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## CHAPTER 7

### RESULTS AND DISCUSSION

Evaluation of the optimization methods and proposed algorithms is the most important and critical stage of a research work. This part is involved in measuring the algorithms proposed by analysing its influence on improving the efficiency of the underlying research problem. This research work proposed various optimization methods and algorithms that can improve the detection of ALL. Various experiments were conducted to evaluate the performance of the algorithms proposed in the research methodology. The experiments were employed to understand the effectiveness of the algorithms proposed to perform the various tasks of ALL-C (noise removal, segmentation, feature extraction, fusion and selection and classification) that were enhanced in their working. The results of these experiments were used to identify the algorithm that provides maximum benefit the concerned task. The experiments were also used to analyse the cumulative effect of the algorithms from each phase on ALL-C. For this purpose, the experiments were designed in three stages.

Stage 1 : Analysis of Preprocessing Algorithms,

Stage 2 : Analysis of ALL-C Using ML Classifiers, and

Stage 3 : Analysis of ALL-C Using DL Classifiers.

These Stage 2 and Stage 3 experiments used the pre-processed objects from Phase I of the research methodology as input to ALL-C systems using ML and DL classifiers. The proposed algorithms were compared with its unenhanced versions and conventional algorithms. This chapter presents details regarding the datasets and performance metrics used in the experiments along with the tabulation and discussion of the results obtained.

#### 7.1. EXPERIMENTAL SETUP

The datasets used by the experiments along with the performance metrics used to evaluate the algorithms proposed in each stage of the experiments are presented in this section.

### 7.1.1. Dataset Used

All the experiments were conducted using a Leukemia dataset, called ALL-IDB, proposed by Labati *et al.* (2011), and downloaded from <https://homes.di.unimi.it/scotti/all>. The ALL-IDB dataset has images captured with optical laboratory microscope together with a Canon Powershot G5 camera. All images are stored in JPEG (Joint Photographic Experts Group) format with 24 bit color depth at 256 x 256 pixel resolution. The dataset has 130 normal and 130 ALL type leukemia annotated images of blood cells. Thus, the dataset size is 260 images. The ALL-IDB has healthy and ALL leukemia samples and do not include the three subtype categories (L1, L2 and L3). As the scope of this research work is to classify blood cells into normal and ALL subtypes, additional 50 microscopic blood images for typical L1, L2 and L3 type cells were downloaded through Google image search were added to the dataset. The additional images, apart from including subtypes also helped to avoid overfitting. Thus, the modified ALL-IDB dataset had 130 normal blood cell images and 180 blood cells images with leukemia. Some examples are shown in Figure 7.1.

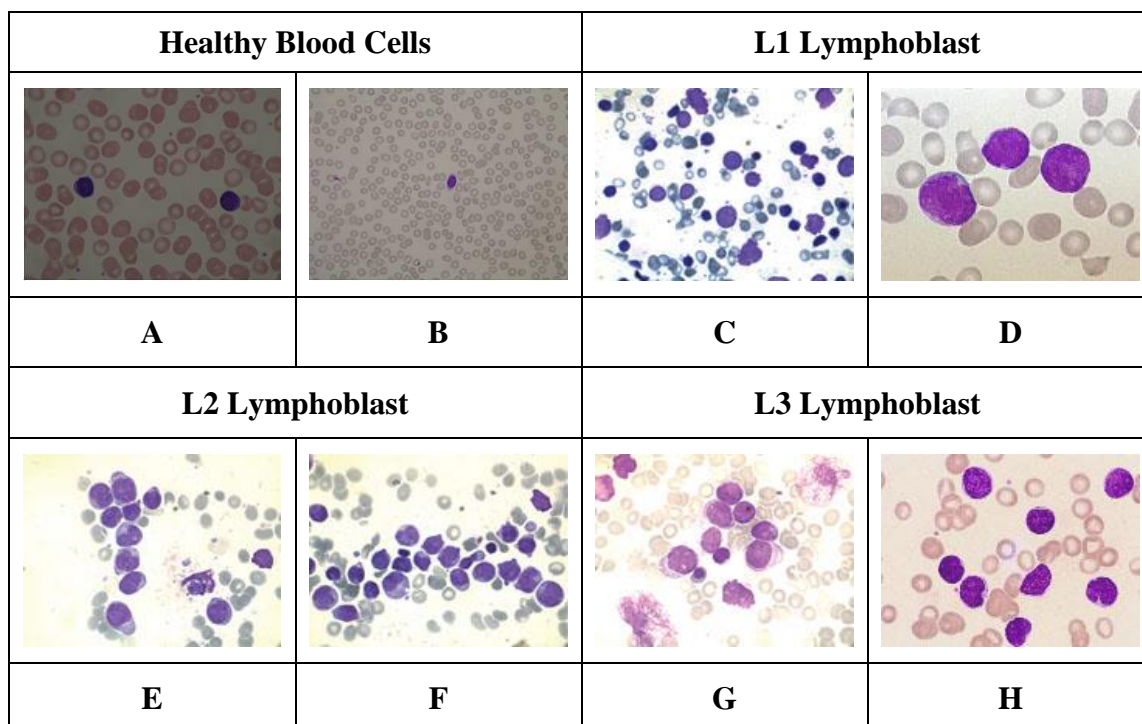


Figure 7.1 : Blood Cell Sample Images

### 7.1.2. Performance Metrics

This section details the performance metrics used to evaluate the algorithms proposed in the three phases of the research methodology.

#### (i) Stage 1 Experiments - Preprocessing Algorithms

The focal point of Stage 1 experiments is to evaluate the preprocessing algorithms, namely, enhancement algorithms and segmentation algorithms.

- **Image Enhancement Algorithms**

The image enhancement algorithms were evaluated using four performance measures that analysed the quality preservation ability in terms of Peak Signal to Noise Ratio (PSNR - dB), edge preservation ability in terms of Figure of Merit (FoM), structure preserving capacity in terms of Mean Structural Similarity Index (MSSI) and execution speed (seconds).

- **Segmentation Algorithms**

The second part of Stage 1 experiments is involved with the evaluation of segmentation algorithms. The evaluation is based on finding the difference between the ground truth segmented image and the segmented image. Apart from this, three performance metrics, namely, stability criterion, anti-noise criterion and speed were also used during evaluation.

#### (ii) Stages 2 and 3 Experiments - ALL Classifiers using ML and DL

The classification step of ALL-C system performs various steps like multiple feature extraction, feature fusion, feature selection and classification while using machine learning classifier. The same with DL classifier performs classification that extracts features automatically and performs classification. Both types of classifiers were evaluated using four metrics, namely, sensitivity, specificity, accuracy and speed of classification, all of which were estimated using the data provided by the confusion matrix (as given in Figure 5.11) ([http://www.stat.psu.edu/online/courses/stat509/17\\_diagnos/17\\_diagnos\\_print.htm](http://www.stat.psu.edu/online/courses/stat509/17_diagnos/17_diagnos_print.htm)). Apart from this the execution speed is also considered as a parameter to evaluate the performance of the classifiers.

$$\text{Sensitivity (\%)} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}} \times 100 \quad (7.1)$$

## 7.2. ANALYSIS OF PREPROCESSING ALGORITHMS

This section presents the results of the experiments that were used to evaluate the enhancement and segmentation (WBC identification) algorithms.

### 7.2.1. Analysis of Enhancement Algorithms

The unified enhancement approach proposed in this research work combines contrast enhancement, noise removal and edge enhancement. The coding scheme used is shown in Table 7.1.

To analyse the overall efficiency of the enhancement algorithms, the results obtained after testing all images in the dataset was averaged, for each performance metrics. The average results thus obtained are tabulated in Table 7.2.

**TABLE 7.1**

**CODING SCHEME - ENHANCEMENT ALGORITHMS**

<b>Code</b>	<b>Description</b>
HE	Histogram Equalization Algorithm
AHE	Adaptive Histogram Equalization Algorithm
CLAHE	Contrast Limited Adaptive Histogram Equalization
DWT	Discrete Wavelet Threshold-Based Denoising Algorithm
K-SVD	K Singular Value Decomposition-Based Denoising Algorithm
DWT-KSVD	Hybrid DWT and KSVD-Based Denoising Algorithm
EE-SF	Edge Enhancement Algorithm Using Sigmoid Function
EEE-SF	Enhanced Edge Enhancement Algorithm Using Sigmoid Function
UCED	Unified Contrast Adjustment, Edge Enhancement and Denoising Algorithm

TABLE 7.2

## PERFORMANCE ANALYSIS OF THE ENHANCEMENT ALGORITHMS

	PSNR(db)	MSSI	FoM	Speed(s)
<b>Contrast Enhancement Algorithms</b>				
HE	22.92	0.5489	0.6315	8.03
AHE	25.20	0.4692	0.5489	8.74
CLAHE	30.57	0.6383	0.7260	10.64
<b>Denoising Algorithms</b>				
DWT	35.28	0.8029	0.8987	12.33
K-SVD	37.60	0.8235	0.9136	13.11
DWT-KSVD	41.41	0.8437	0.9319	14.39
<b>Edge Enhancement Algorithms</b>				
EE-SF	21.48	0.3954	0.8836	7.59
EEE-SF	22.22	0.4384	0.8982	7.85
<b>Proposed Unified Approach</b>				
UCED	42.44	0.8519	0.9416	14.74

Comparison of the average PSNR of the enhancement algorithms show that the algorithms used to build the unified algorithms outperform their conventional counterparts. The CLAHE algorithm improved the PSNR, on average, by 25.01% over HE and 17.55% over AHE. Similarly, EEE-SF improved the quality of the input microscopic image, on average, by 3.3% when compared with EE-SF algorithm. The average PSNR gain obtained by DWT-KSVD over DWT and KSVD were 14.80% and 9.19% respectively. However, the unified approach produced maximum PSNR advantage and produced a high average PSNR of 42.44%, which indicates that the enhanced image is very similar to the original image.

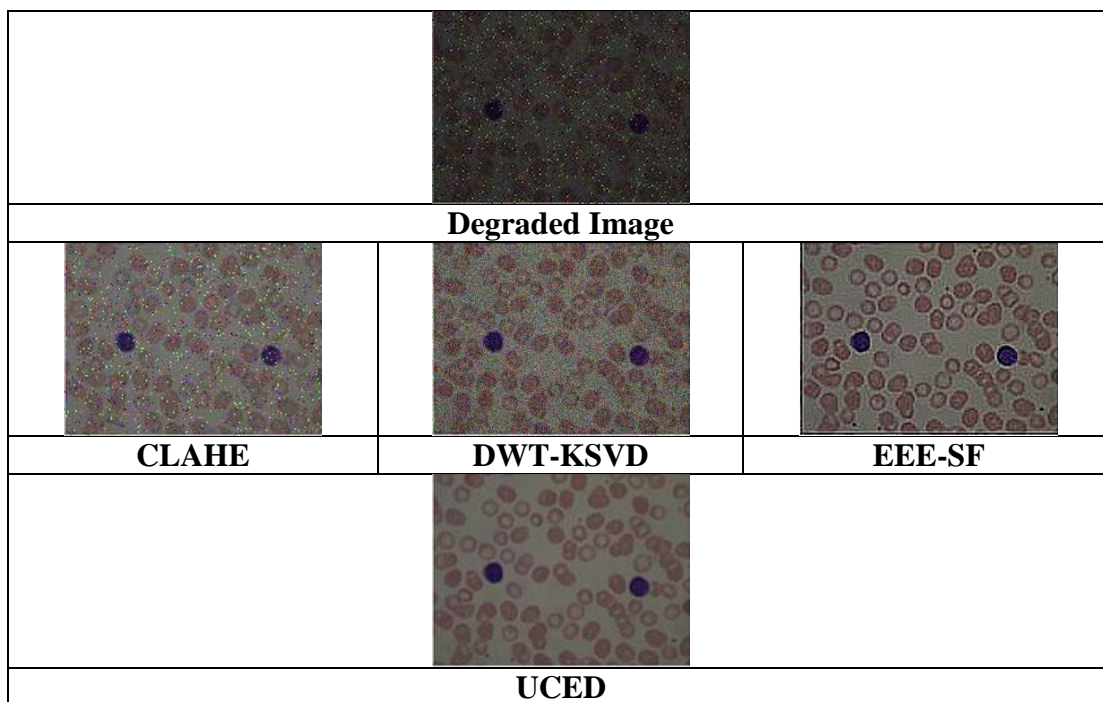
The increase in MSSI values obtained by CLAHE, DWT-KSVD and EEE-SF algorithms when compared with their conventional counterparts, prove that these algorithms are right candidates for UCED algorithm. The UCED algorithm, on average,

achieved, on average, a high MSSSI value of 0.8519. This proves that the structure preservation capacity of the UCED algorithm is very high.

