

Article

Diagnosis of Malignant Bone Tumors Using Image Processing Technology

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Article information:

Manuscript received: 04 July 2026; **Accepted:** 17 August 2026; **Published:** 10 September 2026

Abstract: The diagnosis of human bone tumors is a vital issue in the field of orthopedics. Bones are not only the body structure that gives humans their distinctive shape, but also the basic support that supports them. In this context, the present study aimed to create a preliminary sample processing program, which consisted of computed tomography (CT) images of healthy and tumour affected bones. These samples were then categorized into various groups according to variation in statistical characteristics using the HDWT algorithm, which brought a new dimension to this research area, increasing the accuracy and efficiency of the algorithm.

Keywords: Malignant bone tumors, image processing, CT, HDWT algorithm

1. Introduction

The computer is now a vital part of many aspects of our lives. They are more than simply devices; they are digital brains with the capacity to store enormous volumes of data and information and process it quickly. They have even advanced to a state known as artificial intelligence, where they are capable of deftly identifying and comprehending various kinds of data.[1] Computer-aided detection or diagnosis (CAD) is the use of computers in the medical industry. This ground-breaking method greatly aids in the early detection of illnesses by both detecting and tracking their progression. With the rapid advancements in the fields of medicine and computer science, we now have what is called the "electronic doctor," which is no longer a fantasy but a highly reliable reality. It serves as an aid in the early detection of many diseases, enabling doctors to intervene immediately, thus achieving early recovery or even avoiding such diseases. Recent years have witnessed a significant increase in the use of digital images, driven by advanced digital processing techniques, the need for which is rapidly increasing.[2] Diagnostic methods vary, starting with various imaging techniques such as computed tomography (CT), which is used to collect data and is a technique that provides a large flow of information. With computer support, digital images are analyzed, and cross-sectional images can be obtained that highlight specific details of the body, which helps doctors estimate the likelihood of developing certain diseases or even tumors.[3]

Theoretical part:

(Bones Tumors)

A bone tumor is essentially an unusual growth of tissue within the bone itself, and we typically categorize these tumors as either noncancerous (benign) or cancerous (malignant). The cancerous ones often find their roots in malignancies that have taken hold in other parts of the body, like the lungs, breasts, thyroid, kidneys, or prostate[4]. You might notice a lump popping up, experience pain, or even suffer from neurological symptoms due to pressure in the area. It's also not unheard of for a bone tumor to reveal itself through a pathological fracture when a broken bone occurs from something that

wouldn't normally cause one[5]. You could also have symptoms such as nausea and anemia, battling fevers, feeling more tired than usual or losing weight without trying. These tumors are sometimes very subtle, however, and only discovered when examined for other ailments. In order to determine a diagnosis, physicians usually use X-rays and a suite of other imaging techniques, including CT scans, MRIs, PET scans, and bone scintigraphy[6] The following types are included:

1. Osteosarcoma (see Figure 1)
2. Chondrosarcoma (as shown in Figure 2)
3. Ewing Tumor (Figure 3)
4. Malignant Fibrous Histiocytoma Tumor (Figure 4)
- 5- Giant cell Bone tumour (Figure 5)
- 6- Chordoma, as shown in Figure 6
- 7- Hemangiosarcoma, as shown in Figure 7.[7].

