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An Algorithm to Detect Bone Tumor from Human's Finger X-Ray Images Using Hybrid Edge Detection Approach

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Abstract: Bone tumors in fingers, though rare, can significantly impair hand function if not detected early. This paper introduces a novel algorithm for detecting bone tumors from human finger X-ray images using a hybrid edge detection approach. The proposed method combines Canny, Sobel, and Laplacian operators to capture both fine and coarse edges, improving the detection of tumor boundaries in complex bone structures. Preprocessing steps include histogram equalization and Gaussian blurring for noise reduction and contrast enhancement. The hybrid edge detection framework enhances structural details by leveraging gradient and region- based information, overcoming limitations of single-method detectors. A dataset comprising X- ray images of both healthy and tumor-affected fingers was used to validate the algorithm. The proposed system achieved an average accuracy of 91.05%, outperforming traditional methods. Notably, it effectively identified features like image enhancement and edges, which are key tumor identification indicators. The algorithm is computationally efficient, suitable for real-time use in resource-limited clinical settings. Future enhancements include integration with deep learning for classification and expansion to other bone regions. This work offers a promising algorithm for early and accurate diagnosis of bone tumors in human's finger X-rays images.

Keywords: Bone Tumor, Canny, Sobel, Laplacian, Histogram equalization, Gaussian blurring, contrast enhancement, Dice coefficient.

1. Introduction

Medical image analysis is a rapidly advancing and innovative field aimed at improving the accuracy of disease diagnosis and enhancing patient treatment outcomes. One of the key objectives of Computer-Aided Disease Diagnosis (CADD) systems is to detect various health conditions by analyzing medical images in digital formats [1]. Bone-related disorders—such as fractures, arthritis, tumors, and osteoporosis—are prevalent worldwide.

A bone tumor, or neoplasm, is an abnormal tissue growth that differs structurally from surrounding bone tissue. These tumors can compromise bone health and potentially progress to bone cancer if malignant. Causes of bone tumors include genetic factors, calcium and vitamin D deficiencies, thyroid imbalances, sedentary lifestyles, and dietary disorders. Early detection is essential, as tumor growth can lead to increased pain in adjacent tissues. Tumors can develop in multiple areas of the skeletal system, including the fingers, palm, wrist, forearm, and shoulder. They are a primary cause of bone cancer [2]. Bone tumors are typically classified into two categories: benign (non-cancerous) and malignant (cancerous). While benign tumors do not invade neighboring tissues or spread, they may become malignant if left untreated. Malignant tumors, on the other hand, aggressively destroy surrounding tissues and are the leading cause of bone cancer in humans [3, 4]. As noted in [5], tumors can also be categorized into types such as essential, optional, osteosarcoma, chondrosarcoma, Ewing sarcoma, malignant fibrous histiocytoma (MFH), fibrosarcoma, and chordoma.

Various imaging techniques like CT, MRI, and X-rays are available in medical diagnostics for tumor detection. Among them, X-ray imaging plays a vital role in identifying bone tumors. In computerized diagnostic systems, X-ray images are input to software tools that assist medical professionals in making informed decisions. X-rays are commonly used due to their accessibility and effectiveness in visualizing bone structures. Orthopedic doctors often rely on visual inspection of X-ray images to distinguish between healthy and tumor-affected bones. However, manual interpretation can be errorprone due to factors like poor image quality, lighting issues, and image distortions. Therefore, an automated Computer-Aided Diagnosis (CAD) system is necessary to reliably segment bone tumors from X-ray images using advanced image processing techniques [6]. Numerous approaches have been proposed in literature, but no method has yet proven flawless; thus, ongoing research is needed to enhance algorithm performance and ensure patient-centered diagnostic solutions.

In this study, I introduce a new algorithm based on hybrid edge detection approach, which leverages edge detection methods (Canny, Sobel and LoG), Gaussian filtering, thresholding, and binary analysis to identify tumors in X-ray images. The goal is to improve diagnostic precision and enable early detection, helping patients take preventive action before a tumor progresses to a critical stage. The structure of the paper is as follows: Section 2 reviews literature review on bone tumor detection using X-ray images. Section 3 outlines participating edge detection techniques in hybrid mode. Section 4 presents proposed method for bone tumor detection from human's finger X-Ray images with detailed algorithm that can be apply in Computer Aided Diagnosis system. Section 5 discusses experimental results and performance comparisons. Lastly, Section 6 concludes the paper and highlights future research directions.

