHAPTER 4

RESULTS AND DISCUSSIONS

4.1.Pre-Processing

For texture feature extraction, most of the papers noted that it is best not to over-preprocessing the image to avoid texture changes. Therefore, before extracting the image features, the image are only converted into grayscale using below coding. 40 images of each pattern are used throughout this project which total up equals to 200 images as five patterns are used as reference. The patterns are; homogeneous, fine-speckled, coarse-speckled, nucleolar, and centromere.

```
% Read Image
Image = imread('E:\Documente\FYP\ANA Images\All\Speckled\Test3\1.tif');
% Converting RGB image into Grayscale
Image2 = rgb2gray (Image);
```

4.1.1. Statistical Analysis

The statistical features of the images are extracted based on first order statistics derived from the histogram of the grayscale image. The features extracted are listed in Table 4 together with its formula, as stated in [16]. These first order statistical measures are based on the intensity of every single pixels of an image without considering the relationship with neighboring pixels. The first order statistical measures observe the distribution of color intensity of the images.

4.1.2. Textural Analysis

Texture analysis of an image is basically extracting the image color intensity using second order statistical measures. To differentiate from the first order statistic, second order statistical measures consider the relationship between each pixel to its neighboring pixels.

Table 4: First Order Statistics [16]

Parameters	Description	Formula
Mean, μ	Average value of the distribution.	$\mu = \sum xP(x)$ $x = \text{gray intensity value}$ $P(x) = \text{probability of } x$
Variance, σ^2	A measure of how far the gray intensity spread out for the image.	$\sigma^2 = E[(x - \mu)^2]$ $E = \text{expected value of } (x - \mu)^2$
Skewness, s	A measure of the extent to which the gray intensity distribution "leans" to one side of the mean.	$s = \frac{E(x - \mu)^3}{\sigma^3}$ $\sigma = \text{standard deviation of } x$
Kurtosis, k	The measure of "peakedness" of the histogram.	$k = \frac{E(x - \mu)^4}{\sigma^4}$
Entropy, S	The probability of the same intensity to occurs throughout the image.	$S = -k_B \sum_i p_i \ln p_i$ $k_B = \text{Boltzmann's constant}$

4.2.Feature Extraction

Using the grayscale image, an array of GLCMs is generated using multi-direction to get the average values from all directions.

```

% Create the GLCMs. Call the graycomatrix function specifying the
offsets
% Angle set to 0, 45, 90, 135 degree
glcms = graycomatrix(Image2, 'Offset', [0 1; -1 1; -1 0; -1 -1]);
    
```

The offset values are defined according to which angle of the correlations to be taken based on the list in Table 5, where D is the distance between the center of a pixel and the center of its neighboring pixel. For example in Figure 3, it shows the angle of the reading with distance, D = 1.

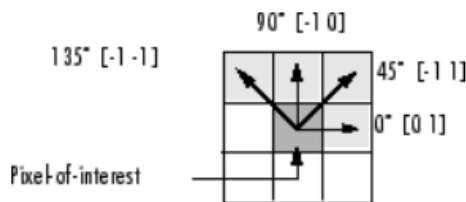


Figure 3: Offset Values with distance, D = 1

Table 5: Offset Values in GLCM[16]

Angle (°)	Offset
0	[0 D]
45	[-D D]
90	[-D 0]
135	[-D -D]

Using 'graycoprops' functions in Matlab, the properties of the gray-level co-occurrence matrices are extracted, which resulting a few sets of arrays based on the number of offset used. The properties are as in Table 6.

The result appears in sets of arrays, (i,j,n) , where i and j represents the row and column numbers, and n represents the offset number. For example, $A(:, :, 1)$ is an array of rows and columns for offset [0 1], $A(:, :, 2)$ for offset [-1 1] and so on.

```
% Derive statistics from the GLCMs using the graycoprops function.
stats = graycoprops(glcms, 'Contrast', 'Correlation');
stats2 = graycoprops(glcms, 'Homogeneity', 'Energy');

% Display the statistical values derived from GLCM
display(stats);
display(stats2);
```

Table 6: Gray-Level Co-occurrence Matrix Properties - Graycoprops [16]

Property	Description	Formula
Contrast	A measure of the intensity contrast between a pixel and its neighbor over the whole image. Contrast = 0 for constant image	$\sum_{i,j} i - j ^2 p(i, j)$ $p(i, j) = \text{probability of } (i, j) \text{ coordinate in GLCM}$
Correlation	A measure of how correlated a pixel is to its neighbor over the whole image. Correlation = -1 or 1 for a perfectly positively or negatively correlated image	$\sum_{i,j} \frac{(i - \mu_i)(j - \mu_j)p(i, j)}{\sigma_i \sigma_j}$ $\mu = \text{mean}$ $\sigma = \text{standard deviation}$
Energy	Sum of squared elements in the GLCM. Energy = 1 for constant image	$\sum_{i,j} p(i, j)^2$
Homogeneity	Measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal. Homogeneity = 1 for a diagonal GLCM	$\sum_{i,j} \frac{p(i, j)}{1 + i - j }$

Applying all of the properties over the grayscale image, a set of values will be obtained for the analysis. These values will be used for further analysis using statistical measures such as mean, variance, and entropy.

4.3. Discussions

Initially, the images analyzed are mixed between positive and intermediate positivity level. The result shows unbalance reading between both positivity levels. Therefore, the images are later separated, and only positive level images are being used for this project. All data can be found in Appendices. The graphs shows the features level representing all five patterns as; H-homogeneous, F-fine-speckled, S-coarse-speckled, N-nucleolar, C-centromere. The data extracted from the images are plotted into graph to visualize the difference between the patterns. The x -axis represents the image name according to its number, while the y -axis represents the value of corresponding graph data.

4.3.1. First Order Statistics

The mean distribution in Figure 4 shows that all of the patterns have almost the same average gray intensity. Except some of the images have a bit higher mean values. This shows that all of the patterns have an average gray intensity level. While centromere's intensity level variance are higher than other patterns' as shown in Figure 5, indicating centromere has more varieties of gray level distribution compare to other patterns.

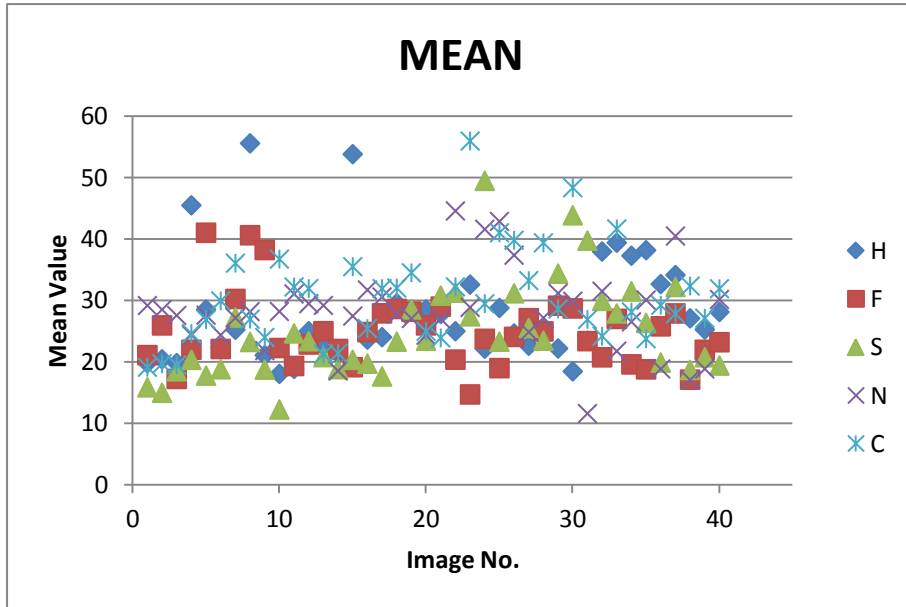


Figure 4: Comparison Chart - 1st Order Statistics (Mean)

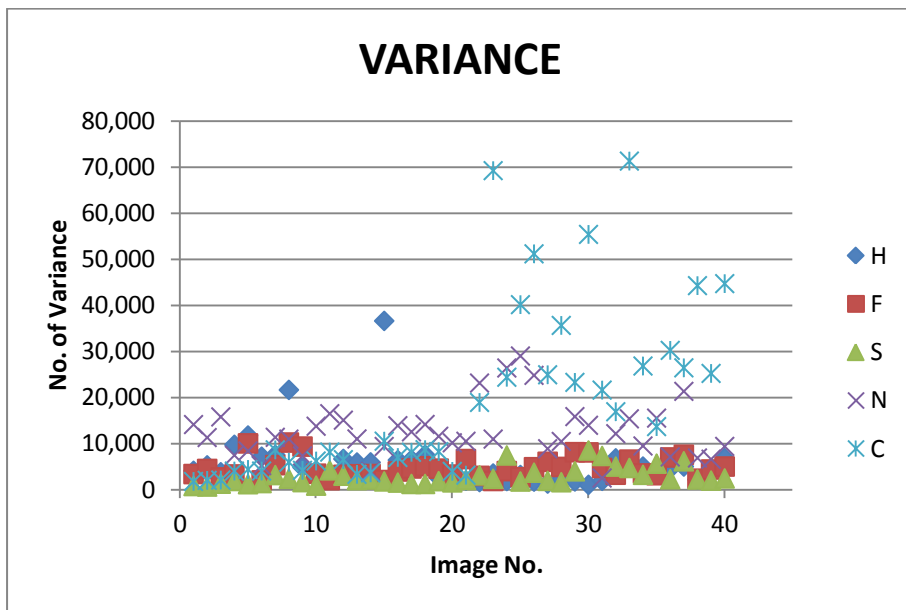


Figure 5: Comparison Chart - 1st Order Statistics (Variance)

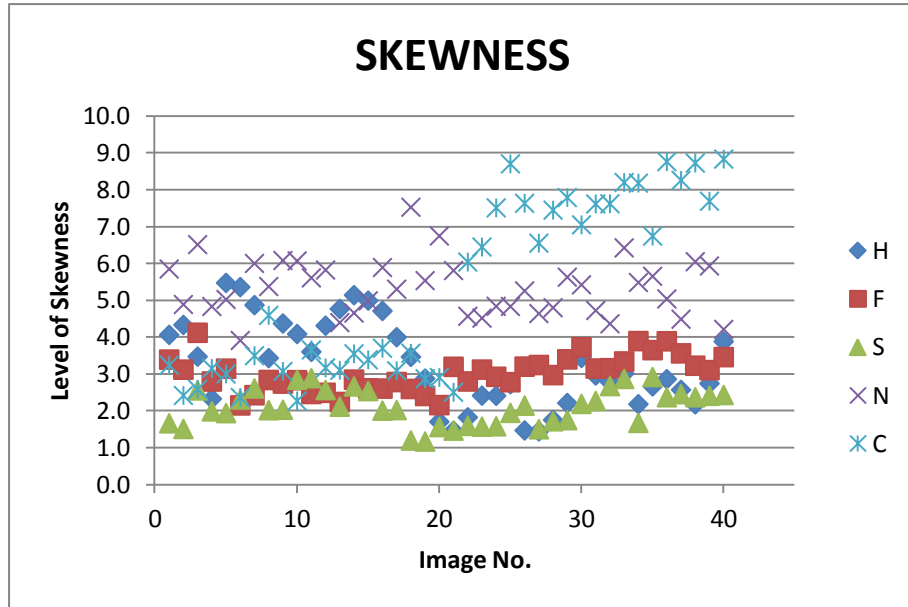


Figure 6: Comparison Chart - 1st Order Statistics (Skewness)

On the other hand, the skewness and kurtosis of the histogram shows the same distribution pattern where nucleolar and centromere have slightly high skewness and kurtosis level than homogeneous, fine-speckled and coarse-speckled. These are shown in Figure 6 and Figure 7. This concludes that the gray level intensity distribution of nucleolar and centromere is highly uneven between the right side and the left side of the mean. The high kurtosis value of nucleolar and centromere represents the narrow peak of the histogram. In other words, nucleolar and centromere pattern has minimum intensity level with high probability distribution.

Meanwhile, for entropy features in Figure 8, homogeneous shows an uneven distribution of entropy level. In average, coarse-speckled have higher entropy than other patterns. High value of entropy indicates highly distributed gray level intensities throughout the image.

For example, in Table 7, the mean of each pattern is the same as each pattern have an average size of images. Larger image might give larger mean values. The variance of gray level for nucleolar and centromere is relatively high compared to homogeneous, fine-speckled, and coarse-speckled. This means that nucleolar and centromere has significantly more gray levels than other patterns.

