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Research Article

BCDNet: A Deep Learning Model with Improved Convolutional Neural Network for Efficient Detection of Bone Cancer Using Histology Images

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Abstract:

Among the several types of cancer, bone cancer is the most lethal prevailing in the world. Its prevention is better than cure. Besides early detection of bone cancer has potential to have medical intervention to prevent spread of malignant cells and help patients to recover from the disease. Many medical imaging modalities such as histology, histopathology, radiology, X-rays, MRIs, CT scans, phototherapy, PET and ultrasounds are being used in bone cancer detection research. However, hematoxylin and eosin stained histology images are found crucial for early diagnosis of bone cancer. Existing Convolutional Neural Network (CNN) based deep learning techniques are found suitable for medical image analytics. However, the models are prone to mediocre performance unless configured properly with empirical study. Within this article, we suggested a framework centered on deep learning for automatic bone cancer detection. We also proposed a CNN variant known as Bone Cancer Detection Network (BCDNet) which is configured and optimized for detection of a common kind of bone cancer named Osteosarcoma. An algorithm known as Learning based Osteosarcoma Detection (LbOD). It exploits BCDNet model for both binomial and multi-class classification. Osteosarcoma-Tumor-Assessment is the histology dataset used for our empirical study. Our the outcomes of the trial showed that BCDNet outperforms baseline models with 96.29% accuracy in binary classification and 94.69% accuracy in multi-class classification.

1. Introduction

The worst and least prevalent kind of cancer is bone cancer kind of cancer among many others. Every year, more instances are documented. Since early detection lowers mortality and restricts the spread of malignant cells, early diagnosis of bone cancer is essential. Bone cancer diagnosis by hand is laborious and needs specific expertise. Globally, there are more than 100 human metabolic illnesses [1]. Cancer is one of these illnesses that poses a serious risk to humankind since it is fatal. Abnormal cell growth is the first sign of cancer, which spreads quickly to other body areas. Numerous factors contribute to cancer, some of which can be prevented and some of which cannot. Numerous factors contribute to cancer, some of which can be prevented and some of which cannot. It is possible to prevent some factors, such smoking, drinking alcohol, and spending a lot of time in the sun. However, genetic factors are unavoidable [2]. Either their parents passed on these genetic characteristics to them or lifestyle modifications like using tobacco products caused them. Furthermore, age is by far the most significant of the uncontrollable elements. An uncommon medical disorder called bone cancer may start out as swelling or soreness in the damaged bone. When aberrant bone cells proliferate gotten out of hand and maybe extended to other bodily parts, bone cancer results. In 2022, there will probably be a 3900 rise in new instances of bone cancer and 2100 fatalities as well [3]. The majority of cases of bone cancer occur in those under 20. Radiology, X-rays, CT scans, MRIs, ultrasounds, phototherapy, and PET machines are a

few of the frequently used modalities in medical imaging [4,5].The Deep Transfer-Based Bone Cancer Diagnosis System that we have suggested Utilizing an X-ray imaging modality, the VGG16 Feature Extraction (DTBV) technique is utilized. Medical X-ray pictures are a significant and important resource for research and illness diagnostics due to their accessibility and affordability Several medical interventions, such as surgery, chemotherapy, radiation therapy, and targeted therapies, have been suggested in recent years to treat this illness [6]. Because of the intricate nature of the bone, detecting cancer in it requires testing [7].

Due to the high cost of the technology and the potential for data processing errors, the manual evaluation of malignant pictures is not cost-effective. Because it makes data analysis and automated information extraction from data sets simple, machine learning (ML) is becoming a common tool in cancer research [8]. Pre-processing medical pictures is a basic method to enhance any machine learning model's performance [9]. Preparing the images beforehand enhances their quality and facilitates more efficient data analysis. Pre-processing techniques for images that are often used include scaling, segmentation, data augmentation, filtering, normalization, and pixel brightness adjustments. Medical image analytics can benefit from the use of current deep learning approaches based on Convolutional Neural Networks (CNNs), as evidenced by previous literature. However, the models are prone to mediocre performance unless configured properly with empirical study. In this paper, we investigated on CNN model with empirical study and proposed a CNN variant named BCDNet which is designed and optimized for detection of a common kind of bone cancer named Osteosarcoma.