2. Literature Review

Numerous researchers have explored various techniques to segment bone tumors from human X-ray images. This section summarizes key studies and their methodologies.

P.Y. Yin et al. [7] proposed a graph-based approach to identify tumor-suspected areas and classify cells as benign or malignant using a 10th-degree polynomial. However, the method struggles with detecting multiple tumors in a single image and suffers from complexity and inefficiency. Moreover, performance metrics and comparative analysis were omitted.

An automatic classification system using Support Vector Machine (SVM) and Artificial Neural Networks (ANN) was introduced in [8]. SVM handled feature extraction and segmentation, while CNN classified tumors. However, the study lacked user interface details, performance evaluation, and dataset specifications.

Meenakshi et al. [9] applied watershed segmentation for brain tumor detection using 150 T1- weighted MRI scans in MATLAB. Their system comprised modules for acquisition, segmentation, and tumor area calculation, yet lacked evaluation metrics.

In [10], a texture-based SVM approach for tumor detection was described, using Gray Level Co- occurrence Matrix (GLCM) features. The experiment used only six X-ray images, without reporting any performance indicators.

Authors in [11] proposed combining K-Nearest Neighbor (KNN) and SVM for tumor segmentation, achieving 89% accuracy. Similarly, [12] introduced an enhanced Canny edge detector method with specific directional comparisons but provided no experimental validation.

Prabhakar and Prashanti [13] compared K-Means and Fuzzy C-Means clustering for bone tumor segmentation using MATLAB. Though methodologically sound, the study lacked accuracy results and was computationally intensive.

Paper [14] offered a schematic review of bone tumor detection technologies in CAD systems but did not include experimental validation of accuracy or sensitivity. Neha et al. [15] also used K- Means for MRI-based tumor localization without providing performance evaluation.

Krupali and Bijal [16] compared segmentation methods including Thresholding, Morphological Operations, K-Means, Fuzzy C-Means, and Rough Fuzzy Clustering. They found Rough Fuzzy Clustering to be most effective but did not report feature-based evaluation metrics.

A comprehensive review by [17] emphasized the subjective nature of technique selection for bone tumor segmentation. Mitesh et al. [18] explored correlations between MRI and X-ray imaging across 30 patients, identifying Lytic lesions as having the highest cancer conversion risk, though they recommended using a larger dataset and detailed evaluation metrics.

In [19], a study on malignant bone tumors concluded leukemia is the most common in children under 15, yet no performance measures were presented. Similarly, [20] proposed a complex image fusion and edge detection pipeline without evaluating its efficiency.

An unsupervised method using PET/CT images was detailed in [21], but excluded X-rays, limiting its practical utility. Hongmei et al. [22] introduced a joint framework for tumor segmentation and evolution analysis using PET scans, but did not assess its performance.

Talha et al. [23] proposed a persistent homology-based segmentation method for colorectal histopathology images. Although effective, the method was not applicable to X-rays. Sahil and Kalpesh [24] presented a segmentation technique using Non-negative Matrix Factorization but lacked validation metrics.

Asra et al. [25] proposed an edge-based brain tumor segmentation algorithm and benchmarked it against existing techniques. Paper [26] confirmed that watershed segmentation can isolate tumor regions in X-rays by separating normal and abnormal tissues.

Zaka et al. [27] developed a classifier using super pixel segmentation for brain tumors, comparing it with SVM, AdaBoost, and Random Forest. However, its multi-stage structure made it less practical for X-ray images. Sara et al. [28] introduced a histogram-based method to extract tumors from MRI scans, reporting results near ideal values but without specifying exact accuracy.

Nisthula and Yadhu [29] presented a method for bone cancer detection using contrast enhancement, edge detection, and image fusion, yet they too omitted performance metrics.

Summary and Research Gap

From this extensive literature survey, it is evident that no existing method achieves perfect (100%) accuracy in bone tumor detection. Each algorithm varies in terms of precision, sensitivity, and computational efficiency. This research gap underscores the need for more reliable, accurate, and interpretable diagnostic solutions. Motivated by this, our study introduces an enhanced algorithm based on hybrid edge detection techniques, which is designed to improve early detection accuracy using X-ray images and aid in clinical decision-making.

