Tumor Classification in Osteosarcoma Using Convolutional Neural Network

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Abstract--- *Oesteosarcoma is the most common type of cancer that starts in the bone and it can spread through all parts of the body. Children between the age group of 10 to 30 and teenagers get affected by primary bone cancer osteosarcoma. It is a rare disease and its end stage tumors are not curable. The aim of this work is to develop a Computer Aided Diagnosis (CAD) system using Convolutional Neural Network (CNN) for Osteosarcoma tumor classification and to minimize the risk of cancer by early diagnosis using the proposed system. This research work is done on the dataset taken from Cancer Image Archive.. The proposed convolutional neural network architecture has been built with ten convolutional layers and the retrieval of accuracy range from 82.14% to 88.64% was achieved. This proposed system can assist the pathologist in diagnosing the Osteosarcoma tumor classification.*

Keywords--- *Medical Image Processing, Deep learning, Convolution Neural Network, Osteosarcoma, Tumor Classification.*

I. INTRODUCTION

Cancer may start at any place in the body and it spreads when the cells grow out of control and crowds out normal cells. There are different types of cancer affecting the human. In this work we have taken a particular cancer type is called Osteosarcoma (Primary bone cancer). Osteo means bone and sarcoma means cancer. This cancer mainly affects the children and teenagers between the age group of 10 to 30. In children and young adults, osteosarcoma usually starts in the areas where the bone is growing quickly, such as near the ends of the leg or arm bones. Osteosarcoma tends to affect the regions around the knee in 60% of cases, 15% around the hip, 10% at the shoulder, and 8% in the jaw and these are the regions were osteosarcoma get affected. Convolutional neural network is a class of deep learning neural network and it is used for classification purpose. The different types of layers used in this process are discussed here. Convolutional neural networks (CNN) are made up of neurons with learnable weights and bias. Each neuron receives some input, performs a dot product and optionally follows it with a non-linearity.

Pooling layer is used for down sampling purpose. The different types of pooling are Max- pooling, Min-pooling, average pooling. Max-pooling is used to calculate maximum value and batch normalization technique is used to improve the speed, performance, and stability of artificial neural networks.Softmax is often used in neural networks, to map the non-normalized output of a network to a probability distribution over predicted output classes as shown in fig 1.

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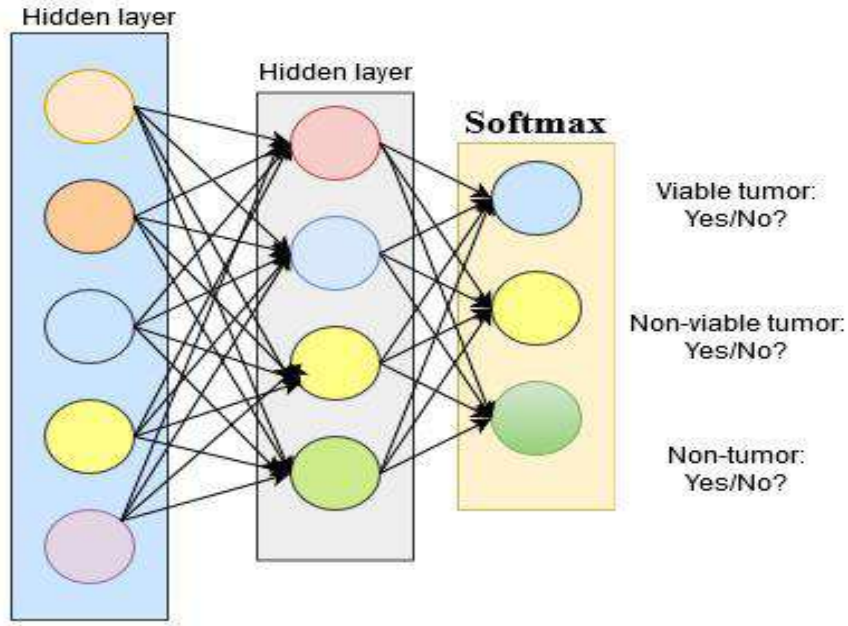

