# Detecting Bone Tumor on Applying Edge Computational Deep Learning Approach

G Megala, P Swarnalatha and R Venkatesan



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Megala G[1[0000-0002-8084-8292]], Swarnalatha P[2[0000-0001-9943-8085]] and Venkatesan R[3[0000-0002-4336-8628]]

[1,2] Vellore Institute of Technology, Vellore 632014, India
[3] SRM TRP Engineering College, Tiruchirappalli. 620014, India
megala.g@vit.ac.in

**Abstract.** Bone cancer (BC) affects the majority of the elderly in today's world. It directly affects the neurotransmitters and leads to dementia. MRI images can spot bone irregularities related to mild cognitive damage. It can be useful for predicting bone cancer, though it is a big challenge. In this research, a novel technique is proposed to detect Bone cancer using Adaboost classifier with a hybrid Ant Colony Optimization (ACO) algorithm. Initially, MRI image features are extracted, and the best features are identified by the Adaboost curvelet transform classifier. The proposed methods yield better classification accuracy of 97% on analyzing MRI images and detecting the bone tumor in it. Three metrics namely accuracy, specificity, and sensitivity are used to evaluate the proposed method. Based on the results the proposed methods yield greater accuracy than the existing systems.

**Keywords:** Ant Colony Optimization, Adaboost Classifier, Bone Cancer, Curvelet Transform, Convolutional Neural Network.

## 1 Introduction

One crucial aspect of cancer diagnosis that must not be disregarded is the ability to properly divide photos into numerous portions. The most popular and crucial medical examination techniques for projecting the infected segment to the foreground from a bone structure are magnetic resonance imaging and computed tomography. The process's purpose (image segmentation) is to separate the image into several segments, each of which is represented in a less complex manner, and then extract meaningful information from the segmented regions. The goal of this study is to use MR scans to detect the existence of a bone malignancy. Image intensity levels have two essential characteristics: discontinuity and similarity. By locating the changes in intensity across the image, discontinuity aids the segmentation process [1].

The process of picture splitting begins with the detection of edges and intensity differences. Support vector machine, K-nearest neighbor, and adaptive neural fuzzy inference system are some of the most popular and widely used classification algorithms. Each one follows its own set of rules. For classification, the first described classifier employs a differential technique. The second method makes use of the feature's similarity principle. The third technique combines neural networks and fuzzy logic, with the neural network assisting in determining the fuzzy system's requirements [2].

For the photo segmentation process, there are pre-set standards. It divides the photo into corresponding regions with similar features, using the pre-set standards. Most present procedures necessitate the manipulation of numerous elements in order to achieve effects with great accuracy [3]. The multi-sensor scales, on the other hand, can function even if the aforesaid conditions are not met. Sarcoma of the Bone is a rare type of bone cancer. One of the agents known to cause bone sarcoma is excessive ionizing radiation exposure.

The structure of this article can be briefly chronicled as follows: Section 2 comprises the extensive Literature Survey. Section 3 explains the proposed technique ad boost curvelet transform classifier and Ant colony optimization algorithms respectively. Section 4 encompasses results and discussion followed by the conclusion of the paper.

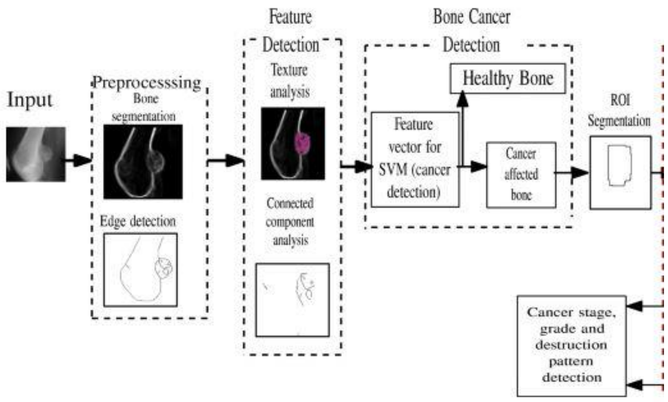


**Fig. 1.** Overall Architecture for Bone cancer Net model

## 2 Related Works

Globally, one of the most fatal diseases is bone cancer and hence its detection and treatment is an area of intense research. Its intricate tissue structure makes the process even more complicated. The study involves the use of the Deep learning method on three major bone cancer types. It can be deduced from the research that nuclei count is paramount to defining the state of malignancy. The results from the study showed increased accuracy and performance [4].

