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Image Based Analysis for Bone Marrow Cancer Detection using Soft Computing Techniques: A Review

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Abstract: Bone marrow is a vital component of the human body, as it contains stem cells that form blood cells and immune system cells. Bone marrow cancer is due to hematologic disorders that affect the blood and can affect the bone marrow, white blood cells, platelets, and red blood cells. Every year, many people are diagnosed with bone marrow cancer. Bone marrow cancer can be detected by extracting features of a white blood cell. White blood cell classification is challenging for hematologists. Hematologists can identify malignant white blood cells by examining a peripheral blood smear under a microscope. However, the process is time-consuming, difficult, and expensive. Image processing and soft computing play a significant role in identifying early indicators of bone marrow cancer. The proposed study aims to investigate the existing cancer detection systems and their components. Further, this study majorly focuses on showing critical analysis of bone marrow cancer detection using image processing that includes enhancement, segmentation, feature extraction, classification, and accuracy which may help hematologists and oncologists to detect bone marrow cancer at early stages. Further, the paper also foresees the future aspects in the area of bone marrow cancer recognition systems. In comparison to manual detection techniques, these soft computing techniques are precise, trustworthy, and quick.

Keywords- *Leukemia, classification, detection, segmentation, and feature.*

1. Introduction

A set of diseases characterized by aberrant, unchecked cell division that often leads to the destruction of nearby tissues are collectively referred to as cancer. Marrow, which resembles a sponge, is found inside bones and it contains stem cells, which can develop platelets, white blood cells, and red blood cells. When cells in the marrow proliferate erratically, bone marrow cancer develops [1].

Blood's colored microscopic images can be used to identify bone marrow malignancies. As seen in Figure 1, a microscopic image contains platelets, red blood cells, and white blood cells. There is no bone marrow cancer when the white blood cell is normal; when the white blood cell is aberrant, then bone marrow cancer is detected.

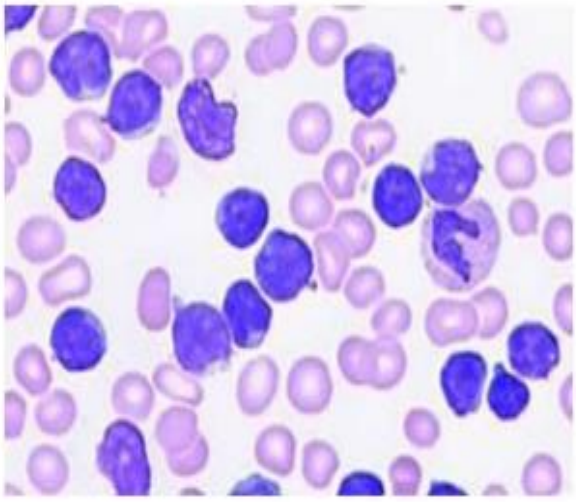

Fig. 1 Microscopic Biopsy Image [2]

1.1 Motivation for Research Work

According to the World Health Organization (WHO) [3], 19,22,789 new cancer cases were reported worldwide in the year 2020, as shown in Figure 2. All in all, 5,44,352 new cases of non-Hodgkin lymphoma have been reported, with 2,59,793 fatalities. There have been 3,11,594 deaths and 4,74,519 new cases of leukemia. A total of 1,76,404 new cases and 1,17,077 fatalities from multiple myeloma have been documented in 2020. Due to Hodgkin lymphoma 83,087 new cases and 23,376 fatalities have been reported around the world.