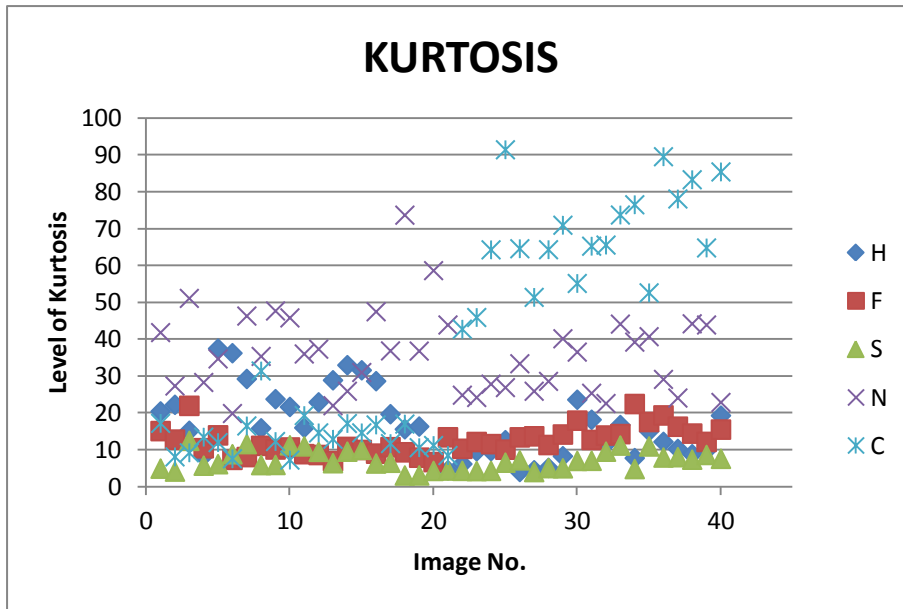


Figure 7: Comparison Chart - 1st Order Statistics (Kurtosis)

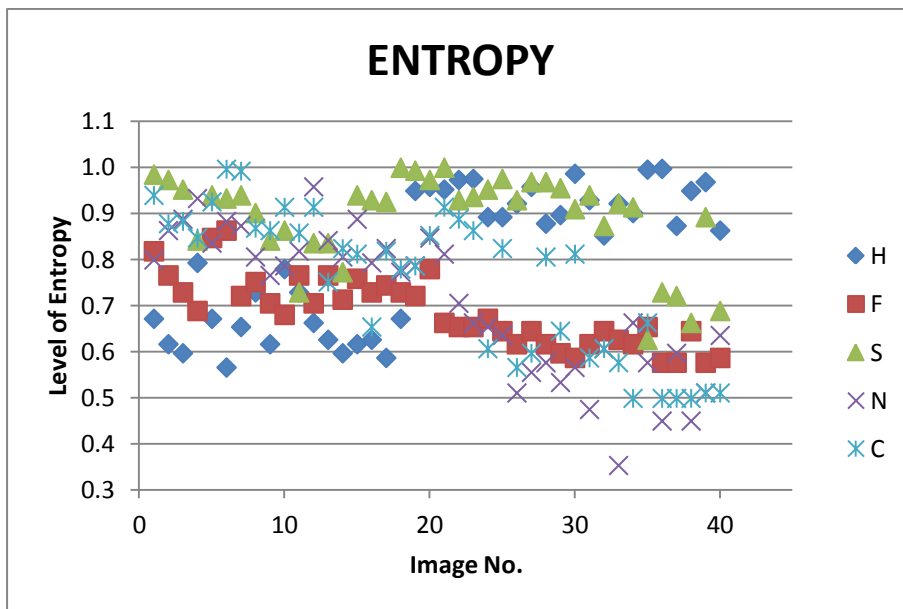


Figure 8: Comparison Chart - 1st Order Statistics (Entropy)

The average skewness of the histogram shows that all patterns have the right side of mean distribution tendency. While the kurtosis values which represent the flatness of the histogram, shows that coarse-speckled has the most flat histogram peak. This indicates the average distribution of gray level in the image as the distribution around the peak is fairly spread across the histogram as in Figure 9. To be compared with centromere's high

value of kurtosis that indicates the sharp peak of the histogram with a wide tail in Figure 10.

The entropy features, representing the measure of the "disorder" of a system, show that the patterns are averagely disorder with values all above 0.5.

Table 7: Average 1st Order Statistics for Each Pattern

Pattern	Mean	Variance	Skewness	Kurtosis	Entropy
Homogeneous	28.1424	5606.3436	3.2622	16.6583	0.8066
Fine-Speckled	24.7734	4607.4190	3.0173	12.4124	0.6854
Coarse-Speckled	24.8844	2757.1519	2.1062	7.0295	0.8891
Nucleolar	28.1622	12531.9148	5.3465	35.8125	0.7066
Centromere	30.4958	19403.8231	5.2912	39.3747	0.7524

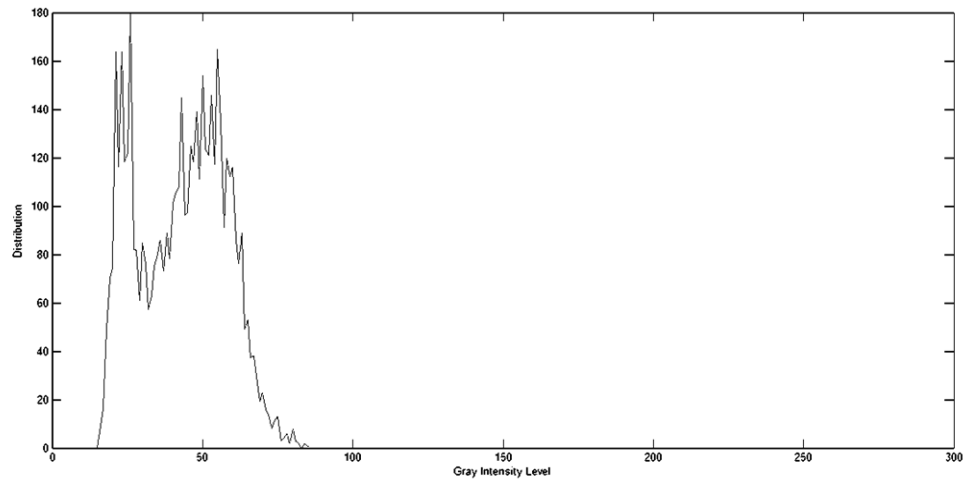


Figure 9: Gray-scale Image Histogram - Coarse-Speckled

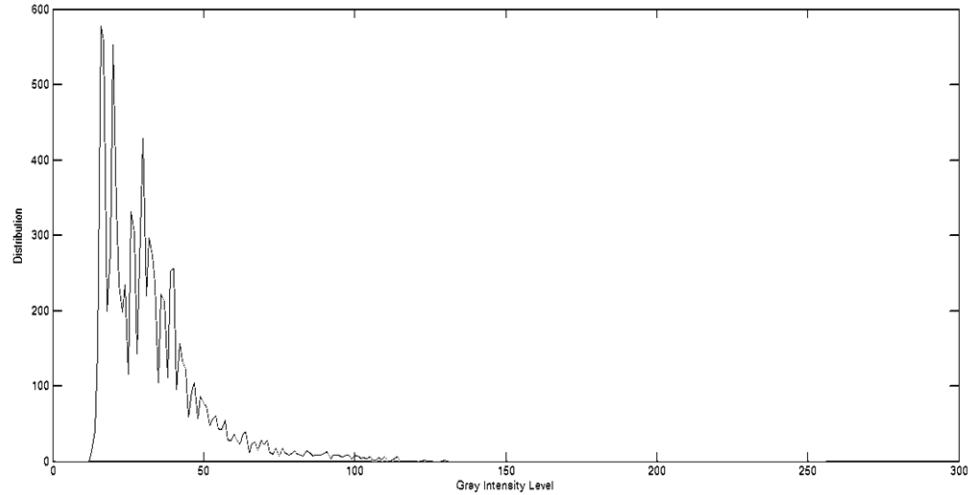


Figure 10: Gray-scale Image Histogram - Centromere

4.3.2. Second Order Statistics

For second order statistics, four main functions in Matlab stated in Table 6 are utilized to analyze the texture of the images. Those calculations are done based on GLCM version of the image.

The image processing on contrast returns a comparable value that distinguishes coarse-speckled features from other pattern since it has higher contrast value. While the other four pattern have a little bit overlapping between each other. This is shown in Figure 11. The contrast basically gives the measurable value of the total gray level contrast of the image.

The correlation level of each patterns are significantly constant between each other and not very reliable to be used as differentiator. The overlapping is laid out in Figure 12. The correlation measures how the pixel related to neighboring pixels and calculates the repetition.

Figure 13 shows that coarse-speckled pattern have less homogeneity than other patterns. It computes the clustering of the surface texture, if it is evenly spread or roughly spread on the pattern. While the energy of nucleolar and centromere able to differentiate those two patterns from others even though without using auto-computed system as plotted in Figure 14.

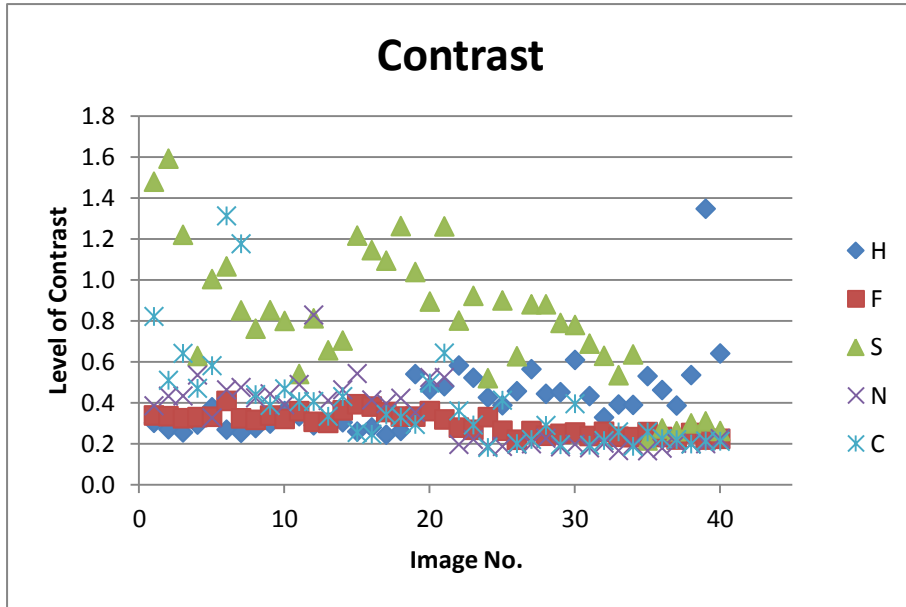


Figure 11: Comparison Chart - 2nd Order Statistics (Contrast)

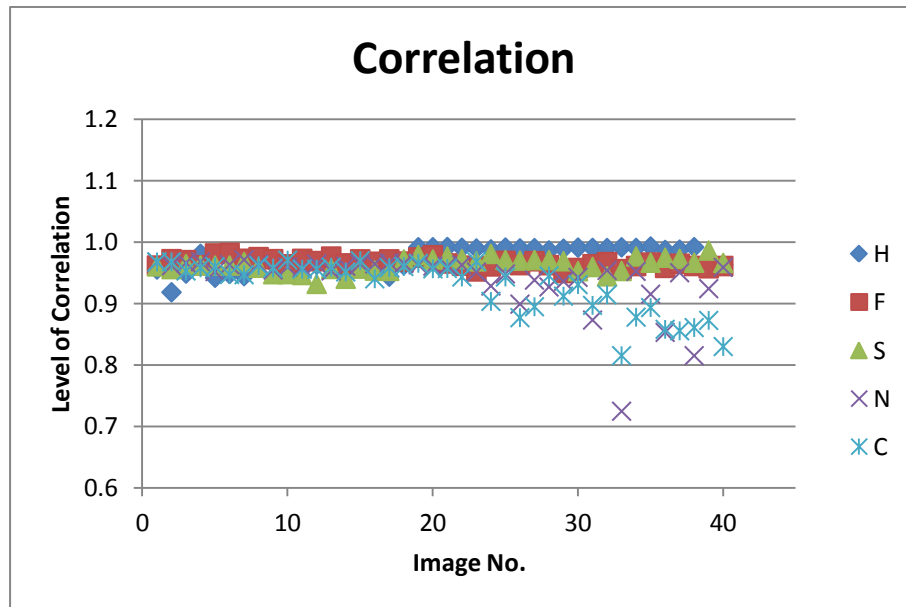


Figure 12: Comparison Chart - 2nd Order Statistics (Correlation)

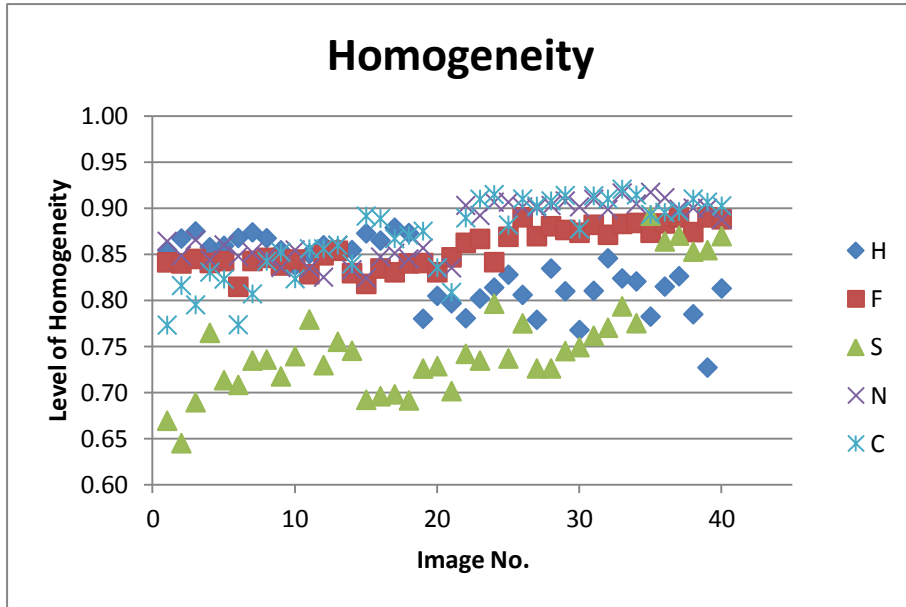


Figure 13: Comparison Chart - 2nd Order Statistics (Homogeneity)

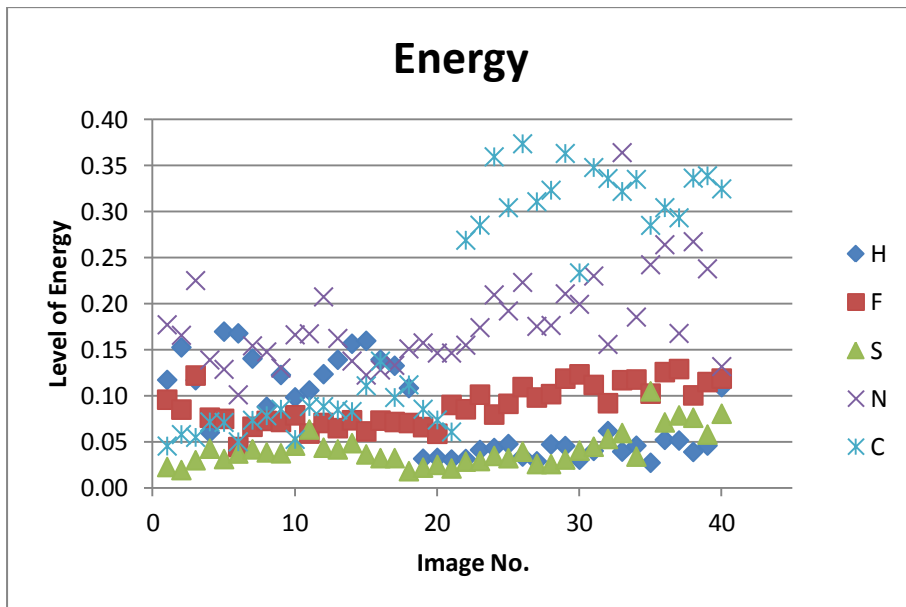


Figure 14: Comparison Chart - 2nd Order Statistics (Energy)

A classification test has been done to check the reliability and accuracy of the features to be used to differentiate the patterns. Variance and correlation features data are not included in the training data for the classifiers. The classification was done using two *K*-NN classifier and ADABOOST classifier. The accuracy of the *K*-NN (44.89%) classifier is better than ADABOOST (41.77%). If we observe the accuracy according to pattern types, ADABOOST classifier gives the best classification accuracy for nucleolar pattern. However, when it comes to homogeneous,

coarse-speckled, and centromere patterns, the accuracy is significantly low. The accuracy test results are compiled in Table 8 and 9.