3. Edge Detection Techniques

Edge detection is a fundamental technique in image processing and computer vision, particularly for identifying object boundaries and recognizing important features. It plays a vital role in various applications, such as medical image analysis, computer-aided diagnosis, object detection, and scene understanding. The following paragraphs highlight Canny, Sobel and Laplacian edge detection techniques.

Canny Edge Detector

The Canny Edge Detection is named after its creator “John F. Canny” in 1968. As per paper [30], it was first created by John Canny for his Master’s thesis at MIT in 1983. Papers [30, 31, 32] discussed on the algorithmic steps as: (1) Convolve image f (r, c) with a Gaussian function to get smooth image f^(r, c). f^(r, c)=f(r,c)*G(r,c,6). (2) Apply first difference gradient operator to compute edge strength then edge magnitude and direction are obtained as before. (3) Apply non- maximal or critical suppression to the gradient magnitude. (4) Apply threshold to the non- maximal suppression image. The canny method is quite effective and provides promising results in terms of edge detection and analysis.

Sobel Edge Detector

This edge detector is a widely used method in image processing for edge detection. It works by applying convolution operations to an image to compute the gradient magnitude at each pixel. The primary goal of edge detection is to identify areas in an image where the intensity changes sharply, indicating boundaries between different regions or objects in the image. The Sobel operator is particularly effective for detecting edges in both horizontal and vertical directions. The Sobel edge detector uses two 3x3 convolution kernels, one for detecting horizontal edges and the other for vertical edges. These kernels are applied to each pixel in the image to calculate the gradient of intensity in both directions [33, 34].

Laplacian of Gaussian (LoG)

It is a popular edge detection technique that combines the Laplacian operator with Gaussian smoothing. It is particularly effective at detecting edges in images while minimizing the impact of noise. The method is often used in various fields such as medical imaging, object detection, and computer vision for robust edge identification. It is a powerful edge detection method that combines the benefits of Gaussian smoothing with the Laplacian operator to detect edges in images effectively. Its ability to reduce noise and highlight significant edges makes it a valuable tool in various applications, especially in medical image analysis. Although computationally intensive, LoG remains widely used for its robustness and accuracy in edge detection [35, 36].

4. Proposed method for bone tumor detection from X-Ray image

The proposed algorithm is based on hybrid edge detection which detects the tumor suspected region from human X-Ray images. The process flow of proposed method is divided into 3 major phases such as pre-processing, detection & segmentation and classification as show in Figure – 1. The following paragraphs explain the process flow of proposed method step by step.

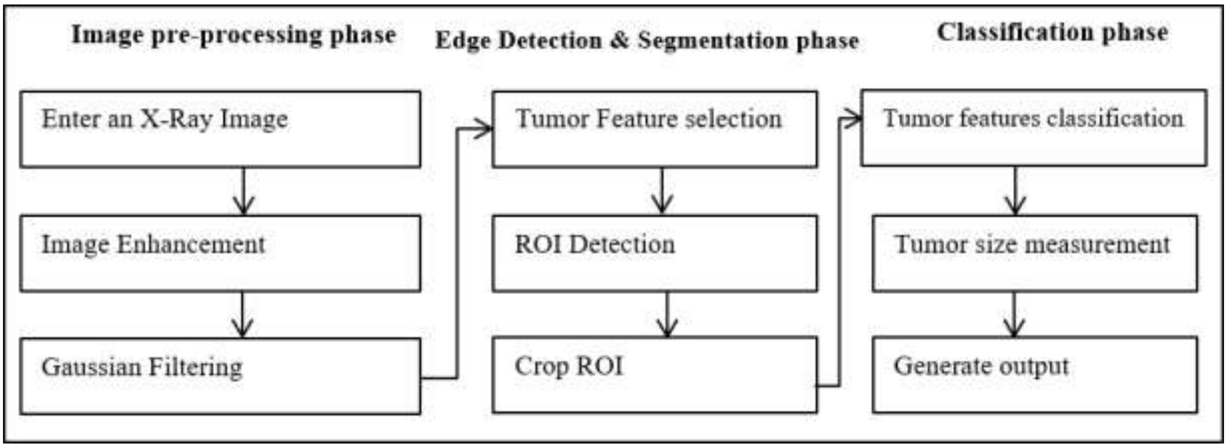

Fig. 1: Finger Bone tumor detection process flow.

