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Identification of Leukemia Cells in Microscopy Digital Image Using Improved Canny Edge Detection Method

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Abstract*— Leukemia is a blood cancer mutates inside the bone marrow. If unidentified at an early stage, it can lead to severe consequences and later death of a person. To diagnose leukemia, machines and manpower skills are required to identify if the illustrative image is healthy or unhealthy. The manual observation of the large number of images may lead to error in the results. One of the biggest barriers in the result's accuracy is identification of concerned region in the overlapped cells. Motivated by the challenges, framework is developed based on image processing for automatic detection of White Blood Cells in the peripheral blood smear image. In this paper, canny edge detection with Circular Hough Transform is applied to count the number of white blood cells. The outcome is to obtain the classification of the sample images whether the sample is unhealthy or healthy sample image. Total 108 multi-cell Acute Lymphoblastic Leukemia images are considered. It was found that the proposed cell separation method yields an accuracy of 98% in comparison to state of the art segmentation technique.

Index Terms*— canny edge detection, image processing, leukemia, segmentation.

I. INTRODUCTION

Human blood contains of three main components: (1) Red Blood Cells (RBCs) or erythrocytes (2) White Blood Cells (WBCs) or leukocytes (3) Platelets [1]. The types of leukocytes are further described in Table I. These components affected by invasive disease called Leukemia, a type of cancer in which the white blood cells abnormally grow and multiply rapidly. It originates inside the bone marrow and progresses swiftly in the blood stream [2]. According to the study of Huether et al. [3] there are variants of leukemia that were identified between 1976& 1999 by the group of American, British & French Hematologists and are broadly divided into acute and chronic leukemia. According to the Leukemia and Lymphoma Society, approximately in every 3 minutes one person is diagnosed with cancer and in every nine minutes someone dies from leukemia in USA. The stats depicted that from 2012 to 2016, there were 74,667 reported cases of Leukemia. The cases of leukemia inclined in 2021, alone in USA, where 1,86,400 people diagnosed with lymphoma or myeloma leukemia and total 6,08,570 deaths reported due to lymphoma cancer [4]. In the year 2022, new reported cases and deaths due to leukemia in comparison to other types of cancer is illustrated in Figure. 1 and 2 [26].

Although in comparison to other types of cancer, the reported cases of leukemia are less as shown in Figure. 1, the chances of survival are third lowest after pancreatic and lung cancer as depicted in Figure. 2. To diagnose leukemia high-cost machines and skills are required to understand the characteristics of the cell and identify its type.

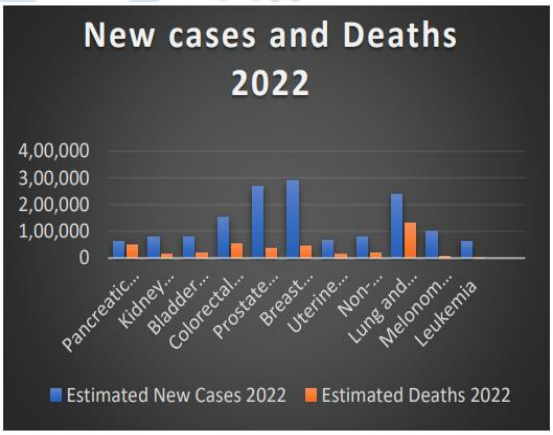

Figure. 1 Cancer Stat Facts: Types of Cancer report 2022

In the study of K. K. Anilkumar et al. [5], immunophenotyping tests, and chromosome and cytochemistry tests are executed to find leukemia under the microscope. The clinical process is time-consuming and demands a high cost for the evaluation of the sample. The obtained results must be verified through expertise. Even with the great skills, manual observation may lead to chances of errors in perfectly classify the sample image. According to the reports of the American Medical Association (AMA), approx. 41.5 million blood counts and differential count tests were conducted in the year 2015 [6]. To overcome time constraint issues, many investigations had been carried out to design the automatic detection of cell organelles by imaging processing technique using microscopy images [3]. Such images are processed by computer system that can analyze

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and to obtain the region of interest to better know the morphology of cell. The advantage of using image processing 0 1,00,000 2,00,000 3,00,000 4,00,000 New cases and Deaths 2022 Estimated New Cases 2022 Estimated Deaths 2022 Identification of Leukemia cells in microscopy digital image using improved canny edge detection method [1]Tulika Kanwar, [2]Rakesh Ahuja, [3]Kanupriya Verma [1]Chitkara University Institute of Engineering and Technology , [2]Chitkara University Institute of Engineering and Technology, [3] Thapar Institute of Engineering and Technology, deemed to be University, Patiala, Punjab, India [1] kanwartulika8@gmail.com, [2] ahuja2305@gmail.com, [3] compkanu@gmail.com 2 over another pre-existing test methods mentioned above are low cost, easy implementation and solving time constraint issue [4].