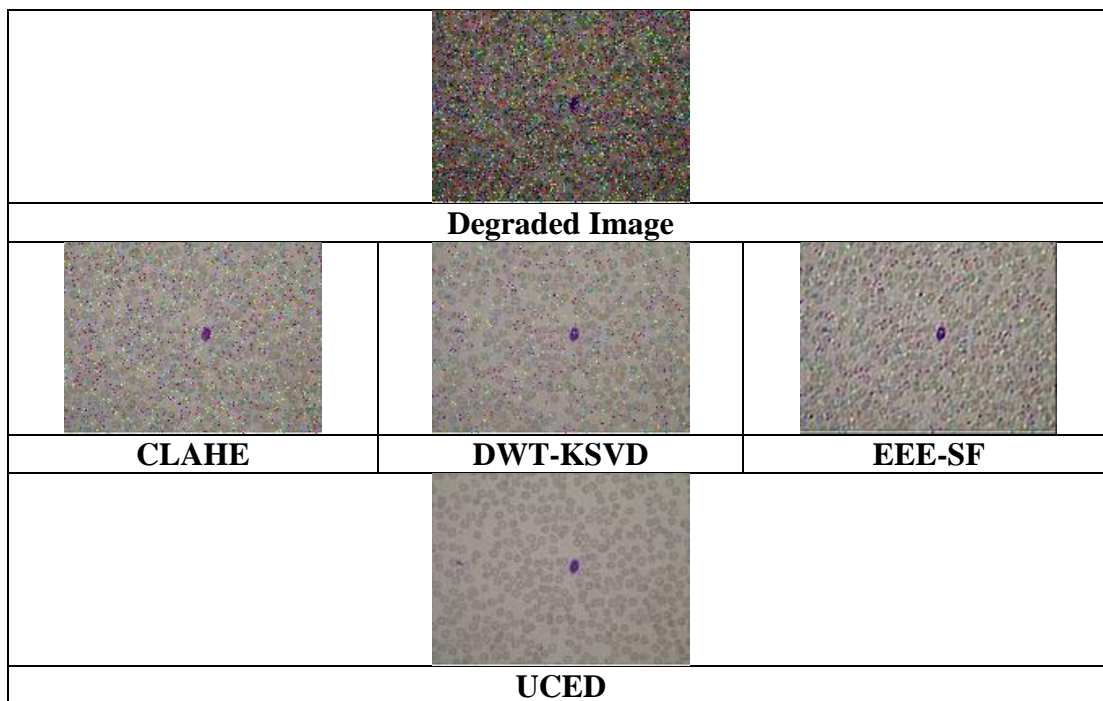
Comparing the FoM ratio revealed that the CLAHE algorithm achieved an average efficiency gain of 13.02% over HE and 24.39% over AHE algorithms, proving that the edge preservation is maximum while using CLAHE algorithm. The edge enhancement algorithms EE-SF and EEE-SF also were efficient in maintaining the edge details of the image. These algorithms produced an average FoM of 0.8836 and 0.8982 respectively. This shows that the enhanced sigmoid function is more efficient in enhancing the edge details. Comparison of noise removal algorithm showed that the average FoM was high with the DWT-KSVD algorithm (0.9319) when compared with DWT (0.8987) and KSVD (0.9319) algorithms. These results prove that the three enhancement algorithms can provide more advantage when combined. This is further emphasized by high PSNR (42.44dB), MSSSI (0.8519) and FoM (0.9416) values obtained by UCED algorithm.

The results pertaining to execution speed, contrary to the trend obtained with other performance measures, shows that the UCED algorithm takes maximum time to produce the enhanced image, when compared with the individual application of the enhancement algorithms. This result was expected as the UCED algorithm needs to perform three enhancement operations. The average speed of CLAHE algorithm was 1.36 seconds, the DWT-SVD algorithm was 4.97 and EEE-SF was 0.64 seconds. So, theoretically, the enhancement algorithm should have taken 6.97 seconds to complete the enhancement operation. However, the execution time required reduced to 5.09 seconds while using the unified approach, as the components of the UCED algorithm focus only on specific regions, which reduces the time complexity.

Figures 7.2a to 7.2h shows the visual results of the enhancement algorithms for the selected sample images.



