Cancer Detection and Classification through various Image processing methods

E.Lingappa
Research Scholar, Department of CSE, Saveetha Institute of Medical And Technical Sciences, Chennai, Tamil Nadu, Assistant Professor, Malla Reddy College of Engineering, Maisammaguda, Dhulapally, post via Kompally, Secunderabad – 500100

Dr.L.Ramaparvathy
Professor, Department of CSE, Saveetha Institute of Medical and Technical Sciences, Chennai, Tamil Nadu.

Abstract:

One of the most life threatening diseases is Bone cancer. Its early detection is paramount and can save many lives but early detection is very demanding notwithstanding continuous research. Literature review helps us to understand that there are many approaches and techniques deployed to overcome the challenge but its downside cannot be ignored. The proposed method comprises of many steps commencing with preprocessing, edge detection, morphological operation, segmentation and then feature extraction. In the proposed approach, bone cancer can be detected from MRI scan images. There are certain information in the extracted features which plays a vital role in understanding the image. Feature extraction simplifies the process and also segregates various desired shape present in the image enhancing the accuracy of the classification stage. The paper comprises of an extensive study on the development of techniques involved in image processing and then comparison of the present techniques for obtaining the best result. Feature extraction for identifying bone cancer is also discussed in the paper. Future work aims to utilize Artificial Neural Network for classification.

Keywords: *Classification of Tumor, Oncologists, Parameters, Region of Interest, Strengths, Tumor Detection*

I. Introduction

The key to cancer detection process is Image segmentation and bone cancer segments are featured through Magnetic resonance imaging (MRI) or computed tomography (CT). During segmentation the images are broken into several regions and relevant information are then extracted. Segmentation helps in representing the image in less complicated way. This study primarily focuses on the bone tumor detection from MR images. Image segmentation algorithms can be identified based on two basic categories of image intensity values namely discontinuity and similarity. In case of discontinuity, identifying the difference in intensity over the image forms the basis for segmentation. Edge detection technique identifies the difference in intensity between the dissimilar regions and then segmentation is done. In case of latter category, similarity criteria is applied and images are split into regions exhibiting similarity [3]. It comprises of segmentation techniques with predefined criteria namely thresholding, region-based and clustering. In medical image segmentation, bone cancer detection is a challenging task because bone images contain granny portions of tissues and low volume tumor which creates the problem of excessive/less segmentation.

Bone cancer is a multifarious genetic disorder which occurs due to various physiological factors and it directly affects the bone. It leads to abnormal cell growth pervading other adjacent parts of the body. Bone cancers are also called sarcomas. Basically, the bone cancer is classified as either primary or secondary cancer where the actual cause of bone cancer is not known. When the malignant bone tumors start rising in normal bone tissues then it is called primary bone cancer stage. Primary bone cancer rarely arises and it counts for much less than 1 percent of all cancers. Many different segmentation algorithms have been approached throughout the years for bone cancer detection. The existing ones include region growing algorithm, k-means clustering and fuzzy C-means clustering integrated with k-means. Every algorithm has its own advantages and drawbacks and this paper presents a comparative study of the bone cancer segmentation algorithms with the proposed algorithm. In this paper, an object labeling algorithm has been approached for the segmentation of bone cancer and presents a comparison with the other existing segmentation algorithms.

Benign tumors starts in bone tissue but if the abnormal cell growth pervades other adjacent parts of the body through the bloodstream and lymph vessels then it is called malignant bone cancer. An estimation in the year 2014 of bone cancer patients provided by the American cancer society shows that about 3020 new cases are diagnosed with 1460 deaths expected. Magnetic resonance imaging (MRI) or computed tomography (CT) is used for the scanning of the bone anatomy.

In United States it is estimated that this year 3,600 people of all ages (2,120 men/boys and 1,480 women/girls) will be diagnosed with primary bone cancer. Approximately 400 of these cases will occur in people between age group of 15 to 19. The estimated deaths are 1,720 (1,000 men/boys and 720 women/girls).