Table 8: Percentage of Accuracy based on Patterns

Feature Type	Percent Accuracy (%)					
	Homogeneous	Fine-Speckled	Coarse-Speckled	Nucleolar	Centromere	Overall
1st Order	32.33	34.45	35.56	63.33	37.78	40.69
2nd Order	46.67	76.67	26.67	84.44	61.11	59.11
1st + 2nd Order	31.11	50.00	17.78	63.33	37.78	40.00

Table 9: Percentage of Accuracy based on Classifiers

Classifier Type	Percent Accuracy (%)					
	Homogeneous	Fine-Speckled	Coarse-Speckled	Nucleolar	Centromere	Overall
5-NN	45.56	52.22	28.89	58.89	57.78	48.67
3-NN	52.22	44.45	26.67	56.66	61.11	48.22
ADABOOST	12.22	64.44	24.45	95.56	17.78	42.89

CHAPTER 5

CONCLUSION AND RECOMMENDATION

5.1. Conclusion

From the result obtained, it is clear that the homogeneity and correlation of the patterns are relatively the same. Therefore we must avoid using these features alone to differentiate the patterns as it might give wrong classification information. It is significant that coarse-speckled pattern have more independent values of each features with less overlap with other patterns.

To conclude the current progress, it shows that not every feature extracted from the GLCM analysis can be used to differentiate HEP-2 cell patterns. More texture features are suggested to be explored as in [9] to get more texture information from the image and gain more properties to be used as input to the classifier. Nevertheless, more types of classifier should be tested to get a better classification of the patterns. Further analysis needs to be done in order to make use of the GLCM values to differentiate both patterns. Other statistical method might also be used to observe if it can produce some significant values to be used as differentiator.

5.2. Future Works and Recommendations

Finally, for the next stage, it is suggested to make use and compare other texture features function as stated in [9] to get more comparable data. Some of the listed functions in [9] is the same as in MATLAB function, but most of other functions are still not made available in MATLAB for direct function call as it is still under improvement. Therefore it will benefit the medical industry if it can be verified to be used for more classification vectors.

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APPENDICES

APPENDIX A: Key Milestone and Gantt Charts

No.	Activities	Week																											
		Final Year Project 1 (FYPI)														Final Year Project 2 (FYP2)													
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1.	Topic Selection	█	●																										
2.	Preliminary Research		█	█	●																								
3.	Extended Proposal				█	●																							
4.	Further Research					█	█	█	●																				
5.	Proposal Defense						█	█	█	●																			
6.	Pre-Processing							█	█	█	█	█	█	█	●														
8.	Draft Report														█	█	█	█	█	█	█	█	█	█	█	█	█	█	█
9.	Interim Report																												
10.	Feature Extraction																												
11.	Classification																												
12.	Results Gathering and Data Analysis																												
13.	Progress Report																												
14.	Draft Report																												
15.	Dissertation (soft bound)																												
16.	Technical Paper																												
17.	Oral Presentation																												
18.	Dissertation (hard bound)																												

APPENDIX B: 1st Order Statistics - Homogeneous

Image	Mean	Variance	Skewness	Kurtosis	Entropy
1	19.8047	4008.5735	4.0661	20.4300	0.6708
2	20.4258	5188.4415	4.3367	22.2300	0.6157
3	19.8047	3693.9617	3.4754	15.1792	0.5960
4	45.5000	9655.6471	2.3316	8.3658	0.7922
5	28.5273	11672.8777	5.4767	37.4657	0.6708
6	22.3711	7074.5794	5.3624	36.2345	0.5651
7	25.2344	7453.9370	4.8739	29.2420	0.6530
8	55.5898	21576.7684	3.4363	15.8489	0.7281
9	21.0938	4751.7088	4.3765	23.7578	0.6157
10	18.0469	2767.5821	4.0897	21.6453	0.7788
11	18.8594	3081.0311	3.6053	15.9889	0.7281
12	24.9961	6590.3568	4.3157	22.8879	0.6620
13	22.5469	5813.1507	4.7707	28.8813	0.6253
14	21.2930	5840.2001	5.1447	32.9764	0.5960
15	53.8281	36556.7390	4.9957	31.5921	0.6157
16	23.6250	6334.5176	4.7161	28.6395	0.6253
17	24.0234	6412.5563	4.0034	19.6811	0.5859
18	29.5508	7475.4092	3.4691	15.5954	0.6708
19	28.5469	2543.2762	2.8802	16.3214	0.9485
20	28.5469	2039.6605	1.7071	5.8858	0.9573
21	27.8125	1858.9373	1.4622	4.4218	0.9515
22	24.9961	1562.9686	1.8276	6.1479	0.9723
23	32.5898	3427.6468	2.4178	9.6068	0.9745
24	22.1484	1783.7191	2.4123	9.6410	0.8915
25	28.7891	3097.2808	2.7280	12.6213	0.8915
26	24.6289	1664.4931	1.4724	3.9987	0.9209
27	22.6367	1240.0910	1.4477	4.4554	0.9573
28	25.6484	2232.2210	1.7576	5.0949	0.8774
29	22.1875	1699.7765	2.2169	8.2663	0.8960
30	18.4570	972.9785	3.4413	23.6063	0.9857
31	23.4375	1831.8314	2.9647	18.1669	0.9284
32	37.9688	6711.6618	2.7852	11.5753	0.8518
33	39.4063	5447.3245	3.0137	16.7334	0.9209
34	37.2891	4931.4063	2.1857	7.7591	0.9004
35	38.1875	3655.7294	2.6704	15.0425	0.9947
36	32.6719	4475.8056	2.8649	12.1654	0.9964
37	34.1406	4936.5998	2.5734	10.2423	0.8725
38	27.0938	2113.5441	2.1815	8.8126	0.9485
39	25.2656	3318.8625	2.7464	9.8316	0.9677
40	28.1250	6759.8902	3.8869	19.2914	0.8624
Average	28.1424	5606.3436	3.2622	16.6583	0.8066

APPENDIX C: 1st Order Statistics - Fine-Speckled

Image	Mean	Variance	Skewness	Kurtosis	Entropy
1	21.1016	3305.0563	3.3956	15.0927	0.8174
2	25.9453	4411.5735	3.1226	12.7743	0.7650
3	17.2266	2579.6896	4.1238	21.9455	0.7281
4	21.9688	3214.9480	2.8012	10.4478	0.6879
5	41.0313	9959.2539	3.1483	13.9371	0.8464
6	22.1016	1924.6249	2.1528	7.2872	0.8624
7	30.2461	5236.7745	2.4294	8.0448	0.7204
8	40.6250	10147.1529	2.8415	11.0928	0.7506
9	38.2227	9268.5345	2.7448	10.1047	0.7044
10	22.2578	3381.5646	2.8364	10.6417	0.6794
11	19.3359	1970.5377	2.4625	8.8358	0.7650
12	22.8359	3138.5298	2.4943	8.6019	0.7044
13	24.9961	3257.6745	2.2445	6.9401	0.7650
14	22.1016	3306.0524	2.8513	10.7970	0.7125
15	19.1328	1997.9039	2.6152	9.9668	0.7579
16	24.8594	3856.7096	2.6084	8.9719	0.7281
17	27.9063	4518.8775	2.7858	10.7154	0.7433
18	28.6172	5001.5705	2.5987	9.3355	0.7281
19	28.1875	4478.8039	2.4082	7.8753	0.7204
20	25.9453	3194.4519	2.1602	6.6807	0.7788
21	29.0078	6557.6862	3.1998	13.4029	0.6620
22	20.3672	2909.7941	2.8022	10.2789	0.6530
23	14.6953	1801.7735	3.1236	12.1334	0.6530
24	23.7500	3946.9176	2.9288	11.5551	0.6708
25	18.9844	2618.0625	2.7822	10.0459	0.6439
26	24.0703	4783.0382	3.2044	13.3897	0.6157
27	27.1172	5960.0254	3.2486	13.6736	0.6439
28	24.9609	4852.4142	2.9751	11.3144	0.6157
29	29.1484	8052.6838	3.4018	14.1601	0.5960
30	28.7109	8006.8887	3.7293	17.9290	0.5859
31	23.3828	4627.1392	3.1532	12.6846	0.6157
32	20.7500	3166.8157	3.1614	13.8837	0.6439
33	27.0000	6433.6784	3.3446	14.2731	0.6253
34	19.5938	3440.5324	3.8978	22.4367	0.6157
35	18.7891	3053.4298	3.6520	17.5621	0.6530
36	25.7930	6912.3374	3.8927	19.3427	0.5756
37	27.8906	7498.3880	3.5650	16.2766	0.5756
38	17.1094	2294.9684	3.2296	14.4142	0.6439
39	21.9688	4292.9324	3.1097	12.1546	0.5756
40	23.2031	4936.9703	3.4631	15.4969	0.5859
Average	24.7734	4607.4190	3.0173	12.4124	0.6854

APPENDIX D: 1st Order Statistics - Coarse-Speckled

Image	Mean	Variance	Skewness	Kurtosis	Entropy
1	15.8594	709.7919	1.6673	4.9118	0.9840
2	14.9766	600.4230	1.5136	4.1112	0.9723
3	18.4766	1217.2544	2.5602	12.4511	0.9515
4	20.3438	1804.7912	1.9912	5.7155	0.8408
5	17.7734	1109.1406	1.9435	6.1165	0.9389
6	18.8047	1351.3970	2.3136	8.8214	0.9320
7	27.2344	3088.8076	2.6117	11.5764	0.9389
8	23.2422	2304.5294	2.0223	5.8751	0.9004
9	18.7500	1560.3137	2.0361	5.9109	0.8408
10	12.2461	794.0686	2.8491	11.2395	0.8624
11	24.6406	4113.5409	2.8927	10.9537	0.7281
12	23.3750	2951.5294	2.5701	9.4661	0.8351
13	20.7813	1989.1912	2.1179	6.3889	0.8351
14	18.8203	2124.6421	2.6671	9.5209	0.7720
15	20.3438	1713.5441	2.5420	10.0182	0.9389
16	19.7109	1458.3318	2.0103	6.2984	0.9284
17	17.6328	1163.7705	2.0259	6.5095	0.9247
18	23.2969	1158.9154	1.1998	3.0402	0.9989
19	28.5469	1766.7900	1.1711	3.0650	0.9925
20	23.4531	1504.8056	1.5656	4.2864	0.9723
21	30.8008	2013.1719	1.4693	4.3858	0.9989
22	31.2656	3024.2743	1.5972	4.3119	0.9284
23	27.4219	2279.6409	1.5765	4.2468	0.9355
24	49.4883	7344.6822	1.5867	4.2930	0.9515
25	23.2969	1687.6370	1.9507	6.5285	0.9745
26	31.1719	3611.5390	2.1468	7.1623	0.9284
27	25.5234	1829.5681	1.5060	3.9852	0.9677
28	23.4609	1531.0808	1.7219	5.0499	0.9677
29	34.3750	3907.3333	1.7517	5.0014	0.9544
30	43.8750	8419.6549	2.1942	6.9993	0.9089
31	39.7500	7235.2549	2.2726	7.0407	0.9389
32	29.9414	4927.8358	2.6774	9.5102	0.8725
33	27.8906	4629.8233	2.8714	11.1678	0.9209
34	31.5000	3140.2588	1.6787	4.7947	0.9130
35	26.3477	5567.6002	2.9229	10.9344	0.6253
36	19.8906	2191.3449	2.3740	7.9311	0.7281
37	32.2070	6082.0393	2.4575	8.0174	0.7204
38	18.6914	2129.9946	2.3745	7.3396	0.6620
39	20.7539	1889.0098	2.4132	8.6220	0.8915
40	19.4141	2358.7534	2.4350	7.5817	0.6879
Average	24.8844	2757.1519	2.1062	7.0295	0.8891