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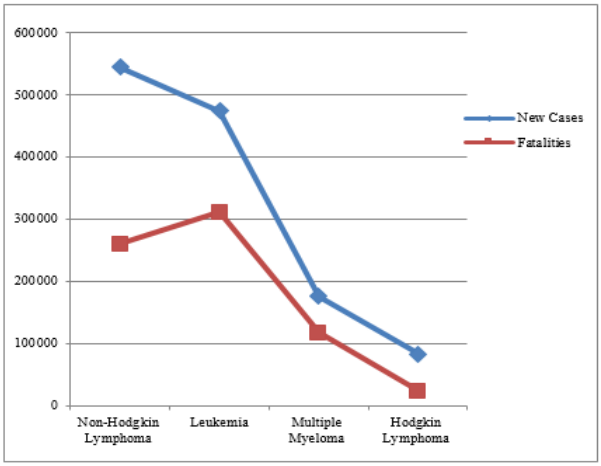

Fig. 2 Bone marrow cancer new cases and fatalities worldwide in 2020

The number of bone marrow cancer-related fatalities in India is shown in Table 1. All in all, 40,159 deaths in India in 2020 were attributable to lymphomas, or 0.47% of all deaths. And there are 3.44 fatalities for every 100,000 people [4]. India's rank is 136 in the world for lymphoma-related deaths. In the world as a whole, 136 people die from lymphomas per year in India. Leukemia caused 33,383 deaths in India, or 0.39% of all fatalities. Additionally, 2.79 deaths occur for every 100,000 people [5]. India ranks 129 in the world for leukemia-related deaths.

Table 1 Number of Deaths in India 2020 due to Bone Marrow Cancer

Types of Bone Marrow Cancer	Death	% of Total Death	Death Rate per 1,00,000	World Rank
Lymphomas	40,159	0.47	3.44	136
Leukemia	33,383	0.39	2.79	129

India will see 48,419 new cases and 35,392 fatalities from leukemia disease in the year 2020. In India, there have been 35,828 new cases and 20,390 deaths as a result of non-Hodgkin lymphoma. In contrast, multiple myeloma caused 12,556 fatalities and 14,641 new cases in India [6]. A total of 9,221 new cases and 3,513 deaths from Hodgkin lymphoma have been recorded in India. Leukemia death rates are significantly higher than Hodgkin's, as shown in Figure 2.

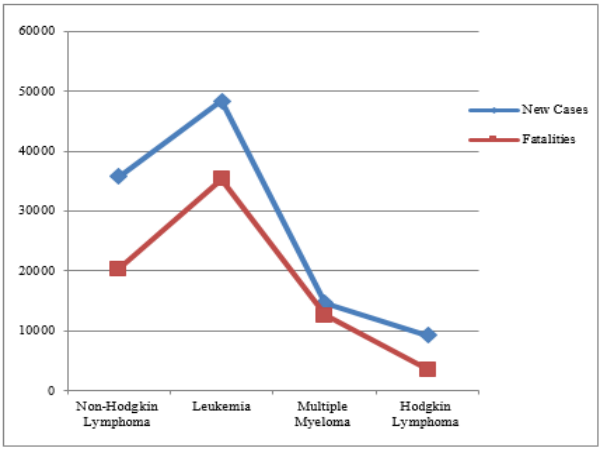

Fig. 3 New Cases and fatalities due to Bone Marrow Cancer in India

The rest of the paper is organized into four sections. Section 2 contains a background study, the existing framework is covered in section 3, section 4 contains the comparison of existing methods for bone marrow cancer detection, and section 5 contains the conclusion and future aspects.

2. Background Study

This section discusses the techniques for detecting bone marrow cancer using image processing methods. In general, the process of detecting bone marrow cancer through microscopic images of a blood sample was divided into several stages: image augmentation, image preprocessing, image segmentation, feature extraction, and detection of bone marrow cancer.

2.1 Image Augmentation

When there aren't enough photos or data sets, image augmentation is used. Rotating, zooming, Shifting, shearing, flipping, and rotating can all increase the number of images. These procedures can be used to increase the number of images or samples [7]. For picture alteration, there are numerous data augmentation procedures, including shearing, rotation, width shifting, height shifting, horizontal flipping, zooming, horizontal flipping, etc.