In adults, chondrosarcoma makes up more than 40% of primary bone cancers. The average age of diagnosis for this type of bone cancer is 51. The next most common type of bone cancer in adults is osteosarcoma (28%), followed by chordoma (10%), Ewing sarcoma (8%), and UPS/fibro sarcoma (4%). The remaining types of bone cancer are rare. In teens and children, osteosarcoma (56%) and Ewing sarcoma (34%) are diagnosed far more often than chondrosarcoma (6%). Less than 5% of chondrosarcoma and chordoma cases occur in this age group. Scientists and Doctors are delving deeper to understand bone cancer, prevention, treatment and how to provide the best care. The following areas of research may include new options for patients through clinical trials. It is necessary to discuss with the doctor about the best diagnostic and treatment options.

During cancer bout**,** it is important to improve the body's natural defenses. That is the reason why Immunotherapy/biologic therapy is important. In some countries (except United States) a nonspecific immune system stimulator known as Mifamurtide (Mepact) is approved as a bone cancer treatment.

As yet, chronic cancer cannot be cured but the extended treatment can control the disease for some time. Similar to other chronic diseases, the aim of extended treatment for cancer is to help patients live as much as possible. Health care team can play a paramount role to help manage the challenges of survivorship and extended treatment as battling cancer is definitely not easy.

For most chronic cancers Chemotherapy is often recommended. During this, the patient may receive the same drug/drugs that were initially used to treat the disease. Or it can be a new drug or combination of drugs. Many types of chemotherapy can now be taken as a prescription pill by mouth instead of intravenously.

II. Literature Survey

In this work the metabolomics data from osteosarcoma patients were collected and then subjected to three classification techniques namely logistic regression, support vector machine (SVM) and random forest (RF). The receiver operating characteristic curves is used for comparison and performance analysis. The classifiers effectively distinguish the healthy and tumor cases. Of the three methods, random forest shows better result for cross-validation in training set with accuracy rate of 97% and achieving an overall accuracy rate of 95% with 0.99 AUC on testing set [1].

A comparative and thorough analysis of the existing techniques in bone cancer segmentation is done in this work. For the bone tumor segmentation, an algorithm (object labeling) is also proposed. Quantitative techniques such as structural similarity index measurement (SSIM) and dice similarity coefficient (DSC) are considered as the basis for the comparison between the existing and proposed algorithm. Comparative assessment infers that the proposed system yields DSC 96.04% (the highest mean) and mean of SSIM 98.33% compared to others [2].

Early detection of bone tumor is paramount. With this focus, the study uses an algorithm called connected component labeling and classification of bone tumor conducted with artificial neural network (ANN). For training and testing of the neural network, about 220 MR images of bone are collected from patients earlier confirmed and the texture features of these images are used. The proposed method is proven to be highly efficient in classification of bone tumor with 92.50% success [3].

For the early detection of bone cancer, this study uses fuzzy C-mean clustering method. In order to verify the accuracy of the proposed method, 120 MR images from earlier confirmed patients are used. And using adaptive neuro fuzzy inference system (ANFIS), the categorization between benign and malignant bone cancer is done. The collected bone images have been again thoroughly investigated before separating into training and testing images. In terms of precision, sensitivity and specificity, the proposed method yields an accuracy of 93.75% [4].

The method proposed in this work for detecting bone tumor in MRI images is by integrating some pre-processing techniques. Average and bilateral filter are integrated for eliminating noise and smooth images. The integration process enhances the image quality making them fit for segmentation as well as morphological operations (for removing false segments). To detect the existence of bone cancer and determining its stage, the k-means algorithm is used. Results prove that the proposed system successfully obtains the smooth picture with edges representing the portion influenced by the illness without the spatial and spectral noises [5].

This study conducts an extensive analysis on some enhanced canny edge detector that is used for edge detection in images. The study concludes that all existing canny edge detector have some limitation. Therefore, by analyzing the drawbacks, the future work would encompass all methods to enhance Canny edge detector in identifying contours in natural images [6].

Besides the primary cancer, it is essential to detect bone metastatic tumor. However, such tumors originate from erratic regions and are very small making them difficult to detect. This paper propose a method to detect bone metastatic tumors based on a generative adversarial network model trains with barely non-metastatic bone tumor images and detects bone metastatic tumor in an unsupervised manner. For each test CT image anomaly score is defined. From the results, it can be inferred that the anomaly scores between the two images varies significantly. Therefore it can be efficiently used for detecting such tumors in CT images [8].