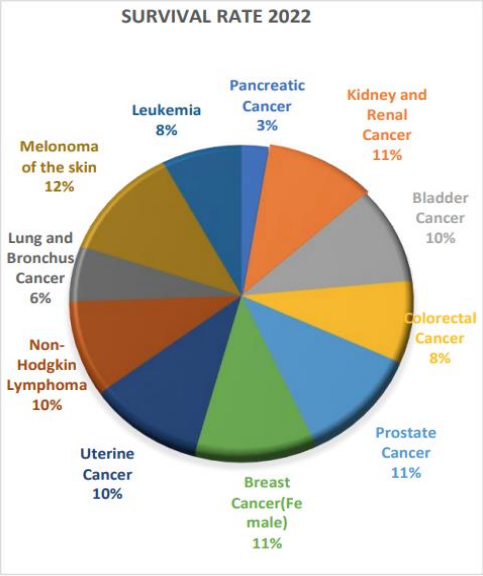
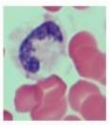
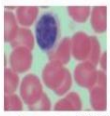
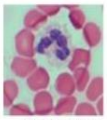


Figure. 2 Cancer Stat Facts: Survival Rate in different types of cancer

Table I. Types of leukocytes present in bloodstream

Granulocytes	Agranulocytes
 Basophils (<1%)	 Lymphocytes (25-35%)
 Neutrophils (50-70%)	 Monocytes (4-10 %)
 Eosinophils (<5%)	

In image processing, Computer Aided Detection (CAD) tools helps in identifying the region of interest from microscopy images. In this tool, segmentation is the crucial part for identifying the features [5]. Image segmentation is the most crucial part of image processing. The aim is to divide the number of objects sharing the same properties. In microscopy, it is used for automatic detection of required regions by using some algorithm. It helps in reduction of complexity of image analysis [3]. Technically segmentation is broadly divided in two categories: label-based approach where it identifies object's shape, size and depth. Regionbased types of approach is used to extract the region from image with similar pixels or pixels sharing similar characteristics. N. M. Zaitoun et al. [7] and Lin et al. [8] further classified the segmentation-based approach into clustering, edge, watershed, thresholding and CNN in order to extract the required objects as discussed further in the paper.

In the remainder of the paper, the sections have organized in the following manner. Section II illustrated the related work done using segmentation-based techniques. Section III explained the methodology of the proposed method and material used for developing this method. Section IV discussed the outcomes of proposed technique. Finally, Section V elaborated the conclusion and future scope of the paper.

II. LITERATURE REVIEW

The aim of the proposed method to extract the internal properties of cell from the complex image. Further the segmentation is performed with other state-of-art methods [9].

The paper presented edge detection segmentation technique to extract RBCs from sample image. The limitation of the paper is obtaining unclosed cell images after segmentation process. The future work of the author extends to improve the segmentation result using integration of active shape technique [10].

The developed framework is the combinations of PIC microcontroller, image processing and machine learning for image acquisition and counts the constituents in urine sample. The future work extends to increasing the ROI for higher accuracy, widening the range of moving lens and performing the developed application on other body fluids like saliva [11].

The nature inspired developed model where the gradients of intensities represented as nutrients concentration and drives the bacteria to search for nutrients rich location as imitating the behavior of Escherichia coli. The technique identifies the edges as the path of bacteria. Further the performance is compared with SUSUAN, Canny, Verma's and an Active Contour Model (ACM) as edge detection. The future work of author for developing the adaptive parameter framework for this algorithm [12].