The importance of early detection in the treatment of cancer cannot be overstated. Using image processing techniques, the study provides a cost-effective and simple way of detecting lymphatic cancer. The retrieved feature parameters are used to differentiate the normal tissues from the malignant lesions. The integration of image processing with machine learning algorithms such as SVM and random forests results in enhanced accuracy [5][6]. N-fold cross validation is performed on the selected features while training.

Segmentation and classification are very vital processes to locate fractures in bones. The proposed Wavelet Transform-based segmentation technique not only keeps the important information of the image, but it yields an appropriate segmented image. Results prove that the proposed method is viable for all types of X-ray images with enhanced accuracy [7]. For metastatic bone lesions in prostate cancer patients, the study proposes a classification system based on deep learning. In order to establish the best possible technique for bone lesion categorization, deep classifiers were employed using a lesion extraction plan. Research proves that the part revealing the maximum information of a lesion image is texture followed by volumetric information [8].

The process of cancer detection can be enhanced through continuous research. The paper proposes a method of Convolution Neural Networks, supervised learning, and morphological operations were used. Classification of the type of cancer is carried out through CNN which reduces training time to a considerable extent. And from the extracted portion, the percentage area of cancer is evaluated. The integration method is proven to be more practical rather than using individual methods [9]. Using machine learning, the study aims to make a comprehensive analysis for the diagnosis and cure of cancer in different organs/parts of the human body. The effective application of different machine learning techniques such as supervised, unmonitored, and deep learning is demonstrated in the study. Solving the complications related to cancer diagnosis and accurate treatment is a challenging process [10].

Using different techniques of machine learning, the research encompasses a comprehensive assessment of all the processes and developments involved in cancer detection. It also undertakes a comparative analysis of many methods and highlights their advantages as well as disadvantages. Finally, it brings out the challenges and aspects to be incorporated for future work in order to enhance the process of cancer detection and cure [11].

A multi-stage process using automatic image processing for early detection of melanoma skin cancer is proposed. Adaptive principal curvature helps in the first stage, color normalization is used for separating the lesions and the ABCD rule is deployed for feature extraction. Experimental results of the proposed method show higher accuracy and enhanced speed [12].

A structured review of sixteen works involved in the detection of leukemia using machine learning is carried out in the research. It can be inferred that compared to other existing techniques deep learning proves to yield better results with regard to precision. The study also encourages the use of ML techniques by technicians in laboratory applications [13].

The importance of early discovery and classification of ruptures caused by proximal humerus fractures cannot be overstated. The goal of this research is to see if a deep learning algorithm can help with the above process. After that, a deep convolutional neural network was trained, which resulted in great accuracy. The findings demonstrate the effectiveness of artificial intelligence in detecting and classifying proximal humerus ruptures [14].

Acute Lymphoblastic Leukemia and Multiple Myeloma are classified differently. is a time-consuming and error-prone manual technique. The study uses the SN-

AM dataset to reduce mistakes made during the manual procedure and save time. In comparison to traditional machine learning techniques, the suggested model achieved an overall accuracy of 97.2, making it a useful method for identifying the type of malignancy in the bone marrow [15].

The paper proposes a multi-step process for enhancing bone cancer segmentation. The success of the system in accurately detecting the tumor is because of using a fuzzy-possibilistic classification algorithm. The isolated cancer tissue from the experiment after surface measurement yields satisfactory results [16].