For a fast and accurate classification of bone fractures, this study develops a computer based analysis system by making use of the data obtained from the x-ray / CT images. Techniques such as feature extraction, pre-processing, segmentation and edge detection are used in order to process the fractured bone images collected from hospital. Subsequently, to compare the efficiency of different methods, processed images are then segmented. The programming tool used here is MATLAB 7.8.0. The major drawback for the proposed method is the difficulty in locating the fracture in CT and few X-ray images. However, it shows an accuracy of 85% [8].

In order to automatically divide MR perfusion images of bone tumor, a multi-scale feature-based neural network classifier is presented. It segments the images into three namely viable, non-viable and healthy. The proposed method facilitates merging of dynamic and spatial properties. Subsequently, the highest discriminative power can be examined and categorize the best type of subset for a specific application at hand. Results conclude that an extensive research is still required for finding the accuracy of viable tumor area [9].

In this paper, a medical image segmentation procedure is proposed. It uses fuzzy connectedness with new spatial adjacency model committed to the examination of magnetic resonance studies. This system is examined on the bone tumour images that are recorded. Segmentation results entails for further enhancing the system [10].

This paper proposes a technique to identify the tumor size and subsequently identify its stage. Scanned images from different body parts collected from different diagnostic labs are involved in this study. To examine the tumor tissue, segmentation process is done using Region Growing Algorithm. Then, empirical calculation of the size of the tumor and its stage is done [11].

In this study, two ablation methods are examined to verify their viability in treating bone tumors. An antenna with just one slot is designed and a 4 MHz spherical transducer sound proliferation is conducted for MW and US ablation respectively. Four antennas with the finest features are chosen to heat up bone. So 6.9 mm and 4.9 is the ideal length position with 2.45 GHz-2.60 GHz being conductive for the antennas to work. Results prove that both techniques are feasible for bone tumor treatment [12].

This study proposes a method for the fusion of PET and MR brain images build on IHS model and log-Gabor wavelet transform. Image decomposition is done using the latter method. Subsequently, fusion roles such as “the maximum selection’ and “two-stage” are employed for the sub-band with high-frequency and low-frequency respectively. Finally, the fused color image is obtained from the new intensity component by reverse log-Gabor wavelet transform to the two sub-bands. The alterations in the anatomy and color are determined with effectively-reduced color alteration in the fused image. Investigation results prove that this method outperforms framelet-transform-based method [13].

To determine the features associated with the obliteration of bones in tumors, this study conducts a comparative examination on the execution of different types of texture features processed from radiographs of bone tumors. Testing is done on the two x-ray images of bone for both normal and abnormal parts. Parallel to radiographic pattern variations caused by bone tumor, the Mean average intensity and entropy were found as the best performing features. Experimental results prove that fractal dimension is the best feature for examining texture smoothness caused by bone destruction [14].

In this paper different image segmentation algorithms are examined and its advantages and limitations are analyzed. Then the development trend of image segmentation are presented as follows: 1) the images are diverse and uncertain. Therefore, it is necessary to integrate different methods and leverage its advantages build on multi-feature fusion. This enhances segmentation effect.2) for enhancing segmentation effect, parameter selection is done using machine learning algorithm. For eg. Threshold selection in threshold segmentation and K values selection in the K-means algorithm. 3) For enhanced image segmentation, the region of interest is framed using CNN model [15].

An image processing techniques is used in this work for identification and classification of cancer. It utilizes filtering and gray conversion, edge detection, morphological operation, segmentation, feature extraction and classification. Subsequently, they are applied to train and test the neural network. Bone cancer from CT scan images are successfully detected using the proposed system [16].

In this paper bone image segmentation is done using k- means clustering algorithm based on the calculation of the mean intensity. To determine the existence or lack of bone cancer in the medical images, threshold values are proposed. This system is not only applicable for jpeg images but also for digital imaging communication of medicine in its original set up. The proposed approach takes less computational time and shows 95% accuracy [17].

This paper proposes a technique to determine the phase and location of cancer in long bones based on the examination of X-ray image. The proposed method integrates different methodologies for the analysis. Bones are segregated by removing selected features from the images using support vector machine (SVM). Classification of the stage, grade and detection of the pattern causing bone-destruction are done using a decision tree classifier. The credibility of this method can be proven from many satisfactory test cases [18].