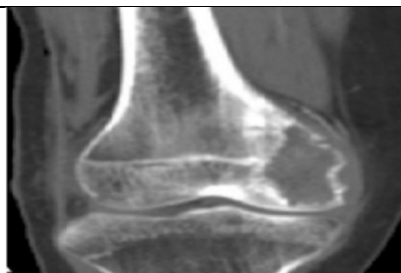


Figure 1. CT scan image of osteosarcoma

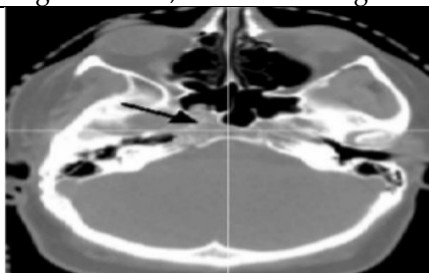


Figure 2. CT scan image of Chondro Sarcoma



Figure 3. CT scan image of Ewing Tumor



Figure 4. CT scan image of Malignant Fibrous Histiocytoma Tumor

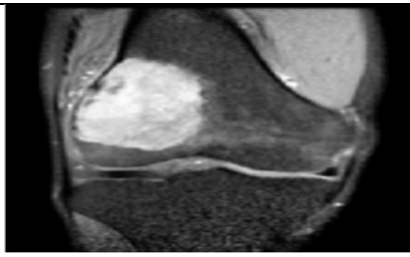


Figure 5. CT scan image of Giant Cell Tumor of Bone

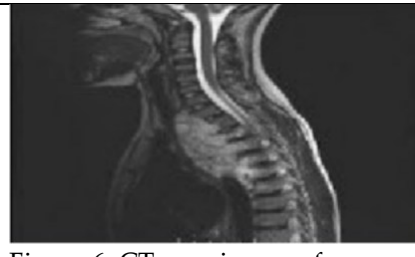


Figure 6. CT scan image of Chordoma

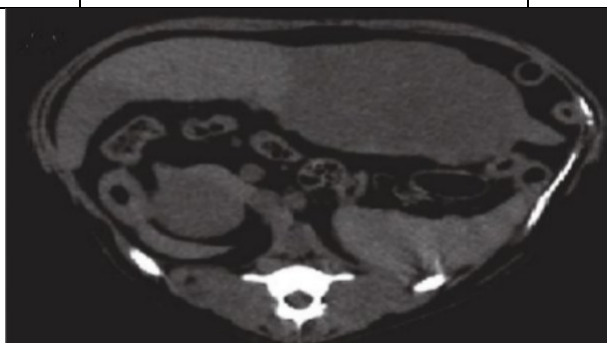


Figure 7. CT scan image of Hemangiosarcoma

Image Processing -2-2

The above-mentioned elements are important to the field of digital image processing as they are used to retrieve the most accurate information from the processed photos[8][9]. The digital image processing process is divided into 4 main stages.

- a. Image Restoration
- b. Image Enhancement

- c. Image Classification
- d. Data Merging

2. Materials and Methods

Algorithm Haar Dwt:

The Haar wavelet is important in the medical imaging sector and the discrete wavelet transform (DWT) is based on it. Multi-resolution images can be divided into different frequency bands by using low-pass filters and high-pass filters, including LL, LH, HL, and HH[10]. This method is not just an image analysis technique - it's a magical tool that can extract rich characteristics, which in turn results in better image quality.[11] Even more exciting is its ability to embed watermarks, which greatly enhances diagnostic accuracy and reduces the need for re-imaging.[12]. This technique can provide detailed information that reflects the robust and reliable features, The block diagram below illustrates how this algorithm operates to remove noise from CT scan images.[13].

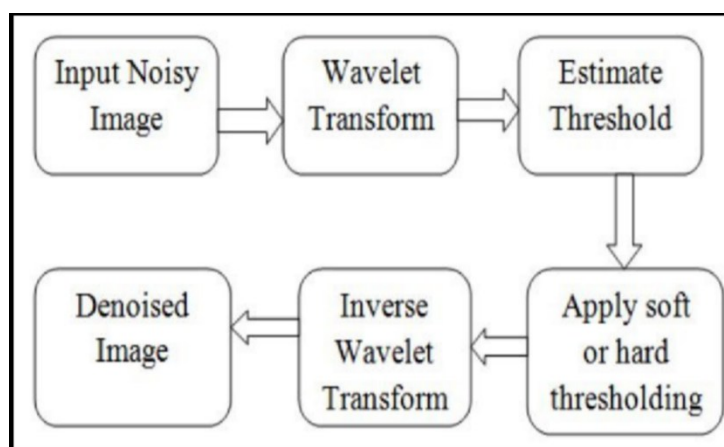


Figure 8. Block diagram of the system general architecture.