N. Ahmed et al. [8] used Open CV and KERAS Python libraries to increase the number of images for detecting bone marrow cancer using a Convolutional Neural Network (CNN). They considered two datasets; the first dataset had 354, and the second one had 549 microscopic images. In augmentation, the original image was first rotated 40% clockwise, 40% shifting, 30% zooming, 20% anticlockwise, and 20% flipping. A total of seven images were generated from the single original image. After data augmentation, the total number of images was 2478 in the first dataset and 3843 in the second dataset. Finally, they conclude that CNN outperforms with 88% accuracy as compared to other models. S. Shafique et al. [9] increased

the number of images to detect bone marrow cancer using a Deep Convolutional Neural Network (DCNN). They considered 227x227 pixel resolution for two datasets; the first dataset had 108, and the second one had 260 microscopic images. Up to 760 additional photos were added using a data augmentation technique, where 260 photos represented normal instances, and 500 images were affected by leukemia. A total of 500 leukemia images were separated into 266 images for the L1 leukemia subtype, 153 images for the L2 subtype, and 81 images for the L3 subtype. Finally, they obtained an accuracy of 99.50% for leukemia detection by using data augmentation. M. Claro et al. [10] used image augmentation techniques to increase the number of images for detecting Acute Lymphoblastic Leukemia (ALL), Acute Myeloid Leukemia (AML), and normal White Blood Cell (WBC) by using the CNN technique. The authors applied 2415 photos from 16 different data sets. Since the total number of photos was very low for applying the CNN technique, the original image was rotated, flipped, zoomed, and sheared. The range of rotation was from 0^0 to 40^0, and the image was flipped both vertically and horizontally. When compared to the originals, using all of these augmentation techniques increased the number of images by a factor of twenty. In conclusion, they stated that they obtained an accuracy of 97.18% for detecting leukemia cells. Table 2 highlights some augmentation techniques. The comparison of augmentation techniques based on technique, the dataset used and accuracy is presented.

2.2 Image Preprocessing

Image preprocessing is required to get image data ready for model training. There are various methods for picture preprocessing, including color, enhancing, sharpening, and altering the image's color, contrast, brightness, etc.

J. Rawat et al. [11] used image preprocessing techniques to improve the quality of images for detecting ALL and AML. To improve the contrast of the image, the histogram equalization technique was used. A total of 420 microscopic blood images were acquired as a dataset from the American Society of Hematology. They applied a statistic filter to reduce image noise and smooth the image. Finally, they conclude that a genetic algorithm using Support Vector Machine (SVM) with a Gaussian radial basis kernel outperforms other models with 99.5% accuracy. Y. Li et al. [12] proposed a dual-threshold method preprocessing technique to detect WBC from ALL images. Initially RGB color image was converted to grayscale and HSV image to extract the H channel image. In all, 130 images were used from datasets provided by the Department of Information and Technology. To enhance the performance of image preprocessing the Global Contrast Stretching (GCS) technique was used. In conclusion, they stated that they obtained an accuracy of 97.85% for detecting WBC. R. Kumar et al. [13] used a preprocessing technique for detecting WBC from blood smear images. The authors applied 85 sample blood smear images out of which 62 images were used for training and 23 images were used for testing. They applied a median filter to enhance the edges, and reduce the noise in the image and a bright stretching method for enhancing the brightness, and contrast level of the image. Finally, they conclude that Relevance Vector Machine (RVM) outperforms with 91% accuracy as compared to other models. Table 2 highlights some preprocessing techniques. The comparison of preprocessing techniques based on technique, the dataset used and accuracy is presented.

2.3 Image Segmentation

The nucleus of the WBC must be distinguished from the other blood cells during image segmentation. Both manual and automatic cropping techniques are available.

