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Bone Cancer Detection Using Convolution Neural Network – An overview

Manjula Vasant Kiresur
Dept. of Electronics and Communication
R N S Institute of Technology
Bangalore, India

Manoj P
Dept. of Electronics and Communication
R N S Institute of Technology
Bangalore, India

Abstract — For human diagnosis, image processing can be used to evaluate pictorial data. Since the malignant tumor which is cancerous, will spread to other tissues of the bod. Consequently, it is important to identify the bone cancer in a prior stage with more accuracy. CT (Computerized Tomography), Ultrasound, X-ray, MRI (Magnetic Resonance Imaging), etc. are the different techniques in medical imaging.

In this paper, a low-cost and high-efficiency tumour detection method based on deep learning and x-ray images is proposed.

Keywords — Medical Imaging, X-Ray Images, Convolution Neural Networks, Bone Cancer.

I. INTRODUCTION

For both men and women, reason for the most common cause of death is cancer. Today the most important problem in health and medicine context is cancer. Earlier diagnosis and timely treatment are very effective to improve and survival so image processing as a decisive tool can help the physician to diagnose cancer early **[1]**. Bone cancer is a condition that develops as a result of uncontrolled growth in the bone's tissues. Curing the sickness totally is possible through the early discovery of cancer. The necessity of procedures for recognizing the presence of cancerous nodule in beginning phase is getting attention these days.

In a phase known as metastasis, growth that extends beyond the bone and to other parts of the body. When uncontrolled growth is detected early on, it opens the door to a variety of treatment choices, reducing the chances of unnecessary surgery and increasing the chance of survival. Surgery, chemotherapy, and radiotherapy are also options for treatment. Survival rates differ based on many factors. The stage of the disease, general health, and other factors all play a role, but only 14% of people diagnosed with bone cancer survive five years after their diagnosis. Often it's impossible to tell what stage of illness you're in because the symptoms aren't visible.

There are three modalities regularly utilized for bone imaging: MRI, CT scan, and X-ray. A potential sarcoma appears as an opening within the bone on an X-ray. To create a grey scale representation of the body, electromagnetic radiations are used in x-rays which are of high-energy. CT imaging, which works similarly to an X-ray, is used to produce images of the body which is cross-sectional. Magnetic Resonance Imaging (MRI) is a technique that uses powerful magnets and radio waves to create an accurate picture of a specific body part. More data and resolution are available with X-ray and CT imaging. As a result, hybrid imaging modalities are often used to incorporate the benefits of various techniques while addressing their shortcomings.

In 2009-2013, in England 55% Survive bone sarcoma for 10 or more years, and bone sarcoma survival is highest at age limit 15-59 years. In last 25 years, survival rate of bone sarcoma survival rate has not changed in England **[2]**.

In this paper, we propose bone cancer detection method at low cost using X-ray images. Utilizing a proficient preparing method is considered as a fundamental step to improve the in general visual representation of clinical pictures, and as an outcome gives better results. We use various image processing techniques such as contrast enhancement, classification and edge detection using CNN(Convolution Neural Network) to detect cancerous tissue in the bone in a simple, fast, and reliable way.

The paper is organized as section 1 which gives the brief introduction and overview of the bone cancer, section 2 gives the literature review, section 3 is about system proposed for problem statement, and section 4 is about conclusion.

II. LITERATURE REVIEW

Following section gives you the literature survey on different techniques on detecting bone cancer. Survey includes various techniques used for preprocessing, segmentation and other process applied on various biomedical images.

HelaBoulehmi et al [3] has proposed GGD analysis technique. Commonly known as bone malignancy, Bone sarcoma is a rare condition characterized by irregular tissue development within the bone and a high risk of spreading to other areas of the body. Teenagers and young adults are commonly affected. With respect to any remaining sorts of cancer (brain, stomach, lung...), there are no distinguished reasons for bone malignancy. In this manner, just an early identification could assist expanding the odds with enduring a bone sarcoma. Combining image processing techniques with medical imaging approaches (like X-rays, MRI, and CT scans) can help identify bone tumours with greater precision.

Hossain E[4] has suggested the study of connected components and neural networks required for the identification and then classification of tumour cells of the bone MR images. The bone tumour can be detected by using algorithm known as connected component labelling. The Artificial Neural Network (ANN) is used in this study to identify bone tumours. In this study, bone MR images of recently examined patients are collected, and the texture features of these images are used to train and evaluate the neural network. By removing the high- frequency noise main edges of the objects are conserved by Although anisotropic diffusion filter (ADF).