**Figure 7.2a : Visual Results of Enhancement Algorithms - Image A**



**Figure 7.2b : Visual Results of Enhancement Algorithms - Image B**

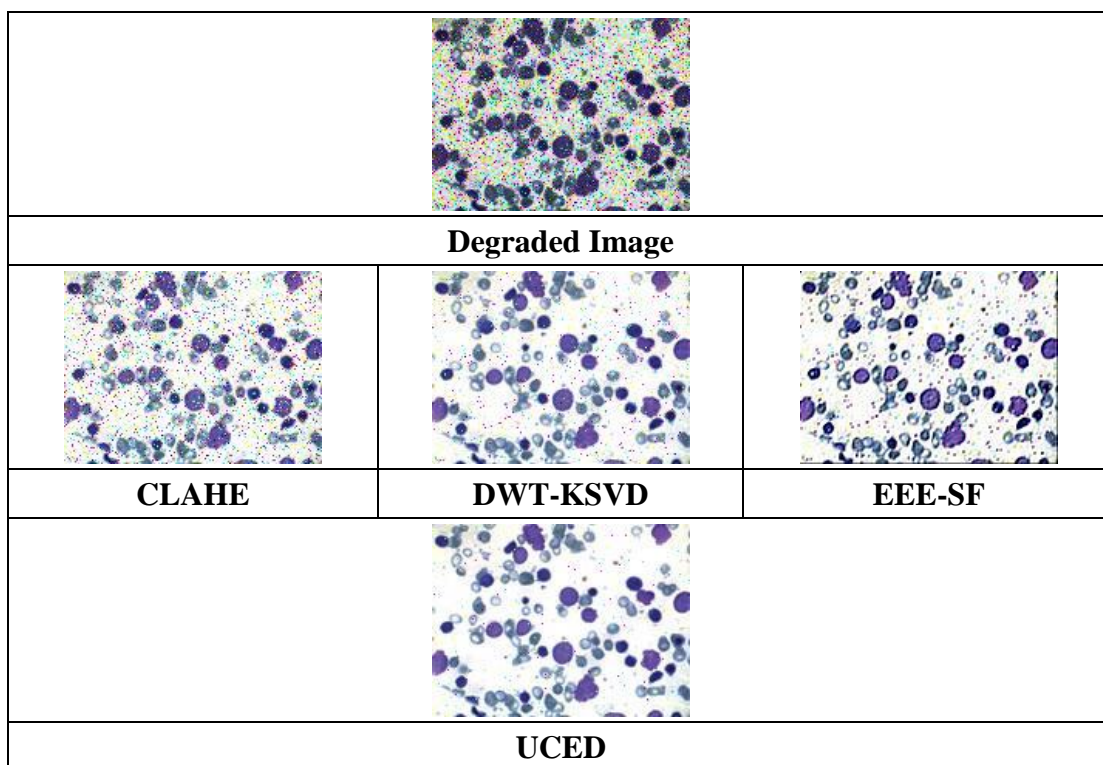


Figure 7.2c : Visual Results of Enhancement Algorithms - Image C

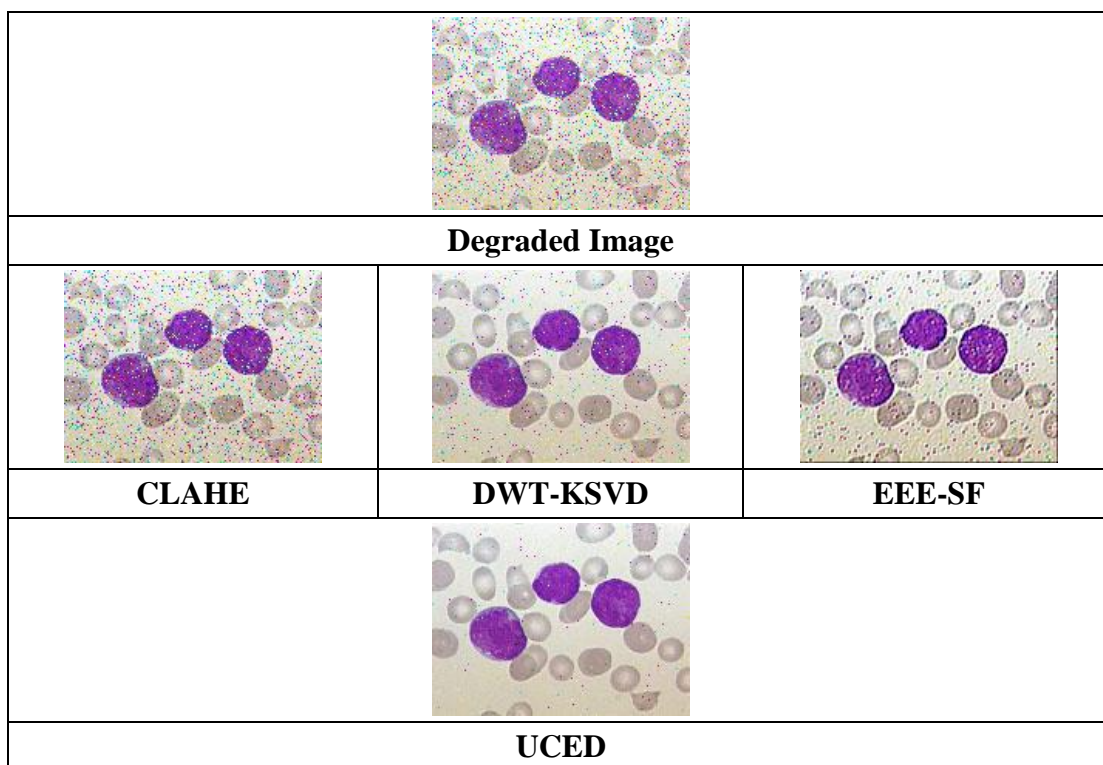


Figure 7.2d : Visual Results of Enhancement Algorithms - Image D

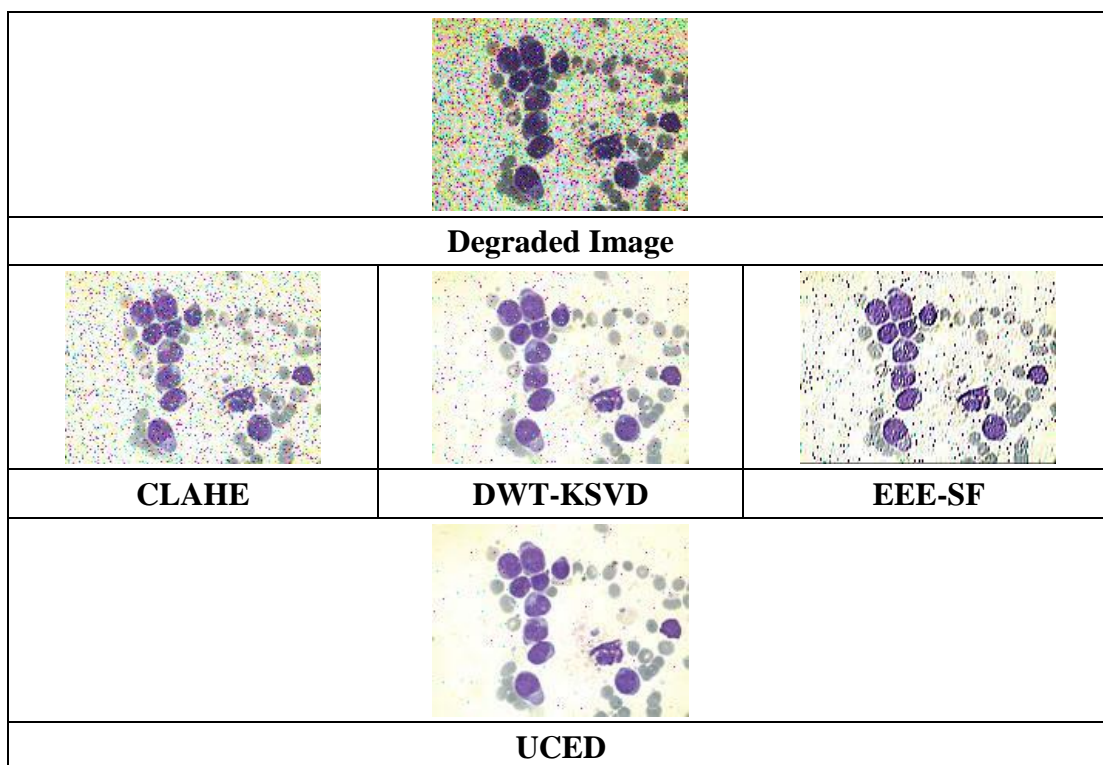


Figure 7.2e : Visual Results of Enhancement Algorithms - Image E

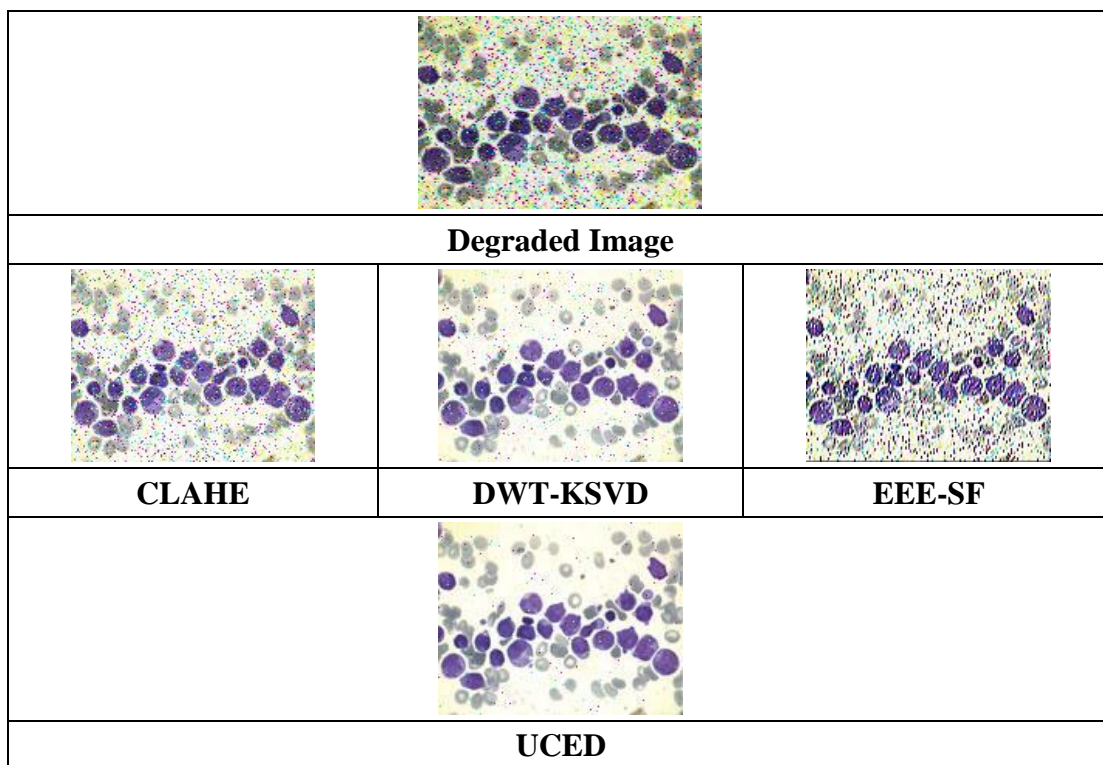
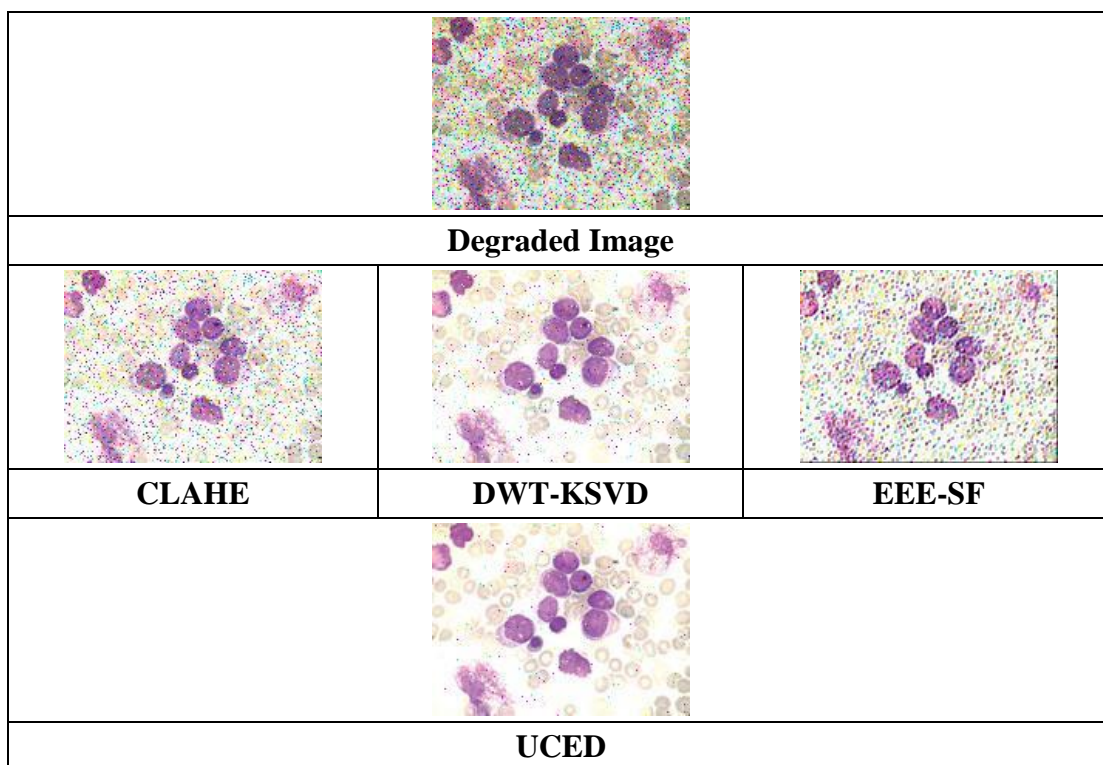
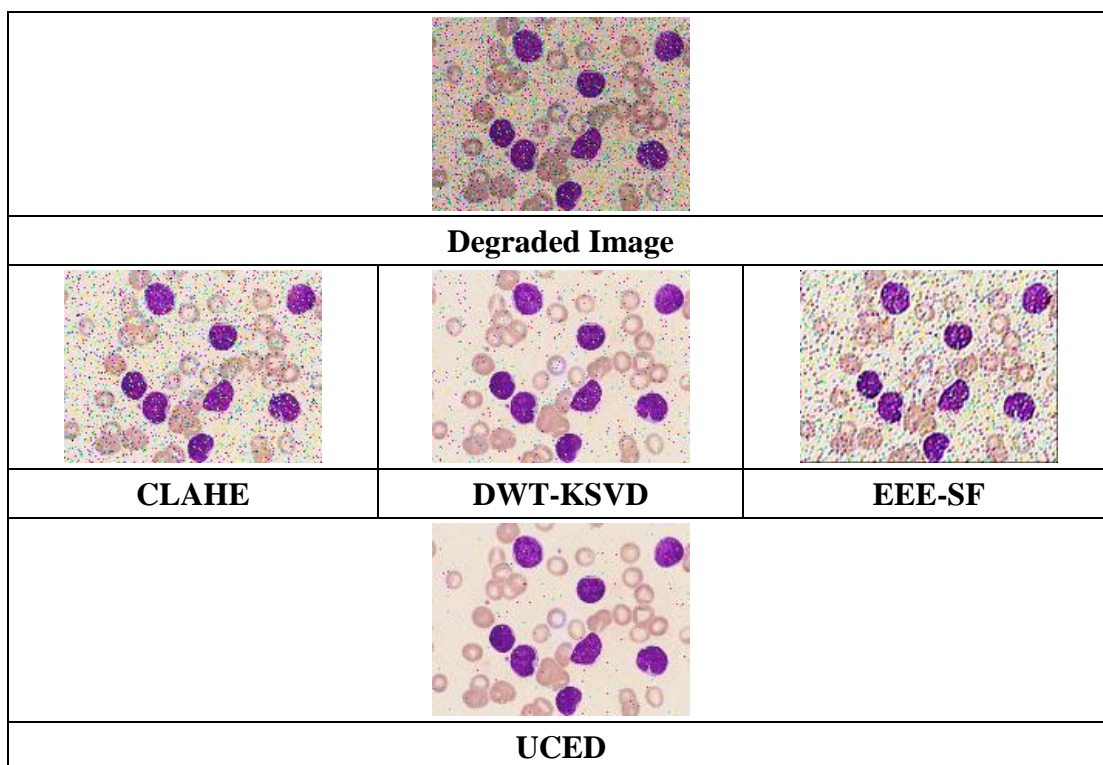


Figure 7.2f : Visual Results of Enhancement Algorithms - Image F

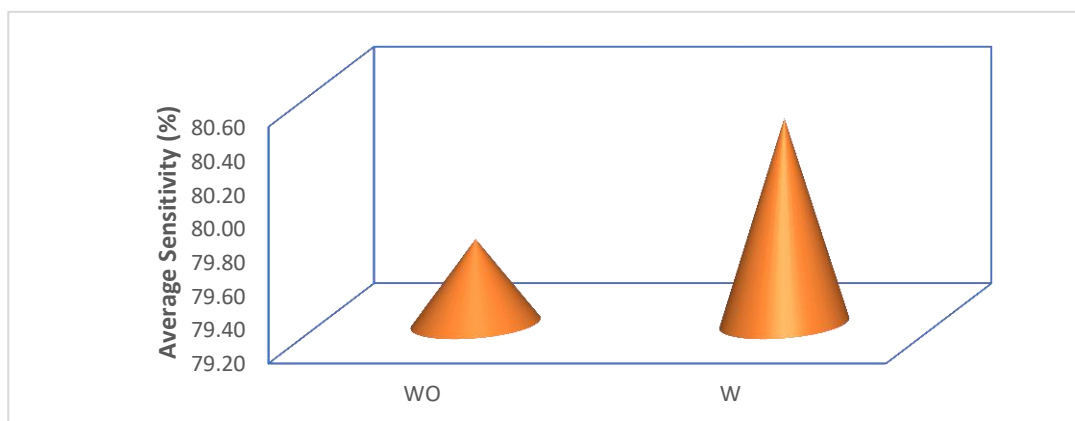


**Figure 7.2g : Visual Results of Enhancement Algorithms - Image G**

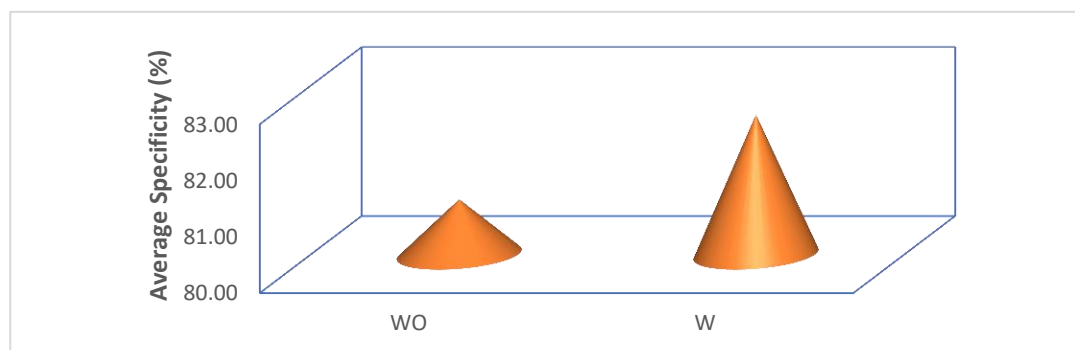


**Figure 7.2h : Visual Results of Enhancement Algorithms - Image H**

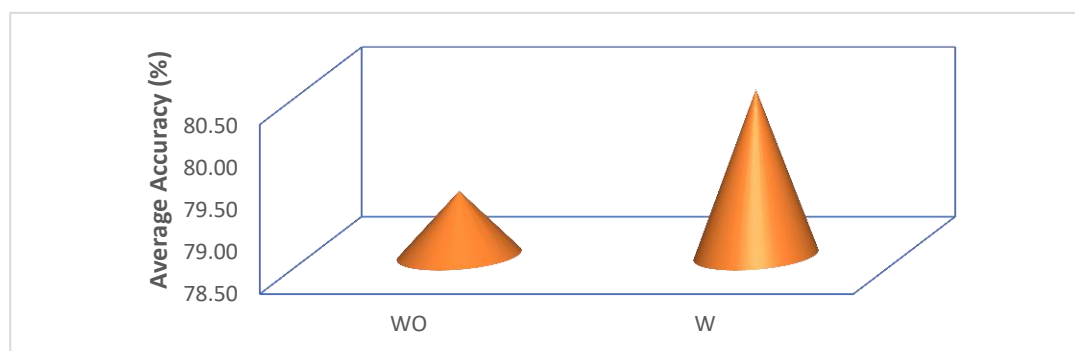
Another set of experiments was used to analyse the effect of the unified enhancement algorithm on ALL-C. These experiments used SVM classifier. Figures 7.3a to 7.3c present the results of this comparison while using sensitivity, specificity and accuracy respectively, as performance evaluation metrics. In these figures, WO denotes ALL-C without out the use of enhancement algorithm and W denotes ALL-C with the use of enhancement algorithm.



(a) Sensitivity



(b) Specificity



(c) Accuracy

**Figure 7.3 : Effect of Noise Removal Algorithm on ALL Classification**

The above charts prove the importance of noise removal algorithm in ALL-C systems. The inclusion of noise removal algorithm improves sensitivity by 0.89%, specificity by 1.83% and accuracy by 1.49%.

### 7.2.2. Analysis of Segmentation Algorithms

Segmentation is the process that is used to separate the microscopic image into WBC, RBC and background regions. The coding scheme used during discussion is given in Table 7.3.

**TABLE 7.3**  
**CODING SCHEME - SEGMENTATION**

<b>Code</b>	<b>Description</b>
WS-WBC	Watershed Segmentation Algorithm to Identify WBC
EWS-WBC	Enhanced Watershed Segmentation Algorithm to Identify WBC
KM-WBC	K-Means Clustering Algorithm to Identify WBC
PFKM-WBC	Parameterless Fast K-Means Clustering Algorithm to Identify WBC
CSA-WBC	Combined Segmentation Algorithm for WBC Identification

Table 7.4 shows the average stability criterion, average anti-noise criterion values obtained during segmentation along with the execution time (speed in seconds). While estimating the anti-noise criterion, the noise criterion is estimated using the noise added images from Section 7.1.2.

**TABLE 7.4**  
**PERFORMANCE ANALYSIS OF SEGMENTATION ALGORITHMS**

<b>Algorithm</b>	<b>Average Stability Criterion</b>	<b>Average Anti-Noise Criterion</b>	<b>Speed</b>
WS-WBC	57.87	49.31	1.65
EWS-WBC	62.20	58.85	2.04
KM-WBC	75.77	68.28	1.22
PFKM-WBC	76.84	76.22	0.96
CSA-WBC	78.07	79.70	2.12

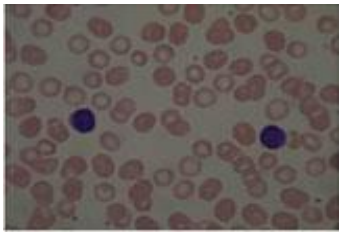
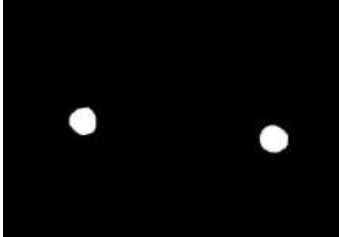
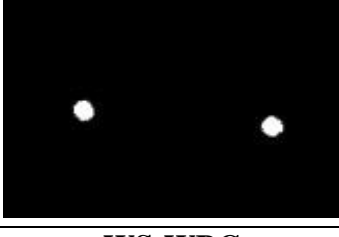
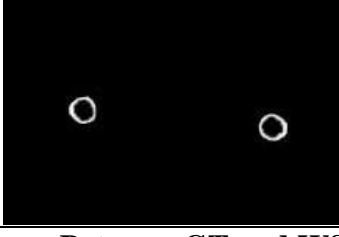
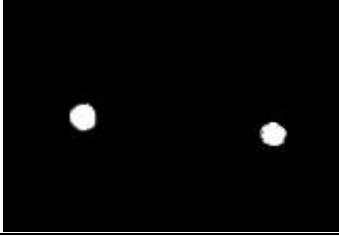
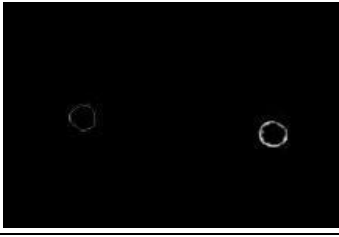
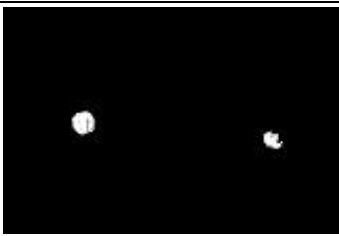
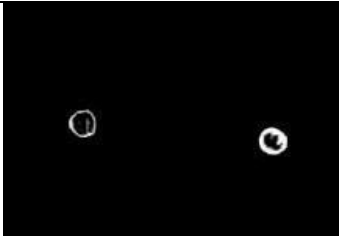
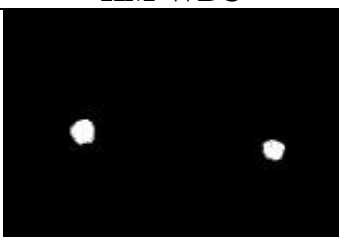
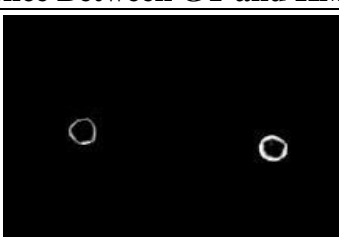
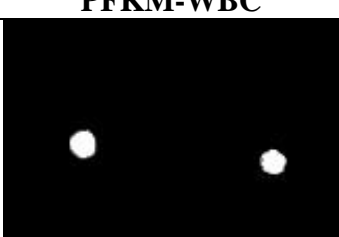

The CSA-WBC is an algorithm that combines enhanced watershed and enhanced K-Means clustering based segmentation algorithms to group WBC, RBC and background. Analysis of WS and EWS algorithms show that the EWS is more effective than its conventional counterpart. A similar trend was envisaged with KM and PFKM algorithms also. Thus, the CSA-WBC, combining these enhanced algorithms, naturally was more effective in separating blood cells and background from the microscopic images and the results produced are more stable. The results pertaining to anti-noise criterion also proves that the proposed algorithm is effective even in the presence of noise.