An algorithm known as Learning based Osteosarcoma Detection (LbOD). It exploits BCDNet model for both binomial and multi-class classification.

Osteosarcoma-Tumor-Assessment is the histology dataset utilized in our investigation of the empirical data. Our experimental results revealed that BCDNet outperforms existing baseline models. This is how the rest of the paper is organized. The literature on current techniques for detecting bone cancer is reviewed in Section 2.

Our technique is presented in Section 3. The findings of our tests are shown in Section 4. Section 5 discusses on the significance of our methodology and its limitations. We wrap up our study in Section 6 and leave room for more investigation.

2. Related work

This section reviews literature on prior works on bone cancer detection. Patil et al. [10] observed that DNA mutations are frequently the cause of osteosarcoma, a bone cancer that attacks long bones. Achieving 90.36% accuracy is possible by early detection through X-rays and deep learning models. Altameem [11] focused on deep neural networks, fuzzy rank correlation, and image processing are used in the higher prediction rate of automatic bone cancer detection. Feleki et al. [12] found that promising advances in nuclear medicine, deep-learning algorithms, namely a CNN model, demonstrate 92.50% accuracy in identifying bone metastases in breast cancer patients. Alva et al. [13] used deep learning and image processing techniques, digital histopathology achieves a success rate and is key for difficult bone cancer cases. Rao et al. [14] approached for detecting bone cancer has been suggested, which uses FCM segmentation and SVM-based M3 filtering to achieve 92% accuracy for early diagnosis.

Huo et al. [15] worked with radiologists, a DCNN model improved diagnostic efficiency for lung cancer bone metastases detection on CT. Khan et al. [16] suggested bone suppression techniques enhance nodule identification on lung radiographs. Effective outcomes were demonstrated using CNN and AE-like models with certain loss functions. Kao et al. [17] used pre-training, deep learning, and YOLO v4 on scintigraphy images, efficient bone metastasis diagnosis was investigated; the findings showed promise with less false positives. Xu et al. [18] used V-Net and W-Net for deep learning on 68GaMore accurately than other approaches, Pentixafor PET/CT detects multiple myeloma bone lesions. Zhao et al. [19] observed that the AI built on a deep neural network improves the diagnosis of bone metastases in cancers of the breast, prostate, lung, and other organs, which is beneficial to medical professionals.

Papandrianos et al. [20] presented effective CNN models that outperform existing CNN designs in terms of higher accuracy in detecting bone metastases from prostate cancer. Do et al. [21] presented the Seg-Unet model, which offers multi-level characteristics for optimization and a high accuracy for the classification and segmentation of knee bone tumors. Patel et al. [22] investigated the use of computer science and biological knowledge to forecast bone cancer. For precise diagnosis, it discusses Deep Learning and picture segmentation methods. Yang et al. [23] focused on X-ray picture segmentation and classification of knee bone tumors using a Multi-Level Seg-Unet model. It exhibits better segmentation outcomes and accuracy. The goal of future research is to identify tumors more broadly and with improved

performance. Sharma et al. [24] aimed to identify bone cancer automatically using X-ray, MRI, or CT scan pictures. Expanding datasets and using sophisticated algorithms to optimize attributes for improved performance are two areas of future investigation. Segmentation and fuzzy approaches are used in [25] for bone cancer diagnosis.