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The paper presented an automated model for fast and reliable counting of cells and its colonies by developing ImageJ macro–Cell Colony Edge and a CellProfiler Pipeline Cell Colony Counting. This is further compared with open-source digital methods and open count. The drawback of this model is sudden change in grayscale can leads to miscounting of merged colonies. This method failed in identifying edges on low resolution and unfocused images [13]. Pancreatic Cancer 3% Kidney and Renal Cancer 11% Bladder Cancer 10% Colorectal Cancer 8% Prostate Cancer 11% Breast Cancer(Fe male) 11% Uterine Cancer 10% NonHodgkin Lymphoma 10% Lung and Bronchus Cancer 6% Melonoma of the skin 12% Leukemia 8% SURVIVAL RATE 2022 3 The author demonstrated enhanced edge detection method to identify acute leukemia sub-types in touching cells using canny edge detection method and Support Vector Machine (SVM) as classifier for ALL subtypes. The accurate identification of ALL is still a challenging task for the researcher [16].

For the identification of leukemia and its subtypes the edge detection is performed using thresholding and to achieve accurate classification of ALL, deep learning method is applied.

The proposed work is then compared with other segmentation techniques like KNN, SVM and Naïve Bayesian. The future work of the author is to improving the accuracy using segmentation and exploring other deep learning models [19].

The developed method obtains and count RBCs from urine sample. Canny edge detection identifies the edges of the ROI and Circular Hough Transform (CHT) detect circular shape of the region to obtain particular size circle, radius is defined with minimum and maximum 6 pixels. The future work of the author is to apply morphological image processing to improve the examination of urine sample image. Adding Artificial Neural Network to train the model to identify the morphological features in urine sample [22].

Table II. Review of edge detection segmentation techniques using microscopy images

Ref.	Segmentation technique	Dataset	Performance measure	Test Set Size
[9]	Grabcut method Gradient Circular Hough Transform	ALL_IDB Cellavision	0.9963 (Precision) 0.8791 (Recall) 0.9341 (f-measure)	1324
[10]	Canny operator Thresholding	RBCs dataset in Broad Bioimage Benchmark Collection (BBBC)	87.95% (accuracy)	5
[11]	Prewitt operator Artificial Neural Network (ANN)	Self-prepared dataset from urine sample	89.5% (accuracy)	100
[12]	Bacterial Foraging based Edge Detection (BFED)	Synthetic images Real cell images [23],[24]	0.49126 (F-measure)	5
[13]	Macro-cell Colony edge CellProfiler Pipeline	Cell images [25]	-------	12
[16]	Canny edge Support Vector Machine (SVM)	Public dataset	75.24% (accuracy)	668
[19]	Threshold Method	MIAS dataset	97.78% (accuracy)	330
	Convolutional Neural Network (CNN)			
[22]	Canny edge Circle Hough Transform (CHT)	Self-prepared images in Raspberry pi	90.439% (accuracy)	20

From Table II it is observed that few works are done on microscopy images using the edge segmentation technique. Due to the complexity of cell images, accuracy is still a challenging task. Considering these gaps, this paper presents an improved method for the identification of leukemia cell boundaries present in the sample image using edge detection and feature extraction discussed further in the paper in detail.

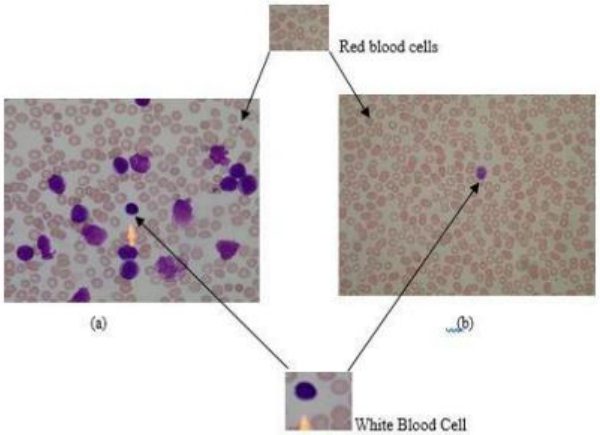

Figure. 3 (a) Unhealthy sample image **(b)** Healthy sample image

III. DATASET AND TOOLS

The proposed method applied on images available in Kaggle [14]. There are two versions of database presented as ALL_IDB1 and ALL_IDB2 consisting of peripheral blood smear images as shown in Figure 3. In the Table III the properties of images obtained from databases are mentioned.