For restoring iterative image of the CT-based attenuation map, a priori knowledge is used in this paper. dICD reconstruction is carried out using replicated sinogram specifics with spatial and mixture penalties of varying strengths. Their collaborated penalties results in lower RMSE and yields uniformity in variance and bias. It is a promising system with very less patient dose. However, based on results using a best-case histogram, this paper concludes that the benefits from mixture penalty are not practical as it requires additional hyperparameter selection [19].

III. STAGES IN BONE CANCER DETECTION PROCESS

Steps in identifying bonce cancer:

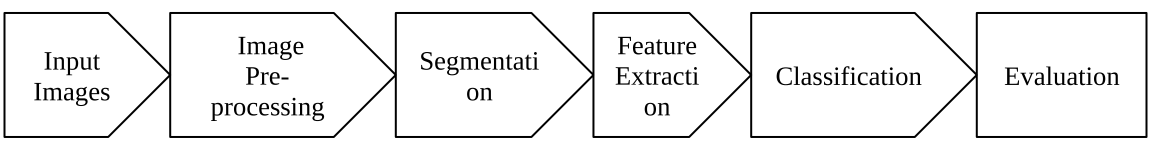

Fig.1: Different stages in bone cancer detection

Training Phase:

Prior to segmentation of the clean images, the Training phase utilizes the process of standard noise removal for pre-processing the MRI images. Kalmann Clustering algorithm is used for image segmentation. Eigen Vectors are extracted after segmentation and values are computed. It is followed by the construction of Eigen matrix using the above values. Autocorrelation technique is applied and the features reframed and named as EVAM. The cancer and non-cancerous images are distinguished from the range value for EVAM. The Super index based C-

Means Algorithm will represent the ranges of the cancer in the database with correlating labels which will then behave as the model for the testing phase.