Based on spectral intensity ratios, the study proposes a classification technique for three bacteria. The function of autofluorescence microscopy prompted by light was also thoroughly examined in the work. In order to fulfill experimental conditions, the unnecessary lights were removed with the help of narrowband filters. The classification yielded very high sensitivity and specificity [17].

In order to aid both investigative and remedial processes, the paper deploys CNN and Open CV Python for the identification of bone tumors and prediction of the different phases of cancer. Training data is utilized to distinguish malignant cells from those of non-cancerous ones. The method requires less manual intervention and is proven to be cheaper [18][19].

## 3 Methodology

### 3.1 AdaBoost Curvelet transform Classifier

To extract features from MRI images, the curvelet transform is used. The wavelet-based retrieval of the image is done to extract features without directional sensitivity. A multiresolution geometric analysis curvelet transform is done to the discrete wavelet transform to address the missing directional selectivity.

For a multiple scale analysis, the image f (x, y) is represented as a continuous ridgelet coefficient expressed as in equation (1), and the curvelet transforms can broaden their ridgelet transforms:

$$R_f(a, b, \theta) = \iint \psi_{a,b,\theta}(x, y) f(x, y)\, dx\, dy \tag{1}$$

In which $a, b$ denotes the scale parameter, with a > 0, b. $R_f$ denoting the translation parameter, and $\theta$ denoting the orientation parameter. All of these coefficients are used to reconstruct the image, and the ridgelet is defined in equation (2).

$$\psi_{a,b,\theta}(x, y) = a^{\frac{1}{2}} \psi\left(\frac{x\cos\theta + y\sin\theta - b}{a}\right) \tag{2}$$

The wavelets are the ridges' transverses, and $\psi$ denote the orientation of a ridgelet, which is a constant line defined by x cos $\theta$ + y sin $\theta$ = const. Ridgelets are the basic building pieces for achieving a high anisotropy that captures edges better than a traditional sinusoidal wavelet (Fatma Taher & Naoufel Werghi 2012) [9]. Also, the curvelets spectra envelop the image completely in the frequency plane and hence it is a powerful and effective tool to extract image features.

The 2-D image is represented by the Cartesian array f [m, n], $0 \le m < M$, $0 \le n < N$ is transformed to the curvelet based on Fourier sample wrapping. A scale j, an orientation l, and two different spatial location factors have been used to index the resulting curvelet coefficient (k1,k2). The image is broken down into multiple subbands with different scales and orientations. Curvelet texture descriptors are created using statistical procedures, and these discrete curvelet coefficients are determined using an equation.(3):

$$C^D(j,l,k_1,k_2) = \sum_{0\le m\le M} f[m,n]\phi^D_{j,l,k_1,k_2}[m,n] \tag{3}$$

In which, each $\phi^D_{j,l,k_1,k_2}[m,n]$ designated digital Curvelet waveform in this frequency range has sub-bands that use the effective parabolic scaling law. The image is decomposed into Oscillating behavioural edges exhibited through the curvelets. These wrapping-based transforms can be considered multi-scale transforms which use pyramid structures with a number of orientations on both scales [20]. The curvelets are generally realized in the frequency domain to achieve the best efficiency. They are robust to be used in medical image feature extraction due to their capability of approximating curved singularities in edge-based features. Fourier product of the curvelet and image transformed in the frequency domain is done. Applying Inverse Fourier to the image-curvelet product yields the curvelet coefficients.