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Table III. Sample image details in their respective databases

Dataset / Image Properties	ALL_IDB1	ALL_IDB2
Size of each image	1712*1368	257*257
Bit depth	24	24
Image type	sRGB	sRGB
Number of sample images	108	260

The proposed framework is developed and analyzed in MATLAB R2018a. Experiments were conducted on a HP Pavilion 15 Notebook PC (Core i3-3217U 8GB RAM Full HD and 500 GB hard disk with Microsoft Windows 10).

IV. PROPOSED METHOD

In this paper, the method is developed to obtain the White Blood Cells (WBCs) from the overlapped or touched cell image by eliminating the other components like red blood cells and platelets. The developed method is based on CAD technology to count the WBCs and find its nucleus region present in sample image as shown in Figure 2.

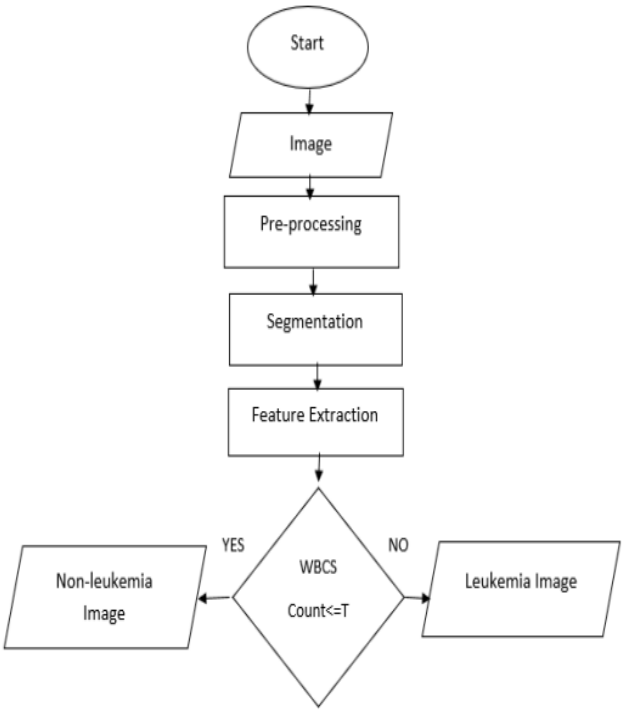

Figure 4 The proposed model for cancer cell segmentation

Following are the steps followed in the proposed model as mentioned in the Figure 4:

- In the first step, pre-processing techniques are applied to improve result accuracy.
- After the pre-processing, segmentation technique is applied to extract the region of interest.
- Once the image extracted, feature extraction is applied to classify the image as healthy or non-healthy.
- From feature extraction, WBCs count are obtained. If the count is less than or equal to Threshold (T), the sample is non-leukemia image else leukemia image.

A.Pre-processing

In the first phase; the red channel is obtained from the RGB cell image where Red(R), Green (G), and Blue (B) are the primary colour of the light added to form wide array of colours. Colours represent the important selective information for various purposes under computer vision like segmentation, classification, indexing, etc. Colours conversion to gray-scale provides dimension reduction operation to intensity value (I). Generally, the red channel is the 8-bit gray-scale image where each pixel represents the intensity information of pixels (x, y) [27]. In this channel image, all the objects with high concentration of red pixel value become white, while the other two colours set to 0. Here, extraneous information is eliminated to extract relevant information from the concerned region with the help of masking. Masking performs gray-scale image conversion to the binary image. Hence, the method develops an image of white background due to the presence of the objects represented by red channel pixels and black foreground due to the presence of WBCs constituting blue channel pixels