A. Kandil et al. [14] used K-means clustering to segment acute leukemia cells automatically. The author applied two datasets of colored microscopic images; in which the first dataset had 642 images with a resolution of 632*480 pixels, and the second dataset had 115 images with a resolution of 256*256 pixels. In conclusion, they stated that the green portion of the image carries the most helpful contrast information. Finally, they conclude that the K-mean methodology outperforms with 99.51% accuracy as compared to the other two techniques, with Kekre Proportionate Error (KPE) and Linde-Buzo-Gray (LBG). N. Patel et al. [15] employed the K-mean clustering technique for the automatic segmentation of leukemia cells. The authors applied 7 microscopic images from 27 images of the datasets. The WBC becomes dark when the microscopic image is converted into a grayscale. To enhance the performance of the model histogram equalization and the Zack algorithm were used for grouping different types of leukemia cells. The accuracy achieved by this technique was 93.7%. M. Joshi et al. [16] applied Otsu's technique for the segmentation of WBC from microscopic pictures to identify leukemia cells. The authors considered 108 microscopic images to train the model. They applied the K-nearest neighbors' method to categorize aberrant WBC by calculating the area, perimeter, and circularity of cells. The accuracy achieved by this technique was 93%. J. Rawat et al. [17] designed a Computer Aided Classification (CAC) system to detect AML and ALL. They considered a dataset of 240 images having 60 images of ALL, 80 images of AML, and 100 images of healthy patients. They applied the SVM method to classify AML and ALL. A maximum accuracy of 99.5% was obtained to classify acute leukemia cells. H. Fakhouri et al. [18] used a hybrid methodology to detect leukemia from hematology microscopic images. They considered a dataset of 100 images having 50 images of normal cases,

and 50 images of different kinds of leukemia cases. They calculated the percentage of WBC and classify different types of leukemia. Acute leukemia can be identified in binary images if the range of the black pixels is between 0.1 and 0.2. Chronic leukemia is identified if the percentage of black pixels is greater than 0.2. E. Abdulhay et al. [19] used SVM to segment and categorize blood leucocytes. The authors applied 100 blood leucocytes microscopic images out of which 28 showed normal leucocytes while the other 72 showed aberrant leucocytes. They applied Local Binary Pattern (LBP) to enhance the performance of the model by measuring the texture of microscopic images. The accuracy achieved by the SVM technique was 95.3%.

A. Rehman et al. [20] proposed CNN to segment acute lymphoblastic leukemia cells. The author applied 330 samples of L1, L2, and L3 color microscopic images. The color microscopic images are first transformed into HSV (hue, saturation, and intensity) to separate S components from it. Finally, they conclude that the proposed CNN outperforms with 97.78% accuracy as compared to the other methods. S. Alferez et al. [21] used a Fuzzy C-Means classifier to automatically classify Chronic Lymphocytic Leukemia (CLL) and Hairy Cell Leukemia (HCL). They considered 340 images that were collected from the hospital clinic in Barcelona. They applied the watershed segmentation method to segment the nucleus by using RBG's green components. The accuracy for categorizing HCL cells was 98%; for normal cells, it was 75.6%; and for CLL cells, it was 62.7%. F. Kazemi et al. [22] used the K-mean clustering algorithm to segment subtypes of AML. The authors applied a dataset of 165 images of AML and normal cells. They applied a color segmentation technique to segment WBC from other blood components. An SVM technique was used to classify different types of AML cells like M2, M3, M4, and M5. Finally, they conclude that the proposed SVM outperforms with 96% accuracy as compared to the other methods. S. Mohapatra et al. [23] applied Functional Link Artificial Neural Network (FLANN) for the segmentation of acute leukemia cells. The author applied a dataset of 100 images. They applied the CIELAB methodology to identify the luminance of the image. And the three values of the RBG are split into two fixed values. Finally, they conclude that the proposed method outperforms with 98.28% accuracy as compared to the other methods. M. Benazzouz et al. [24] applied an SVM classifier to segment WBC from other blood components. They considered a dataset of 27 microscopic images to detect the nucleus, cytoplasm, and erythrocytes of cells. They applied the microscopic image segmentation method for pixel classification and dimension reduction. The accuracy for segmenting the nucleus and cytoplasm was 95.02% and 84.53%. Table 3 highlights some image segmentation techniques. The comparison of image segmentation techniques based on technique, the dataset used and accuracy is presented.

2.4 Feature Extraction

Characteristics of the cancer cell are compared to those of healthy WBC to determine its features. Major axis, minor axis, perimeter, perimeter, radius, minor axis, major axis, etc. features are extracted from WBC.