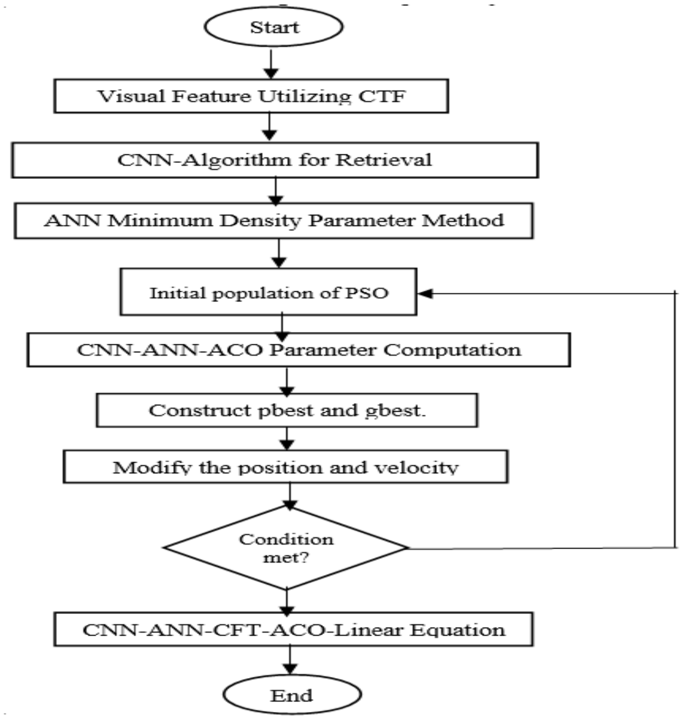


**Fig. 2.** Proposed Bone Cancer Detection

### 3.2 Ant Colony Optimization

Pre-processing methods for MRI images improve the detection of problematic areas. Two phases involved are the pre-processing and augmentation technique. To begin with, a positioning system removes MRI film artifacts such as labels and X-ray tags. Second, the Ant Colony Optimization (ACO) technique is used to get rid of high-frequency components. Comparing the results of the DL-EDAD technique to those of the median, adaptive, and spatial filter systems. Before extensive data interpretation and separation, pre-processing including tracking functions that include noise removal is frequently necessary. This pre-processing is frequently characterized as radiological or geometrical improvements.

The pheromone concentration of the paths and an intuitive assessment are the only criteria used to choose high-frequency segments. A specific ant, k, choose which node to move to next throughout the construction process using a probabilistic action selection rule that calculates the likelihood that ant, k, will move from the current node, i, to the following node, j.:

$$p_{ij}^{k} \frac{[T_{ij}]]^{\alpha}[n_{ij}]^{\beta}}{\sum_{\substack{k \\ Ni}} [T_{ij}]^{\alpha}[n_{ij}]^{\beta}} if\ j \in N_i^k \tag{4}$$

Here $T_{ij}$is the arc or edge from node i to j.$N_i^k$implies the neighboring nodules for a specific ant k, consideringnode i as start node. The constants correspond to the subject and initutivechanges, respectively. Finally, $n_{ij}$indicates the heuristics movements from node i to j.

In the proposed approach, all of the images were focused on the sensory receptors. Various fields can be found inside a photograph. The images were taken from the Kaggle dataset repository, which in this case included a variety of images. For the assessment of pixel intensities in various sectors, there are significant factors. There were captured about 50 images of the multiple patients. The actions and performance of the patient are ensured to be normal and accurate by the approach.

**Algorithm 1:** Training visual modal on modified CNN

**Input:** BC image of size 256*256 *3
**Output:** The weight parameters in .pkl files for no of EPOCHS and BATCH.

1. Import tf , cv2, numpy,
2. Define hyper parameters that are as follow
   Learning rate = 0.5, Batch size = 25, Epochs = 2
3. Initialize placeholder.
4. Create tf session using tf.sessiontf.Session(config=config) .
5. Import model and initialize with preprocessed vggface model.
6. Initialize optimizer, we used Adam optimizer and pass it with learning rate as mentioned above using tf.train.AdamOptimizer(learning_rate=LEARNING_RATE).
7. Read image data and labels from tf record reader with function tf. TFRecordReader() and decode it.
8. Shuffle the batch with function tf.train.shuffle_batch().
9. Run the tf session and store the weight parameters in .pkl files for no of EPOCHS and BATCH.
10. Save the whole session and dump it to files to use in prediction using tf.train.Saver().