From the speed results, it can be seen that the proposed CSA-WBC algorithm takes maximum time to produce the segmentation results. This is due to the fact that it has to perform three algorithms, enhanced watershed, enhanced K-Means and combine their results to obtain the final result. However, as the proposed CSA-WBC produces more stable and accurate segments, when compared to other algorithms, it was decided to use this algorithm to identify the WBCs.

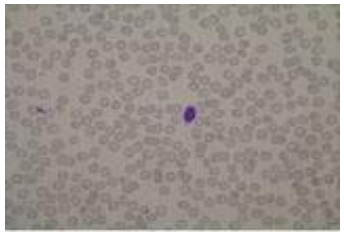

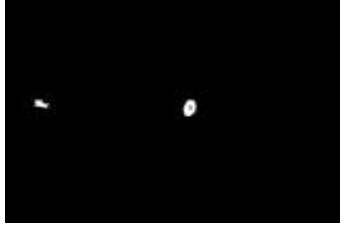



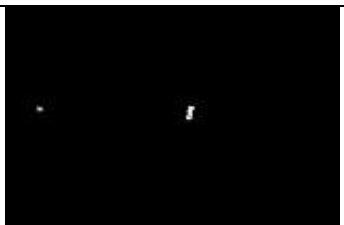
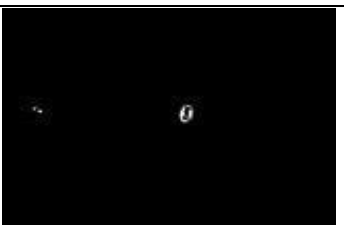

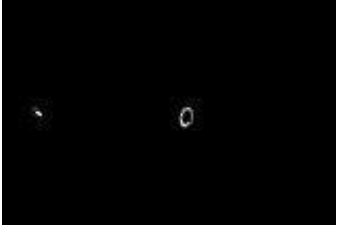
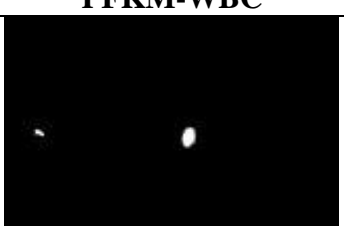

Figures 7.4a to 7.4h show the difference between the Ground Truth (GT) image and the segmentation result of the test images A-F respectively.

The difference between GT and segmented results obtained by the various segmentation algorithms, further stress that the proposed algorithm produces segmentation results that is very similar to the GT.

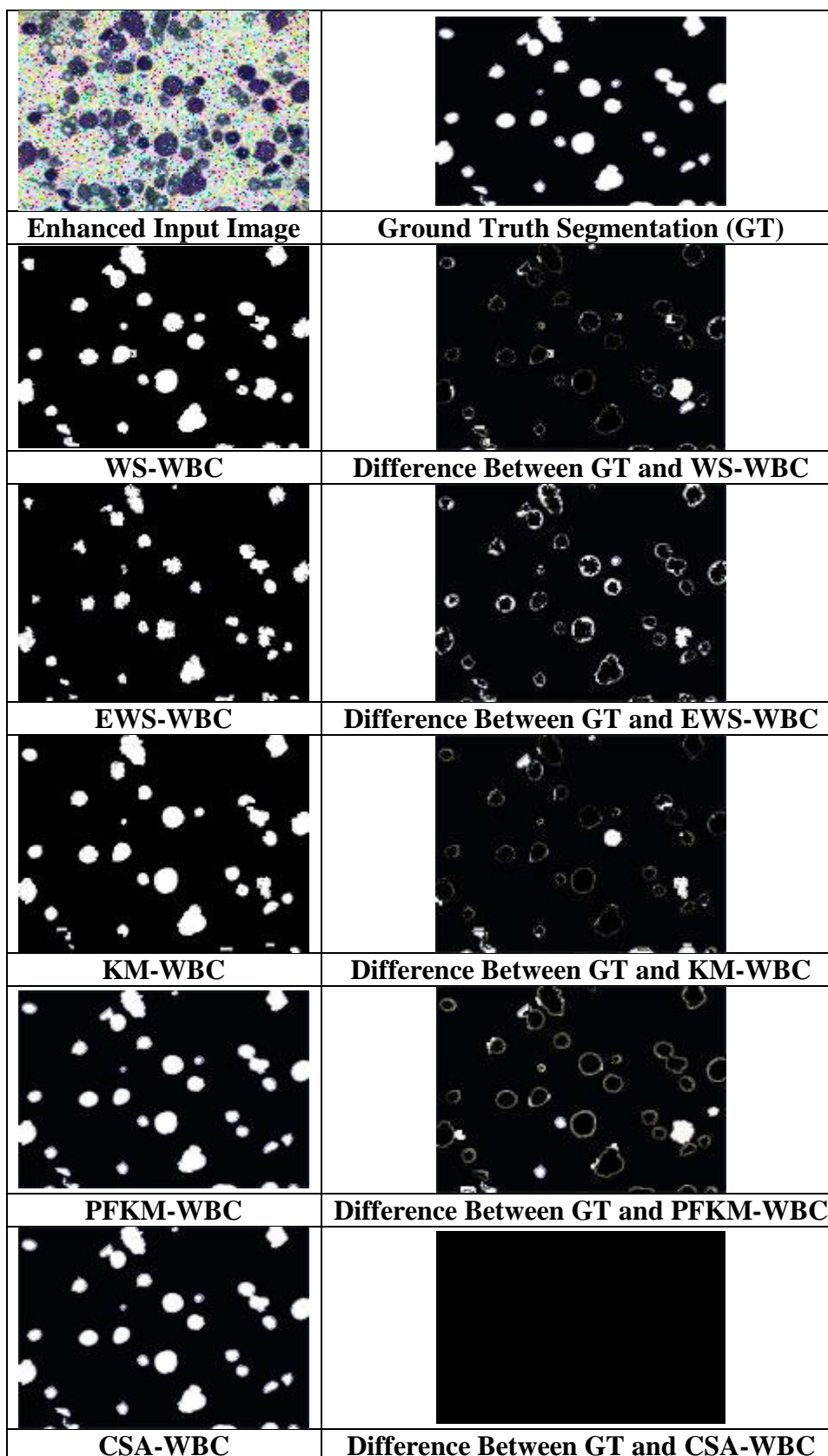
Figures 7.5a to 7.5c compare the effect of segmentation algorithm on ALL-C systems. In these figures, WO S denotes ALL-C without using WBC identification and W S denotes ALL-C using WBC identification. The classifier used during experimentation was SVM.

	
<b>Enhanced Input Image</b>	<b>Ground Truth Segmentation (GT)</b>
	
<b>WS-WBC</b>	<b>Difference Between GT and WS-WBC</b>
	
<b>EWS-WBC</b>	<b>Difference Between GT and EWS-WBC</b>
	
<b>KM-WBC</b>	<b>Difference Between GT and KM-WBC</b>
	
<b>PFKM-WBC</b>	<b>Difference Between GT and PFKM-WBC</b>
	
<b>CSA-WBC</b>	<b>Difference Between GT and CSA-WBC</b>

**Figure 7.4a : Visual Comparison of Segmentation Algorithms - Image A**

	
<b>Enhanced Input Image</b>	<b>Ground Truth Segmentation (GT)</b>
	
<b>WS-WBC</b>	<b>Difference Between GT and WS-WBC</b>
	
<b>EWS-WBC</b>	<b>Difference Between GT and EWS-WBC</b>
	
<b>KM-WBC</b>	<b>Difference Between GT and KM-WBC</b>
	
<b>PFKM-WBC</b>	<b>Difference Between GT and PFKM-WBC</b>
	
<b>CSA-WBC</b>	<b>Difference Between GT and CSA-WBC</b>

**Figure 7.4b : Visual Comparison of Segmentation Algorithms - Image B**



**Figure 7.4c : Visual Comparison of Segmentation Algorithms - Image C**

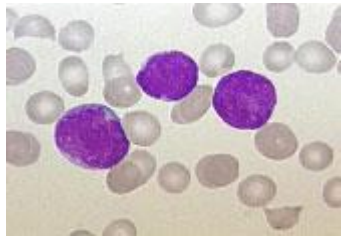
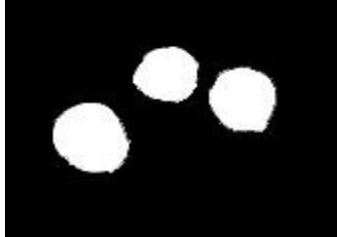

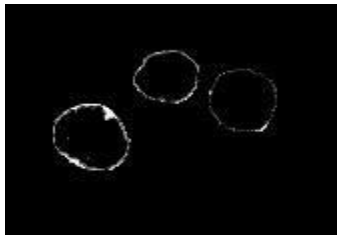
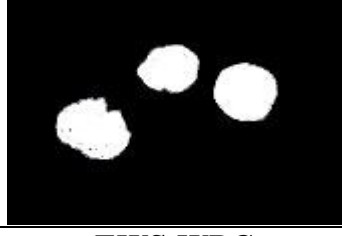
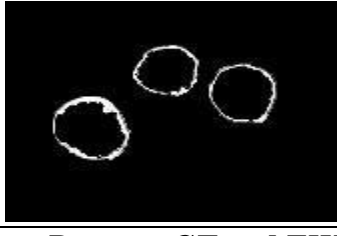
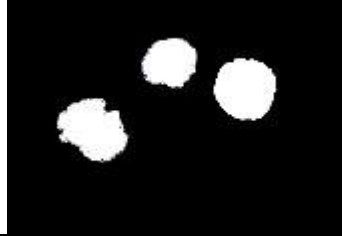

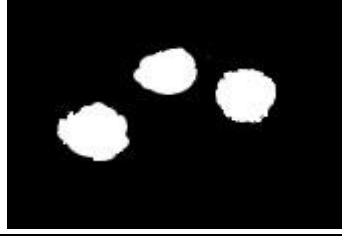
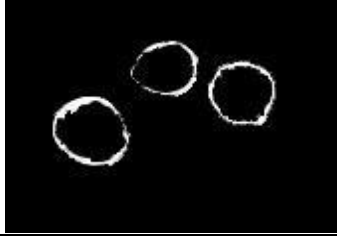
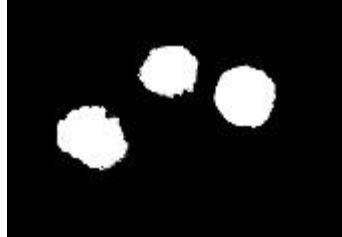

	
<b>Enhanced Input Image</b>	<b>Ground Truth Segmentation (GT)</b>
	
<b>WS-WBC</b>	<b>Difference Between GT and WS-WBC</b>
	
<b>EWS-WBC</b>	<b>Difference Between GT and EWS-WBC</b>
	
<b>KM-WBC</b>	<b>Difference Between GT and KM-WBC</b>
	
<b>PFKM-WBC</b>	<b>Difference Between GT and PFKM-WBC</b>
	
<b>CSA-WBC</b>	<b>Difference Between GT and CSA-WBC</b>

Figure 7.4d : Visual Comparison of Segmentation Algorithms - Image D

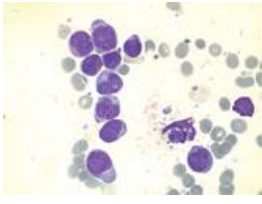
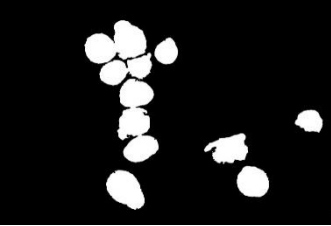