M. Amin et al. [25] employed feature extraction techniques by using MATLAB Image Processing Toolbox for detecting ALL cells. The authors applied 302 microscopic images, out of which 146 are of lymphocytes and 156 are of acute lymphoblastic leukemia. They applied the K-means algorithm for segmenting the nucleus from the WBC and Support Vector Machine (SVM) to extract the geometric features of the nucleus. The accuracy achieved by the SVM classifier is 97%. M. Amin et al. [26] used SVM for the classification of ALL into L1, L2, and L3 subtypes. They considered datasets of 312 images out of which 146 images of ALL subtypes and 166 images of normal cells. To enhance the performance of the model they used the Principal Component Analysis (PCA) method to condense 77 different types of variables data sets including hue, saturation, entropy, and others. Finally, they conclude that the accuracy of detecting ALL of the type L3 is 99%. M. Subhan et al. [27] used the Hough transform and KNN algorithm for detecting leukemia cells. They applied MATLAB commands for calculating the area, perimeter, and radius of leukemia cells. The accuracy achieved by these methods is 93%. L. Putzu et al. [28] used SVM to classify ALL cells from color microscopic images. They considered the dataset of 33 images. They applied a fresh approach to feature extraction from cropped photos to enhance the performance of the model. Finally, they conclude that the SVM method outperforms with 93% accuracy as compared to other models. E. Francis et al. [29] used a Multilayer Perception (MLP) neural network to classify leukemia cells. They considered a dataset of 1000 colored microscopic biopsy images. In this instance, thirteen features, including area, radius, red, blue, and green, were retrieved. The accuracy achieved by this method is 98.66%. Table 4 highlights some feature extraction techniques. The comparison of feature extraction techniques based on technique, the dataset used and accuracy is presented.

2.5 Detection of Bone Marrow Cancer

Finding out whether an image is a non-cancer image or a normal image, a cancer image, or an abnormal image is the main goal in detection.

Z. Moshava et al. [30] proposed a new assemble classifier to identify aberrant ALL cells. They considered two datasets, the first dataset having 109 images and the second dataset having 260 images. They applied Decision Tree

(DT), K-Nearest Neighbour (KNN), and Naive Bayes (NB) in the first classified Support Vector Machine (SVM), and five SVM kernel functions are used in the second classifier. Finally, they conclude that the first classifier outperform with 98.12% accuracy. T. Pansombut et al. [31] used CNN to identify ALL cells. They considered a dataset of 363 images taken from the American Society of Hematology. Finally, they conclude that the CNN method outperforms with 80% accuracy as compared to the random forest classifier and the Multi-Layer Perception (MLP) models. P. Viswanathan [32] used the Fuzzy C-mean technique to identify leukemia. He considered the dataset of microscopic pictures of ALL. He applied several curvature features of the nuclei to determine the nature of the curves and edges such as the length of the maxima and minima. The accuracy achieved by this method is 98 %. N. Harun et al. [33] used modified K-means, Fuzzy C-Means, and moving K-means algorithms to identify acute leukemia cells from microscopic images. The author applied 100 images out of which 50 depicted ALL and 50 depicted AML. Finally, they conclude that the K-means algorithm outperforms with 98.26% accuracy as compared to other models. M. Amin et al. [34] used the Fuzzy C-means algorithm for detection, and SVM was used to classify ALL cells. The author applied the dataset of 312 images which was provided by Fabio Scotti. They find the nucleus by transforming the image into HSV (hue, saturation, and intensity) images and determine the area, radius, perimeter, etc. of the nucleus by counting the number of pixels. Finally, they conclude that L3 leukemia classification outperforms with 98.26% accuracy as compared to other models. K. Lakshminarayan et al. [35] used a fuzzy C-means segmentation technique to detect ALL cells from microscopic images. They considered a dataset of 49 images of acute lymphoblastic leukemia and 59 images of healthy cells. They applied a random forest classifier to enhance the performance of the model. The accuracy achieved by this method was 93.70%.