The tumour can become shaded, making it difficult to detect. One of the most robust classification algorithms is the proposed ANN approach. The proposed classification method has a 92.5 percent accuracy rate, which is satisfactory.

NGOC-HUYNH HO [5] has proposed, On radiographs, Regenerative Semi-Supervised Bidirectional W-Network Based Knee Classification of bone tumors led by three-zone bone division. This paper is a shows new development and evaluation Deep learning architecture, i.e., a W bidirectional network, which is semi-supervised regenerative (RSS – BW), for tumor prediction of Knee bone condition from radiographs. First, the knee bone is divided into three regions i.e. the femur, tibia, and fibula, by constructing an bidirectional W-network which is an automatic coding model. Using these regions as input data, the RSS - BW architecture consists of an automatic coding model for bone regeneration Structures, which is an backcone model for feature extraction uses a pre-trained images, and then model is established for knee bone tumor classification which is predicting model.

To improve diagnosis accuracy, an automated system was created that can distinguish tumour states by reducing noise from X-ray scans. The proposed RSS-BW model was shown to achieve acceptable performance with higher accuracy than traditional models, suggesting that it could be used in clinical settings.

Abhilasha Shukla et al [6], In this paper, present an analysis of bone cancer and features that can be used to predict the form of cancer. This paper discusses related work that uses computer vision to detect cancer in the human body. The techniques described in the following paper, such as Sobel, Prewitt, Canny, and Region Growing Image Segmentation, can be used to segment x-ray and MRI images. The results of edge-based and area-based image segmentation techniques applied to an X-ray image to detect osteosarcoma carcinomas on the bone using MATLAB are also shown in the paper. Finally, the paper came to a conclusion by determining the best segmentation approach for a greyscaled picture with potential implications.

The results show that k-mean and region-growing image segmentation techniques appear to be the best for detecting tumour bone from X-Ray images.

Terapap Apiparakoon et al. [7] present a new neural network model for dividing and classifying irregular hotspots, which is a semi-supervised treatment of bone cancer metastases in the chest. MaligNet, the proposed model, is an instance segmentation model that uses ladder grids to capture both labelled and unclassified data. A data set will be produced using labelled and unlabelled data from 544 and 9280 to evaluate the proposed model's results. The proposed model outscored a convolutional neural network based on the core mask area, the Mask-R, CNN, by 3.92 percent, with mean precision, sensitivity, and F1score of 0.852, 0.856, and 0.848, respectively.

In the metastasis classification mission, the model achieves a sensitivity of 0.657 and a specificity of 0.857, indicating the great potential for automated diagnostics using bone scintigraphy in clinical practise.

Eftekhar Hossain [8] proposed a paper which defines Bone cancer detection and classification technique using fuzzy clustering and neuro fuzzy classifier. This research looks at using a fuzzy C-mean clustering tool to identify bone cancer. To test the accuracy of the proposed procedure, a total of 120 magnetic resonance imaging (MRI) images of the bone were used. The Adaptive Neuromuscular Inference System (ANFIS) was used to distinguish both benign and malignant bone cancer in this research.

GLCM was taken from MR images to train and test the ANFIS network. A correct cross-validation was performed on bone images captured for separation into training and test images. The accuracy, sensitivity, and specificity of the classification result were evaluated using three output matrices: accuracy, sensitivity, and specificity. The proposed method of bone cancer classification has a 93.75 percent accuracy rate.

Azmira Krishna [9] propose a system to detect cancer cell in the first stage using CNN and water shed based segmentation. Cancer is a great danger to human life. About 74 percent of people who are diagnosed with cancer die as a result of their illness. Cancer cell detection at an early stage may minimize death rates. CT (computed tomography) is one of the most popular methods used by oncologists to detect cancer cells. Computer-assisted cancer detection plays a critical role in early cancer detection. The classification of CT images is the first step in computer-assisted cancer cell detection. For effective classification CT of the scanned images, the CNN-based classification method which is combined with Gaussian filtering which includes watershed segmentation.

500 CT scans of the bones, brain, lung, kidneys, and neck were obtained from Manipal Hospitals and Vijayawada's Department of Oncology. CNN classification based on CT image scans achieves a 94.5 percent accuracy score.