APPENDIX E: 1st Order Statistics - Nucleolar

Image	Mean	Variance	Skewness	Kurtosis	Entropy
1	29.1797	14054.0852	5.8539	41.8261	0.7987
2	28.5156	11229.3801	4.8915	27.3422	0.8624
3	27.5625	15711.8157	6.5160	51.1149	0.8869
4	24.3750	7374.9647	4.8364	28.2956	0.9320
5	27.6094	8330.3017	5.0274	34.6919	0.8351
6	24.3750	5139.3647	3.9150	19.8618	0.8822
7	27.1680	11283.6932	6.0057	46.3170	0.8725
8	28.1875	10888.6549	5.3787	35.3647	0.8050
9	21.8359	7250.0122	6.0858	47.6899	0.7650
10	28.2031	13684.0605	6.0743	45.8169	0.7856
11	31.0703	16415.0774	5.6135	36.0213	0.8174
12	29.4844	15007.3723	5.8271	37.3362	0.9573
13	29.2031	10929.4880	4.4002	21.9887	0.8408
14	18.5352	3870.0850	4.6599	25.9030	0.8050
15	27.4648	9295.5988	4.9898	30.9953	0.8869
16	31.7109	13812.1514	5.8951	47.4852	0.7922
17	30.5703	12467.6735	5.3051	36.8581	0.8234
18	27.7734	14081.8857	7.5306	73.6964	0.7720
19	27.0703	11500.3166	5.5392	36.8047	0.7856
20	24.3438	10092.6814	6.7503	58.6454	0.8464
21	27.0000	10420.2824	5.8131	43.8892	0.8113
22	44.5820	23065.3109	4.5713	24.8362	0.7044
23	28.8750	10902.7922	4.5212	24.2071	0.6620
24	41.5938	26338.8382	4.8425	27.8325	0.6530
25	42.8750	28943.1686	4.8376	26.8976	0.6347
26	37.3750	24739.3490	5.2600	33.3774	0.5097
27	24.8594	8809.5566	4.6445	25.9086	0.5544
28	27.1719	10383.6331	4.8044	28.5887	0.5756
29	31.1719	15780.8958	5.6323	40.1603	0.5325
30	29.8828	13887.1078	5.4258	36.5340	0.5651
31	11.5898	2450.4782	4.7280	25.3531	0.4739
32	31.5000	12068.1569	4.3679	22.5820	0.6059
33	21.7500	15299.5608	6.4280	44.1325	0.3524
34	26.5234	9405.1289	5.4882	39.2400	0.6620
35	30.0781	15449.9468	5.6566	40.7202	0.5756
36	18.8438	7018.1794	5.0425	29.1294	0.4489
37	40.5000	21265.0980	4.4919	24.0704	0.5960
38	17.0547	6795.3303	6.0542	44.2202	0.4489
39	18.8594	6524.0821	5.9362	43.8938	0.5097
40	30.1641	9311.0318	4.2164	22.8703	0.6347
Average	28.1622	12531.9148	5.3465	35.8125	0.7066

APPENDIX F: 1st Order Statistics - Centromere

Image	Mean	Variance	Skewness	Kurtosis	Entropy
1	19.1250	1698.9647	3.2445	17.1998	0.9389
2	19.6914	1934.9907	2.4221	8.1061	0.8774
3	19.5000	2007.4588	2.5896	9.2082	0.8822
4	24.6094	3960.4350	3.1574	13.4449	0.8464
5	26.8945	4319.0437	3.0050	11.9750	0.9247
6	29.9414	3959.0828	2.3673	7.5824	0.9956
7	36.0703	8557.1794	3.5018	16.4900	0.9914
8	26.9531	5881.3468	4.5958	31.3975	0.8675
9	23.9883	4115.6979	3.0749	12.2646	0.8624
10	36.7383	6132.7116	2.2732	7.2240	0.9130
11	32.2070	8075.6785	3.6581	19.3134	0.8571
12	31.9453	6444.7735	3.1704	14.6116	0.9130
13	21.2500	3247.8745	3.1063	12.8690	0.7506
14	21.4102	3578.0703	3.5530	17.1466	0.8234
15	35.5078	10444.8705	3.3916	14.6121	0.8113
16	25.4297	6904.0813	3.7034	16.7604	0.6530
17	31.9375	8025.6667	3.0938	11.7092	0.8174
18	32.0313	8600.2578	3.5669	16.9943	0.7788
19	34.5117	8171.0038	2.8779	10.5887	0.7856
20	24.9648	3891.1478	2.9097	11.1871	0.8518
21	23.9063	3072.8461	2.5085	8.4700	0.9130
22	32.2227	18856.7855	6.0422	42.7517	0.8869
23	55.9727	69181.5326	6.4511	45.9264	0.8624
24	29.4766	24319.0112	7.5137	64.2961	0.6059
25	41.0156	40089.8900	8.7077	91.4537	0.8234
26	39.8086	51125.0573	7.6376	64.5916	0.5651
27	33.2422	24868.8588	6.5563	51.3910	0.5960
28	39.3984	35575.0642	7.4525	64.3327	0.8050
29	28.6172	23216.7548	7.7929	70.9575	0.6439
30	48.3750	55339.2000	7.0539	55.1643	0.8113
31	26.9063	21536.2971	7.6193	65.2723	0.5859
32	24.1875	16842.1373	7.6258	65.5831	0.6059
33	41.6563	71256.6108	8.2023	73.7419	0.5756
34	28.1250	26766.1176	8.1843	76.5267	0.4980
35	23.7617	13601.5940	6.7472	52.6200	0.6620
36	29.2266	30161.5563	8.7677	89.5667	0.4980
37	27.8438	26370.0853	8.2616	78.0938	0.4980
38	32.3516	44215.5465	8.7294	83.3252	0.4980
39	27.1172	25155.5548	7.6933	64.8010	0.5097
40	31.9141	44652.0867	8.8368	85.4383	0.5097
Average	30.4958	19403.8231	5.2912	39.3747	0.7524

APPENDIX G: 2nd Order Statistics - Homogeneous

Image	Contrast				Mean	Correlation				Mean
1	0.2535	0.3397	0.2600	0.3559	0.3023	0.9630	0.9491	0.9620	0.9467	0.9552
2	0.2458	0.2907	0.2271	0.3190	0.2707	0.9263	0.9108	0.9333	0.9021	0.9181
3	0.2179	0.2741	0.2294	0.2999	0.2553	0.9562	0.9448	0.9539	0.9396	0.9486
4	0.2518	0.3185	0.2552	0.3487	0.2936	0.9835	0.9789	0.9833	0.9769	0.9807
5	0.3161	0.4444	0.3173	0.4356	0.3784	0.9518	0.9310	0.9521	0.9323	0.9418
6	0.2318	0.3058	0.2317	0.3067	0.2690	0.9558	0.9401	0.9558	0.9399	0.9479
7	0.2222	0.2768	0.2280	0.2871	0.2535	0.9520	0.9389	0.9503	0.9366	0.9444
8	0.2460	0.3020	0.2378	0.3212	0.2767	0.9777	0.9724	0.9785	0.9706	0.9748
9	0.2421	0.3278	0.2723	0.3521	0.2986	0.9714	0.9601	0.9674	0.9572	0.9640
10	0.2883	0.3790	0.3042	0.4682	0.3599	0.9632	0.9499	0.9611	0.9381	0.9531
11	0.2697	0.4211	0.2874	0.3593	0.3344	0.9659	0.9453	0.9636	0.9534	0.9570
12	0.2397	0.3546	0.2570	0.3090	0.2901	0.9699	0.9544	0.9675	0.9603	0.9630
13	0.2550	0.3615	0.2576	0.3380	0.3030	0.9694	0.9557	0.9691	0.9586	0.9632
14	0.2668	0.3488	0.2546	0.3494	0.3049	0.9607	0.9475	0.9629	0.9475	0.9546
15	0.2222	0.3110	0.2285	0.2765	0.2595	0.9633	0.9481	0.9620	0.9538	0.9568
16	0.2381	0.3314	0.2378	0.3119	0.2798	0.9610	0.9447	0.9612	0.9480	0.9538
17	0.2101	0.2699	0.2214	0.2758	0.2443	0.9519	0.9370	0.9495	0.9356	0.9435
18	0.2220	0.2979	0.2326	0.2984	0.2627	0.9684	0.9568	0.9667	0.9567	0.9622
19	0.4104	0.7537	0.4336	0.5639	0.5404	0.9935	0.9880	0.9931	0.9910	0.9914
20	0.3779	0.6073	0.3520	0.5242	0.4654	0.9931	0.9888	0.9936	0.9903	0.9914
21	0.3980	0.5990	0.3528	0.5749	0.4812	0.9932	0.9897	0.9940	0.9901	0.9917
22	0.4141	0.7623	0.4772	0.6761	0.5824	0.9934	0.9876	0.9923	0.9890	0.9905
23	0.4386	0.6500	0.3686	0.6333	0.5226	0.9911	0.9866	0.9925	0.9869	0.9893
24	0.3787	0.5359	0.3039	0.4870	0.4264	0.9893	0.9847	0.9914	0.9861	0.9879
25	0.3711	0.3691	0.2515	0.5603	0.3880	0.9913	0.9913	0.9941	0.9869	0.9909
26	0.4167	0.5145	0.3042	0.5924	0.4570	0.9905	0.9882	0.9931	0.9864	0.9896
27	0.5172	0.6410	0.3409	0.7583	0.5644	0.9909	0.9886	0.9940	0.9865	0.9900
28	0.3763	0.4574	0.3505	0.5923	0.4441	0.9884	0.9857	0.9892	0.9815	0.9862
29	0.3359	0.5450	0.3636	0.5640	0.4521	0.9919	0.9867	0.9913	0.9863	0.9890
30	0.4208	0.5390	0.5082	0.9706	0.6097	0.9937	0.9919	0.9924	0.9854	0.9908
31	0.3461	0.4189	0.3406	0.6261	0.4329	0.9923	0.9906	0.9924	0.9860	0.9903
32	0.2604	0.3544	0.2811	0.4201	0.3290	0.9922	0.9893	0.9916	0.9873	0.9901
33	0.3162	0.5012	0.3197	0.4300	0.3918	0.9930	0.9888	0.9929	0.9904	0.9913
34	0.2836	0.4663	0.3429	0.4663	0.3898	0.9930	0.9883	0.9915	0.9883	0.9903
35	0.4033	0.5681	0.4176	0.7333	0.5306	0.9944	0.9921	0.9942	0.9897	0.9926
36	0.3732	0.4963	0.3516	0.6293	0.4626	0.9896	0.9859	0.9902	0.9822	0.9870
37	0.2990	0.4530	0.3188	0.4763	0.3868	0.9905	0.9853	0.9898	0.9846	0.9875
38	0.3413	0.4747	0.4800	0.8468	0.5357	0.9946	0.9925	0.9924	0.9866	0.9915
39	0.9668	1.7273	1.0211	1.6776	1.3482	0.9730	0.9507	0.9714	0.9521	0.9618
40	0.4319	0.7535	0.5576	0.8216	0.6412	0.9754	0.9564	0.9683	0.9524	0.9631

Image	Homogeneity				Mean	Energy				Mean
1	0.8759	0.8388	0.8719	0.8320	0.8547	0.1242	0.1104	0.1238	0.1099	0.1171
2	0.8784	0.8578	0.8867	0.8462	0.8673	0.1591	0.1481	0.1598	0.1427	0.1524
3	0.8921	0.8669	0.8869	0.8541	0.8750	0.1240	0.1129	0.1228	0.1076	0.1168
4	0.8761	0.8496	0.8731	0.8326	0.8578	0.0642	0.0582	0.0632	0.0543	0.0600
5	0.8753	0.8423	0.8785	0.8416	0.8594	0.1795	0.1637	0.1743	0.1608	0.1695
6	0.8846	0.8514	0.8846	0.8507	0.8678	0.1751	0.1614	0.1743	0.1599	0.1677
7	0.8893	0.8627	0.8862	0.8575	0.8739	0.1464	0.1362	0.1460	0.1325	0.1403
8	0.8818	0.8563	0.8846	0.8479	0.8676	0.0928	0.0841	0.0930	0.0821	0.0880
9	0.8797	0.8425	0.8646	0.8313	0.8545	0.1304	0.1185	0.1258	0.1152	0.1225
10	0.8646	0.8239	0.8520	0.8109	0.8378	0.1070	0.0930	0.1020	0.0908	0.0982
11	0.8736	0.8311	0.8619	0.8349	0.8504	0.1132	0.0994	0.1098	0.1002	0.1057
12	0.8816	0.8355	0.8727	0.8500	0.8600	0.1316	0.1157	0.1275	0.1187	0.1234
13	0.8764	0.8324	0.8741	0.8425	0.8564	0.1458	0.1313	0.1456	0.1332	0.1390
14	0.8693	0.8391	0.8752	0.8351	0.8547	0.1636	0.1515	0.1618	0.1487	0.1564
15	0.8903	0.8513	0.8864	0.8635	0.8729	0.1679	0.1514	0.1655	0.1535	0.1596
16	0.8830	0.8433	0.8822	0.8515	0.8650	0.1468	0.1326	0.1443	0.1323	0.1390
17	0.8954	0.8670	0.8900	0.8639	0.8791	0.1401	0.1280	0.1374	0.1246	0.1325
18	0.8908	0.8599	0.8846	0.8576	0.8732	0.1138	0.1045	0.1131	0.1016	0.1082
19	0.8221	0.7215	0.7963	0.7808	0.7802	0.0355	0.0270	0.0333	0.0304	0.0316
20	0.8308	0.7572	0.8360	0.7960	0.8050	0.0350	0.0284	0.0357	0.0308	0.0325
21	0.8207	0.7561	0.8357	0.7753	0.7970	0.0331	0.0268	0.0342	0.0286	0.0307
22	0.8270	0.7487	0.7956	0.7516	0.7807	0.0357	0.0285	0.0329	0.0279	0.0313
23	0.8204	0.7682	0.8403	0.7798	0.8022	0.0437	0.0370	0.0451	0.0384	0.0411
24	0.8281	0.7795	0.8547	0.7937	0.8140	0.0450	0.0395	0.0482	0.0401	0.0432
25	0.8299	0.8364	0.8766	0.7689	0.8280	0.0484	0.0476	0.0534	0.0406	0.0475
26	0.8133	0.7892	0.8582	0.7635	0.8060	0.0348	0.0319	0.0396	0.0293	0.0339
27	0.7839	0.7525	0.8481	0.7316	0.7790	0.0292	0.0259	0.0351	0.0247	0.0287
28	0.8439	0.8320	0.8769	0.7860	0.8347	0.0488	0.0459	0.0528	0.0407	0.0471
29	0.8470	0.7838	0.8320	0.7773	0.8100	0.0509	0.0425	0.0474	0.0406	0.0453
30	0.8118	0.7779	0.7834	0.6984	0.7679	0.0347	0.0307	0.0318	0.0251	0.0306
31	0.8375	0.8111	0.8362	0.7571	0.8105	0.0430	0.0392	0.0437	0.0343	0.0400
32	0.8749	0.8354	0.8606	0.8123	0.8458	0.0659	0.0592	0.0647	0.0565	0.0616
33	0.8511	0.7818	0.8456	0.8172	0.8239	0.0427	0.0345	0.0421	0.0377	0.0393
34	0.8644	0.7932	0.8325	0.7927	0.8207	0.0514	0.0422	0.0475	0.0417	0.0457
35	0.8235	0.7718	0.8060	0.7287	0.7825	0.0307	0.0258	0.0291	0.0230	0.0272
36	0.8448	0.7964	0.8357	0.7834	0.8151	0.0574	0.0485	0.0551	0.0473	0.0521
37	0.8632	0.8010	0.8435	0.7978	0.8264	0.0577	0.0473	0.0539	0.0463	0.0513
38	0.8466	0.8001	0.7886	0.7049	0.7850	0.0440	0.0392	0.0395	0.0329	0.0389
39	0.7571	0.7056	0.7488	0.6973	0.7272	0.0502	0.0423	0.0492	0.0416	0.0458
40	0.8368	0.8035	0.8284	0.7836	0.8131	0.1162	0.1066	0.1135	0.1008	0.1093