Fig. 1: Softmax Layer

Softmax function is as in Eqn. 1 is a logistic regression function and it normalizes an input value into a vector of values that follows a probability distribution whose total sums up to 1.

$$P\left(Y = \frac{j}{\theta(i)}\right) = \frac{e^{\theta(i)}}{\sum_{j=0}^{k} e^{\theta k(i)}} \quad (1)$$

$$where\ \theta = (\sum_{i=0}^{k} WiXi) = W^T X$$

W-weight matrix, X-Feature matrix, i-position

RELU (Rectified Linear Unit) is a kind of activation function as in Eqn. 2.

$$y = max(0, x) \quad (2)$$

II. Related Works

Related work and existing work are discussed here about tumor classification [1] and most of the existing work for tumor classification involves thresholding with region growing, k means, Otsu and morphological features like area and shape structures. Arunachalam et al presented multi-level Otsu thresholding followed by shape segmentation to identify viable tumor, necrosis and non-tumor regions in osteosarcoma histology slides. Malon et al trained a convolution neural network to classify mitotic and non-mitotic cells using morphological features like color, texture [2], and shape. Convolution neural Networks are used to learn the feature of the image itself and there is no need of any external classifier to learn about the image [3]. In this paper we subject our metabolomic data on osteosarcoma patients collected by the SJTU team used the three classification methods: logistic regression, support vector machine (SVM) and random forest (RF). The performances are evaluated and compared using receiver operating characteristic curves. All three classifiers are successful in distinguishing between healthy control and

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tumor cases, with random forest outperforming the other two for cross-validation in training set (accuracy rate for logistic regression, support vector machine and random forest are 88%, 90% and 97% respectively). Random forest achieved overall accuracy rate of 95% with 0.99 AUC on testing set [4]. Conditional Random Field (CRF) model to incorporate multiple features, especially the texture context features, which are based on the relative position of pixels texture and make a significant difference in more accurately determining which class a pixel belongs to it [5]. A combination of pixel-based and object-based methods which utilize tumor properties such as nuclei cluster, density, and circularity to classify tumor regions as viable and non-viable [6]. A K- Means clustering technique is used for tumor isolation using colour normalization, followed by multi- threshold Otsu segmentation technique classified tumor region as viable and non-viable.

III. PROPOSED METHODOLOGY

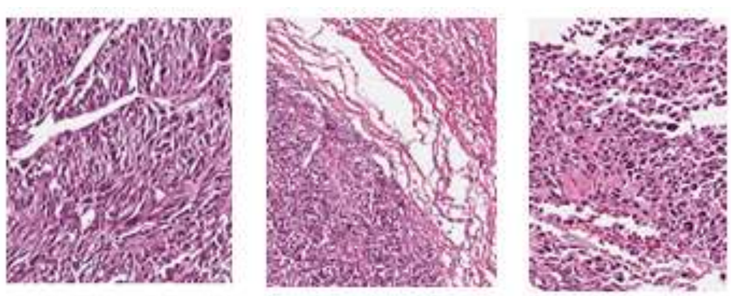
In proposed methodology CNN architecture along with different comparisons are discussed here [7].Constant filter size with different number of filters produces better accuracy. The CNN Architecture consists of different types of layers such as image input layer, convolution layer, max pooling layer, batch normalization layer and some of the activation function such as RELU layer and softmax layer are used in this architecture. In this method ten convolutional layers are used with constant filter size of [5X5] and the number of filters get ranging from 16 to 160. The Initial learning rate of the architecture is 0.001 and the Max epoch is 300 and the Mini batch size is 16 and the accuracy gets improved up to 82.14% and the data augmentation technique is used to improve the accuracy. Data augmentation technique is used to increase the image content present in the dataset and the accuracy gets improved from 82.14% to88.64%.

A. Block A

In this architecture the image input passes through the convolutional layer, batch normalization layer, RELU layer and finally it reaches the max pooling layerand the input image is sent to the block A which consist of convolutional layer with constant filter size of [5X5] with different number of filters.

B. Block B

It consist of constant convolutional layer, batch normalization layer, RELU layer with different number of filters. Combined output of block A and block B reaches the fully connected layer and finally it reaches the classification layer which consist of three different classes such as viable tumour, Non-viable tumour and Non-tumour.