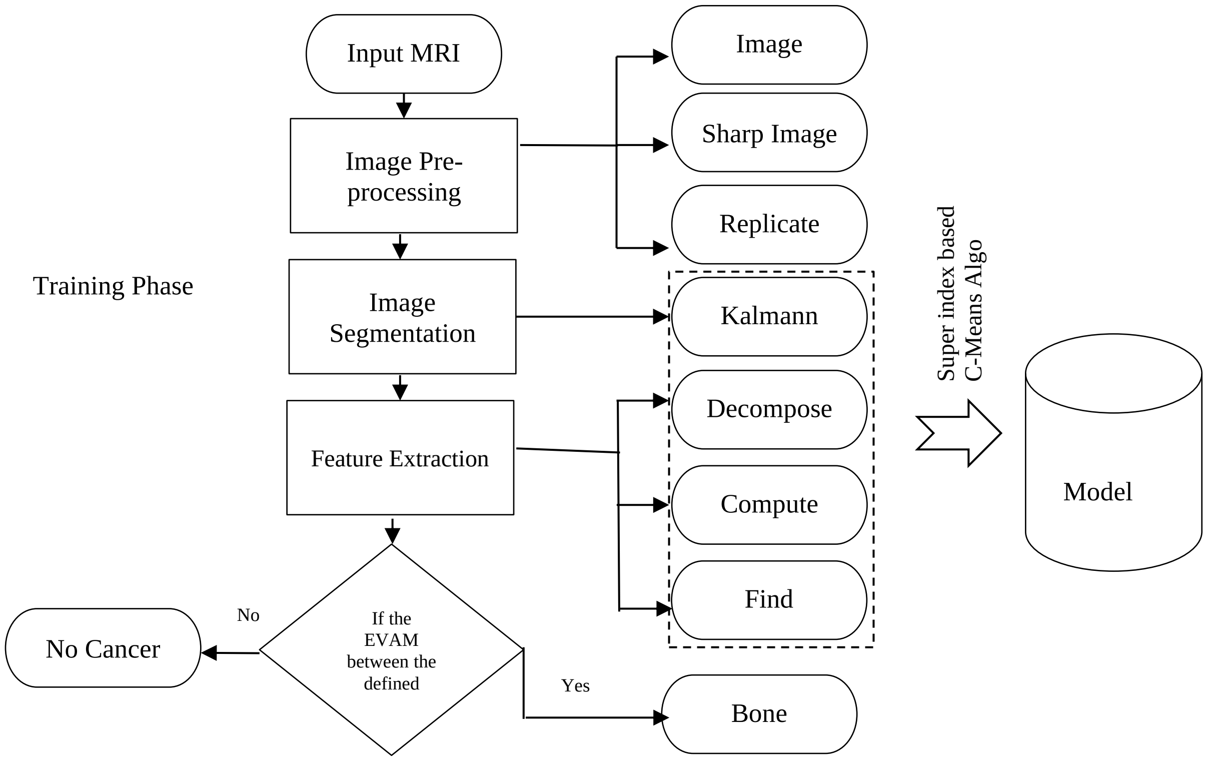

Fig.2: Training Phase in Proposed work

Testing Phase:

Before the clean images are segmented, the testing phase utilizes the process of standard noise removal for pre-processing the MRI images. In this phase, Kalmann Clustering algorithm is used for image segmentation. Eigen Vectors are extracted after segmentation and values are computed. It is followed by the construction of Eigen matrix using the above values. Autocorrelation technique is applied and the features reframed and named as EVAM. Finally the images can be classified with EVAM value