Balaji et al. [26] emphasized histopathology digitization for effective bone cancer detection. The Convolutional Extreme Learning Machine classifies data using extracted features and achieves excellent accuracy. Deep learning is explored in [27] using fluoroscopic images. Coyle et al. [28] presented an automatic technique for hyoid bone localization in swallow movies that makes use of a single shot multibox detector (SSD-500). The results indicate improved dysphagia diagnosis accuracy. Togo et al. [29] suggested utilizing anomaly detection and a generative adversarial network model to detect bone metastatic tumors using CT images. Banu et al. [30] discussed about bone marrow cancer and suggests an improved hybrid strategy that makes use of dynamic multi-objective convolutional neural networks and adaptive multi-objective CAT algorithms for accurate segmentation and classification. It outperforms current models in cancer cell recognition, accuracy. Manoj et al. [31] investigated the detection of bone cancer and presents a successful hybrid method using CNNs and adaptive CAT algorithms. Early-stage detection at a reasonable cost is provided by the suggested approach during routine examinations. Yadav et al. [32] used X-ray pictures, a deep neural network model was created to automatically detect bone fractures. With data augmentation, over fitting was reduced and 92.44% accuracy was achieved, outperforming current models. It is advised to do additional validation on a bigger dataset. Bodne et al. [33] observed that frequently bone stress injuries and frequently not painful. MRI scans in asymptomatic patients demonstrate healing. Knee injuries are common and can happen in some interesting places. Krois et al. [34] specified that the periodontal bone loss in dental radiographs was detected in this work using CNNs. Both the model and dentists performed similarly. Huo et al. [35] used radiology reports using deep learning for detection of bone cancer. Maji et al. [36] investigated on carcinogenesis which is a dangerous hereditary illness that causes unchecked cell division that results in organ-damaging tumors. It's critical to discover early. Jain et al. [37] investigated and focus on bone tumors, cancer diagnosis using CNN and OpenCV. There is potential for telemedicine applications using this technology. Nayana et al. [38] focused on bone cancer detection, emphasizing imaging techniques, pre-processing with a median filter, and CNN classification, achieving higher accuracy. Subbaraya et al. [39] examined the use of image processing to identify early signs of bone cancer and suggests a technique that uses KNN classifier and k-means segmentation to achieve better accuracy in ultrasound pictures. Walke and Patil [40] used MRI imagery for bone cancer detection while Suganeshwari et al. [41] proposed a hybrid model using VGG16 and SVM for feature extraction and cancer detection. From the literature, it was observed that existing Convolutional Neural Network (CNN) based deep learning techniques are found suitable for medical image analytics. However, the models are prone to mediocre performance unless configured properly with empirical study.

3. Proposed Framework

The suggested structure and methods used for automated detection are presented in this section of bone cancer known as Osteosarcoma.

3.1 Problem Definition

Provided a bone histology sample, proposing a bone cancer automatically detected and classified using a deep learning system Osteosarcoma is the challenging problem considered.

3.2 Our Framework

Outline of the proposed framework that exploits our improved CNN architecture known as BCDNet is shown in Figure 1. The framework takes a benchmark histology dataset [42] as input. It has pre-processing approach considering techniques like resizing, normalization and data augmentation to improve data prior to training deep learning model. Data is split into training and test datasets. Our proposed deep learning model known as BCDNet, discussed in Section 3.3, is trained with the training data. The model has provision to extract features progressively and learn complex relationships and patterns. In the training process, the model's parameters are optimized to reduce loss and improve accuracy in bone cancer detection. The learned model is saved for future reuse. The model is tested with test samples and then performance of the model is evaluated. The proposed framework is evaluated with histology images and found that the improved CNN model BCDNet has potential to improve learning process and capture complex patterns and relationships from training images. Further information on the suggested CNN variant BCDNet is given in Section 3.3.