Viable tumour

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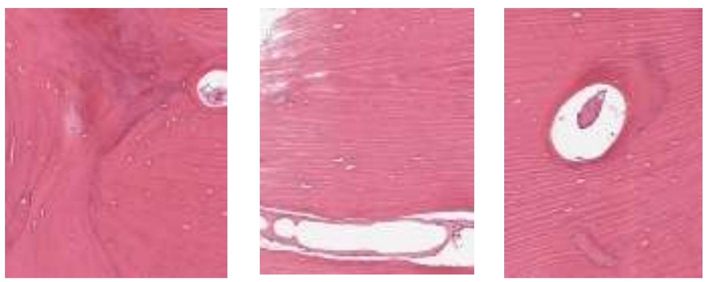
Sample Images

Non-Viable tumour

Non-Tumour



IV. DATASET DETAILS

The sample images are taken from Cancer Image Archive dataset and the dataset consist of number of images in training set 1 is 560 image and the number of images in training set 2 is 600 images. Total number of image is 1160 and the dimension of image range is [1024X1024]. Computer-aided diagnosis (CAD) is defined as a diagnosis made by a radiologist who considers a computerized analysis of the cancer in his or her diagnostic decision making. Machine learning has great potential for therapeutic development and healthcare, ranging from discovery to diagnosis to decision[8].

Table 1: Comparison with Batch Normalization and Without Batch Normalization Layer

Parameters	Initial learning rate	Max Epoch	Mini Batch size	Accuracy (%)
Without batch normalization	0.0001	40	8	62.5
With batch normalization	0.0001	40	8	67.8

Batch normalization is used to increase the speed of the process. We are comparing the single architecture with batch normalization layer and without batch normalization layers to know whether the accuracy of the CNN architecture gets improved or not. While using batch normalization layer we are getting the accuracy of 67.86% and without using the batch normalization layer we are getting the accuracy of 62.50%.Without using batch normalization layer the accuracy of CNN get reduced.

So we are using the batch normalization layer to get better accuracy and the time consumption of the CNN architecture get reduced these are the changes mentioned in Table 1.