APPENDIX H: 2nd Order Statistics - Fine-Speckled

Image	Contrast				Mean	Correlation				Mean
1	0.2755	0.3583	0.2952	0.4245	0.3384	0.9691	0.9589	0.9667	0.9514	0.9615
2	0.2663	0.3742	0.3003	0.3981	0.3347	0.9780	0.9683	0.9750	0.9663	0.9719
3	0.2712	0.3654	0.2829	0.3794	0.3247	0.9756	0.9663	0.9744	0.9651	0.9704
4	0.2800	0.3788	0.2758	0.3859	0.3301	0.9682	0.9562	0.9687	0.9554	0.9621
5	0.2742	0.3596	0.2938	0.4005	0.3320	0.9847	0.9796	0.9835	0.9773	0.9813
6	0.3446	0.4523	0.3316	0.5089	0.4093	0.9851	0.9802	0.9857	0.9777	0.9821
7	0.2711	0.3593	0.2819	0.3852	0.3244	0.9772	0.9694	0.9763	0.9672	0.9726
8	0.2602	0.3351	0.2828	0.3887	0.3167	0.9798	0.9738	0.9780	0.9696	0.9753
9	0.2785	0.3787	0.2945	0.3995	0.3378	0.9771	0.9684	0.9757	0.9667	0.9720
10	0.2626	0.3333	0.2807	0.4090	0.3214	0.9705	0.9620	0.9684	0.9534	0.9636
11	0.3134	0.3881	0.2836	0.4524	0.3594	0.9761	0.9701	0.9785	0.9651	0.9725
12	0.2483	0.3469	0.2751	0.3584	0.3072	0.9751	0.9646	0.9722	0.9634	0.9688
13	0.2530	0.3412	0.2588	0.3546	0.3019	0.9801	0.9730	0.9797	0.9719	0.9762
14	0.3151	0.4301	0.2949	0.4129	0.3632	0.9699	0.9584	0.9720	0.9601	0.9651
15	0.3376	0.4388	0.3100	0.4861	0.3931	0.9758	0.9681	0.9779	0.9647	0.9716
16	0.3160	0.4242	0.3235	0.4633	0.3818	0.9734	0.9639	0.9729	0.9606	0.9677
17	0.3122	0.3990	0.2841	0.4252	0.3551	0.9752	0.9678	0.9778	0.9657	0.9716
18	0.2920	0.3897	0.2686	0.3820	0.3331	0.9722	0.9624	0.9746	0.9632	0.9681
19	0.2801	0.3585	0.2830	0.4090	0.3326	0.9788	0.9726	0.9786	0.9688	0.9747
20	0.2890	0.4285	0.3109	0.4102	0.3597	0.9828	0.9741	0.9814	0.9752	0.9784
21	0.2744	0.3518	0.2670	0.3820	0.3188	0.9702	0.9612	0.9710	0.9579	0.9651
22	0.2356	0.3213	0.2508	0.3077	0.2789	0.9675	0.9552	0.9656	0.9571	0.9614
23	0.2324	0.3036	0.2310	0.3063	0.2683	0.9587	0.9457	0.9590	0.9451	0.9521
24	0.2776	0.3897	0.2823	0.3711	0.3302	0.9668	0.9528	0.9664	0.9551	0.9603
25	0.2289	0.3074	0.2215	0.2972	0.2638	0.9734	0.9639	0.9743	0.9651	0.9692
26	0.1831	0.2498	0.1994	0.2471	0.2198	0.9689	0.9570	0.9661	0.9575	0.9624
27	0.2200	0.2810	0.2320	0.3163	0.2623	0.9738	0.9663	0.9724	0.9621	0.9687
28	0.1983	0.2888	0.2159	0.2546	0.2394	0.9689	0.9543	0.9662	0.9597	0.9623
29	0.2041	0.2874	0.2236	0.2791	0.2485	0.9590	0.9412	0.9548	0.9429	0.9495
30	0.2155	0.2864	0.2209	0.2973	0.2550	0.9644	0.9520	0.9638	0.9502	0.9576
31	0.2048	0.2647	0.2100	0.2726	0.2381	0.9689	0.9595	0.9682	0.9583	0.9637
32	0.2299	0.2768	0.2100	0.3173	0.2585	0.9709	0.9646	0.9736	0.9595	0.9671
33	0.2032	0.2726	0.1999	0.2617	0.2343	0.9620	0.9482	0.9625	0.9503	0.9557
34	0.2077	0.2697	0.1943	0.2574	0.2323	0.9651	0.9542	0.9678	0.9563	0.9609
35	0.2363	0.2697	0.2074	0.3149	0.2570	0.9692	0.9645	0.9733	0.9586	0.9664
36	0.1906	0.2835	0.2126	0.2458	0.2331	0.9657	0.9485	0.9618	0.9554	0.9578
37	0.1845	0.2603	0.1983	0.2402	0.2208	0.9706	0.9580	0.9684	0.9612	0.9646
38	0.2152	0.2893	0.2130	0.2928	0.2526	0.9671	0.9549	0.9674	0.9544	0.9609
39	0.1826	0.2590	0.1914	0.2488	0.2204	0.9649	0.9496	0.9632	0.9516	0.9573
40	0.1908	0.2678	0.1941	0.2444	0.2243	0.9670	0.9530	0.9663	0.9571	0.9608

Image	Homogeneity				Mean	Energy				Mean
1	0.8650	0.8310	0.8571	0.8126	0.8414	0.1032	0.0910	0.1010	0.0875	0.0957
2	0.8681	0.8221	0.8531	0.8176	0.8402	0.0920	0.0798	0.0889	0.0789	0.0849
3	0.8656	0.8282	0.8631	0.8234	0.8451	0.1287	0.1169	0.1264	0.1153	0.1219
4	0.8629	0.8186	0.8633	0.8179	0.8407	0.0817	0.0705	0.0826	0.0696	0.0761
5	0.8660	0.8324	0.8560	0.8166	0.8428	0.0808	0.0721	0.0780	0.0685	0.0748
6	0.8358	0.7951	0.8409	0.7876	0.8148	0.0476	0.0411	0.0481	0.0401	0.0442
7	0.8662	0.8272	0.8606	0.8175	0.8429	0.0722	0.0623	0.0704	0.0602	0.0663
8	0.8716	0.8381	0.8603	0.8152	0.8463	0.0792	0.0701	0.0765	0.0648	0.0726
9	0.8625	0.8214	0.8547	0.8133	0.8380	0.0775	0.0670	0.0759	0.0656	0.0715
10	0.8699	0.8391	0.8606	0.8082	0.8445	0.0860	0.0768	0.0830	0.0689	0.0787
11	0.8479	0.8167	0.8593	0.7902	0.8285	0.0629	0.0559	0.0652	0.0514	0.0589
12	0.8763	0.8313	0.8629	0.8257	0.8490	0.0777	0.0656	0.0741	0.0640	0.0704
13	0.8743	0.8354	0.8723	0.8340	0.8540	0.0702	0.0602	0.0690	0.0596	0.0647
14	0.8475	0.8045	0.8559	0.8107	0.8296	0.0780	0.0668	0.0802	0.0683	0.0733
15	0.8387	0.8022	0.8480	0.7830	0.8180	0.0657	0.0577	0.0668	0.0545	0.0612
16	0.8552	0.8234	0.8560	0.8043	0.8347	0.0781	0.0697	0.0780	0.0659	0.0729
17	0.8484	0.8130	0.8593	0.8017	0.8306	0.0762	0.0679	0.0773	0.0644	0.0714
18	0.8560	0.8178	0.8675	0.8196	0.8402	0.0744	0.0645	0.0771	0.0653	0.0703
19	0.8626	0.8280	0.8600	0.8120	0.8406	0.0711	0.0627	0.0705	0.0592	0.0659
20	0.8591	0.8065	0.8468	0.8101	0.8306	0.0650	0.0536	0.0617	0.0544	0.0587
21	0.8644	0.8316	0.8681	0.8232	0.8468	0.0951	0.0848	0.0965	0.0834	0.0900
22	0.8832	0.8422	0.8754	0.8495	0.8626	0.0920	0.0789	0.0891	0.0809	0.0852
23	0.8842	0.8497	0.8845	0.8490	0.8668	0.1075	0.0950	0.1082	0.0939	0.1011
24	0.8638	0.8155	0.8608	0.8263	0.8416	0.0861	0.0726	0.0847	0.0746	0.0795
25	0.8861	0.8469	0.8893	0.8545	0.8692	0.0975	0.0841	0.0975	0.0856	0.0912
26	0.9084	0.8758	0.9003	0.8767	0.8903	0.1172	0.1038	0.1127	0.1037	0.1093
27	0.8904	0.8609	0.8844	0.8436	0.8698	0.1050	0.0938	0.1029	0.0903	0.0980
28	0.9009	0.8565	0.8921	0.8729	0.8806	0.1099	0.0930	0.1057	0.0981	0.1017
29	0.8981	0.8576	0.8882	0.8623	0.8766	0.1280	0.1100	0.1235	0.1125	0.1185
30	0.8924	0.8585	0.8897	0.8536	0.8735	0.1320	0.1170	0.1288	0.1149	0.1232
31	0.8981	0.8692	0.8956	0.8657	0.8822	0.1185	0.1062	0.1167	0.1052	0.1116
32	0.8851	0.8619	0.8950	0.8434	0.8713	0.0963	0.0882	0.0996	0.0832	0.0918
33	0.8984	0.8641	0.9003	0.8698	0.8831	0.1236	0.1089	0.1235	0.1112	0.1168
34	0.8964	0.8657	0.9028	0.8718	0.8842	0.1232	0.1106	0.1240	0.1123	0.1175
35	0.8836	0.8672	0.8974	0.8460	0.8735	0.1062	0.0995	0.1103	0.0930	0.1022
36	0.9047	0.8584	0.8937	0.8777	0.8836	0.1349	0.1153	0.1295	0.1227	0.1256
37	0.9077	0.8714	0.9009	0.8805	0.8901	0.1372	0.1207	0.1335	0.1244	0.1289
38	0.8927	0.8560	0.8935	0.8548	0.8743	0.1069	0.0942	0.1072	0.0930	0.1003
39	0.9092	0.8707	0.9043	0.8766	0.8902	0.1235	0.1065	0.1208	0.1085	0.1148
40	0.9048	0.8666	0.9030	0.8782	0.8882	0.1262	0.1099	0.1245	0.1137	0.1185