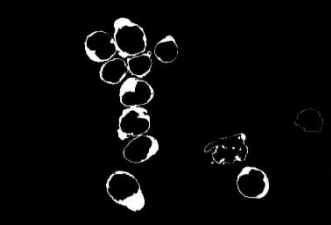
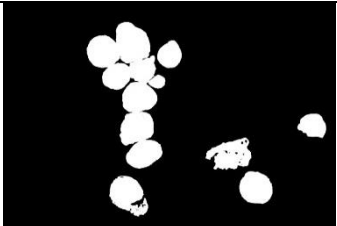
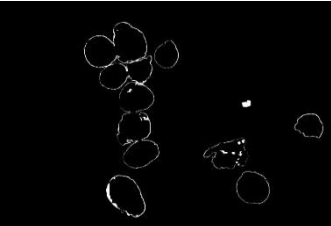
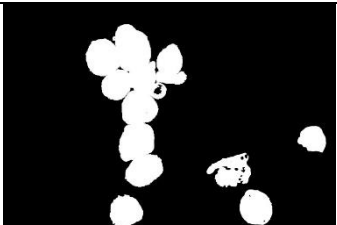
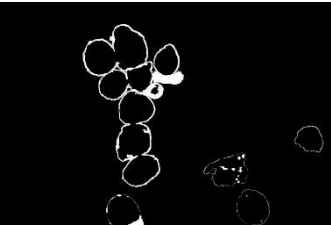
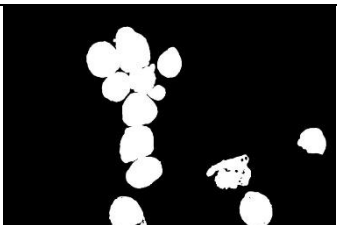
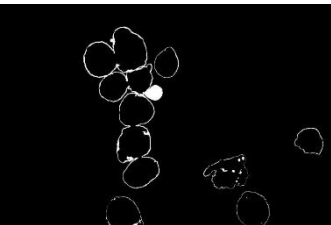
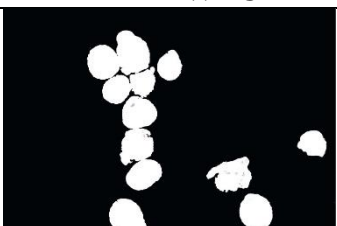
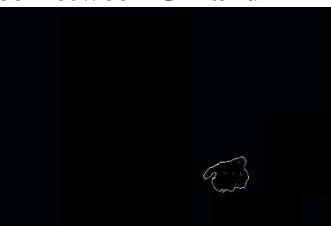
	
<b>Enhanced Input Image</b>	<b>Ground Truth Segmentation (GT)</b>
	
<b>WS-WBC</b>	<b>Difference Between GT and WS-WBC</b>
	
<b>EWS-WBC</b>	<b>Difference Between GT and EWS-WBC</b>
	
<b>KM-WBC</b>	<b>Difference Between GT and KM-WBC</b>
	
<b>PFKM-WBC</b>	<b>Difference Between GT and PFKM-WBC</b>
	
<b>CSA-WBC</b>	<b>Difference Between GT and CSA-WBC</b>

Figure 7.4e : Visual Comparison of Segmentation Algorithms - Image E

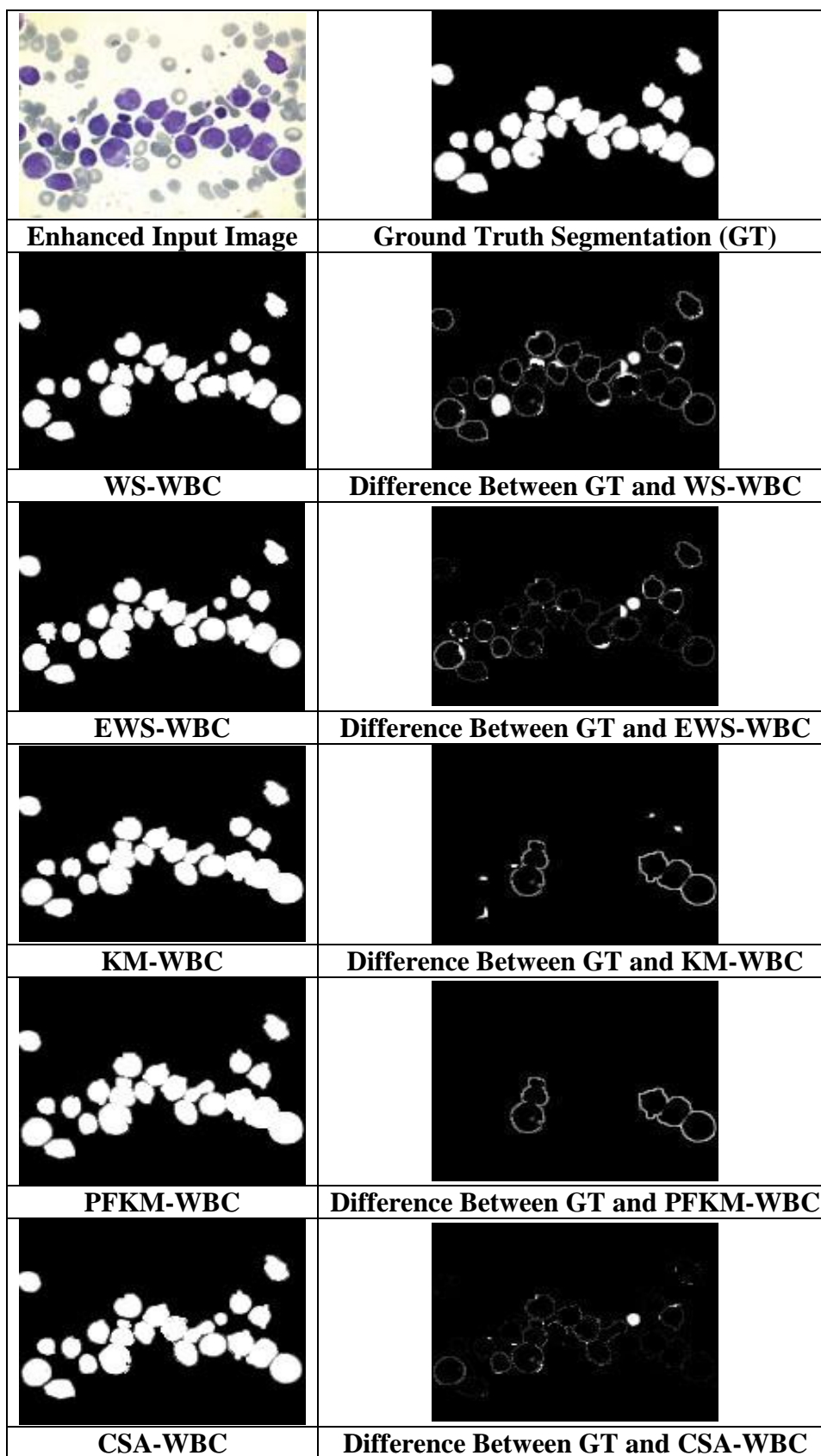
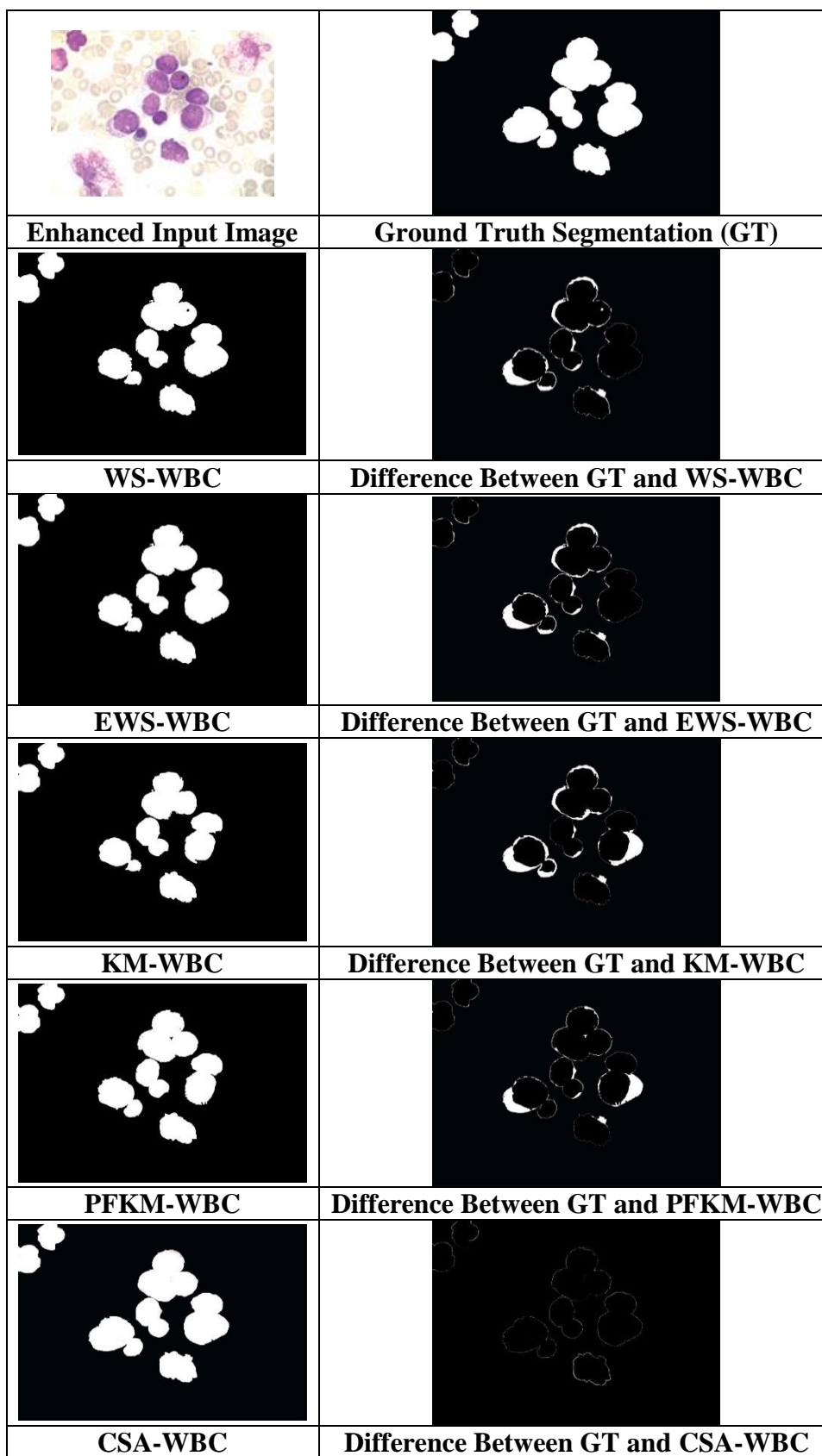
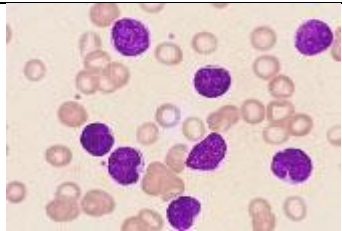
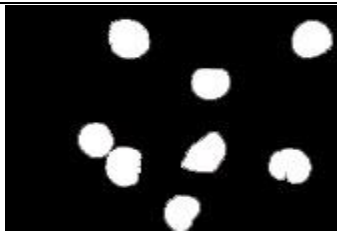
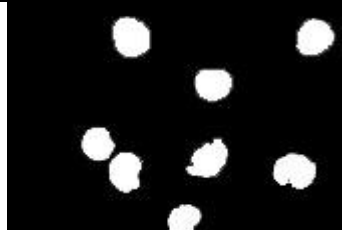
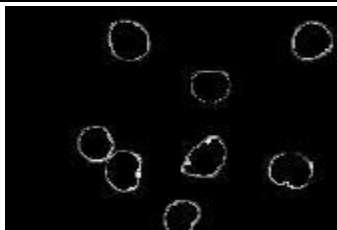
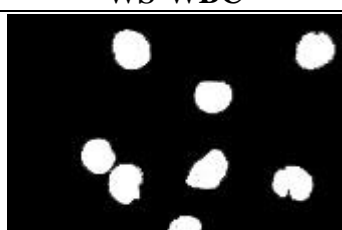
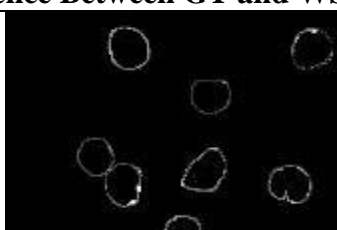
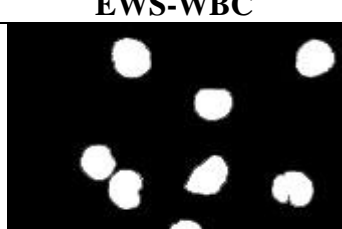
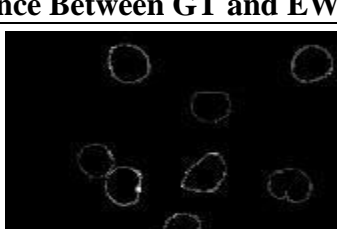
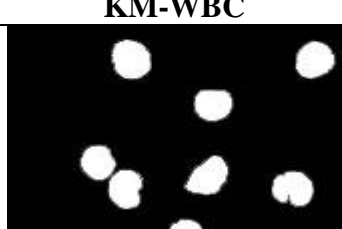
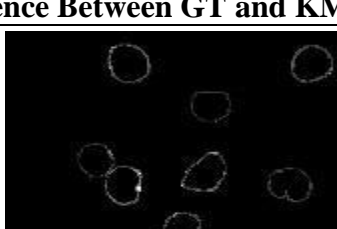
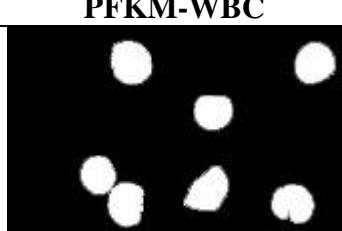



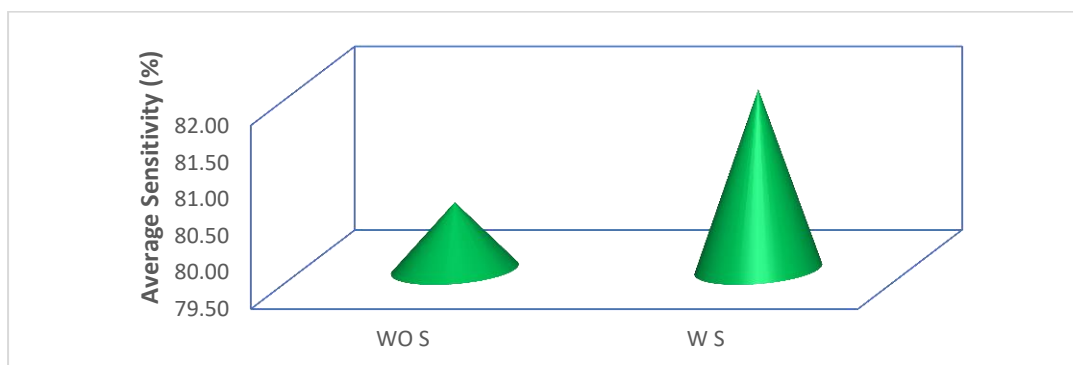
Figure 7.4f : Visual Comparison of Segmentation Algorithms - Image F