Eftekhar Hossain [10] suggests a study in which the position of bone lesions is determined using a wavelet-based segmentation technique. The separated bone tumour section is also ready for classification. The k-closest neighbour (KNN) classifier is used in this study to classify bone tumours as cancerous or non-cancerous. For the development of a learned classifier model, various pictures are gathered and GLCM features are separated from these pictures. 92.5% accuracy was obtained for the proposed model which used KNN classifier.

Riandini [11] proposes a system in which the K-Nearest Neighbor (KNN) and highlight extraction methods are used to compute and investigate algorithms for x-ray image characterization. On small example size information of 46 Thorax x-ray pictures, Gray Level Co-event Matrix (GLCM) was used. T-score of these pictures had been estimated utilizing DEXA scan before as an avocation. The proposed technique uses the GLCM and KNN feature extraction and image classification strategies to estimate the thickness of the clavicle cortex.

Besides, the precision which is acquired from the whole usage capacity in accurately surveying osteoporosis is 97.83%.

Kishor Kumar Reddy [12] proposes a method for determining tumour size and determining the cancer stage based on the size. According to the growth zone algorithm, scanned images of various parts of the human body are obtained from various diagnostic laboratories, and segmentation is used to assess the tumour, from which the tumour size and stage on which the tumour depends are experimentally determined.

The values of tumour size for the respective bone cancer images are tabulated based on the experimentation. A If the tumour size is less than 5, it is classified as Stage 1, and if the tumour size is greater than 5, it is classified as Stage 2.

PATRICE MONKAM [13] provides a thorough review of these approaches and their performance. The authors give comprehensive overviews of recent developments in lung nodule analysis using CNNs. CNNs have been shown to have a positive impact on lung cancer early detection and treatment. They hope to demonstrate how sophisticated deep learning methods can be used to analyse pulmonary nodules. A summary of various CNN-based methods for pulmonary nodule detection and classification developed in 2018 is presented. Other deep learning models, such as recurrent neural networks (RNNs) and auto-encoders (AEs), were not considered because of their higher computational complexity and lower recognition efficiency when compared to CNNs.

Applying CNNs to the identification of pulmonary nodules, as well as their classification into malignant and benign, has yielded impressive results, making them a promising approach to improving lung cancer early detection, treatment, and management.

WANGXIA ZUO [14] proposed a multi-resolution convolutional neural network (CNN) for classification of lung nodule candidates that extracts features of various levels and resolutions from different depth layers in the network. To begin, we move information from the source CNN model, which has been used for edge detection and model optimization, to a new multi-solution model that is suitable for image classification. Then, information is moved from the source training progression to Calculation, which takes into account all of the model's side-output branches. Furthermore, the objective equation and loss function have been changed to be an image-wise computation rather than a pixel-wise calculation. To train and evaluate the classifier designed to identify candidate lung nodules, sample production and data optimization are completed.

The experimental results on the LUNA16 dataset show that when used to identify the lung nodule filter, our system achieves an accuracy of 0.9733, a precession of 0.9673, and an AUC of 0.9954. Furthermore, by using test samples in three different sizes for multi-resolution CNN testing (26x26, 36x36, and 48x48), the accuracy for all three trials surpassed 92.81 percent.

Madhuri Avula Narasimha [15] proposed a study study, which used the kmeans clustering algorithm to segment bone images. By measuring the mean density of the selected area, the segmented image is also processed for bone cancer detection. To identify medical images for the presence or absence of bone cancer, threshold values have been proposed. This system uses jpeg files, but if any changes are made, it also works with the original DICOM (digital medical communication imaging) format.

The identification of bone cancer is improved with the use of mean pixel intensity value thresholding. This paper proposes a computer-aided diagnostic method for detecting bone cancer from CT scan or MRI images, which is also applicable to DICOM(digital imaging communication of medicine) medical images in their original format. This approach yields 95 percent accuracy while requiring less computation time.