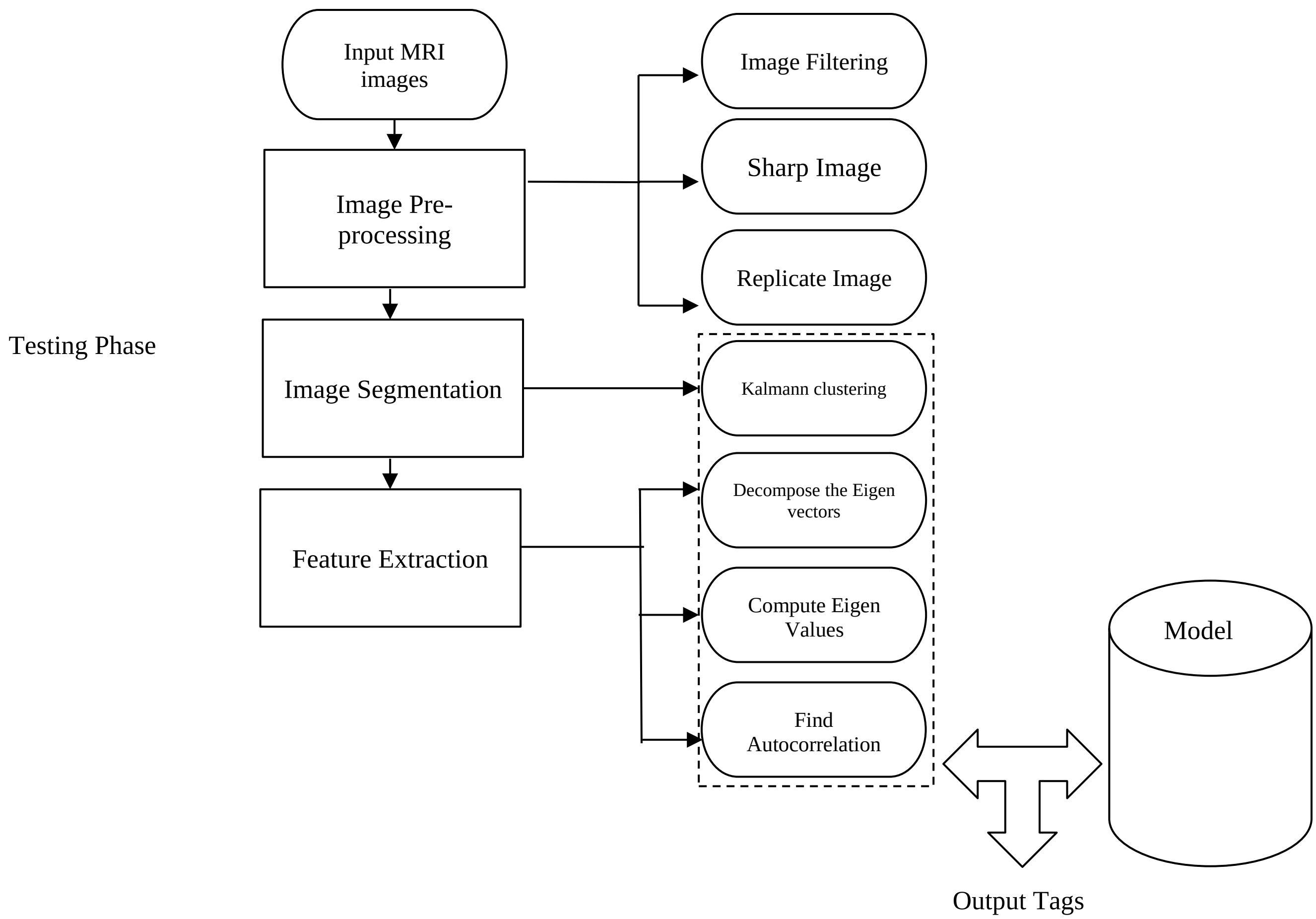

Fig.3: Testing Phase in proposed work

IV Feature Extraction: Kalmann Clustering and Eigen Vector Extraction

Step 1: Input image: data set X ={xi}where 1≤ i ≤ n. Each xi has d dimensions, so

X ⊂ Pairwise affinity matrix:

Step 2: Affinity matrix: W(i,j) = e−||xi−xj||^2 /2σ^2 ………………(2)

where 1≤ i,j ≤ n.

Step 3: Degree matrix: D(i,i) =sumj(W(i,j)) ……………. (3)

Step 4: Construct Lij = Aij/(DiiDjj)^1/2 ……. (4)

The row and column degree helps in normalizing. R^{nXd}

Step 5: Find the k largest eigenvectors of L, called y1,...,yk.

Form the matrix of column vectors X = [y1y2 ...yk]∈ R^{nXk}

Step 6: Normalize the rows: Xij = Xij/(sumj(Xij2)) …………….. .(5)

Step 7: Selected normalized eigenvectors is averaged.

Input considered for the process is the MRI image wherein the noises are removed using Pre-processing techniques. In MATLAB, wiener filter is applied to the image which execute two-dimensional adaptive noise removal filtering. When degeneration of image occurs with constant power adaptive noise, this image can be filtered by using Wiener2-lowpass filters. It uses Pixel wise adaptive Wiener method depending on the details estimated from the local area of every pixel. Image duplication is done to ensure the availability of all the pixels incorporated in the matrix for calculation without doing away with the first row and first column. Affinity matrix is calculated prior to which the whole pixel values are taken into a matrix of rows and columns. Then the distance between the pixels in an image is calculated using affinity matrix. It is N x N matrix with each element A (*i*,*j*) the affinity between data point x_*i* and x_*j* . The two affinities possess kernel size which is difficult. Since the two data points with large intensity difference requires to be in different cluster, the kernel size *I* should be small. But for distance-based affinity it is possible for the two data points to be in same cluster though far away. Therefore, the kernel size *d* should not be very small and limitation need not be strictly imposed for distance affinity. Calculation of the Degree matrix (2) plays a vital role for eigenvalues and eigenvectors calculation in image segmentation

Super index based C-Means Algorithm:

1. Initialize $U=[u_{ij}]$ matrix, $U^{(0)}$
2. At k-step: calculate the centers vectors $C^{(k)}=[c_j]$ with $U^{(k)}$

$$c_j = \frac{\sum_{i=1}^{N} u_{ij}^{m} \cdot x_i}{\sum_{i=1}^{N} u_{ij}^{m}}$$

3. Update $U^{(k)}$, $U^{(k+1)}$

$$u_{ij} = \frac{1}{\sum_{k=1}^{C} \left(\frac{\left\| x_i - c_j \right\|}{\left\| x_i - c_k \right\|} \right)^{\frac{2}{m-1}}}$$

4. If $\| U^{(k+1)} - U^{(k)} \| < \varepsilon$ then STOP; otherwise return to step 2.

V. Discussion and Evaluation

Detection of bone cancer at an early stage will ease the process of treatment but it still remains a challenge. There are very complex parameters involved in bone cancer formation because of which most of the experiments does not yield satisfactory result. Data mining from MRI images comprising of huge datasets for extracting the desired results still remains perplexing.