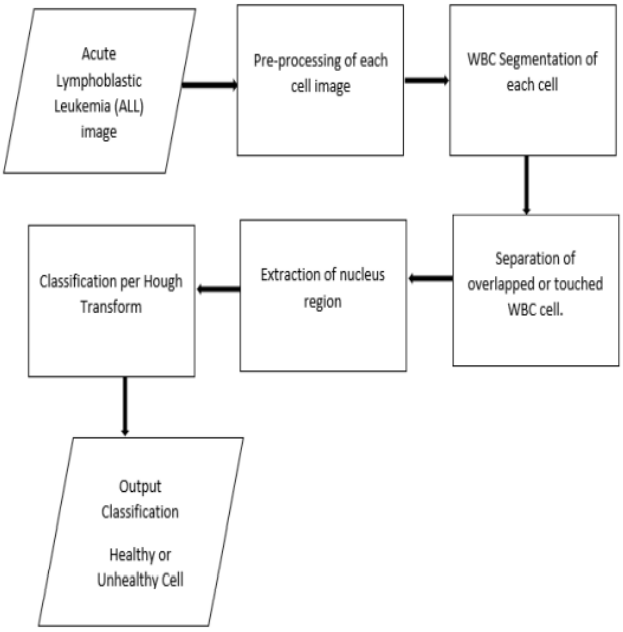

Figure 5 Block diagram for the identification and classification of WBCs

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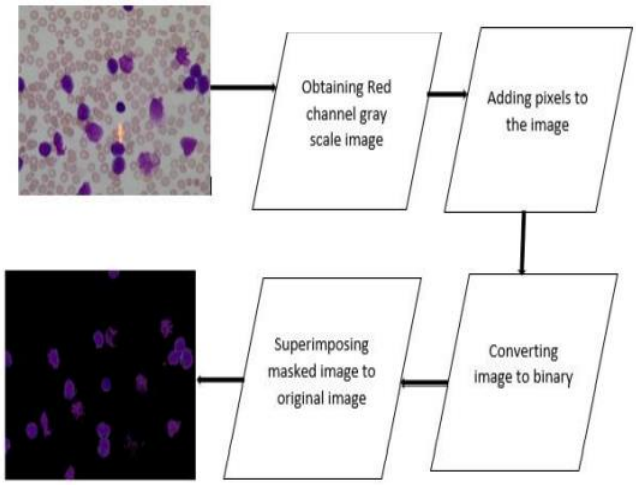
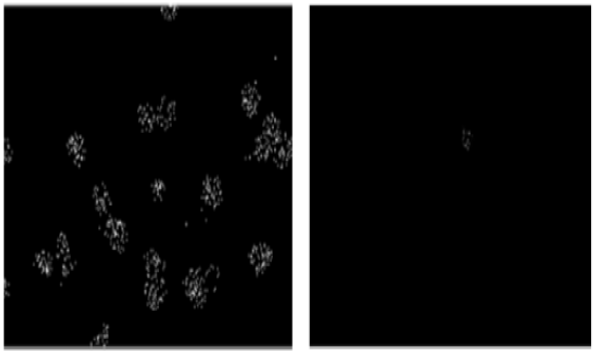


Figure 6 Block diagram representation of extraction of nucleus of WBCs

B. Nucleus segmentation of each WBC

The next step is segmentation of WBC nucleus where hue saturation value is applied followed by gaussian filter as it helps to improve edge detection. Hue gives outer edge information of each WBC nucleus and gaussian suppresses unwanted edges. After the gaussian filter, canny edge detection is implemented on the hue image. Canny edge detection [15] widely used method to find out the sharp intensity changes and distinguish the object from image. In this method sensitivity is used as threshold (TH). Here, TH is two-element vector in which first element is low threshold and second element is high threshold. The scalar is applied for high threshold and 0.4* TH for low threshold. Canny identifies the boundary of each touching or overlapped WBCs area. In Figure 3. it shows the more detailed view of outer edge of touching cells using the proposed method [16].



(c) **(d)**

Figure 7 (c) canny edge detection on unhealthy sample image **(d)** canny edge detection on healthy sample image

C. Feature Extraction of each WBC

The main aim of the feature extraction is to classify the image by detecting the shape of the edge region. Circle Hough Transform (CHT), one of its techniques is used to identify circular objects from the irregular boundaries of the region. In a two-dimensional space, circle is a set of all points that are at the same distance (radius). In the (x, y) coordinates of space it is represented as [22]:

$$(X - A)^2 + (Y - B)^2 = R^2 \qquad (1)$$

Where A and B are the center of circles and R is the radius. X and Y are horizontal and vertical axis respectively representing the center of circle in 2- dimensional space. In order to find the coordinates of A and B the equation is represented as:

$$X = A + R(\theta) \qquad (2)$$
$$Y = B + R(\theta) \qquad (3)$$

Other parameters also considered in feature extraction to identify the nucleus of WBCs:

A. Object Polarity: It by default identifies the illuminated object in the darker background of the image or vise-versa. The paper considered bright object polarity to find the illuminated object from the dark background.