**Figure 7.4g : Visual Comparison of Segmentation Algorithms - Image G**

	
<b>Enhanced Input Image</b>	<b>Ground Truth Segmentation (GT)</b>
	
<b>WS-WBC</b>	<b>Difference Between GT and WS-WBC</b>
	
<b>EWS-WBC</b>	<b>Difference Between GT and EWS-WBC</b>
	
<b>KM-WBC</b>	<b>Difference Between GT and KM-WBC</b>
	
<b>PFKM-WBC</b>	<b>Difference Between GT and PFKM-WBC</b>
	
<b>CSA-WBC</b>	<b>Difference Between GT and CSA-WBC</b>

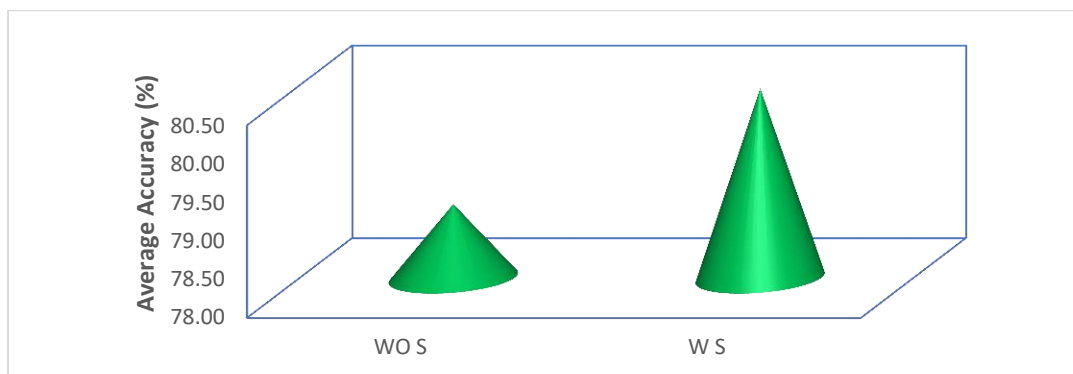
**Figure 7.4h: Visual Comparison of Segmentation Algorithms - Image H**



(a) Sensitivity



(b) Specificity



(c) Accuracy

**Figure 7.5 : : Effect of Segmentation Algorithm on ALL Classification**

From the result analysing the effect of segmentation algorithm on ALL-C, it is clear that the usage of segmentation algorithm to identify WBCs has improved the classification performance. The ALL-C system while using segmentation improved classification performance by 1.88% (sensitivity), 1.67% (specificity) and 1.87% (accuracy).

Thus, the results presented in this section prove the importance of preprocessing step in ALL-C and help to improve the performance of ALL-C systems, thus meeting the objective formulated.

### 7.3. ALL-C CLASSIFICATION USING MACHINE LEARNING CLASSIFIER

As mentioned in Chapter 5, multiple features (texture, shape, color and irregularity features) were extracted and fused to form a single super vector. The MRMR algorithm was used to select optimal features from this super vector. This section present the results of experiments that analysed the effect of feature fusion, feature selection and enhanced classifiers while performing ALL-C. Table 7.5 presents the coding scheme used in this section.

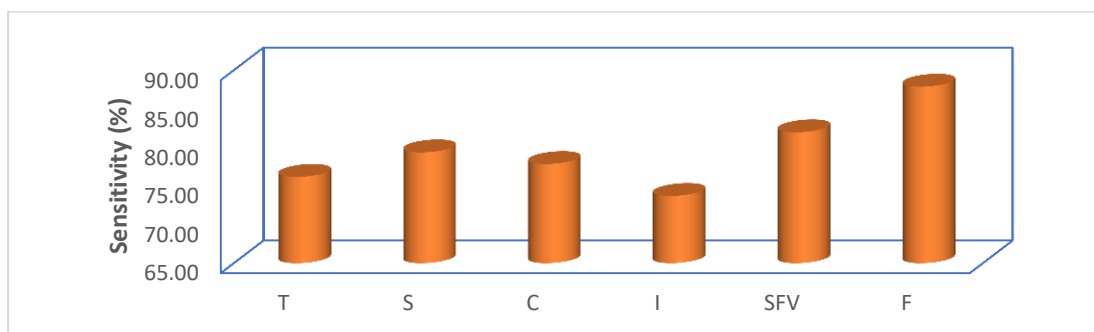
**TABLE 7.5**

**CODING SCHEME - ALL-C CLASSIFICATION USING ML CLASSIFIERS**

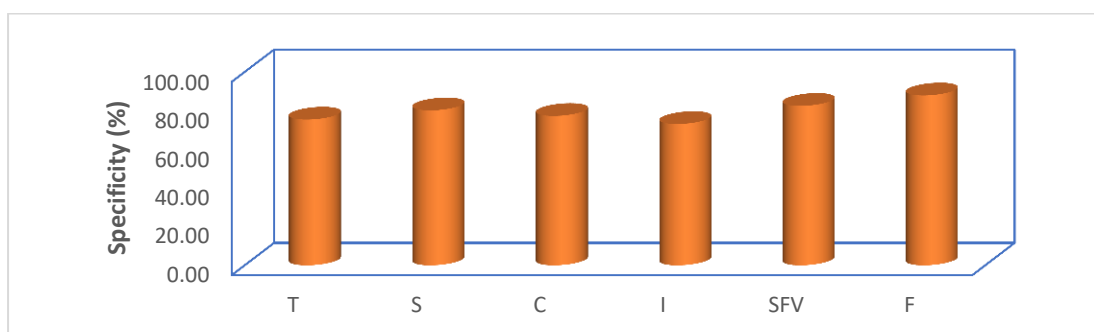
<b>Code</b>	<b>Description</b>
T	Texture Feature
S	Shape Feature
C	Color Feature
I	Irregularity of the Nucleus Boundary Feature
SFV	Super Feature Vector
F	Optimal Feature Vector
SVM	Support Vector Machine
ESVM	Ensemble System Based on SVM
ESVM-DCS	ESVM using DSC
ESVM-DES	ESVM using DES
ESVM-EDCS	ESVM using Enhanced DCS
ESVM-EDES	ESVM using Enhanced DES

#### 7.3.1. Effect of Feature Fusion and Selection of ALL-C System

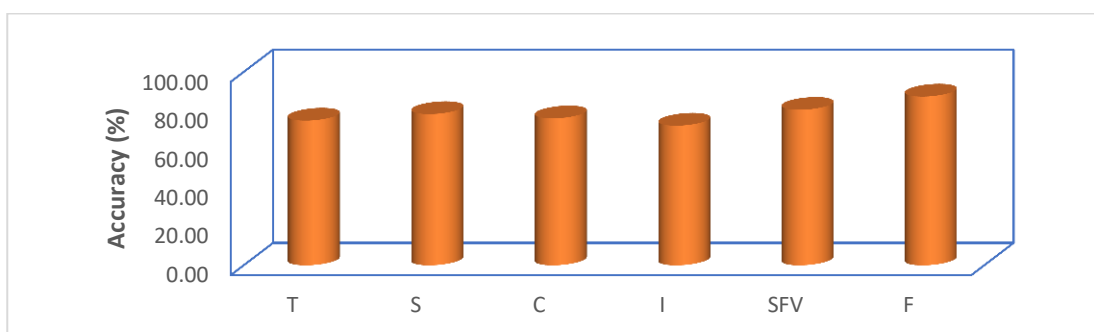
The effect of multiple features and feature selection algorithms, on sensitivity, specificity, accuracy and execution time, is shown in Figures 7.6a to 7.6d respectively. The classifier used during experimentation is SVM classifier.



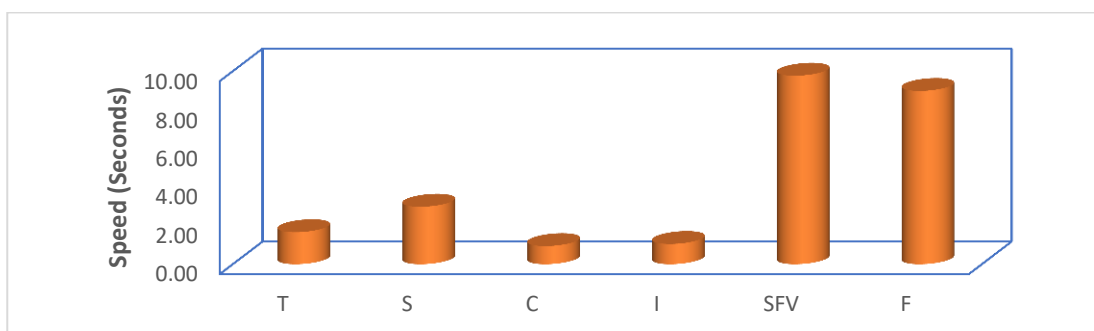
(a) Sensitivity



(b) Specificity



(c) Accuracy



(d) Execution Time

**Figure 7.6 : Effect of Feature Fusion and Feature Selection Algorithms on ALL-C System**

The above analysis clearly shows that both fusion and selection of features have positive impact on ALL classification with all selected performance metrics, except for execution time. The SVM classifier produced a sensitivity in the range of 73.32%-79.36% (sensitivity), 73.10%-80.17% (specificity) and 72.24%-78.24% (accuracy). This was improved to 81.96% (sensitivity), 82.49% (specificity) and 80.46% (accuracy) while using super vector. This justifies the usage of multiple fused feature vector for performing ALL-C. The usage of MRMR further improved classification results by 6.73% (sensitivity), 6.12% (specificity) and 7.83% (accuracy) when compared with SVM classifier with fusion algorithm. This proves that the MRMR selects only optimal features with maximum discrimination capacity without redundancy.

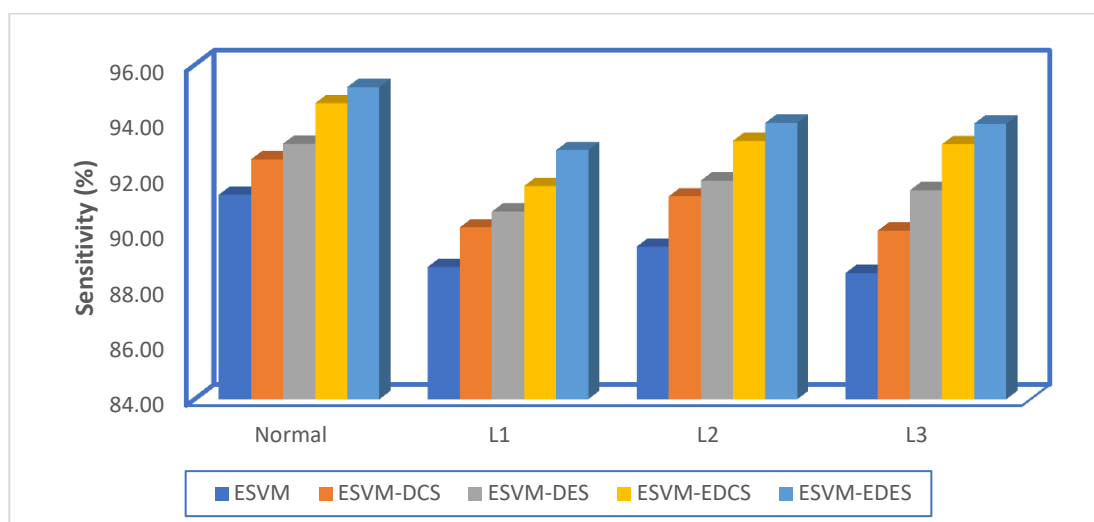
The execution time of classification is high when using fusion algorithm. This is due to the fact that the speed complexity of a classifier is directly related to the size of the feature set, which is high while using multiple features. The size of super vector is  $m \times n$ , where  $m$  is the number of attributes and  $n$  is the number of WBC cells, from which the features are extracted. In this research  $m$  is equal to 50, as the fusion algorithm uses size normalization. This increase in the size of feature vector also increases the time taken to classify blood cells. On the other hand, the usage of feature selection algorithm has reduced this time complexity by 8.8%. This reduction in execution time combined with the high accuracy obtained by the optimal vector, encouraged the usage of F in further steps of the proposed ALL-C systems.

### 7.3.2. Analysis of Ensemble Classifiers on of ALL-C

Phase II proposes the use of SVM-based homogeneous ensemble classifiers to improve the performance of ALL classification. This section presents the results of experiments that compares the SVM-based ensemble classifier with the proposed enhanced ensemble classifiers. The results presented compare the conventional ensemble system (ESVM) and existing systems (ESVM-DCS and ESVM-DES) with the proposed systems (ESVM-EDCS and ESVM-EDES).

- **Sensitivity**

Figure 7.7 shows the performance of the ALL-C systems that use ensemble classifiers to group the WBCs as normal/L1/L2/L3, in terms of sensitivity.



**Figure 7.7 : Sensitivity of Ensemble Classifiers**

The comparison reveal that both the proposed systems are efficient when compared to conventional and existing systems. The ESVM-EDCS and ESVM-EDES achieved a maximum average precision of 93.89% and 93.99% respectively, which is definitely an improved result, when compared with ESVM with 89.52%, ESVM-DCS with 91.03% and ESVM-DES with 91.81%. Comparing the two proposed ALL-C systems showed that the ESVM-EDES is more efficient.

Table 7.6 shows the advantage of ESVM-EDES over the single SVM classification system along with efficiency gain obtained by the proposed system.