N. Chatap et al. [36] proposed a Support vector machine (SVM) and K nearest neighbors to identify leukemia cells. The authors applied a dataset of 121 microscopic color images. They used a green plane of microscopic images to enhance the performance of the model. The accuracy achieved by this model was 93%. L. Vogado et al. [37] proposed SVM and CNN models to classify ALL and leukocytes. They considered a dataset of 377 blood smear images. Finally, they conclude that the proposed model outperforms with 99.20% accuracy. M. Shaheen et al. [38] used the Alexnet model to identify AML. The authors applied 4000 microscopic peripheral images out of which 1000 images belong to lymphocytes, 1500 images of normal, and 1500 images of abnormal monocytes. Finally, they conclude that the proposed model outperforms with 98.58% accuracy as compared to the LeNet-5 model. S. Shafique et al. [39] used DCNN to identify and categorize ALL cells. They considered two datasets; the first dataset had 108, and the second one had 260 microscopic images. They applied a data augmentation technique to enhance the performance of the model by increasing the number of images up to 760. Finally, they conclude that the proposed model outperforms with a 99.50% accuracy in identification and 96.06% accuracy in subtype classification as compared to other models. S. Mishra et al. [40] used Computer-Aided Diagnosis (CAD) to detect ALL cells from microscopic blood smear images. They considered a total of 108 images out of which 49 images belonged to abnormal and 59 images belonged to normal cells. They applied the Random Forest and Adaboost for the classification of cells. Finally, they conclude that the proposed model outperforms with 99.66% accuracy as compared to other models. M. Claro et al. [41] proposed a CNN model to distinguish WBC, AML, and ALL. They considered 16 different datasets having 2415 images. The applied data augmentation method to enhance the performance of the model. Finally, they conclude that the proposed model outperforms with 97.18% accuracy as compared to other models. Table 5 highlights some bone marrow cancer detection techniques. The comparison of bone marrow cancer detection techniques based on technique, the dataset used and accuracy is presented.

3. Existing Framework

This section discusses how the bone marrow cancer detection system works. The following steps are shown in Figure 4 and are used to detect the abnormal WBC that causes bone marrow cancer.

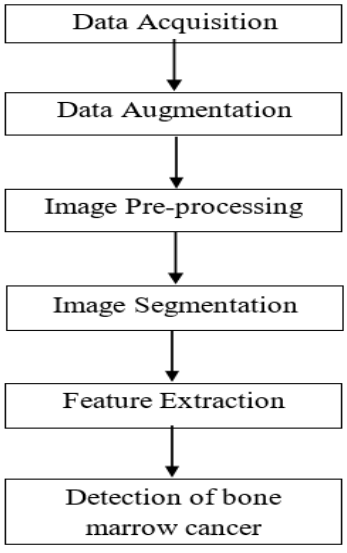

Fig. 4 Steps for detecting Bone Marrow Cancer Detection

The first step is to collect the data from different sources. The data is microscopic blood cell images which can be obtained from open sources of image banks. These images are provided by different hospitals. And it can be also

collected directly from hospitals that are dealing with cancer patients. Then image augmentation is used when there aren't enough images or datasets. The number of images can be increased by shifting, zooming, flipping, shearing, and rotating. By using these steps the number of images or samples can be increased [42]. There are different data augmentation steps for image transformation like rotation, height shifting, width shifting, zooming, horizontal flip, shearing, etc. To prepare image data for model training, image preprocessing is necessary. There are different techniques for image preprocessing image sharping, image enhancement, changing the contrast, brightness, and color of the image, etc. [43]. Then in image segmentation, the WBC nucleus has to be separated from the other blood cells. It can be done by manual cropping or by automatic cropping [44]. The characteristics of the cancer cell are extracted and compared to those of normal WBC. Some of the features which are extracted from WBC are area, perimeter, radius, minor axis, major axis, etc. [45]. In detection, it has to be found out whether the image belongs to a normal image, or non-cancer image, an abnormal image, or a cancer image.