B. Sensitivity: It define the percentage of actual positive values in an image [17].

C. Two-stage Method: It is a process for feature selection where first stage extracting the global pattern and second stage at local pattern [18].

D. Classification of each WBC using image processing

For the classification of sample images, number of encircled WBCs are calculated from Figure 8. In this study, threshold (t) is considered which represents minimum unhealthy WBC present in sample image.

Suppose C is the number of identified center of WBCs

If $C \leq t$
then image is healthy
else
unhealthy

Figure 8 Encircled unhealthy WBCs using CHT

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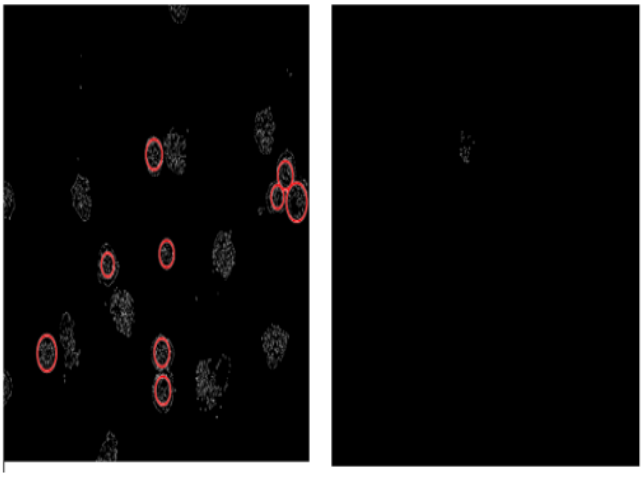
In Figure 8, all the region in the 2-dimensional space that lies within those parameters (radius and center) are encircled. Considering leukemia and non-leukemia sample cell images, those with unhealthy WBCs are detected discarding the irrelevant information like ink stain from Figure 9 (e) also not detecting healthy WBCs from Figure 9 (f). The shape and type of healthy WBCs are already described in Table I.



(e) **(f)**

Figure 9 (e) unhealthy WBCs detection in leukemia image **(f)** no unhealthy WBC detection in nonleukemia imag

V. RESULTS

To evaluate the performance, the technique is implemented on dataset and result is compared with other edge segmentation technique as mentioned in Table II using accuracy. The result is based on how accurately the technique finds the boundaries of WBC and count its presence in sample image. From Figure 10, it is observed that the technique yields 98% accuracy on identifying WBCs even in the complex overlapped cell images and outperforming the rest of the techniques.

VI. CONCLUSION AND FUTURE SCOPE

In this paper, based on extensive review of segmentation method for segmenting peripheral blood smear images an automatic WBC segmentation method is demonstrated based on image processing. The segmentation of leukocytes carried out using canny edge detection to determine the nucleus boundary of WBCs. The feature like circle is selected by Circle Hough Transform from overlapped or touched cell images. The experiment conducted on ALL_IDB database and the analysis of cell segmentation is performed by comparing with state-of-the-art segmentation and edge detection techniques depicted in Figure 7 and 8 respectively. In the future work deep learning can be used for the classification of other type acute leukemia like AML.

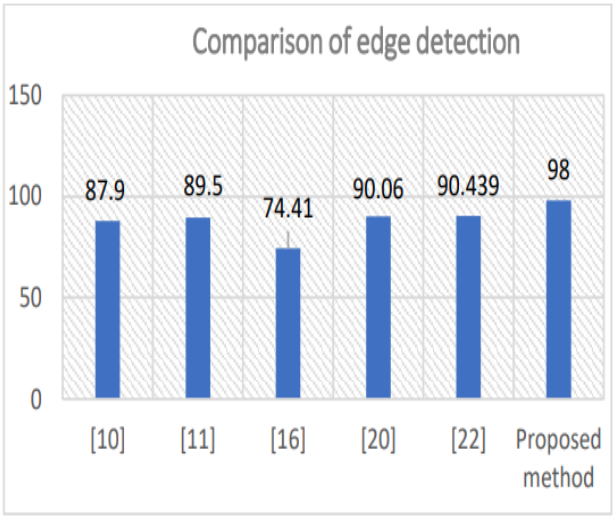


Figure 10 Comparison of different edge detection techniques methods with proposed method

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