Table 1: Metastases distribution

Bone region	Metastases Distribution (%)
cranium	8.67
cervical	6.9
dorsal	18.99
lumbar	18.43
Ribs-stern	12.5
clavicle-homoplat	3.7
Humerus	6.04
Pelvis	13.72
Femur	5.77

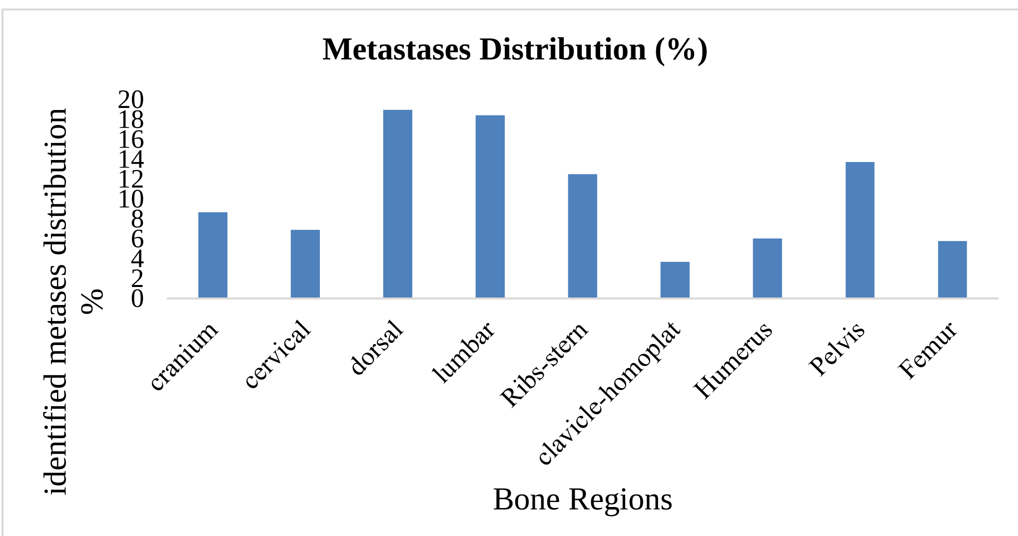

Fig.4: metastases distribution

Table 1 and Fig.4 shows metastases distribution plotted for different parts of human body. The proposed algorithm segmented the metastases. The different regions of the body are represented by X-axis and Y – Axis represents the percentage of metastases which will change depending on the clarity of the image.

Table 2: Time taken for segmentation of metastases for various region

Bone region	**Time taken to Segmentation (ms)**
cranium	1.67
cervical	1.9
dorsal	2.9
lumbar	1.4
Ribs-stern	1.5
clavicle-homoplat	3.7
Humerus	2.04
Pelvis	3.72
Femur	1.77