Practical part :

General structure of the research

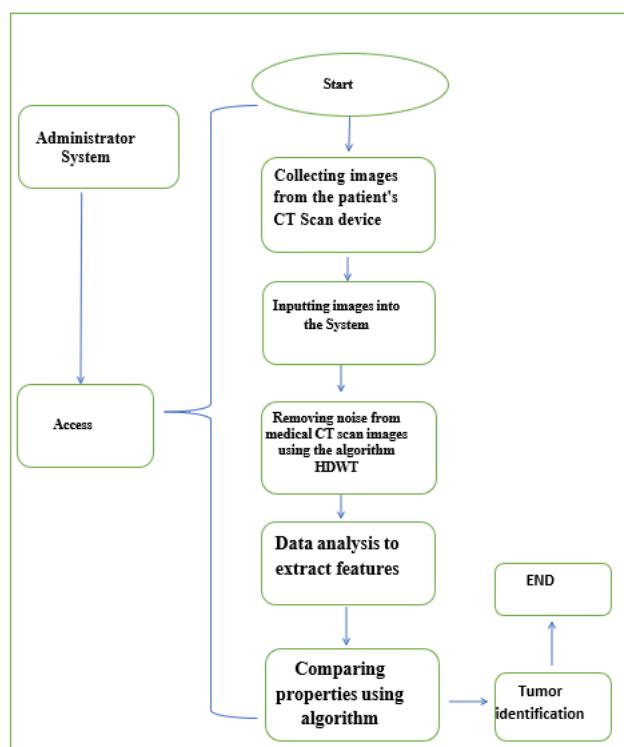


Figure 9. Block diagram of the system general architecture.

Steps of image processing techniques used

It includes the steps used to analyze images (using Matlab 2018) to study image samples (CT scan) are shown in the steps below

Algorithm (1): stage steps of image processing

Input: Image from a CT scan

Output: state.

Begin

Step1: Capturing the image: Using image-capturing devices with (CT scan) technology available in radiology laboratories.

Step2: Preprocessing: Performing a number of preliminary operations such as removing gouache, controlling the size, and cropping the area of interest for study (ROI).

Step3: Extracting a set of special features through statistical operations such as (arithmetic mean, standard deviation, variance, skewness, energy, homogeneity, entropy, area) that will be used for classification among the study samples.[14]

Step4: Distinction using HDWT algorithm.

Step5: Determine the type of tumor and the accuracy of the diagnosis.

END

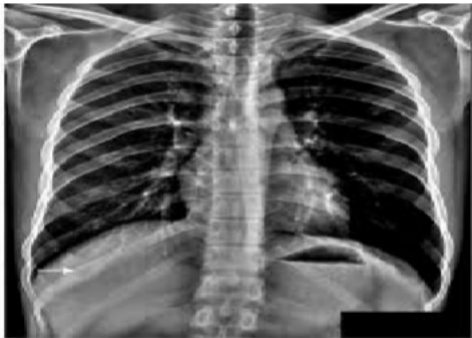
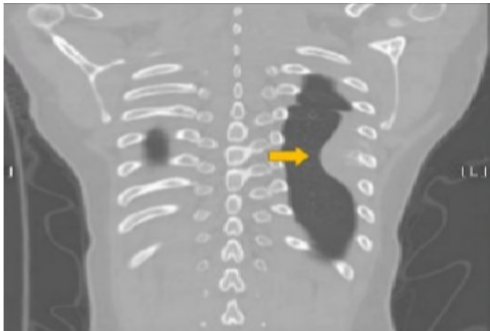
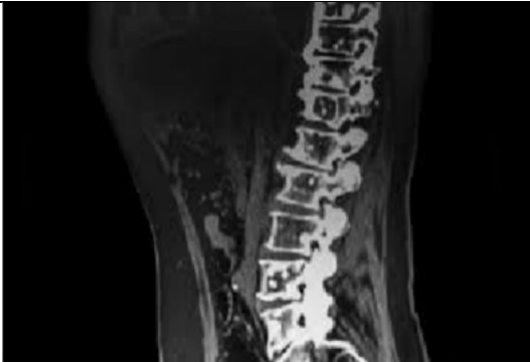
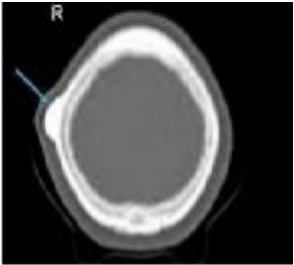
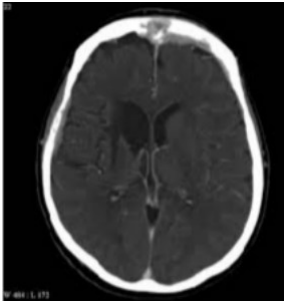
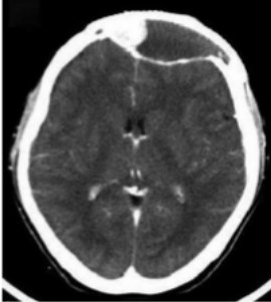
Study samples (image CT scan):