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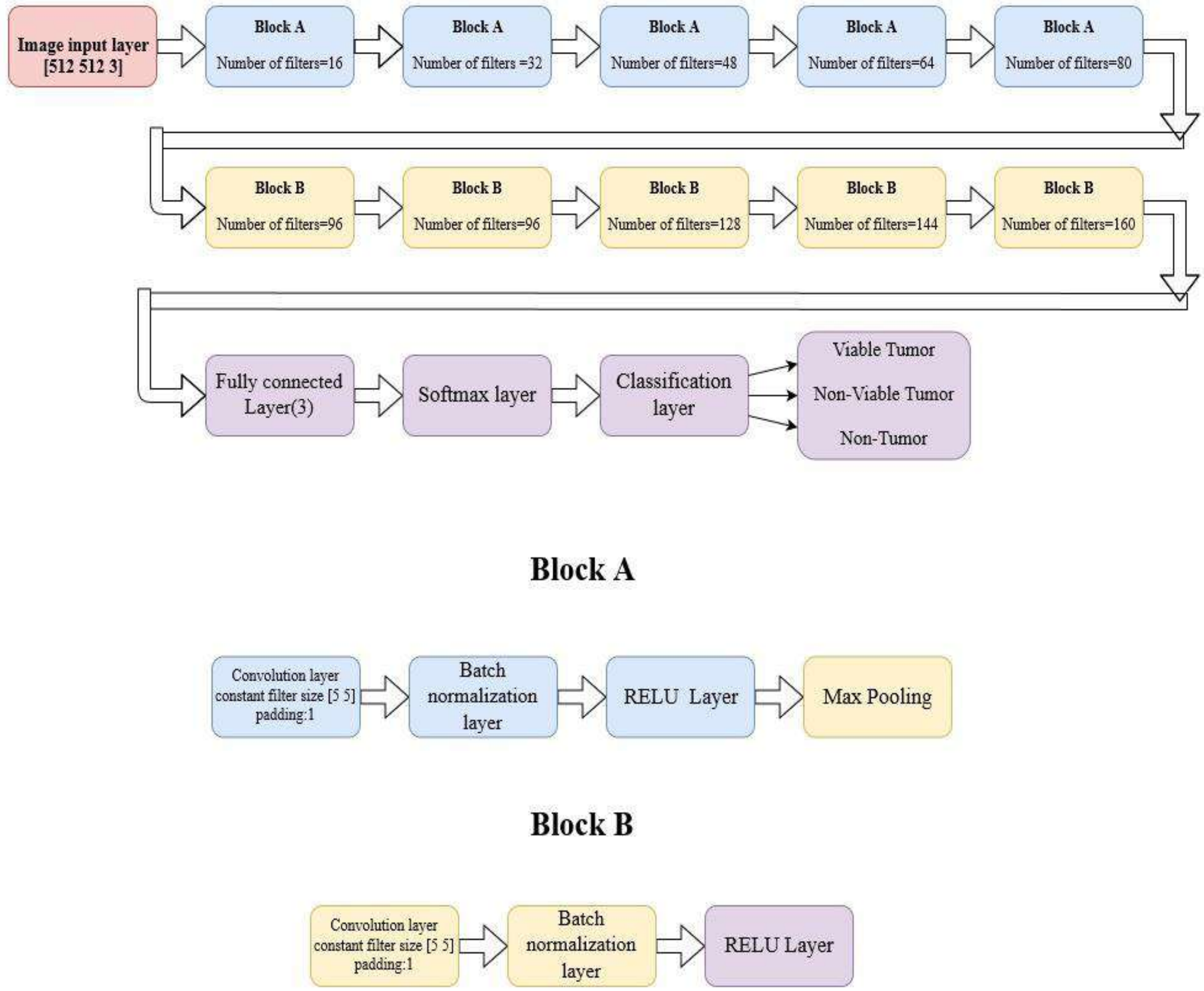

Fig 3: Proposed architecture

The constant initial learning rate and Mini Batch size are kept constant to get better accuracy of 68%.On comparing the first two level of accuracy consist of constant mini batch size, Initial learning rate with decreasing the max epoch and the performance accuracy get increases. 68% of accuracy consists of eight convolution layer with constant filter size. While varying the epoch from 400 to 300 the accuracy is increased from 62.5% to 68% and the accuracy gets increased due to decreasing the value of max epoch with constant filter size is shown in Table 2.

Table 2: Accuracy with Varying Epoch

Initial learning rate	**Max epoch**	**Mini batch size**	**Number Of layers**	**Accuracy (%)**
0.001	400	16	10	62.5
0.001	300	16	10	68

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Table 3: Accuracy for Different Filter Size

Initial learning rate	Max Epoch	Mini Batch size	Number of Convolution layers	Constant filter size	Accuracy (%)
0.001	300	16	10	[7 7]	62.5
0.001	300	16	10	[3 3]	68
0.001	300	16	10	[5 5]	82.14
0.001	400	16	10	[5 5]	76

In this table the initial learning rate, max epoch, mini batch sizes are kept constant and we are varying the constant filter size to get better accuracy. By varying the filter size and the number of filters from 16 to 160 we are getting a better performance accuracy of 82.14% and these changes are explained in Table 3.

Table 4: Data Augmentation Technique

Types of tumour	Images before Data Augmentation	Images after Data Augmentation	Combination of Original image and Augmented image
Non- Tumour	238	714	952
Non-Viable Tumour	147	441	588
Viable Tumour	176	528	704
Total	561	1683	2244

Data augmentation technique is used to increase the image content given in the dataset. In this technique flipping methods like horizontal flip, vertical flip and horizontal and vertical flip methods are introduced to increase the image content from 561 to 2244.When the number of image get increases the performance measures and the accuracy get increases to 88.64% and it is shown in Table 4.