Raul Victor Medeiros da Nóbrega [16] proposed method which aims to investigate the efficiency of deep transfer learning for lung nodule malignancy classification. Convolutional Neural Networks (CNNs) such as VGG16, VGG19, MobileNet, Xception, InceptionV3, ResNet50, ResNetResNetV2, DenseNet169, DenseNet201, NASNetMobile, and NASNetLarge have been used as function extracts for exploiting the Image Database Resource Initiative and the Lung Image Database Consortium (IDRI / LIDC) have been used for this purpose. After that, Naive Bayes, MultiLayer Perceptron (MLP), Support Vector Machine (SVM), Near Neighbors (KNN), and Random Forest (RF) classifiers were used to classify the deep features returned. In addition, rating scales Area Under the Curve (AUC), Accuracy (ACC), Precision (PPV), True Positive Rate (TPR), and F1-Score were computed to equate classifier output with itself and others in the literature.

CNN-ResNet50 with SVM-RBF was the best deep extractor and classifier combination, with an ACC of 88.41 percent and an AUC of 93.19 percent. Even with CNN previously tested on non-clinical videos, these findings are comparable to relevant work. As a result, deep transfer learning has proven to be a useful technique for extracting representative imaging biomarkers from CT chest images for classification of lung malignant nodule tumours.

Sarfaraz Hussein [17] proposes a multiview deep Convolutional Neural Network model for nodule characterization (CNN). To begin, we use median intensity projection to create a 2D patch for each dimension. After that, the three images are combined to form a tensor, with the images acting as separate channels for the input image. The trained network is used to extract features from the input image using the malignancy score, followed by a Gaussian Process (GP) regression. The results are complementary to deep multi-view CNN, though there are several enhancements to be found.

These characteristics were discovered to be extremely important and to be complementary to the multi-view deep learning features.

Finally from **Azmira Krishna** we obtain the performance of CNN using MATLAB 2018b tool is used for CT images. The table shown below gives the Performance measures using Accuracy, Specificity and Sensitivity. Above performance is tried to be achived for X-ray images.

Class	Accuracy	Specificity	Sensitivity
Kidney	94.5	92	90
Brain	93.2	90	89
Lung	95	93	93
Bone	93	92	93
Neck	92	94	93

Table: performances of CNN on various class

I. PROPOSED SYSTEM

Problem Statement: Detection of bone cancer in the early stages at low cost help in the fast recovery and methods like invasive surgical methods can be avoided to cure the cancer.

From the technologies discussed in the literature survey, we propose a system for the early detection of the bone cancer at low cost using X-ray images and early stages. We use supervised classification method using CNN.

From the problem statement stated above we propose a system to extract the features of bone tumor and it used to increase the resolution and efficiency level of an input. Medical imaging technique which we saw in previous section, from which X-ray scans are considered for imaging process. In the proposed system, the system design is made for detecting the Bone cancer in early stage.

Steps to be followed in this system are Preprocessing, Feature selection, Feature extraction, & Classification.

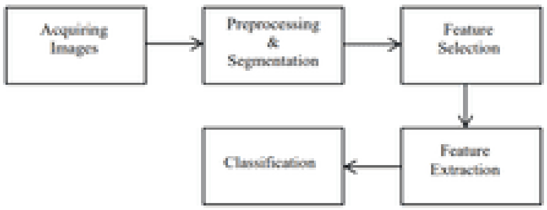

Figure 1: Block Diagram

Preprocessing

Filtering, Histogram equalisation, Image enhancement, noise reduction, and other pre-processing methods must be used to remove the affected component from the images without any noise or blur. Python programme is used for the majority of the image preprocessing. The aim of image preprocessing is to eliminate redundancy in scanned images selectively without affecting information that are essential in the diagnostic phase.

Grayscaling is a technique for converting images from other colour spaces to shades of grey, such as RGB, CMYK, HSV, and so on. It can be completely black or completely white.

When the data in the picture is represented by near contrast values, histogrsm equalisation normally increases the global contrast. This modification could improve the distribution of intensities on the histogram. The majority of the details would be lost due to excessive lighting. This is due to the fact that each histogram is not limited to a single area. For Histogram equalisation, the image's global contrast will be taken into account.

The above problem can be solved using adaptive histogram equalisation. The picture is divided into small blocks called "tiles" in this case (8x8 will be the tile size by default in OpenCV). The histograms for each of these blocks are then normalised. The histogram will be limited to a small area within a small area. Noise would be intensified if it exists. Contrast limiting is used to prevent this.

Edge detection can detect a significant change in the grey level of an image. By reducing the amount of data in the image, it retains the structural properties of the image.