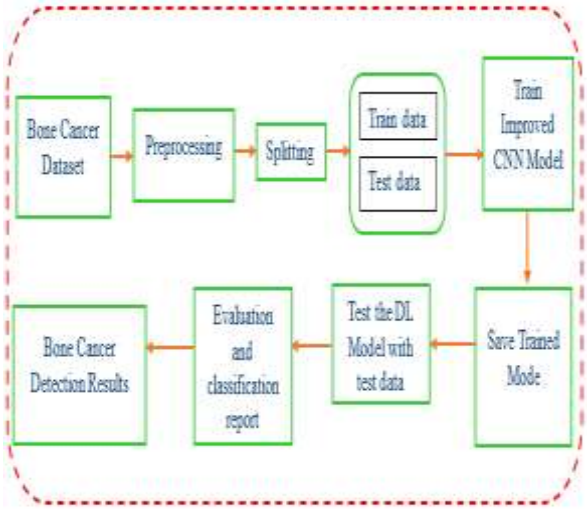

Figure 1: *Proposed framework for automatic detection of bone cancer*

3.3 Proposed BCDNet Model

The purpose of the suggested BCDNet model, which is depicted in Figure 2, is to enhance the process of detecting bone cancer using histology pictures. The proposed CNN was trained and tested using the pre-processed images, which have a 150 × 150 matrix size. The proposed CNN model consists of an input, an output, and many created layers. In particular, five two-dimensional (2D) convolutional layers—each with a 2D maxpooling layer—were employed in this study. Convolution is a linear process between the input and a kernel, sometimes called a filter, which acts as a function detector. The filters are taught to extract certain information from an image and have a restricted receptive field. The convolution layer is referred to as expressed in Eq. 1.

$$X_n^r = \alpha(\sum_{m=1}^{k} X_m^{r-1} * w_{mn}^r + b_m^r) \quad (1)$$

where k is the number of input activation maps, X_n^r is the n^{th}activation map of the current (r^{th}) layer, and X_m^{r-1} is the n^{th}activation map of the preceding layer $(r-1)^{th}$. Weight and bias vectors are denoted by w_{mn}^r and b_m^r. α indicates the activation function, and the * operator is used for convolution operations. The created activation maps are sent to the pooling layer once each activation map has been assigned an activation function. The pooling layer lowers the activation maps' resolution to ensure translation invariance. The activation maps in the convolution layer's d × d (e.g., d = 2) window provide the activation values in the pooling layer. The most popular method is pooling to the fullest extent possible. The completely linked layer creates a classification map at the end by utilizing the information from each activation map in the layer before it.