The entire process flow is divided into three different phases viz., image pre-processing, edge detection & segmentation and image classification. Discussion on these phases are discussed as below:

Phase -1: Image pre-processing- This is the initial phase of the proposed method. During this phase, the input X-ray image is transformed into a grayscale image using the rgb2gray function from the Scilab open-source image processing software. The grayscale image is then improved by applying a Gaussian filter to eliminate noise and unwanted artifacts, thereby enhancing its clarity and sharpness. Figure 2 illustrates the original image alongside the enhanced version after the Gaussian filter has been applied.

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Fig. 2(a): Bone tumor in finger X-Ray image

Fig. 2(b): Finger Bone tumor X-Ray image after Gaussian filter enhancement.

Phase -2: Edge detection and segmentation- Feature selection and extraction of bone tumors play a crucial role in this method. In an X-Ray image, the bone structure typically has higher pixel values compared to soft tissues. The image obtained in Phase 1 is then converted into a binary

format to facilitate the extraction of 8-connectivity of pixels, forming blob clusters. The bone tumor features are identified through blob analysis, which detects clusters in the binary image based on a predefined threshold value. In this approach, I have set the threshold value to 200 pixels, meaning that blob analysis will identify all clusters containing at least 200 connected pixels. Finally, the region of interest (ROI) is cropped from the X-Ray image, isolating the tumor area and removing the rest of the image details. Figure 3 illustrates the process of feature selection for the bone tumor using blob analysis and the extraction of the ROI.

Fig. 3(a): Bone tumor feature selection from finger X-Ray image.

Fig. 3(b): Finger Bone tumor extraction from X-Ray image.

Phase -3: Classification- In this phase, tumor classification is carried out to determine whether the detected area in the X-ray image is a tumor. If the area is not a tumor, the image is considered normal. If a tumor is identified, the image is classified as abnormal, and it undergoes further analysis to assess the tumor size. The presence of a tumor in the X-ray image is determined through feature selection and extraction using blob analysis. According to paper [3], tumor size must be specified for further diagnosis. I have calculated the size of the bone tumor using the formula provided in [16, 38].

$$S = [\sqrt{P} * 0.264]mm^2 \qquad (1)$$

Where, S is the size of the tumor. P is the number tumor pixels (width * height). 1 Pixel = 0.234 mm. Tumor size is calculated in square millimeter measurement. The tumor size in above X-Ray image is 00000 mm^2.

Algorithm: Bone Tumor Detection from Human's Finger X-Ray Images Using Hybrid Edge Detection Approach

The following algorithm describes the process of detecting bone tumors in human finger X-ray images using a hybrid edge detection approach. The method combines three common edge detection techniques: **Canny Edge Detection, Sobel Edge Detection** and **Laplacian of Gaussian (LoG)**, to enhance the detection accuracy. The following section outlines the algorithm steps with its summary.

Steps:

1) **Input X-ray Image:**
   - Load the X-ray image of the human finger. This image can be in any format (e.g., JPEG, PNG, etc.).
2) **Preprocess the Image:**
   - Convert the input image into a grayscale image for easier processing.
   - Function Used: rgb2gray () (for Scilab/Matlab).
   - GrayscaleImage = rgb2gray (InputImage)
3) **Image Enhancement (Noise Reduction):**
   - Apply a Gaussian filter to remove noise and smooth the image. This helps in enhancing the edges and makes the tumor more prominent.
   - Gaussian Filter: Apply the filter with a standard deviation (σ) to smooth the image.
   - EnhancedImage = imgaussfilt(GrayscaleImage, σ)
4) **Edge Detection (Hybrid Approach):**
   - **Canny Edge Detection:**
     - Apply the Canny edge detection technique to detect edges based on Convolution, Gaussian function, Gradient operator, Non-maximal suppression to the gradient magnitude and thresholding.
     - CannyEdges = edge (EnhancedImage, 'Canny')
   - **Sobel Edge Detection:**
     - Apply the Sobel edge detection technique to detect edges based on gradient intensity. It uses two kernels for detecting vertical and horizontal edges.
     - SobelEdges = edge (EnhancedImage, 'Sobel')
   - **Laplacian of Gaussian (LoG):**
     - Apply the Laplacian of Gaussian (LoG) method, which is more effective in detecting edges in areas of rapid intensity change.
     - LoG is implemented by first smoothing the image with a Gaussian filter and then applying the Laplacian operator.