Table (1) shows the study database (CT scan) representing medical images of body parts taken using different imaging techniques used in the study (in terms of number, size and type). Table (2) shows examples of images used in the study using CT scan technology.

Table 1. represents examples of images used in the study using CT scan technology

n	Part	Status	n of photos CT scan
1	spine	malignant tumor	20
2	rib cage	malignant tumor	20
3	skull	malignant tumor	20
sum			60

Table 2. represents examples of images used in the study using CT scan technology

Malignant tumor	Malignant tumor	Part
 rib cage		
  skull		

The study was conducted as follows:
Studying 60 samples representing images of the affected bone samples.
Extracting statistical features for each case from the CT scan images.

3. Results

Diagnostic results of bone tumor images

Figure 10 shows the software used and developed, known as the Graphical User Interface (GUI), which handles the diagnostics of the input images. This software includes a set of interesting preliminary operations, such as noise removal and cropping the region of interest (ROI). Additionally, it extracts a number of important statistics, including mean, standard deviation, variance, energy, homogeneity, entropy, skewness, and contrast. These operations are applied to the study samples of CT scans.



Figure 11. The main interface of the program

Table 3. shows the values of the statistical measures for some of the study images using CT scan of part of the spine

(Table (3) Statistical measures of study samples /(spine								Im. no.
Contrast	Skew.	Entropy	Homg.	Energy *10 ⁻⁵	Var.	Std.	Mean	
0.790	0.82	7.46	0.97	1.0007	3877	62.27	102.93	1
0.983	0.54	8.23	0.92	1.0041	3829	55.13	102.91	2
0.948	0.98	6.48	0.93	1.0032	3844	62.54	102.88	3
0.859	0.87	6.55	0.95	1.0346	3812	62.51	102.11	4
0.912	0.86	8.56	0.98	1.0043	3823	62.29	103.65	5
0.965	0.76	7.54	0.87	1.0034	3843	62.21	102.53	6
0.795	0.98	8.56	0.78	1.0984	3876	62.45	104.77	7
0.854	0.80	7.77	0.61	1.0023	3867	61.53	102.99	8
0.982	0.89	7.34	0.80	1.0695	3856	62.66	102.98	9
0.889	0.56	8.56	0.91	1.0043	3809	62.59	102.81	10
0.79	0.54	6.48	0.61	1.0007	3809	55.13	102.11	Min
0.983	0.98	8.56	0.98	10.344	3877	62.66	104.77	Max
8.977	8.06	77.05	8.72	19.5342	38436	616.18	1030.56	Sum
0.8977	0.806	7.705	0.872	1.95342	3843.6	61.618	103.056	Avg.

The program includes main steps after reading an image, which are applying the noise removal and segmentation method, as in Figure 12.