APPENDIX I: 2nd Order Statistics - Coarse-Speckled

Image	Contrast				Mean	Correlation				Mean
1	1.0380	1.6112	1.1243	2.1480	1.4804	0.9723	0.9567	0.9700	0.9423	0.9603
2	1.1111	1.8518	1.2166	2.1922	1.5929	0.9696	0.9485	0.9666	0.9390	0.9559
3	0.9160	1.5495	0.8945	1.5242	1.2211	0.9732	0.9542	0.9737	0.9549	0.9640
4	0.5406	0.7273	0.4457	0.8020	0.6289	0.9674	0.9557	0.9732	0.9512	0.9619
5	0.7415	1.3084	0.7666	1.2018	1.0046	0.9718	0.9498	0.9709	0.9539	0.9616
6	0.8362	1.4771	0.7735	1.1795	1.0666	0.9701	0.9468	0.9723	0.9575	0.9617
7	0.6555	1.1572	0.6510	0.9431	0.8517	0.9749	0.9555	0.9751	0.9638	0.9673
8	0.6246	0.9793	0.5616	0.8837	0.7623	0.9659	0.9460	0.9693	0.9513	0.9581
9	0.6822	1.0601	0.6321	1.0354	0.8524	0.9583	0.9345	0.9616	0.9361	0.9476
10	0.6169	1.0377	0.6124	0.9339	0.8002	0.9599	0.9320	0.9604	0.9387	0.9477
11	0.4321	0.6607	0.4302	0.6408	0.5409	0.9576	0.9341	0.9574	0.9360	0.9463
12	0.6114	1.0379	0.6403	0.9624	0.8130	0.9493	0.9125	0.9467	0.9189	0.9318
13	0.5261	0.8526	0.4962	0.7519	0.6567	0.9652	0.9426	0.9672	0.9494	0.9561
14	0.5768	0.8331	0.5158	0.8917	0.7043	0.9514	0.9288	0.9567	0.9238	0.9402
15	0.9366	1.3889	0.8846	1.6585	1.2171	0.9668	0.9504	0.9686	0.9408	0.9566
16	0.9000	1.5228	0.8148	1.3460	1.1459	0.9636	0.9378	0.9672	0.9450	0.9534
17	0.8244	1.4082	0.8144	1.3313	1.0946	0.9650	0.9393	0.9652	0.9426	0.9530
18	0.8500	1.5917	0.9757	1.6365	1.2635	0.9810	0.9641	0.9782	0.9631	0.9716
19	0.6974	1.1781	0.8307	1.4504	1.0391	0.9858	0.9760	0.9831	0.9704	0.9788
20	0.6621	1.2021	0.6587	1.0562	0.8948	0.9791	0.9616	0.9793	0.9663	0.9715
21	0.9564	1.6214	0.8773	1.5933	1.2621	0.9820	0.9694	0.9835	0.9699	0.9762
22	0.6185	0.9927	0.5838	1.0124	0.8019	0.9785	0.9654	0.9798	0.9647	0.9721
23	0.7215	1.0461	0.6477	1.2752	0.9226	0.9754	0.9642	0.9780	0.9564	0.9685
24	0.3959	0.6523	0.4181	0.6152	0.5204	0.9853	0.9756	0.9844	0.9770	0.9806
25	0.6676	1.0458	0.6704	1.2172	0.9002	0.9783	0.9660	0.9782	0.9604	0.9707
26	0.4491	0.6979	0.5168	0.8468	0.6277	0.9784	0.9662	0.9752	0.9591	0.9697
27	0.6415	1.0163	0.6695	1.1983	0.8814	0.9786	0.9660	0.9778	0.9599	0.9706
28	0.6415	1.0163	0.6695	1.1983	0.8814	0.9786	0.9660	0.9778	0.9599	0.9706
29	0.5917	0.9951	0.5972	0.9776	0.7904	0.9766	0.9606	0.9765	0.9613	0.9687
30	0.5893	0.8542	0.5935	1.0847	0.7804	0.9642	0.9479	0.9639	0.9339	0.9525
31	0.5262	0.7977	0.5315	0.9022	0.6894	0.9691	0.9529	0.9687	0.9467	0.9594
32	0.4095	0.7098	0.5692	0.8305	0.6298	0.9639	0.9370	0.9495	0.9263	0.9442
33	0.4023	0.6459	0.4361	0.6550	0.5348	0.9645	0.9430	0.9615	0.9422	0.9528
34	0.4764	0.6714	0.5025	0.8959	0.6366	0.9824	0.9752	0.9815	0.9669	0.9765
35	0.1677	0.2394	0.2048	0.2527	0.2161	0.9740	0.9626	0.9682	0.9605	0.9663
36	0.2145	0.3212	0.2486	0.3158	0.2750	0.9802	0.9700	0.9770	0.9705	0.9744
37	0.2132	0.2992	0.2338	0.2997	0.2615	0.9778	0.9685	0.9756	0.9684	0.9726
38	0.2778	0.3299	0.2262	0.3654	0.2998	0.9687	0.9628	0.9748	0.9588	0.9663
39	0.2500	0.3675	0.2620	0.3587	0.3096	0.9887	0.9834	0.9882	0.9838	0.9861
40	0.2119	0.2905	0.2322	0.3151	0.2624	0.9726	0.9620	0.9699	0.9588	0.9658

Image	Homogeneity				Mean	Energy				Mean
1	0.7115	0.6529	0.6935	0.6198	0.6694	0.0260	0.0209	0.0244	0.0189	0.0226
2	0.6941	0.6175	0.6676	0.6011	0.6451	0.0225	0.0174	0.0208	0.0162	0.0192
3	0.7209	0.6649	0.7207	0.6518	0.6896	0.0331	0.0277	0.0329	0.0259	0.0299
4	0.7825	0.7443	0.8073	0.7253	0.7649	0.0451	0.0394	0.0486	0.0369	0.0425
5	0.7506	0.6823	0.7438	0.6772	0.7135	0.0347	0.0279	0.0348	0.0274	0.0312
6	0.7365	0.6579	0.7436	0.6954	0.7084	0.0402	0.0326	0.0411	0.0352	0.0372
7	0.7654	0.6922	0.7609	0.7206	0.7348	0.0455	0.0368	0.0453	0.0393	0.0417
8	0.7611	0.7001	0.7703	0.7121	0.7359	0.0416	0.0339	0.0431	0.0352	0.0385
9	0.7443	0.6854	0.7551	0.6856	0.7176	0.0407	0.0334	0.0422	0.0334	0.0374
10	0.7676	0.7076	0.7696	0.7137	0.7396	0.0504	0.0409	0.0497	0.0422	0.0458
11	0.8100	0.7508	0.8048	0.7517	0.7793	0.0695	0.0577	0.0683	0.0577	0.0633
12	0.7696	0.6904	0.7574	0.7017	0.7298	0.0496	0.0380	0.0473	0.0394	0.0436
13	0.7848	0.7208	0.7831	0.7321	0.7552	0.0458	0.0369	0.0459	0.0382	0.0417
14	0.7687	0.7193	0.7821	0.7116	0.7454	0.0521	0.0443	0.0543	0.0432	0.0485
15	0.7175	0.6804	0.7266	0.6442	0.6922	0.0389	0.0347	0.0400	0.0314	0.0363
16	0.7162	0.6630	0.7375	0.6674	0.6960	0.0344	0.0285	0.0370	0.0290	0.0322
17	0.7341	0.6610	0.7254	0.6719	0.6981	0.0361	0.0287	0.0352	0.0289	0.0322
18	0.7567	0.6588	0.7051	0.6456	0.6915	0.0222	0.0158	0.0191	0.0151	0.0181
19	0.7839	0.7117	0.7407	0.6682	0.7261	0.0260	0.0209	0.0230	0.0177	0.0219
20	0.7815	0.6851	0.7521	0.6962	0.7287	0.0294	0.0214	0.0271	0.0217	0.0249
21	0.7500	0.6575	0.7312	0.6676	0.7016	0.0242	0.0178	0.0234	0.0186	0.0210
22	0.7901	0.7087	0.7693	0.7001	0.7421	0.0331	0.0249	0.0312	0.0245	0.0284
23	0.7752	0.7117	0.7639	0.6885	0.7348	0.0325	0.0267	0.0325	0.0245	0.0291
24	0.8374	0.7606	0.8132	0.7749	0.7965	0.0400	0.0302	0.0364	0.0318	0.0346
25	0.7857	0.7148	0.7575	0.6901	0.7370	0.0376	0.0305	0.0342	0.0263	0.0321
26	0.8242	0.7608	0.7916	0.7242	0.7752	0.0461	0.0370	0.0414	0.0324	0.0392
27	0.7825	0.6972	0.7467	0.6787	0.7263	0.0308	0.0230	0.0277	0.0215	0.0258
28	0.7825	0.6972	0.7467	0.6787	0.7263	0.0308	0.0230	0.0277	0.0215	0.0258
29	0.7910	0.7116	0.7676	0.7102	0.7451	0.0357	0.0271	0.0330	0.0270	0.0307
30	0.7915	0.7328	0.7720	0.7012	0.7494	0.0459	0.0377	0.0440	0.0339	0.0404
31	0.8068	0.7385	0.7818	0.7200	0.7618	0.0517	0.0405	0.0477	0.0385	0.0446
32	0.8268	0.7501	0.7765	0.7284	0.7705	0.0642	0.0488	0.0539	0.0452	0.0530
33	0.8365	0.7718	0.8068	0.7593	0.7936	0.0693	0.0544	0.0620	0.0521	0.0594
34	0.8184	0.7644	0.7933	0.7252	0.7753	0.0387	0.0323	0.0365	0.0280	0.0339
35	0.9162	0.8803	0.8976	0.8740	0.8920	0.1149	0.0997	0.1071	0.0973	0.1048
36	0.8927	0.8426	0.8765	0.8445	0.8641	0.0793	0.0653	0.0741	0.0653	0.0710
37	0.8935	0.8524	0.8834	0.8525	0.8704	0.0858	0.0730	0.0823	0.0731	0.0786
38	0.8622	0.8402	0.8869	0.8227	0.8530	0.0785	0.0717	0.0867	0.0674	0.0761
39	0.8775	0.8353	0.8725	0.8333	0.8547	0.0626	0.0540	0.0616	0.0531	0.0578
40	0.8943	0.8564	0.8839	0.8449	0.8699	0.0886	0.0760	0.0848	0.0723	0.0804

APPENDIX J: 2nd Order Statistics - Nucleolar

Image	Contrast				Mean	Correlation				Mean
1	0.2954	0.5208	0.3129	0.4134	0.3856	0.9747	0.9557	0.9733	0.9649	0.9672
2	0.2900	0.5574	0.3849	0.4990	0.4328	0.9742	0.9504	0.9656	0.9556	0.9614
3	0.2479	0.4881	0.4154	0.5833	0.4337	0.9804	0.9620	0.9675	0.9546	0.9661
4	0.4078	0.6553	0.4067	0.6729	0.5357	0.9753	0.9607	0.9755	0.9596	0.9678
5	0.2730	0.3591	0.2659	0.4090	0.3268	0.9599	0.9466	0.9614	0.9393	0.9518
6	0.3770	0.5264	0.3544	0.5958	0.4634	0.9699	0.9581	0.9717	0.9526	0.9631
7	0.3239	0.5313	0.4065	0.6394	0.4753	0.9802	0.9678	0.9752	0.9612	0.9711
8	0.3144	0.5023	0.3590	0.5215	0.4243	0.9732	0.9574	0.9694	0.9558	0.9639
9	0.3481	0.5145	0.3532	0.5605	0.4441	0.9641	0.9473	0.9637	0.9426	0.9544
10	0.3081	0.4518	0.3152	0.4867	0.3904	0.9677	0.9529	0.9670	0.9493	0.9592
11	0.3734	0.6079	0.3995	0.5783	0.4898	0.9683	0.9487	0.9661	0.9512	0.9586
12	0.6089	1.0042	0.6112	1.0925	0.8292	0.9736	0.9568	0.9734	0.9530	0.9642
13	0.3305	0.5064	0.3179	0.4910	0.4114	0.9620	0.9422	0.9636	0.9439	0.9529
14	0.3761	0.6274	0.3438	0.5080	0.4638	0.9678	0.9467	0.9707	0.9568	0.9605
15	0.4328	0.6754	0.4088	0.6553	0.5431	0.9714	0.9555	0.9730	0.9569	0.9642
16	0.3187	0.4942	0.3412	0.5028	0.4142	0.9725	0.9575	0.9706	0.9568	0.9643
17	0.3036	0.5005	0.3340	0.4459	0.3960	0.9738	0.9570	0.9712	0.9617	0.9659
18	0.3240	0.4964	0.3450	0.5255	0.4227	0.9731	0.9591	0.9714	0.9567	0.9651
19	0.2538	0.4030	0.3199	0.4373	0.3535	0.9733	0.9578	0.9663	0.9542	0.9629
20	0.3722	0.6140	0.4402	0.6686	0.5237	0.9719	0.9540	0.9668	0.9499	0.9606
21	0.3722	0.6140	0.4402	0.6686	0.5237	0.9719	0.9540	0.9668	0.9499	0.9606
22	0.1735	0.2117	0.1699	0.2306	0.1964	0.9669	0.9595	0.9675	0.9559	0.9624
23	0.1911	0.2436	0.1904	0.2598	0.2212	0.9579	0.9462	0.9578	0.9426	0.9511
24	0.1611	0.2023	0.1713	0.2171	0.1879	0.9391	0.9225	0.9349	0.9169	0.9283
25	0.1587	0.2110	0.1707	0.2077	0.1870	0.9558	0.9413	0.9526	0.9422	0.9480
26	0.1724	0.2191	0.1770	0.2213	0.1975	0.9116	0.8874	0.9098	0.8864	0.8988
27	0.1806	0.2171	0.1715	0.2298	0.1998	0.9438	0.9325	0.9468	0.9285	0.9379
28	0.2042	0.2570	0.1893	0.2572	0.2269	0.9342	0.9169	0.9390	0.9169	0.9268
29	0.1609	0.1888	0.1678	0.2228	0.1851	0.9441	0.9346	0.9421	0.9228	0.9359
30	0.1635	0.2195	0.1807	0.2270	0.1977	0.9523	0.9361	0.9473	0.9339	0.9424
31	0.1536	0.1898	0.1670	0.2101	0.1801	0.8941	0.8648	0.8822	0.8503	0.8729
32	0.1704	0.2287	0.1842	0.2275	0.2027	0.9611	0.9477	0.9578	0.9480	0.9537
33	0.1367	0.1781	0.1572	0.1940	0.1665	0.7760	0.7028	0.7421	0.6766	0.7244
34	0.1673	0.2023	0.1695	0.2444	0.1959	0.9593	0.9505	0.9585	0.9403	0.9521
35	0.1429	0.1808	0.1488	0.1906	0.1658	0.9273	0.9067	0.9241	0.9017	0.9149
36	0.1604	0.1938	0.1619	0.1976	0.1784	0.8682	0.8394	0.8673	0.8362	0.8528
37	0.1838	0.2209	0.1748	0.2304	0.2025	0.9546	0.9454	0.9567	0.9430	0.9499
38	0.1747	0.2145	0.1830	0.2286	0.2002	0.8391	0.8011	0.8313	0.7878	0.8148
39	0.1753	0.2192	0.1769	0.2305	0.2005	0.9335	0.9169	0.9328	0.9126	0.9240
40	0.1905	0.2432	0.1997	0.2691	0.2256	0.9651	0.9554	0.9635	0.9506	0.9587