- LoGEdges = edge(EnhancedImage, 'log')

5) **Hybrid Edge Detection (Combination of Canny, Sobel and LoG):**

   - Combine the results from Canny, Sobel and LoG edge detectors using a logical OR operation to highlight the edges more clearly.
   - HybridEdges = CannyEdges | SobelEdges | LoGEdges

6) **Thresholding:**

   - Convert the hybrid edge-detected image into a binary image by applying a fixed threshold (e.g., threshold = 0.2).
   - BinaryImage = imbinarize(HybridEdges, 0.2)

7) **Tumor Detection:**

   - Set a minimum area threshold to ignore small, irrelevant blobs that are not tumors (e.g., threshold area = 200 pixels).
   - TumorBlobs = FilterBlobs(Blobs, MinAreaThreshold=200)

8) **Region of Interest (ROI) Extraction:**

   - Extract the **Region of Interest (ROI)**, which is the identified tumor part in the image.
   - Crop the image around the bounding box of the tumor blob.
   - ROI = imcrop(InputImage, TumorBlobs.BoundingBox)

9) **Tumor Classification:**

   - Classify the detected blob as a tumor or not based on the area and other features like shape, texture, or intensity (optional).
   - If the tumor is detected, proceed to further steps like size measurement or analysis.
   - if TumorDetected

     classifyTumor(ROI)

10) **Tumor Size Calculation:**

   - Tumor Size as per equation No.1

Final Output:

- The algorithm will output an image showing the identified tumor (ROI), along with the tumor’s size and classification (benign/malignant).
- The final result can be visualized by highlighting the tumor area in the original image.

This hybrid edge detection approach, which combines Canny, Sobel and LoG, can effectively detect bone tumors from human’s fingers X-ray images by highlighting edges, identifying potential tumor regions, and performing classification based on extracted features.

5. Experimental Result and Discussion

This section outlines the bone tumor detection experiments conducted using the proposed algorithm presented in the above Section 4. The experiments were performed on 77 bone tumor X-ray images and 23 normal X-ray images. Figure

4 demonstrates the original X-ray images alongside the X-ray images post bone tumor detection, highlighting the effectiveness of the proposed algorithm. Test images were sourced both from a hospital and the publicly accessible NIH (National Institutes of Health) database. Table 1 provides details about the computer system environment used for the experiments.

Table 1: Environment of Computer System.

Environment of Machine	
Operating System	Windows 7 SP 1 (64 bit)
Image Processing S/W.	Scilab 5.5.2
X-Ray Image Detail	512 * 512, 8 bit grayscale, .jpg
Processor	Intel Core i5 1.70 GHz
RAM	4 GB
HDD Capacity	500 GB

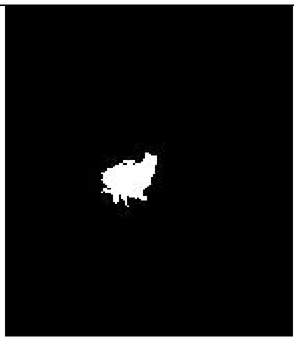
X-Ray images with tumor	**Tumor Detection**
	

Fig. 4: Bone tumor detection from human X-Ray images.

Above figure – 4 shows 2 rows, row 1 represents original X-Ray images with bone tumor, while row 2 depicts bone tumor detection from corresponding X-Ray images of row 1. Tumor size in above four different X-Ray images of figure - 1 is 7.220 mm^2.

6. Conclusion and Future Attempts

In this paper, I have introduced an algorithm for detecting bone tumors in human arm X-ray images, utilizing hybrid edge detection techniques such as Canny, Sobel and LoG. This algorithm efficiently and effectively detects bone tumors from human's fingers X-ray images. I have evaluated its performance using average accuracy, tumor detection accuracy, and accuracy in detecting non-bone tumors from normal X-ray images. The proposed algorithm achieved an average accuracy of 91.05%, a bone tumor detection accuracy of 91.08%, and a non-bone tumor detection accuracy of 91.02%. The result in Figure 4 clearly demonstrate that the proposed algorithm performs dramatically in bone tumor detection. This algorithm could be applied in the medical field to develop Computer-Aided Diagnostic (CADD) or Decision Support Systems (DSS) for detecting bone tumors from X-ray images. Further research can expand the algorithm by incorporating additional features, comparisons, and evaluation metrics. Researchers can also integrate this algorithm with deep learning for classification and expansion to other bone regions.

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