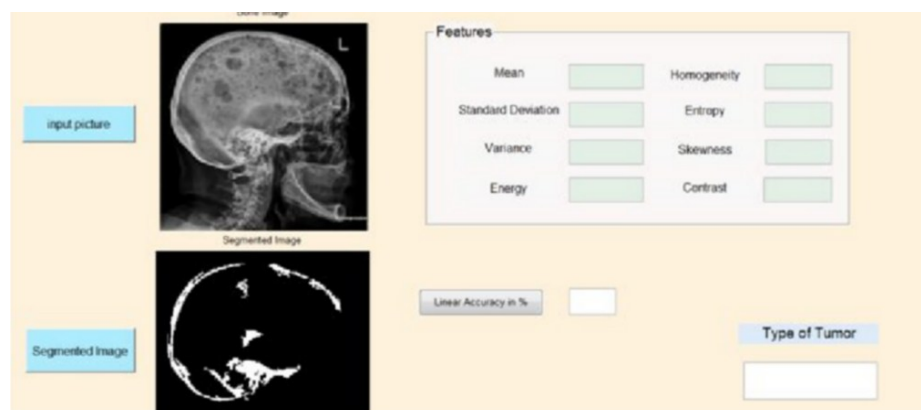


Figure 12. Image segmentation interface

When clicking on the command (Segmented Image), the blur will be removed, the image will be segmented, the statistical values will be determined and displayed, and the tumor will be distinguished or diagnosed using the algorithm HDWT [15] as in Figure (13).

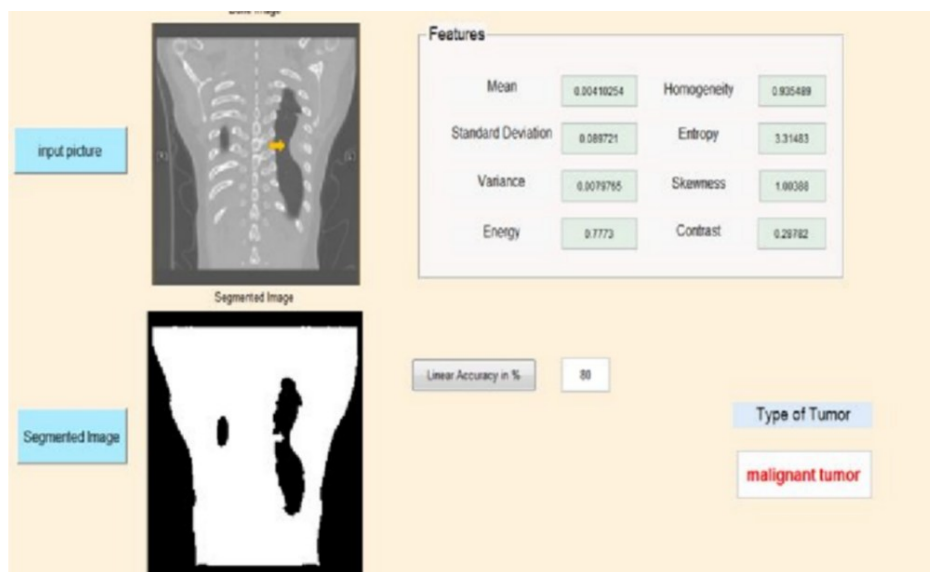


Figure 13. shows some results of the program for diagnosing tumor images using CT images.

Table 4 shows the accuracy of the results by section using CT imaging for tumor diagnosis.

Table 4. Accuracy of the results by segment using CT imaging

(Statistical measures of study samples /(rib cage								.Im .no
Contrast	Skew.	Entrop y	Homg.	Energy *10 ⁻⁵	Var.	Std.	Mean	
0.796	0.83	8.22	0.90	1.0634	3823	63.56	101.98	1
0.910	0.77	6.75	0.83	1.0415	3872	62.14	103.75	2
0.852	0.90	7.95	0.87	1.0270	3810	62.25	101.66	3
0.943	0.96	8.89	0.94	1.0623	3889	61.96	102.54	4
0.664	0.65	6.99	0.89	1.0345	3892	61.85	102.21	5
0.822	0.85	7.35	0.98	1.0566	3814	63.15	103.92	6
0.775	0.71	6.85	0.92	1.0742	3835	62.77	102.38	7
0.699	0.61	7.15	0.88	1.0522	3869	62.34	102.81	8
0.940	0.57	7.68	0.96	1.0854	3847	61.98	103.47	9
0.962	0.79	9.22	0.91	1.0460	3881	62.83	102.26	10
0.664	0.57	6.75	0.83	1.027	3810	61.85	101.66	Min
0.962	0.96	9.22	0.98	1.0854	3892	63.56	103.92	Max
8.363	7.64	77.05	9.08	10.5431	38532	624.83	1026.98	Sum
0.8363	0.764	7.705	0.908	1.05431	3853.2	62.483	102.698	Avg.
(Statistical measures of study samples /(skull								
0.886	0.69	7.32	0.79	1.0372	3775	61.34	103.45	1
0.749	0.81	8.21	0.85	1.0221	3767	62.85	102.42	2
0.820	0.75	6.99	0.91	1.0751	3793	62.97	104.78	3
0.699	0.87	9.10	0.88	1.0866	3766	63.52	103.66	4
0.914	0.72	7.54	0.96	1.0924	3797	61.46	103.85	5