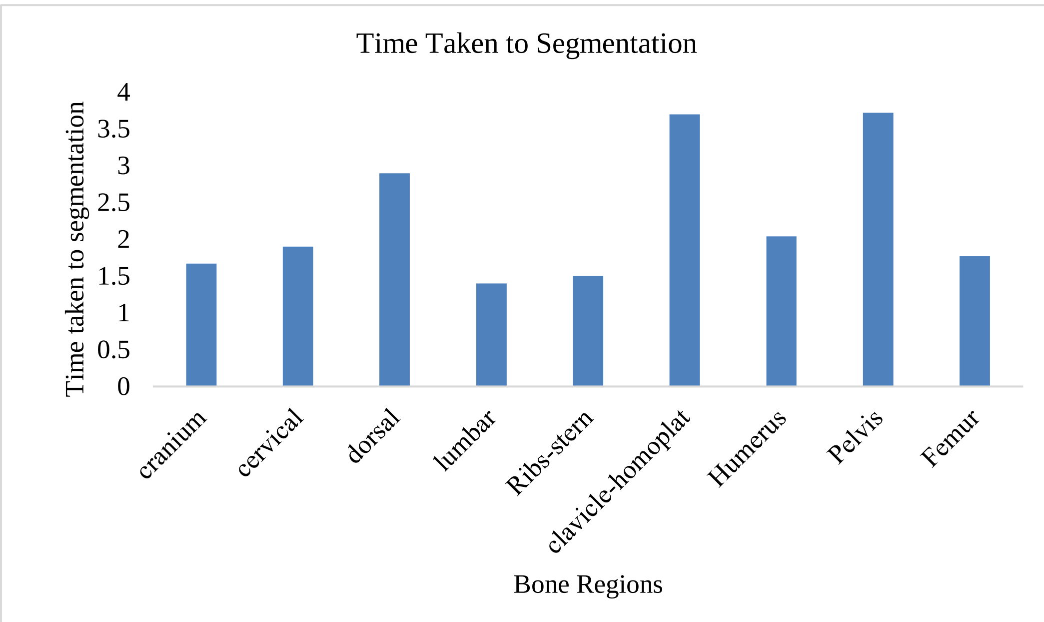

Fig. 5: Time taken for segmentation of metastases for various region

In Table 2 and Fig.5, the time taken for segmentation of metastases for various region of the body is plotted. The proposed algorithm segmented the metastases. The different regions of the body are represented by X-axis and Y – Axis represents the time taken for segmentation of metastases of various regions with percentage varying according to image clarity.

Table 3: Classification

Bone region(100 images)	Classification %
cranium	70
cervical	89
dorsal	91
lumbar	78.3
Ribs-stern	96.5
clavicle-homoplat	68.7
Humerus	89.04
Pelvis	87.72
Femur	90.77

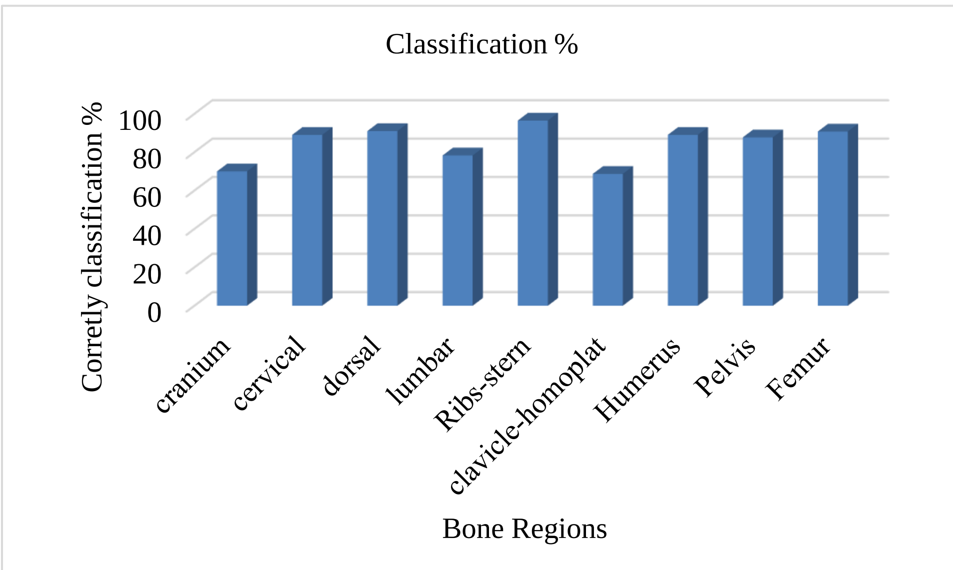

Fig.6: Classification

The classification percentage of tumour for various region of the body is plotted in Table 3 and Fig.6. In the proposed algorithm C-Means clustering algorithm is used for training followed by testing of image using training model. The graph is plotted according to the result. The different regions of the body are represented by X-axis and Y – Axis represents the percentage of correct classification that will vary depending on image clarity.

VI. Conclusion

Despite ceaseless research in the field of bone cancer, early detection of it still remains a challenge which otherwise could save many lives. The extensive literature survey throws clarity on the existing approaches and techniques but its downside cannot be ignored. The proposed method comprises of many processes wherein bone cancer can be detected from MRI scan images. Feature extraction in the proposed method eases the process and also segregates various desired shape present in the image enhancing the accuracy of the classification stage. The present technique is compared for yielding the optimum result. Overall the proposed technique proves efficient in early detection of bone cancer.

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