V. PERFORMANCE MEASURES

A. Sensitivity

Sensitivity is also called the true positive rate measures the proportion of actual positives that are correctly identified. In the terminology true or false refers to the assigned classification being correct or incorrect, while positive or negative refers to assignment to the positive (or) negative category.

$$Sensitivity = \frac{True\ positive}{True\ positive + False\ negative}$$

B. Specificity

Specificity is also called the true negative rate measures the proportion of actual negatives that are correctly identified and Specificity relates to the test's ability to correctly reject healthy patients without a condition and the performance measures of proposed architecture is mentioned in Table 5.

$$Specificity = \frac{True\ negative}{True\ negative + false\ positive}$$

A group of true positive, true negative, false positive and false negative is a confusion matrix. In the field of machine learning and the problem of statistical classification, a confusion matrix, also known as an error matrix, is a

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specific table layout that allows visualization of the performance of an algorithm, typically a supervised learning one. Sensitivity detects the presence of disease by means of true positive rate and specificity detects the absence of disease.

C. F-Measure

It is a measure of test accuracy and it consists of precision and recall. Precision (p) is the number of correct positive results divided by the number of all positive results and recall(r) is the number of correct positive results divided by the number of all relevant samples

$$\mathrm{F-measure} = \frac{2 * \mathrm{Precision} * \mathrm{Recall}}{(\mathrm{Precision} + \mathrm{Recall})}$$

$$\mathrm{Precision} = \frac{\mathrm{Truepositive}}{\mathrm{Truepositive} + \mathrm{Falsepositive}}$$

$$\mathrm{Recall} = \frac{\mathrm{Truepositive}}{\mathrm{Truepositive} + \mathrm{Falsenegative}}$$

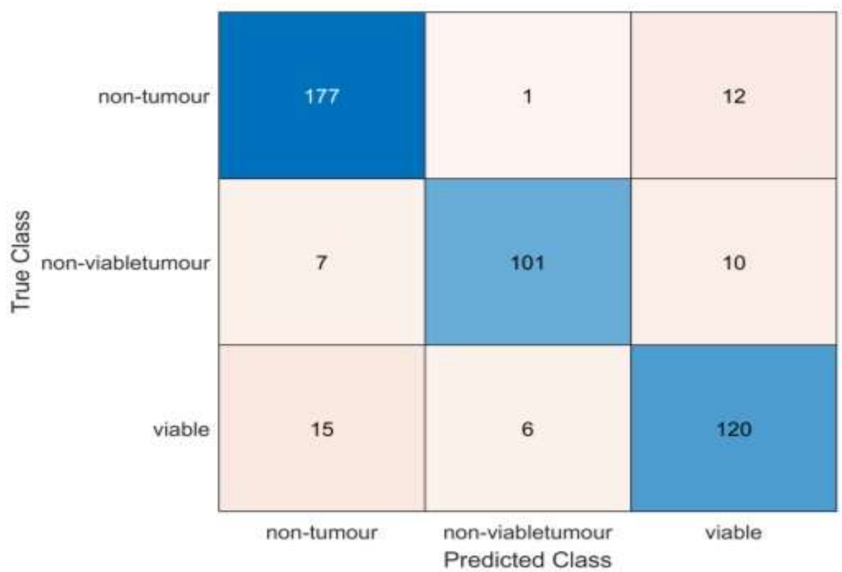

Fig. 4: Confusion Chart with Accuracy of 88.64%

Table 5: Performance Measures of Proposed Architecture

Tumor	Sensitivity (%)	Specificity (%)	F-measure (%)
Non tumor	93.15	91.5	90.97
Non-viable tumor	85.5	95	89.32
Viable tumor	85.1	93.15	84.7

VI. CONCLUSION

The input image size, number of layers in CNN, filter size, number of filters, and value of the CNN's parameters has been varied in each of the architectures. Still the architecture will be fine-tuned to achieve the best accuracy. In literature survey random forest classifier is used to get better accuracy and here we are using CNN architecture which extracts the features on its own. In future these methods are converted to mobile application in smart phones and it is easy for diagnosis purposes. Depth of the convolution layer increases to get best accuracy. These methods are used to assist the pathologist and 88.64% accuracy has been obtained using CNN for Osteosarcoma tumor classification into (viable tumor vs. non-viable tumor vs. non-tumor). This fully automated system can then be used for clinical diagnosis.

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