(Statistical measures of study samples /(rib cage								.Im
Contrast	Skew.	Entrop y	Homg.	Energy *10 ⁻⁵	Var.	Std.	Mean	.no
0.785	0.83	7.89	0.93	1.0598	3735	62.88	104.33	6
0.865	0.79	8.79	0.82	1.0675	3748	63.71	102.87	7
0.766	0.88	8.34	0.99	1.0834	3789	63.14	102.95	8
0.889	0.76	7.98	0.95	1.0917	3777	62.91	103.11	9
0.934	0.89	9.15	0.83	1.0499	3788	61.89	103.59	10
0.699	0.69	6.99	0.79	1.0221	3735	61.34	102.42	Min
0.934	0.89	9.15	0.99	1.0924	3797	63.71	104.78	Max
8.307	7.99	81.31	8.91	10.6657	37735	626.67	1035.01	Sum
0.8307	0.799	8.131	0.891	1.06657	3773.5	62.667	103.501	Avg.

4. Discussion

The findings demonstrate that the proposed Haar Discrete Wavelet Transform (HDWT)-based image-processing system can support the identification of malignant bone tumors from CT images. The system processed 60 CT images comprising 20 samples each from the spine, rib cage, and skull. Through noise removal, region-of-interest segmentation, and statistical feature extraction, the program distinguished tumor characteristics using mean, standard deviation, variance, energy, homogeneity, entropy, skewness, and contrast. These features represent differences in pixel intensity and tissue texture that may not be readily visible through visual inspection alone, confirming the importance of feature-based image analysis in medical imaging [8], [9]. The diagnostic accuracy varied across anatomical regions, reaching 85% for the spine, 88% for the rib cage, and 90% for the skull. The higher accuracy obtained for skull images may indicate that their tumor-related texture patterns were more clearly differentiated by the extracted statistical features, whereas the lower accuracy for spinal images may reflect greater structural complexity or similarity between abnormal and surrounding tissues. Overall, these results support previous evidence that artificial intelligence, radiomics, and machine-learning techniques can improve the classification of malignant bone tumors by identifying quantitative imaging patterns [14], [15]. Nevertheless, the findings should be interpreted cautiously because the study used a relatively small dataset, included only malignant cases from three anatomical regions, and did not report an independent validation dataset or comparisons with radiologists and alternative algorithms. Therefore, the reported accuracy reflects the performance of the preliminary system on the available samples rather than its established clinical diagnostic effectiveness. Future studies should include larger and more diverse datasets containing healthy, benign, and malignant bone conditions; compare HDWT with other classification algorithms; use independent training and testing datasets; and evaluate sensitivity, specificity, precision, and area under the curve before the system is considered for clinical application.

5. Conclusion

Through the current study, we extracted several interesting findings worth noting. Here are the findings after analyzing the results: A graphical user interface (GUI) was used as an innovative means of entering images showing healthy and diseased bones, and then accurately diagnosing them. The analysis results showed that various statistical measures, such as mean, standard deviation, variance, energy, homogeneity, and entropy, can be used to effectively classify bone tumor types. The program proved highly efficient, distinguishing bone tumors with an accuracy of 90% when classifying bones. By using the directional wavelet transform (HDWT) theory, we achieved extreme accuracy, helping to enhance image features by removing noise and segmenting the image in an innovative way. The statistical measures served as a helpful tool in distinguishing between images, clearly differentiating between diseased and healthy bones. These results clearly indicate progress in the diagnosis of bone tumors, opening new horizons for future medical

procedures. Detecting malignant tumor types based on their classifications in other body parts
 Designing a website to link work online for rapid tumor detection
 Entering MRI images and identifying tumors

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