Image	Homogeneity				Mean	Energy				Mean
1	0.8868	0.8410	0.8730	0.8562	0.8642	0.1914	0.1676	0.1796	0.1693	0.1770
2	0.8785	0.8288	0.8547	0.8326	0.8487	0.1786	0.1579	0.1689	0.1568	0.1656
3	0.8977	0.8574	0.8659	0.8425	0.8659	0.2409	0.2180	0.2271	0.2139	0.2249
4	0.8621	0.8266	0.8602	0.8285	0.8444	0.1470	0.1321	0.1440	0.1319	0.1388
5	0.8778	0.8493	0.8785	0.8360	0.8604	0.1360	0.1232	0.1352	0.1198	0.1286
6	0.8639	0.8397	0.8661	0.8221	0.8479	0.1069	0.0974	0.1061	0.0934	0.1009
7	0.8792	0.8424	0.8599	0.8269	0.8521	0.1668	0.1488	0.1564	0.1446	0.1541
8	0.8721	0.8335	0.8580	0.8260	0.8474	0.1593	0.1421	0.1505	0.1380	0.1475
9	0.8583	0.8209	0.8520	0.8120	0.8358	0.1419	0.1222	0.1345	0.1214	0.1300
10	0.8742	0.8421	0.8703	0.8326	0.8548	0.1770	0.1610	0.1714	0.1550	0.1661
11	0.8588	0.8186	0.8450	0.8175	0.8350	0.1792	0.1620	0.1706	0.1571	0.1672
12	0.8463	0.8139	0.8403	0.8005	0.8253	0.2162	0.2026	0.2145	0.1957	0.2073
13	0.8792	0.8441	0.8759	0.8403	0.8599	0.1718	0.1563	0.1686	0.1519	0.1622
14	0.8526	0.8049	0.8566	0.8194	0.8334	0.1474	0.1294	0.1438	0.1297	0.1376
15	0.8445	0.8055	0.8447	0.8037	0.8246	0.1309	0.1165	0.1279	0.1141	0.1224
16	0.8696	0.8329	0.8606	0.8257	0.8472	0.1375	0.1234	0.1322	0.1185	0.1279
17	0.8752	0.8322	0.8628	0.8351	0.8513	0.1435	0.1272	0.1368	0.1243	0.1329
18	0.8678	0.8274	0.8587	0.8266	0.8451	0.1612	0.1437	0.1556	0.1426	0.1508
19	0.8853	0.8454	0.8620	0.8352	0.8570	0.1693	0.1528	0.1607	0.1466	0.1573
20	0.8631	0.8195	0.8451	0.8139	0.8354	0.1579	0.1413	0.1506	0.1354	0.1463
21	0.8631	0.8195	0.8451	0.8139	0.8354	0.1579	0.1413	0.1506	0.1354	0.1463
22	0.9141	0.8962	0.9153	0.8873	0.9032	0.1600	0.1525	0.1603	0.1465	0.1548
23	0.9061	0.8819	0.9051	0.8758	0.8922	0.1813	0.1688	0.1803	0.1652	0.1739
24	0.9198	0.8997	0.9144	0.8930	0.9067	0.2171	0.2046	0.2144	0.2017	0.2095
25	0.9207	0.8947	0.9147	0.8968	0.9067	0.2011	0.1846	0.1975	0.1849	0.1920
26	0.9139	0.8907	0.9115	0.8895	0.9014	0.2325	0.2156	0.2294	0.2143	0.2230
27	0.9101	0.8923	0.9142	0.8857	0.9006	0.1820	0.1711	0.1823	0.1656	0.1753
28	0.9141	0.8912	0.9153	0.8920	0.9031	0.1832	0.1701	0.1832	0.1685	0.1762
29	0.9197	0.9063	0.9164	0.8900	0.9081	0.2197	0.2077	0.2149	0.2001	0.2106
30	0.9182	0.8915	0.9097	0.8872	0.9017	0.2097	0.1925	0.2052	0.1893	0.1992
31	0.9232	0.9051	0.9165	0.8950	0.9099	0.2397	0.2264	0.2365	0.2171	0.2299
32	0.9148	0.8862	0.9079	0.8866	0.8989	0.1635	0.1501	0.1608	0.1483	0.1557
33	0.9317	0.9109	0.9214	0.9030	0.9168	0.3815	0.3574	0.3688	0.3477	0.3639
34	0.9181	0.9020	0.9171	0.8821	0.9048	0.1912	0.1823	0.1939	0.1739	0.1853
35	0.9289	0.9102	0.9256	0.9052	0.9175	0.2494	0.2379	0.2490	0.2323	0.2422
36	0.9204	0.9040	0.9196	0.9023	0.9116	0.2717	0.2576	0.2705	0.2558	0.2639
37	0.9082	0.8901	0.9126	0.8855	0.8991	0.1730	0.1635	0.1746	0.1593	0.1676
38	0.9129	0.8931	0.9088	0.8863	0.9003	0.2788	0.2605	0.2752	0.2544	0.2672
39	0.9123	0.8915	0.9116	0.8848	0.9000	0.2471	0.2319	0.2449	0.2269	0.2377
40	0.9051	0.8789	0.9005	0.8672	0.8879	0.1397	0.1283	0.1365	0.1218	0.1316

APPENDIX K: 2nd Order Statistics - Centromere

Image	Contrast				Mean	Correlation				Mean
1	0.4795	1.0305	0.7195	1.0587	0.8220	0.9812	0.9592	0.9715	0.9581	0.9675
2	0.3495	0.6243	0.4177	0.6496	0.5103	0.9780	0.9604	0.9736	0.9587	0.9677
3	0.4727	0.8153	0.4844	0.7947	0.6418	0.9654	0.9398	0.9645	0.9413	0.9528
4	0.3161	0.5513	0.4001	0.6161	0.4709	0.9718	0.9506	0.9643	0.9448	0.9579
5	0.3934	0.6722	0.4709	0.7899	0.5816	0.9727	0.9534	0.9675	0.9453	0.9597
6	0.7635	1.7282	1.1066	1.6552	1.3134	0.9692	0.9302	0.9554	0.9332	0.9470
7	0.6886	1.5252	0.9870	1.5075	1.1771	0.9688	0.9310	0.9553	0.9318	0.9467
8	0.3171	0.5673	0.3458	0.5306	0.4402	0.9724	0.9505	0.9698	0.9537	0.9616
9	0.2759	0.4746	0.3189	0.4796	0.3872	0.9698	0.9479	0.9652	0.9473	0.9575
10	0.3354	0.6139	0.3803	0.5444	0.4685	0.9789	0.9611	0.9761	0.9655	0.9704
11	0.2809	0.5215	0.3385	0.4849	0.4064	0.9694	0.9430	0.9632	0.9470	0.9556
12	0.2809	0.5215	0.3385	0.4849	0.4064	0.9694	0.9430	0.9632	0.9470	0.9556
13	0.2390	0.4170	0.2837	0.3970	0.3342	0.9710	0.9486	0.9652	0.9511	0.9590
14	0.3148	0.5565	0.3389	0.5118	0.4305	0.9645	0.9368	0.9616	0.9418	0.9512
15	0.2039	0.3228	0.2007	0.2937	0.2553	0.9757	0.9615	0.9761	0.9650	0.9696
16	0.1722	0.2969	0.2179	0.2980	0.2463	0.9582	0.9276	0.9470	0.9273	0.9400
17	0.2382	0.4374	0.2888	0.4064	0.3427	0.9709	0.9465	0.9649	0.9503	0.9581
18	0.2428	0.4239	0.2682	0.3881	0.3307	0.9707	0.9488	0.9677	0.9531	0.9601
19	0.2261	0.3693	0.2354	0.3471	0.2945	0.9734	0.9562	0.9723	0.9589	0.9652
20	0.3111	0.5785	0.4375	0.6611	0.4970	0.9727	0.9491	0.9617	0.9419	0.9563
21	0.3721	0.7897	0.5816	0.8301	0.6434	0.9750	0.9468	0.9610	0.9441	0.9567
22	0.2167	0.4467	0.3245	0.4559	0.3609	0.9657	0.9296	0.9486	0.9282	0.9430
23	0.2076	0.3592	0.2305	0.3693	0.2917	0.9773	0.9608	0.9747	0.9597	0.9681
24	0.1186	0.2208	0.1698	0.2185	0.1820	0.9368	0.8828	0.9094	0.8840	0.9032
25	0.2402	0.5212	0.3676	0.5219	0.4127	0.9667	0.9282	0.9491	0.9281	0.9430
26	0.1166	0.2484	0.2013	0.2367	0.2007	0.9288	0.8473	0.8764	0.8545	0.8767
27	0.1448	0.2669	0.2039	0.2680	0.2209	0.9308	0.8726	0.9028	0.8721	0.8946
28	0.1801	0.3666	0.2553	0.3577	0.2899	0.9657	0.9304	0.9512	0.9321	0.9448
29	0.1284	0.2340	0.1806	0.2389	0.1955	0.9418	0.8944	0.9186	0.8921	0.9117
30	0.2422	0.4953	0.3494	0.4957	0.3957	0.9574	0.9132	0.9386	0.9132	0.9306
31	0.1198	0.2371	0.1841	0.2308	0.1930	0.9357	0.8732	0.9016	0.8766	0.8968
32	0.1379	0.2398	0.1985	0.2877	0.2160	0.9449	0.9046	0.9210	0.8856	0.9140
33	0.1728	0.3059	0.2367	0.3164	0.2579	0.8757	0.7808	0.8298	0.7732	0.8149
34	0.1194	0.2152	0.1796	0.2354	0.1874	0.9220	0.8593	0.8825	0.8461	0.8775
35	0.1607	0.2920	0.2410	0.3374	0.2578	0.9332	0.8790	0.9003	0.8602	0.8932
36	0.1397	0.2633	0.2189	0.2793	0.2253	0.9118	0.8335	0.8623	0.8234	0.8578
37	0.1367	0.2533	0.2162	0.2754	0.2204	0.9102	0.8338	0.8583	0.8193	0.8554
38	0.1226	0.2283	0.1911	0.2530	0.1987	0.9140	0.8399	0.8661	0.8225	0.8606
39	0.1276	0.2509	0.2078	0.2686	0.2137	0.9237	0.8500	0.8761	0.8394	0.8723
40	0.1272	0.2516	0.2126	0.2577	0.2123	0.8982	0.7980	0.8295	0.7931	0.8297

Image	Homogeneity				Mean	Energy				Mean
1	0.8434	0.7405	0.7753	0.7340	0.7733	0.0562	0.0407	0.0458	0.0386	0.0453
2	0.8651	0.7873	0.8315	0.7806	0.8161	0.0666	0.0518	0.0615	0.0512	0.0578
3	0.8410	0.7670	0.8146	0.7585	0.7953	0.0627	0.0492	0.0595	0.0476	0.0547
4	0.8778	0.8112	0.8396	0.7946	0.8308	0.0831	0.0660	0.0739	0.0630	0.0715
5	0.8668	0.8078	0.8358	0.7824	0.8232	0.0780	0.0697	0.0761	0.0601	0.0710
6	0.8295	0.7436	0.7861	0.7354	0.7737	0.0567	0.0455	0.0540	0.0435	0.0499
7	0.8576	0.7798	0.8122	0.7789	0.8071	0.0838	0.0674	0.0749	0.0671	0.0733
8	0.8820	0.8122	0.8559	0.8198	0.8425	0.0880	0.0702	0.0820	0.0731	0.0783
9	0.8895	0.8281	0.8655	0.8260	0.8522	0.0964	0.0780	0.0894	0.0772	0.0853
10	0.8679	0.7853	0.8385	0.8024	0.8235	0.0606	0.0459	0.0557	0.0481	0.0526
11	0.8913	0.8307	0.8682	0.8344	0.8562	0.0982	0.0812	0.0918	0.0817	0.0882
12	0.8913	0.8307	0.8682	0.8344	0.8562	0.0982	0.0812	0.0918	0.0817	0.0882
13	0.8975	0.8326	0.8706	0.8395	0.8600	0.0969	0.0762	0.0872	0.0779	0.0846
14	0.8797	0.8081	0.8561	0.8150	0.8397	0.0932	0.0744	0.0879	0.0755	0.0828
15	0.9134	0.8703	0.9053	0.8778	0.8917	0.1183	0.1026	0.1163	0.1056	0.1107
16	0.9213	0.8708	0.8961	0.8675	0.8889	0.1524	0.1301	0.1406	0.1271	0.1375
17	0.9046	0.8440	0.8748	0.8452	0.8671	0.1100	0.0907	0.1010	0.0905	0.0980
18	0.9017	0.8475	0.8826	0.8513	0.8708	0.1201	0.1047	0.1176	0.1048	0.1118
19	0.9025	0.8533	0.8895	0.8558	0.8753	0.0931	0.0788	0.0903	0.0788	0.0853
20	0.8820	0.8221	0.8419	0.7964	0.8356	0.0833	0.0712	0.0763	0.0638	0.0736
21	0.8682	0.7840	0.8113	0.7718	0.8088	0.0711	0.0558	0.0626	0.0531	0.0606
22	0.9258	0.8751	0.8893	0.8683	0.8896	0.2830	0.2614	0.2717	0.2588	0.2688
23	0.9290	0.8965	0.9163	0.8981	0.9100	0.2940	0.2786	0.2888	0.2789	0.2851
24	0.9448	0.9000	0.9165	0.8990	0.9151	0.3827	0.3466	0.3615	0.3465	0.3593
25	0.9177	0.8643	0.8839	0.8622	0.8820	0.3162	0.2973	0.3086	0.2941	0.3041
26	0.9434	0.8935	0.9087	0.8953	0.9102	0.3977	0.3598	0.3732	0.3632	0.3735
27	0.9327	0.8866	0.9058	0.8854	0.9026	0.3299	0.2993	0.3140	0.2990	0.3106
28	0.9353	0.8955	0.9117	0.8902	0.9081	0.3338	0.3166	0.3287	0.3130	0.3230
29	0.9400	0.9002	0.9184	0.8975	0.9140	0.3797	0.3538	0.3668	0.3515	0.3630
30	0.9139	0.8589	0.8808	0.8572	0.8777	0.2506	0.2238	0.2356	0.2236	0.2334
31	0.9444	0.8978	0.9140	0.8984	0.9137	0.3706	0.3366	0.3478	0.3357	0.3477
32	0.9397	0.9013	0.9125	0.8878	0.9103	0.3534	0.3280	0.3382	0.3234	0.3357
33	0.9469	0.9082	0.9213	0.9070	0.9208	0.3456	0.3100	0.3231	0.3086	0.3218
34	0.9444	0.9016	0.9153	0.8971	0.9146	0.3592	0.3235	0.3351	0.3216	0.3349
35	0.9286	0.8815	0.8950	0.8689	0.8935	0.3069	0.2771	0.2860	0.2695	0.2849
36	0.9332	0.8792	0.8956	0.8743	0.8956	0.3324	0.2909	0.3041	0.2891	0.3041
37	0.9339	0.8822	0.8953	0.8753	0.8967	0.3241	0.2811	0.2913	0.2760	0.2932
38	0.9421	0.8983	0.9103	0.8898	0.9101	0.3640	0.3259	0.3363	0.3185	0.3362
39	0.9409	0.8918	0.9051	0.8894	0.9068	0.3657	0.3265	0.3362	0.3266	0.3387
40	0.9384	0.8877	0.9005	0.8841	0.9027	0.3571	0.3105	0.3222	0.3082	0.3245