**TABLE 7.6**

**COMPARISON OF SVM ALL-C SYSTEM WITH ESVM-EDES ALL-C SYSTEM  
IN TERMS OF SENSITIVITY (%)**

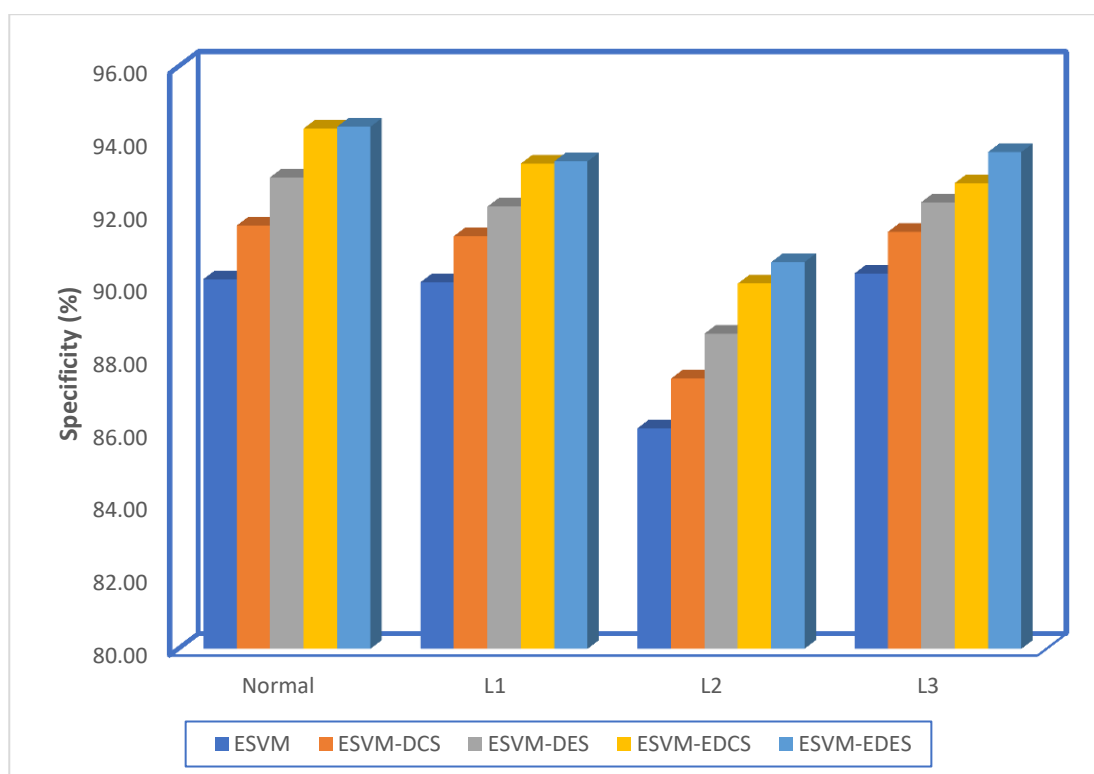
Category	SVM	ESVM-EDES	Efficiency Gain (%)
Normal	89.14	95.21	6.37
L1	87.23	92.94	6.15
L2	88.11	93.92	6.18
L3	86.99	93.89	7.35

The above table clearly shows that the ESVM-EDES system is superior to SVM classifier and achieved an average efficiency gain of 6.51%.

Thus, the results presented show that, ALL-C systems incorporated with the ESVM-EDCS and ESVM-EDES methods, have high ability to predict TPs of each of the four categories, viz., Normal, L1, L2 and L3.

- **Specificity**

Figure 7.8 shows the specificity values obtained by the conventional, existing and proposed ALL-C systems.



**Figure 7.8 : Specificity of Ensemble Classifiers**

The second performance metric considered also proves that the proposed systems' performance is high when compared to ESVM and ESVM with DCS and DES. The average specificity obtained by ESVM classifier was 89.15%, which increased to 90.46% (ESVM-DCS) and 91.51% (ESVM-DES). The specificity is further increased to 92.62% with ESVM-EDCS and 93% with ESVM-EDES systems. Comparison of single SVM classifier performance with ESVM-EDES showed that the winning system had an average efficiency advantage of 5.52%. The comparison results are shown in Table 7.7.

TABLE 7.7

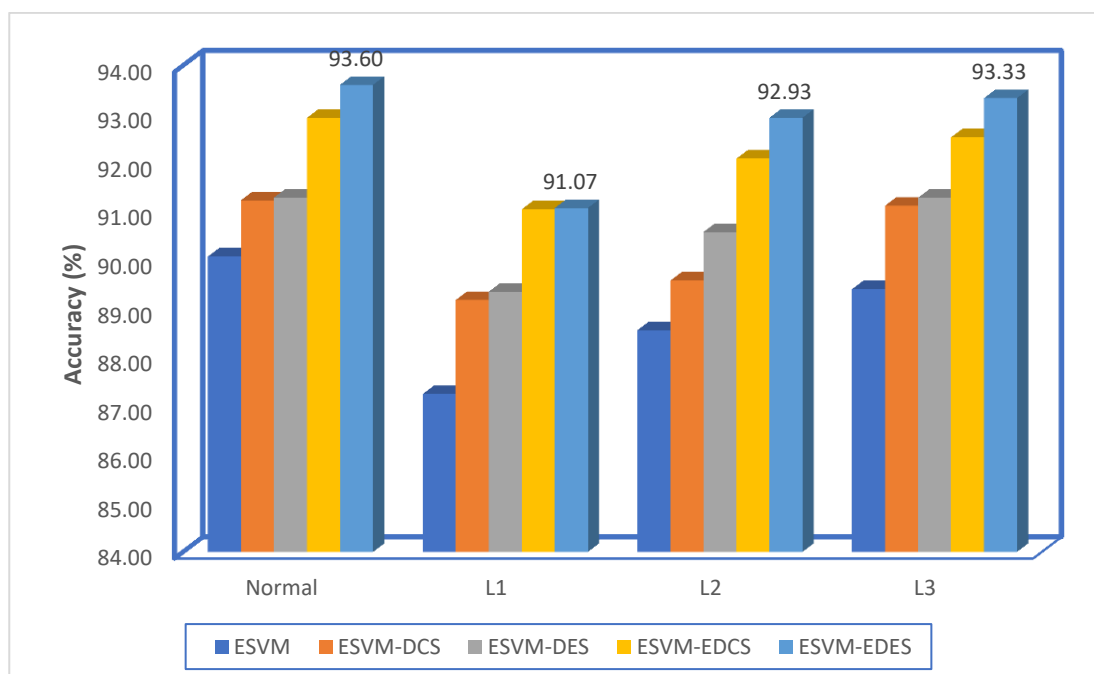
**COMPARISON OF SVM ALL-C SYSTEM WITH ESVM-EDES ALL-C SYSTEM  
IN TERMS OF SPECIFICITY (%)**

Category	SVM	ESVM-EDES	Efficiency Gain (%)
Normal	89.10	94.35	5.56
L1	88.55	93.39	5.18
L2	85.13	90.62	6.06
L3	88.71	93.65	5.28

Thus, the results prove that both the proposed systems' ability to predict true negatives of the four target categories is high.

- **Accuracy**

The classification accuracy obtained by the ALL-C systems while using the various ensemble systems is shown in Figure 7.9.



**Figure 7.9 : Accuracy of Ensemble Classifiers**

The results projected above highlight the fact that usage of EDCS an EDES with ESVM improves the performance of ALL-C with respect to accuracy also. Maximum benefit was obtained while using EDES with SVM (92.73% on average). This was followed by ESVM system that used EDCS algorithm (92.14% on average). The conventional ESVM achieved an average accuracy of 88.82%, while the existing ESVM-DCS and ESVM-DES showed an average accuracy of 90.27% and 90.62% respectively.

Table 7.8 shows the accuracy of ESVM-EDES classifier and single SVM classifier and also projects the efficiency gain of ESVM-EDES over SVM. On average, the ESVM-EDES ALL-C system showed an efficiency gain of 5.87% over SVM classifier.

**TABLE 7.8**  
**COMPARISON OF SVM ALL-C SYSTEM WITH ESVM-EDES ALL-C SYSTEM**  
**IN TERMS OF ACCURACY (%)**

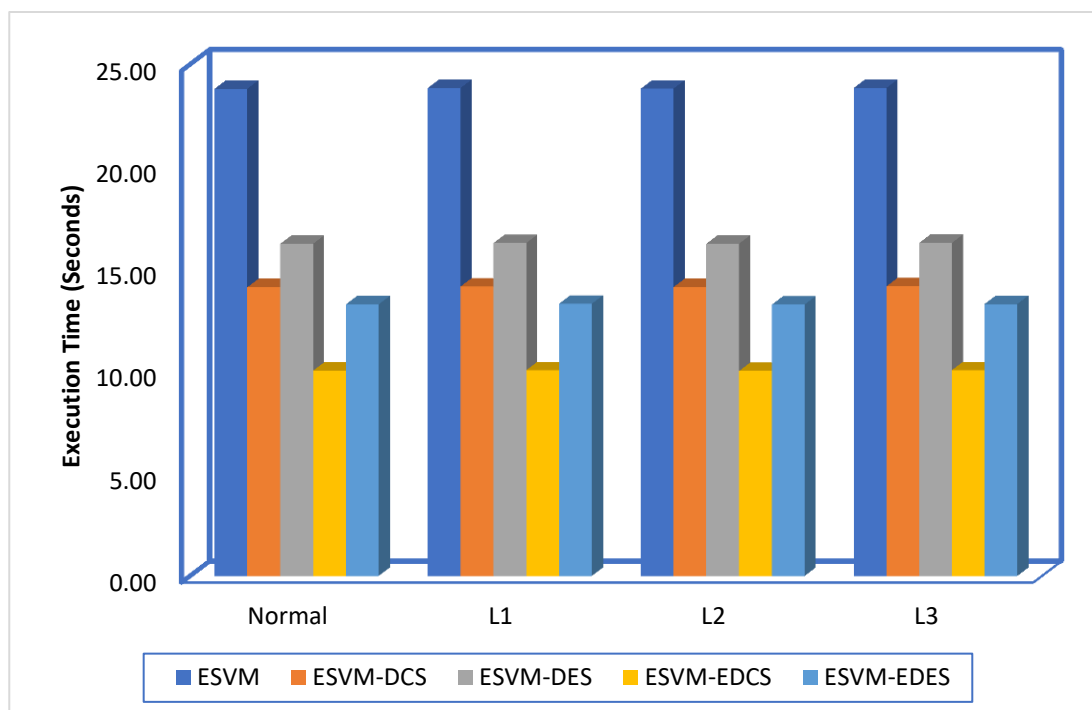
Category	SVM	ESVM-EDES	Efficiency Gain (%)
Normal	88.51	93.60	5.45
L1	85.55	91.07	6.06
L2	87.45	92.93	5.89
L3	87.65	93.33	6.08

- **Execution Time**

An important factor during ALL-C is its speed. Speed analysis of the ensemble classifiers is shown in Figure 7.10.

All the ensemble systems that used DES and DCS algorithms with ESVM decreased the time complexity of the ALL-C systems. On average, the ESVM classifier took 23.83 seconds to classify an input test feature set. This reduced to 14.13 seconds with ESVM-DCS and 16.25 seconds with ESVM-DES. The time taken to classify further reduced to 10.04 seconds with ESVM-EDCS and 13.28 ESVM-EDES. This proves that the pruning algorithm used with DCS and DES to have a positive impact on the execution time. However, at this junction, a different performance trend was observed. Unlike the other three selected performance metrics, with execution time, the ESVM-EDCS classifier

was faster than ESVM-EDES. This is because, the EDCS uses only one single best classifier during ALL-C, while DES executes a set of best-classifiers.



**Figure 7.10 : Execution Speed of the Ensemble Classifiers**

Table 7.9 compares single classifier with the winning classifier SVM-EDCS. Here, again the performance trend changed. The single classifier is quicker than the ESVM-EDCS classifier. This result is obvious as the complexity of ensemble system is high. However, the research work has used several time complexity reducing methods, which has lowered the execution time required.

**TABLE 7.9**

**COMPARISON OF SVM ALL-C SYSTEM WITH ESVM-EDES ALL-C SYSTEM  
IN TERMS OF EXECUTION TIME (SECONDS)**

Category	SVM	ESVM-EDCS	Efficiency Gain (%)
Normal	8.96	10.03	10.67
L1	9.00	10.05	10.50
L2	8.97	10.02	10.51
L3	8.99	10.06	10.59

The main goal of this research work is to design systems that can produce highly accurate identification of ALL and its subtypes. The various results projected in this chapter shows that the proposed classifiers have met this objective and it could be seen that the proposed ensemble classifiers, SVM-EDCS and SVM-EDES, are more powerful, when compared to single SVM classifier and conventional ensemble systems. Thus, from the results, it can be concluded that the proposed algorithms are efficient in identifying Leukemia efficiently.

#### 7.4. ALL-C CLASSIFICATION USING DEEP LEARNING CLASSIFIER

The next phase of the result methodology analyses the application of deep learning classifiers to perform ALL-C. Several performance improvement algorithms were proposed in this phase. The evaluation of these methods are presented in this section. The performance metrics used during evaluation are the same as that of the previous section. The coding scheme used during discussion is presented in Table 7.10.

**TABLE 7.10**  
**CODING SCHEME - ALL-C CLASSIFICATION USING DL CLASSIFIERS**

<b>Code</b>	<b>Description</b>
CNN	CNN Base Model
CNN-SVM	Hybrid CNN and SVM
CNN-ESVM	Hybrid CNN and Ensemble SVM
CNN-ESVM-DCS	Hybrid CNN and Ensemble SVM Using DCS
CNN-ESVM-DES	Hybrid CNN and Ensemble SVM Using DES

The experiments reported in this section was conducted in two stages. The first stage analyzed the performance of ALL-C systems that used single SVM, single CNN and compared them with the conventional hybrid CNN-SVM classifier. As Phase III of the research work enhanced the CNN-SVM classifier, the second stage compared the performance of the proposed hybrid CNN-SVM classifier with its conventional counterpart to ascertain the advantages obtained during ALL identification and classification.