## 4 Experimental Analysis

This section makes use of the BC-Ada boost, BC-PCA-Ada boost, BC-PSO-Ada boost, and BC-PCA-ACO-Ada boost. The number of classification trees can be maximized upto 300. The tree depth can be maximized upto 6. Table 1 is a summary of the findings. The categorization accuracy is shown in Fig.3, the true positive and true negative rates are shown in Fig. 4 and Fig. 5.

**Table 1.** Results

| | Adaboost | CNN-ACO-Adaboost | ANN-ACO- Ada-boost | CNN-ANN-ACO | CNN-ANN-ACO Adaboost |
|---|---|---|---|---|---|
| Accuracy | 82 | 85 | 88 | 91 | 93 |
| Normal True Positive | 89 | 91 | 92 | 95 | 96 |
| True Positive MCI | 67 | 73 | 80 | 82 | 85 |
| True Positive BC | 57 | 58 | 67 | 75 | 78 |
| True Negative Normal | 78 | 81 | 84 | 88 | 90 |
| True Negative MCI | 92 | 93 | 95 | 96 | 98 |

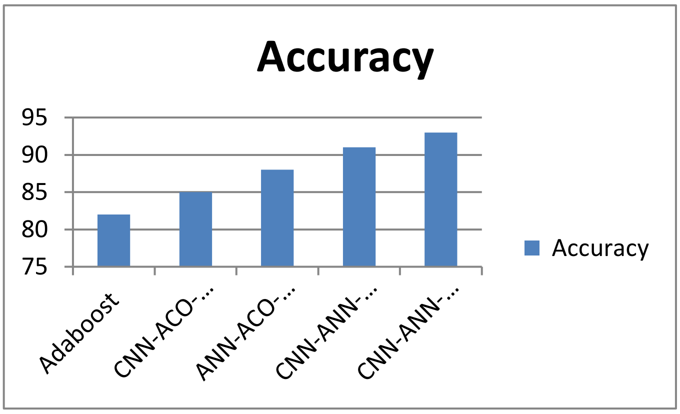


**Fig. 3.** CNN-ANN-ACO-Adaboost accuracy

In Fig 3, it is found that the BC_ANN-ACO-Adaboost has improved classification accuracy by 16.47% than BC-Ada boost, by 12.72% than BC-PCA-Adaboost and by 5.21% than AD-PSO-Ada boost and by 3.34% BC-CNN-ANN-ACO-Ada boost.

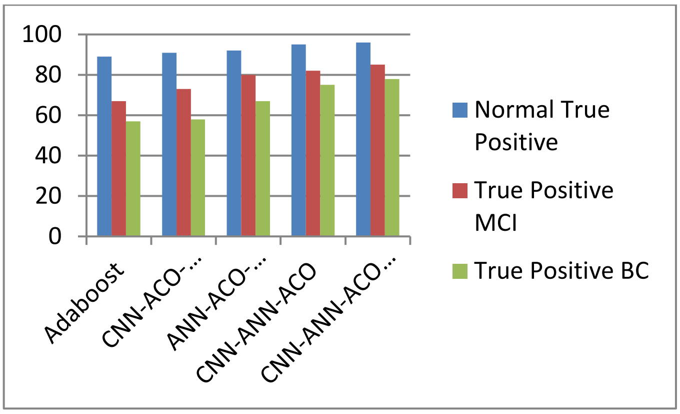


**Fig. 4.** True Positive Rate for BC-CNN-ANN-ACO-Ada boost

The average true positive rate for Adaboost is 9.75% for BC-CNN-PSO-Adaboost, compared to 6.73% for BC-ANN-Ada boost and 3.54% for BC-ACO-Ada boost and 3.21 for BC-CNN-ANN-ACO-Adaboost, as shown in Fig. 4.