APPENDIX L: Accuracy Test - Homogeneous

Classifier	KNNFOS K = 5					KNNFOS K = 3					ADAFOS				
Image No.	Predicted Pattern														
	H	FS	CS	N	C	H	FS	CS	N	C	H	FS	CS	N	C
1		/					/						/		
2					/					/			/		
3		/					/						/		
4	/					/							/		
5			/					/					/		
6			/							/			/		
7	/					/							/		
8		/				/							/		
9			/					/					/		
10	/					/							/		
11				/					/				/		
12	/					/							/		
13	/					/							/		
14				/					/				/		
15		/				/						/			
16			/					/					/		
17				/					/				/		
18		/						/					/		
19		/					/						/		
20				/					/				/		
21	/					/							/		
22	/					/							/		
23	/					/							/		
24	/					/						/			
25				/		/							/		
26	/					/						/			
27		/				/							/		
28			/					/					/		
29	/					/							/		
30				/					/				/		

Classifier	KNNsOS K = 5					KNNsOS K = 3					ADASOS				
	Predicted Pattern														
	H	FS	CS	N	C	H	FS	CS	N	C	H	FS	CS	N	C
1	/					/					/				
2					/					/					/
3	/					/					/				
4	/					/					/				
5	/					/					/				
6	/					/					/				
7	/					/					/				
8	/					/					/				
9	/					/					/				
10	/					/					/				
11				/					/					/	
12				/					/					/	
13	/					/					/				
14	/					/					/				
15	/					/					/				
16	/					/					/				
17	/					/					/				
18	/					/					/				
19	/					/					/				
20	/					/					/				
21	/								/					/	
22	/					/					/				
23				/					/					/	
24	/					/					/				
25	/					/					/				
26	/					/					/				
27	/					/					/				
28	/					/					/				
29				/					/					/	
30	/					/					/				

Classifier	KNNBOS K = 5					KNNBOS K = 3					ADABOS				
	Predicted Pattern														
	H	FS	CS	N	C	H	FS	CS	N	C	H	FS	CS	N	C
1	/					/					/				
2					/					/					/
3	/					/					/				
4	/					/					/				
5			/					/					/		
6			/							/					/
7	/					/					/				
8		/				/					/				
9			/					/					/		
10	/					/					/				
11				/					/					/	
12	/					/					/				/
13	/					/					/				/
14			/					/					/		
15	/					/					/				
16			/					/					/		
17			/					/					/		
18	/					/					/				
19	/					/					/				
20			/					/					/		
21	/					/					/				/
22	/					/					/				
23	/					/					/				/
24	/					/					/				
25			/			/					/				/
26	/					/					/				
27		/				/					/				/
28			/					/					/		
29	/					/					/				/
30				/					/				/		

APPENDIX M: Accuracy Test - Fine-Speckled

Classifier	KNNFOS K = 5					KNNFOS K = 3					ADAFOS				
Image No.	Predicted Pattern														
	H	FS	CS	N	C	H	FS	CS	N	C	H	FS	CS	N	C
1			/					/					/		
2	/					/							/		
3		/					/						/		
4		/					/						/		
5	/					/							/		
6		/					/						/		
7		/					/						/		
8		/				/							/		
9		/					/						/		
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13			/						/					/	
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24	/					/							/		
25				/					/				/		
26		/				/							/		
27	/					/						/			
28			/					/					/		
29	/					/							/		
30			/					/					/		

Classifier	KNNsOS K = 5					KNNsOS K = 3					ADASOS				
	Predicted Pattern														
	H	FS	CS	N	C	H	FS	CS	N	C	H	FS	CS	N	C
1	/					/					/				
2	/					/					/				
3	/					/					/				
4	/					/					/				
5	/					/					/				
6	/					/					/				
7	/					/					/				
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27				/					/					/	
28				/					/					/	
29				/					/					/	
30				/					/					/	

Classifier	KNNBOS K = 5					KNNBOS K = 3					ADABOS				
	Predicted Pattern														
	H	FS	CS	N	C	H	FS	CS	N	C	H	FS	CS	N	C
1			/					/					/		
2	/					/					/				
3		/					/					/			
4		/					/					/			
5	/					/					/				
6		/					/					/			
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26		/				/						/			
27	/					/					/				
28			/					/					/		
29	/					/							/		
30			/					/					/		

APPENDIX N: Accuracy Test - Coarse-Speckled

Classifier	KNNFOS K = 5					KNNFOS K = 3					ADAFOS				
Image No.	Predicted Pattern														
	H	FS	CS	N	C	H	FS	CS	N	C	H	FS	CS	N	C
1			/					/					/		
2			/			/							/		
3			/					/					/		
4	/							/					/		
5	/					/							/		
6		/					/						/		
7		/					/						/		
8			/					/					/		
9		/					/						/		
10			/					/					/		
11	/					/							/		
12			/					/					/		
13			/							/			/		
14		/					/						/		
15			/			/							/		
16		/						/					/		
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18	/					/							/		
19		/				/							/		
20	/					/							/		
21			/					/					/		
22			/					/					/		
23	/						/						/		
24		/					/						/		
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26			/				/						/		
27		/					/						/		
28		/								/			/		
29		/					/						/		
30		/					/						/		

Classifier	KNNsOS K = 5					KNNsOS K = 3					ADASOS				
	Predicted Pattern														
	H	FS	CS	N	C	H	FS	CS	N	C	H	FS	CS	N	C
1			/					/					/		
2		/					/					/			
3			/					/					/		
4			/					/					/		
5			/					/					/		
6		/					/					/			
7		/					/					/			
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26	/					/								/	
27		/					/						/		
28		/					/						/		
29					/	/							/		
30	/					/							/		

Classifier	KNNBOS K = 5					KNNBOS K = 3					ADABOS				
	Predicted Pattern														
	H	FS	CS	N	C	H	FS	CS	N	C	H	FS	CS	N	C
1			/					/					/		
2			/			/							/		
3			/					/					/		
4	/									/					/
5	/					/							/		
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29		/					/						/		
30		/					/						/		

APPENDIX O: Accuracy Test - Nucleolar

Classifier	KNNFOS K = 5					KNNFOS K = 3					ADAFOS				
Image No.	Predicted Pattern														
	H	FS	CS	N	C	H	FS	CS	N	C	H	FS	CS	N	C
1	/					/									/
2				/					/						/
3				/					/						/
4				/					/						/
5				/					/						/
6				/					/						/
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27				/					/						/
28				/					/						/
29				/					/						/
30				/					/						/

Classifier	KNNsOS K = 5					KNNsOS K = 3					ADASOS				
	Predicted Pattern														
	H	FS	CS	N	C	H	FS	CS	N	C	H	FS	CS	N	C
1				/					/					/	
2				/					/					/	
3				/					/					/	
4				/					/					/	
5				/					/					/	
6				/					/					/	
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27				/					/					/	
28				/					/					/	
29				/					/					/	
30				/					/					/	

Classifier	KNNBOS K = 5					KNNBOS K = 3					ADABOS				
	Predicted Pattern														
	H	FS	CS	N	C	H	FS	CS	N	C	H	FS	CS	N	C
1	/					/									/
2				/					/						/
3				/					/						/
4				/					/						/
5				/					/						/
6				/					/						/
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30				/					/						/

APPENDIX P: Accuracy Test - Centromere

Classifier	KNNFOS K = 5					KNNFOS K = 3					ADAFOS				
Image No.	Predicted Pattern														
	H	FS	CS	N	C	H	FS	CS	N	C	H	FS	CS	N	C
1					/					/					/
2					/					/					/
3					/					/					/
4				/					/						/
5				/					/						/
6				/					/						/
7				/					/						/
8				/					/						/
9				/					/						/
10				/					/						/
11				/					/						/
12				/					/						/
13				/					/						/
14				/					/						/
15				/					/						/
16				/					/						/
17				/					/						/
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21	/					/							/		
22				/		/						/			
23			/					/				/			
24		/					/				/				/
25		/					/				/				/
26	/							/			/			/	
27		/						/			/			/	
28	/					/				/			/		
29			/					/			/			/	
30		/				/				/			/		

Classifier	KNNsOS K = 5					KNNsOS K = 3					ADASOS				
	Predicted Pattern														
	H	FS	CS	N	C	H	FS	CS	N	C	H	FS	CS	N	C
1					/					/					/
2					/					/					/
3					/					/					/
4				/					/					/	
5					/					/					/
6				/					/					/	
7					/					/					/
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9					/					/					/
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19					/					/					/
20			/					/					/		
21	/					/					/				
22			/					/				/			
23					/				/	/					
24	/					/					/				
25					/					/				/	
26					/					/				/	
27		/							/		/				
28				/					/					/	
29					/					/				/	
30	/								/		/			/	

Classifier	KNNBOS K = 5					KNNBOS K = 3					ADABOS				
	Predicted Pattern														
	H	FS	CS	N	C	H	FS	CS	N	C	H	FS	CS	N	C
1					/					/					/
2					/					/					/
3					/					/					/
4				/					/					/	
5				/					/					/	
6					/					/					/
7					/					/					/
8				/					/					/	
9					/					/					/
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22					/	/								/	
23			/					/					/		
24		/					/						/		
25		/					/						/		
26	/									/			/		
27		/								/			/		
28	/					/					/				/
29			/					/					/		
30		/				/							/		

APPENDIX Q: MATLAB Algorithm

```
close all
clear all
clc

% Read Image
Image = imread('E:\Documente\FYP\ANA Images\MIVIA_HEp-
2_Images_Dataset\Test Set\Homogeneous\27.png');
% Converting RGB image into Grayscale
Image2 = rgb2gray (Image);

%% 1st Order Statistics

% Plotting histogram for the GrayScale image
Histo = imhist (Image2);

%figure (1);
%plot (Histo);xlabel ('Gray Intensity Level'); ylabel ('Distribution');

% Calculating 1st-Order Statistics of the histogram
Mean = mean (Histo);
Var = var (Histo);
Skew = skewness (Histo);
Kurt = kurtosis (Histo);
Ent = entropy (Histo);

% Defining Output Array for Classification Prupose - 1st Order
Statistics
FOS = [Mean Skew Kurt Ent];

%% 2nd Order Statistics

% Create the GLCMs. Call the graycomatrix function specifying the
offsets
glcms = graycomatrix(Image2,'Offset',[0 1; -1 1; -1 0;-1 -
1],'NumLevels', 50,'Symmetric',true);

% Derive statistics from the GLCMs using the graycoprops function.
stats = graycoprops (glcms,'Contrast', 'Correlation');
stats2 = graycoprops (glcms, 'Homogeneity', 'Energy');

% Calculate the average of the graycoprops function
Contrast = mean ([stats.Contrast]);
Correlation = mean ([stats.Correlation]);
Homogeneity = mean ([stats2.Homogeneity]);
Energy = mean ([stats2.Energy]);

% Defining Output Array for Classification Prupose - 2nd Order
Statistics
SOS = [Contrast, Homogeneity, Energy];
```

```

% Defining Output Array for Classification Prupose - bot 1st Order &
2nd
% Order Statistics
BOS = [Mean Skew Kurt Ent Contrast Homogeneity Energy];

%% Training Program %%

% Assigning Training Data
trainingFOS = xlsread ('E:\Documente\FYP\ANA Images\Training Info\1st
Order Positive.xlsx');
trainingSOS = xlsread ('E:\Documente\FYP\ANA Images\Training Info\GLCM4
MIVIA Positive.xlsx');
trainingBOS = xlsread ('E:\Documente\FYP\ANA Images\Training Info\GLCM
FOS SOS Positive.xlsx');

% Declare Output Class
% Class 1 = Homogeneous
% Class 2 = Fine-Speckled
% Class 3 = Coarse-Speckled
% Class 4 = Nucleolar
% Class 5 = Centromere

Aa = 1;
Bb = 2;
Cc = 3;
Dd = 4;
Ee = 5;

G1 = repmat (Aa, 40, 1);
G2 = repmat (Bb, 40, 1);
G3 = repmat (Cc, 40, 1);
G4 = repmat (Dd, 40, 1);
G5 = repmat (Ee, 40, 1);

group = [G1; G2; G3; G4; G5];
testFOS = FOS;
testSOS = SOS;
testBOS = BOS;

%% classifiers %%

% K-NN Classifier - k = 5
KNNFOS = knnclassify (testFOS, trainingFOS, group, 5);
KNNsOS = knnclassify (testSOS, trainingSOS, group, 5);
KNNBOS = knnclassify (testBOS, trainingBOS, group, 5);

% K-NN Classifier - k = 3
KNNFOS3 = knnclassify (testFOS, trainingFOS, group, 3);
KNNsOS3 = knnclassify (testSOS, trainingSOS, group, 3);
KNNBOS3 = knnclassify (testBOS, trainingBOS, group, 3);

% ADABOOSTM2 Classifier
ensFOS = fitensemble (trainingFOS, group, 'AdaBoostM2', 100, 'Tree');
%figure (2); plot (resubLoss (ensFOS, 'mode', 'cumulative'));
ADAFOS = predict (ensFOS, testFOS);

```

```
ensSOS = fitensemble (trainingSOS, group, 'AdaBoostM2', 100, 'Tree');
%figure (3); plot (resubLoss (ensSOS, 'mode', 'cumulative'));
ADASOS = predict (ensSOS, testSOS);

ensBOS = fitensemble (trainingBOS, group, 'AdaBoostM2', 100, 'Tree');
%figure (4); plot (resubLoss (ensBOS, 'mode', 'cumulative'));
ADABOS = predict (ensBOS, testBOS);

%% Classification Output

ClassFOS = [KNNFOS KNNFOS3 ADAFOS]
ClassSOS = [KNNSOS KNNSOS3 ADASOS]
ClassBOS = [KNNBOS KNNBOS3 ADABOS]
```