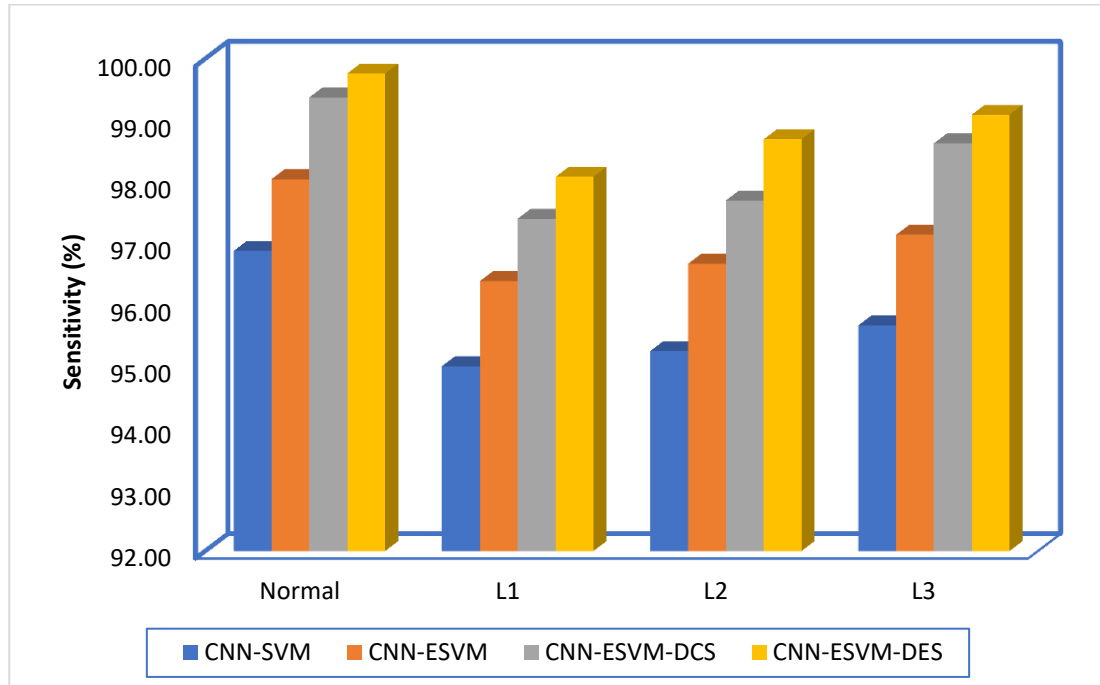
Table 7.11 presents the results obtained while comparing SVM, CNN and CNN-SVM classifiers, in terms of sensitivity, specificity, accuracy and execution time.

**TABLE 7.11**  
**COMPARISON OF SVM, CNN AND SVM-CNN ALL-C SYSTEMS**

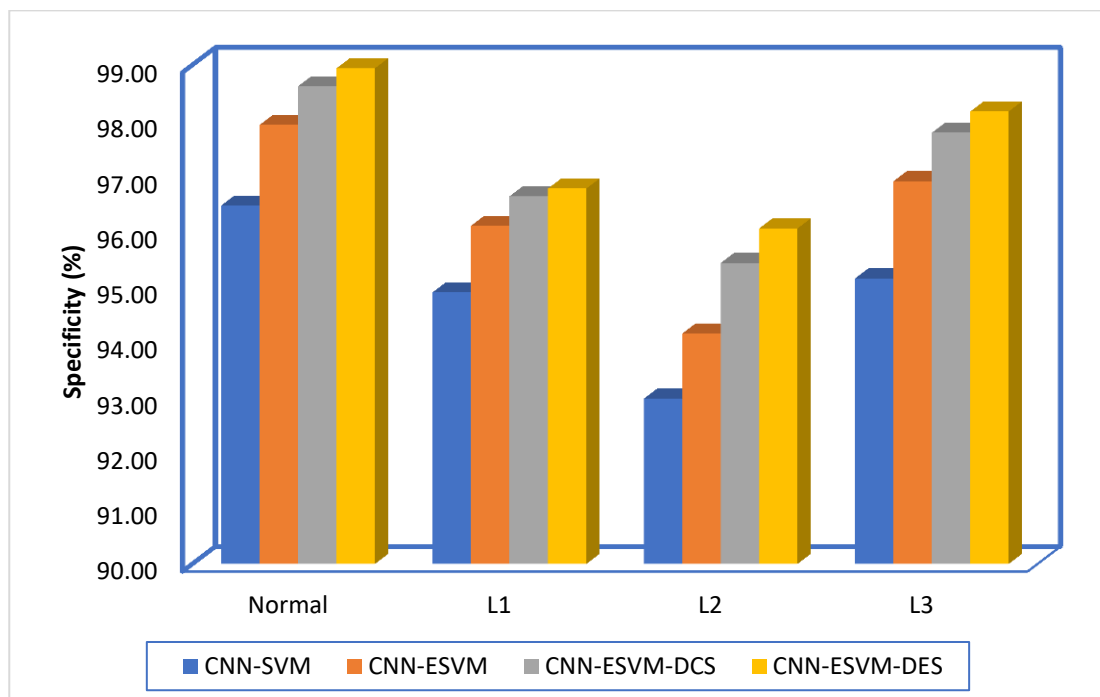
<b>Leukemia Type</b>	<b>SVM</b>	<b>CNN</b>	<b>CNN-SVM</b>
<b>Sensitivity (%)</b>			
Normal	89.14	95.66	96.88
L1	87.23	93.34	95.00
L2	88.11	94.33	95.25
L3	86.99	94.38	95.66
<b>Specificity (%)</b>			
Normal	89.10	94.78	96.46
L1	88.55	93.84	94.90
L2	85.13	91.07	92.98
L3	88.71	94.14	95.15
<b>Accuracy (%)</b>			
Normal	88.51	94.07	95.84
L1	85.55	91.53	92.78
L2	87.45	93.37	94.68
L3	87.65	93.82	95.51
<b>Execution Time (Seconds)</b>			
Normal	8.96	22.94	11.13
L1	9.00	22.96	11.17
L2	8.97	22.94	11.13
L3	8.99	22.96	11.16

From Table 7.15, it is clear that the hybridization of CNN and SVM is successful in improving the performance of the ALL-C system in terms of sensitivity, specificity and accuracy. The CNN-SVM classifier improved, on average, the sensitivity by 9.06% over SVM and 1.34% over CNN classifiers. The hybrid classifier when compared with SVM and CNN improved the average specificity by 6.77% and 1.06% respectively. On the other hand, the average accuracy gain envisaged was 8.22% and 1.77% respectively over SVM and CNN classifiers. While considering the execution time, the hybrid system, while solving the time complexity issue of CNN, was still slower than SVM classifier. These results prove that moving the research in the direction of improving hybrid CNN-SVM classifier will be beneficial during ALL classification.

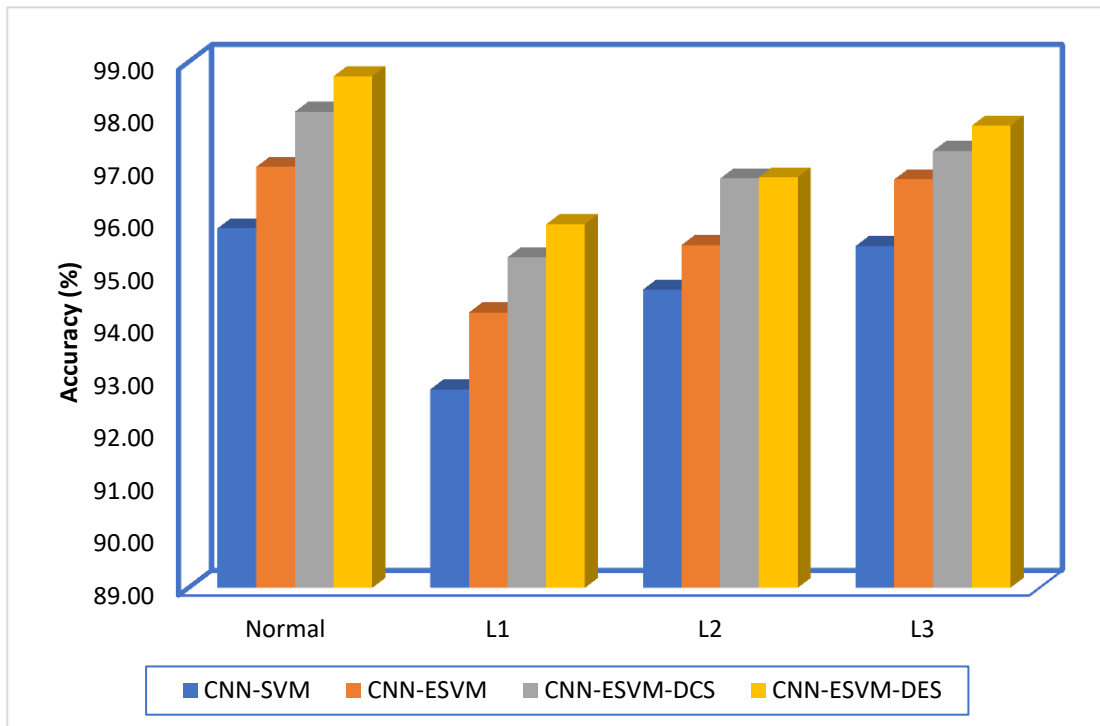
Figures 7.11 to 7.14 present the results obtained by the conventional hybrid CNN-SVM, proposed CNN-ESVM, CNN-ESVM combined with DCS and DES methods with respect to sensitivity, specificity, accuracy and execution time respectively.



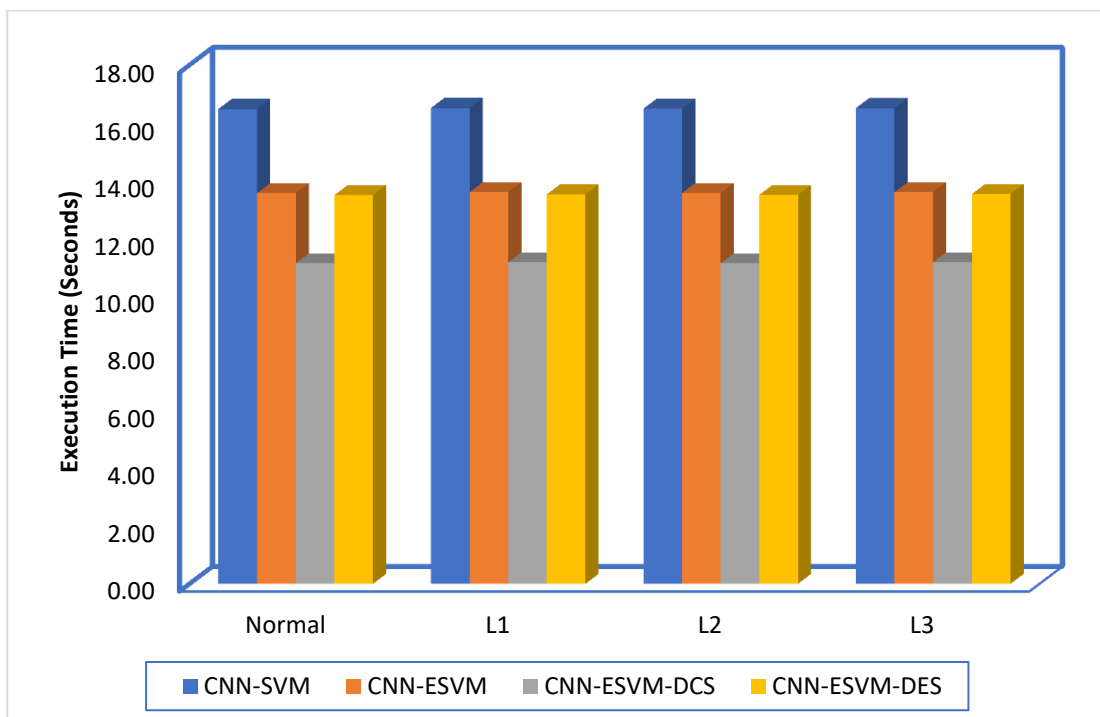
**Figure 7.11 : Sensitivity of CNN-based Hybrid Classifiers**



**Figure 7.12 : Specificity of CNN-based Hybrid Classifiers**



**Figure 7.13 : Accuracy of CNN-based Hybrid Classifiers**



**Figure 7.14 : Execution Time of CNN-based Hybrid Classifiers**

The projected results related prove that the hybrid CNN-SVM classifier combined with DCS and DES provides more benefits during ALL and subtype identification. The proposed CNN-ESVM-DCS classifier achieved a high average sensitivity of 98.27%, average specificity of 97.11% and average accuracy of 96.86%. This classifier achieved an efficiency gain, on average, of 2.62% (sensitivity), 2.31% (specificity) and 2.23% (accuracy) over CNN-SVM classifier. On the other hand, the average efficiency gain over CNN-ESVM was 1.24% (sensitivity), 0.87% (specificity) and 1.01% (accuracy).

The proposed CNN-ESVM-DES classifier further improved the classification process and achieved, on average, 98.91% (sensitivity), 97.48% (specificity) and 97.31% (accuracy). The average efficiency gain of this classifier over CNN-SVM and CNN-ESVM is respectively 3.24% and 1.87% (sensitivity), 2.67% and 1.24% (specificity), 2.68% and 1.47% (accuracy). Comparison of DCS-based and DES-based hybrid classifier showed that the DES-based offers greater advantage in terms of sensitivity (0.64% average gain), specificity (0.38 average gain) and accuracy (0.46% average gain).

The execution time comparison shows that the CNN and Ensemble SVM hybrid classifier as the slowest one. This classifier took, on average, 16.50 seconds, to perform classification. The inclusion of DCS and DES with CNN-ESVM classifier reduced the average execution time to 12.58 seconds and 14.51 seconds. This proves that the inclusion of classifier selection has reduced the time complexity of the ensemble system. Comparing DCS and DES, as with ML classifiers, shows that the DCS-based classifier is fast.

## **7.5. CHAPTER SUMMARY**

The main objective of this research work is to identify algorithms that can improve ALL-C systems in terms of accuracy and speed. In order to improve the accuracy, the research work enhanced ML and DL classifiers. Apart from this, preprocessing of microscopic images with the aim of improving classification was also proposed.