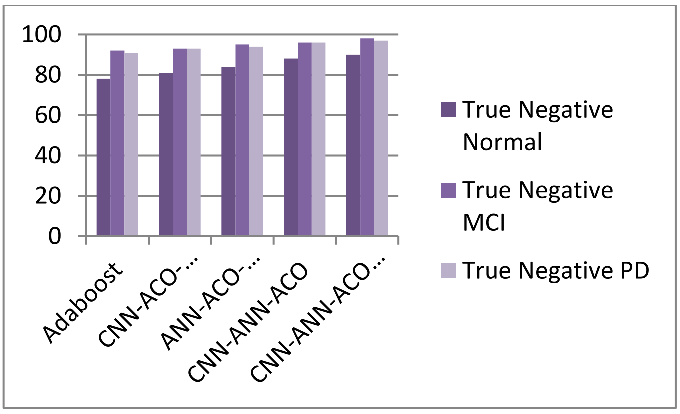


**Fig. 5.** True Negative for BC-CNN-ANN-ACO-Adaboost

Fig. 5 shows that the BC-CNN-ACO-Adaboost has a higher average true negative rate for Adaboost than the Pd-PCA-Adaboost, the BC-CNN-Adaboost, and the BC-ANN-Adaboost and BC-CNN-ANN-ACO-Adaboost.

**Table 2.** Classification Results

| Classification | F-Measure | Sensitivity | Specificity | Accuracy |
|---|---|---|---|---|
| BC-Ada boost | 82.8 | 75.9 | 84.5 | 70.02 |
| BC-CNN-Ada boost | 76.2 | 77.9 | 89.7 | 76.06 |

| | | | | |
|---|---|---|---|---|
| BC-ANN-Ada boost | 90.77 | 84.1 | 91.28 | 86.03 |
| BC-ACO-Ada boost | 83.15 | 76.03 | 84.27 | 88.07 |
| BC-CNN-ANN-Ada boost | 85.4 | 78.4 | 86.5 | 90.2 |
| BC-CNN-ANN-ACO-Adaboost | 90.05 | 80.56 | 88.7 | **97.02** |

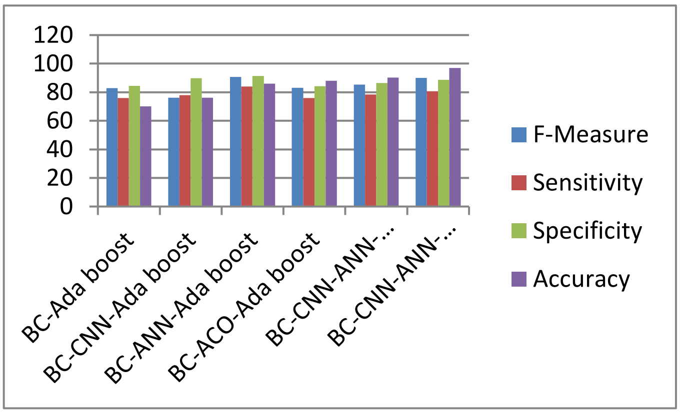


**Fig. 6.** Bone cancer detection results

Fig. 6 shows that the BC-CNN- bonce cancer detection achievement for Ada boost than the BC-ANN-Ada boost, the BC-CNN-Ada boost, and the BC-ANN-ACO-Ada boost and BC-CNN-ANN-ACO-Ada boost

## 5 Conclusion

In this paper, an edge computational deep learning approach is proposed to detect the tumor found in bone MRI images. Detecting Bone cancer is the hardest part which must be diagnosed at an early stage due to its devasting effects. It has been found through a review of the relevant literature that there are several methods used to detect bone cancer, each with its own set of advantages and disadvantages. In the proposed procedure, features are initially extracted by preprocessing, edge detection, morphological operation, segmentation, and testing, before being used to train and evaluate the neural network. CNN with Adaboost curvelet transform classifier methods are used to detect bone malignancy. Finally, the procedure produces the desired result for the system. The experimental analysis shows that the accuracy of 97.02% is achieved corresponding to the ground truth values. In future, other optimization techniques such as elephant herding optimization, shuffle frog leaping optimization and butterfly optimization are to be implemented for improving the performance.

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