Sobel Operator: a discrete differentiation operator called the Sobel Operator. For image edge detection, a gradient approximation of the image intensity function is computed. At the pixels of an image, the sobel operator produces either the normal or the corresponding gradient vector.

Prewitt Operator: The Prewitt Operator senses an image's horizontal and vertical edges and is similar to the Sobel Operator.

Laplacian of Gaussian (LoG): The Laplacian of Gaussian (LoG) is a gaussian-based operator that uses the Laplacian to take the second derivative of an image. When the grey transition seems to be sudden, this works very well. It is based on the zero crossing method of operation.

Canny Operator: In terms of detecting edges, the Canny Operator is identical to the gaussian-based operator. This operator is impervious to noise. The image features are extracted without affecting or altering the feature image. The canny edge detector uses an algorithm derived from the Laplacian of Gaussian operator's earlier work.

As a result of the above, its recommended using Grey scale conversion because it reduces the amount of data needed to display an image. Before using segmentation, use a filter to minimise noise. Canny edge detector is used because of its advantages and because it uses gaussian filter inherently for smoothing before doing segmentation, as discussed in the literature survey by Abhilasha shukla et al.

Feature Selection and Extraction

Variable selection is another name for feature selection. It is the method for selecting a limited number of useful features for potential use. Preprocessing must pick features or regions from the preprocessed image using a genetic algorithm, which is the best at selecting features for biomedical images.

The process of accurately determining the amount of resources needed from a wide collection of data is known as feature extraction. The Extraction stage, which uses Bone Cancer Detection, is a critical stage. Detecting different desired portions or forms using CNN algorithms and techniques. It is necessary to extract the selected features (affected part). The GLCM displays how often different pixel values appear in an image. To begin, use CNN's graycomatrix function to generate a gray-level co-occurrence matrix from an image. The second order conditional joint probability densities of each of the pixels are denoted by a GLCM, which is the probability of grey levels I and j occurring within a given distance 'd' and along the direction 'θ' **[18].**

Classification

In deep learning, a convolutional neural network is a form of deep neural network. The uses can be found in the analysis of visual imagery. Because of their invariance characteristics and shared-weights architecture, they are also known as shift invariant/space invariant artificial neural networks (SIANN).

The term "convolutional neural network" refers to the network's use of convolution, a mathematical process. Convolutional networks, which are a particular form of neural network, use convolution rather than general matrix multiplication in at least one of their layers. An input layer, hidden layers, and output layer are all components of a convolutional neural network. Any feed-forward neural network's middle layers are referred to as secret because their inputs and outputs are covered by the final convolution and activation function. Convolution layers are used in the secret layers. Essentially, it consists of a layer that performs multiplication or other dot products, with ReLU serving as the most common activation mechanism. The following layers are pooling layers, completely linked layers, and normalisation layers. A convolutional network (CNN) is used for classification, as discussed in Azmira Krishna's literature review.

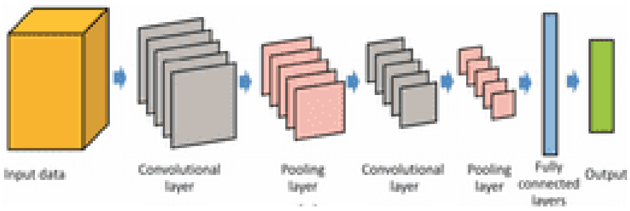

Figure 2: CNNs architecture used in medical imaging

Convolutional layer, pooling layer, fully-connected layers are crucial components of CNNs, as discussed in Kishor Kumar Reddy C, as shown in Figure 2.

The main method for achieving feature discovery in CNNs is convolution, which is done by convolutional layers.

It entails performing a "dot product" mathematical operation on matrices of weights over the entire content of each sample of input data (images, videos, etc.) to produce feature maps.

Pooling is another crucial activity in CNNs. It is often used following the convolution method. Pooling reduces the output's dimensionality, allowing for the retention of more important essential features.

III. CONCLUSION

In this paper we have studied the basic mechanism for tumor detection. In this review article we have specifically focused on the bone cancer detection using greyscale conversion, Canny edge detection for segmentation, GLCM for feature extraction and CNN for classification.

We propose a system which is of less cost and could be checked in during regular checkup which increases efficiency of detecting tumor in early stage. Thus our proposed system provides a different way for detecting the bone cancer with high accuracy.

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