4. Comparison of Existing Me- Thods of Bone Marrow Cancer Detection

WBC detection is the first and most important step of the bone marrow cancer detection system, and the overall recognition of cancerous WBC largely depends on the performance of the extraction stage. The existing techniques for the detection of bone marrow cancer using image processing methods are discussed in Section 2. They are classified based on the technique used for detection. Table 5 highlights some typical bone marrow cancer detection techniques. The comparison of bone marrow cancer detection techniques based on technique, the dataset used and accuracy is presented.

Table 2 Comparison of various augmentation and preprocessing techniques

Presented techniques with references	***Dataset Used***	***Accuracy***
CNN (N. Ahmed et al., 2019; M. Claro et al., 2020)	224*224	97.18% (2415 images)
DCNN (S. Shafique et al., 2018)	227*227	99.50% (368 images)
RVM (R. Kumar et al.,2014)	NA	91% (85 images)
SVM (J. Rawat et al.,2017)	NA	99.5% (420 images)

Table 3 Comparison of various segmentation techniques

Presented techniques with references	***Dataset Used***	***Accuracy***
K-means clustering (A. Kandil et al.,2016; Nimesh Patel et al.,2015; F. Kazemi et al., 2016)	632*480	99.51% (757 images)
Otsu's technique (M. Joshi et al., 2013)	2592*1944	93% (108 images)
Fuzzy C-Means (S. Alferez et al.,2014)	367*360	98% of HCL cells (340 images)
Support Vector Machine (J. Rawat et al.,2017; H. Fakhouri et al. 2018; E. Abdulhay et al., 2018; M. Benazzouz et al. 2013)	NA	99.5% (240 images)
Convolution Neural Network (A. Rehman et al.,2018)	NA	97.78% (330 images)
Functional Link Artificial Neural Network (S. Mohapatra et al., 2012)	NA	98.28% (100 images)

Table 4 Comparison of various feature extraction techniques

Presented techniques with references	***Dataset Used***	***Accuracy***
SVM (M. Amin et al., 2015; M. Amin et al., 2015; L. Putzu et al., 2014)	2592 × 3872	99% (302 images)
KNN (M. Subhan et al., 2015)	NA	94%
MLP **(**E. Francis et al., 2011)	NA	98.66% (1000 images)

Table 5 Comparison of various detection techniques

Presented techniques with references	***Dataset Used***	***Accuracy***
DT, KNN and NB (Z. Moshava et al., 2018)	2592*1944 257*257	98.12% (269images)
CNN (T. Pansombut et	224*224	97.18%

al., 2019; M. Claro et al., 2020)		(2415 images)
Fuzzy-C-Means (M. Amin et al.,2016; P. Viswanathan, 2015; K. Lakshminarayan et al., 2021)	519*775	98.26% (312 images)
K-means (N. Harun et al., 2015)	800*600	98.26% (100 images)
SVM (N. Chatap et al., 2014; L. Vogado et al., 2018)	2592*1944	99.20% (377 images)
ALEXNET (M. Shaheen et al., 2021)	360*363	98.58% (4000 images)
DCNN (S. Shafique et al., 2018)	257*257	99.50% (368 images)
CAD (S. Mishra et al., 2019)	1712*1368	99.66% (108 images)

* NA: Not Available

5. Conclusion and Future Aspects

A bone marrow cancer detection system has an application to detect aberrant WBC by which bone marrow cancer is detected. Various soft computing techniques for the detection, segmentation, and extraction of features of aberrant WBC have been studied, and their performance has been compared based on image size and performance rate. The study concludes that extracting the nucleus of aberrant WBCs is an important step, and the success of the bone marrow cancer detection system is entirely dependent on it. There are different types, shapes, geometrical features like radius, perimeter, area, etc., and texture features of the WBC that are undertaken for the implementation of the techniques. These variations can be summed up as variations in WBC location in the image, the number of WBC in the image, camera distance, and its zoom factor, the background color of WBC, etc. All techniques are applied to a different set of WBCs under different conditions with different software and hardware. In the future, the techniques can be applied to the same set of images using different software for a better comparison of their performance rate. Furthermore, work can be done on developing a real-time application for detecting bone marrow cancer. Algorithms are being applied by researchers to various datasets. So to compare the outcomes, a single platform should be created.

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