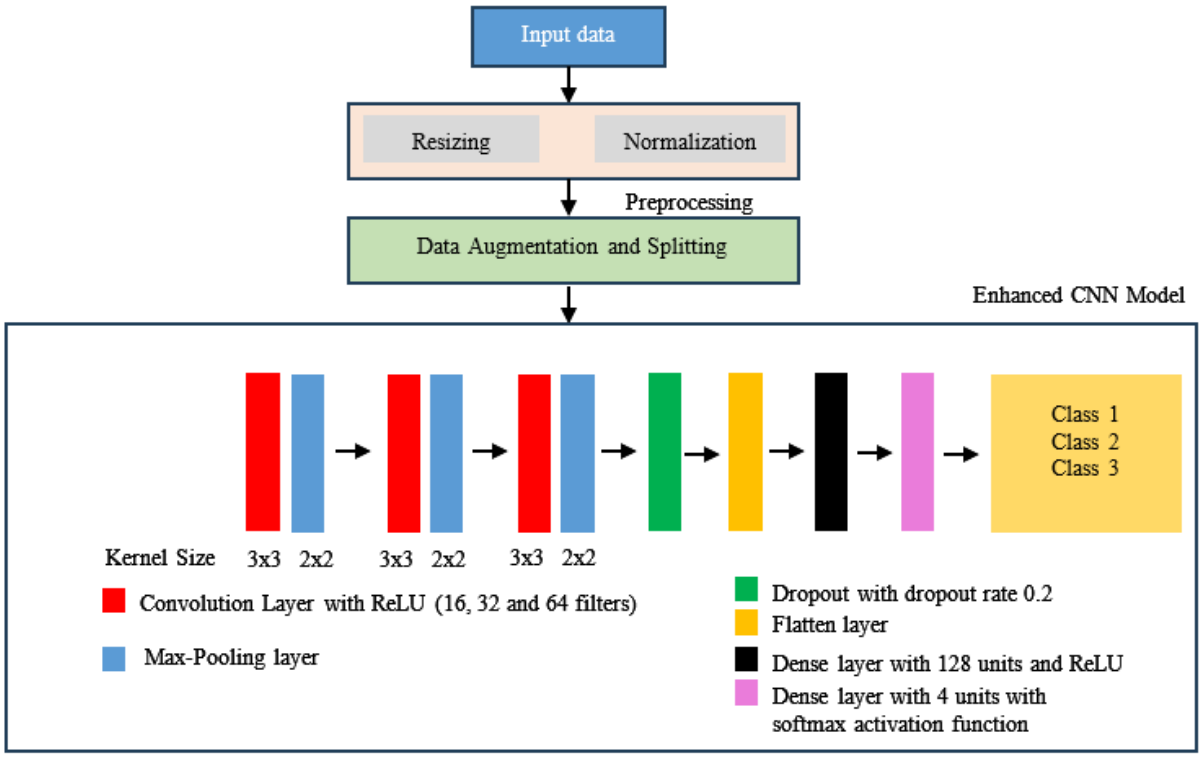

Figure 2: *Proposed deep learning model known as BCDNet based on CNN*

The optimizer makes a substantial training contribution to the deep CNN model by iteratively modifying the parameters of each network layer.The parameters are updated with respect to the parameters in the opposite direction as the gradient of the loss function (i.e., ∇_⊙ L (⊙)) in order to minimize the loss function L (⊙). The intended and projected outputs are compared at each iteration, and the mistake is back-propagated. One of the most used metrics for evaluating performance is cross-entropy.

The primary goal of any optimization strategy is to achieve the situation where the expected and desired outputs are identical and the cross-entropy value is close to zero.

These models offer a deeper differentiation between the representations of each class since CNNs operate internally using convolutions in numerous sliding windows, which allows them to discern patterns locally. For the first and second convolutional layers, the dropout layer has been set to 0.25, and for the succeeding convolutional layers, it is set to 0.3. Rectified Linear Unit, or ReLU, is another name for linear rectification, which serves as the activation function of every convolutional layer. By identifying patterns in the incoming data, the model may forward that information to the subsequent layers. The last two layers are a fully connected (FC) layer with 0.2 dropout and a softmax layer with four neurons. The output of the previous convolution is sent into these layers after it has been flattened. This network layer determines the probability that the input comes from a certain label in order to do classification. Time-series study has shown that this kind of multi-layer structure works well when pooling and filter sizes are increased. [17, 18].

The definition of input into the model is x=x_1,x_2,….x_n, while the output sequence is denoted by y=y_1,y_2,….y_m. The cost matrix (xi) was used to alter the network's last layer's output. If y is the output of the individual model, (L) is the loss function, and (⊄) is the intended class, then (∂^i) is the modified output as in Eq. 2.

$$\partial^i = \text{ł}\left(\zeta_{\odot,} y^i\right), : \partial^i{}_{\not\subset} \geq \partial^i{}_j \forall j \neq \not\subset \qquad (2)$$

This is how the loss function is changed as in Eq. 3.

$$\text{ł} = -\sum_n t_n \log(\partial_n) \qquad (3)$$

where ∂_n includes the cost that is depending on the class (ξ) and is connected to the results on y_n via the operation of softmax [19] expressed in Eq. 4.

$$\partial_n = \frac{\xi_{\not\subset,n} \exp(y_n)}{\sum_k \xi_{\not\subset,k} \exp(y_k)} \qquad (4)$$

The weight of a class is based on how many samples it contains. The goal is to make one sample from class p equal to t samples from class η if class η has t times more samples than class p. As a result, the class weight of p is t times more than that of η.

Layer	Convolution	Max Pooling	Dropout
First layer	filters = 64, kernel_size = (5,5), padding = 'Same', activation ='relu'	pool_size=(2,2)	0.25
Second Layer	filters = 128, kernel_size = (3,3), padding = 'Same', activation ='relu'	pool_size=(2,2), strides=(2,2)	0.25
Third Layer	filters = 128, kernel_size = (3,3), padding = 'Same', activation ='relu'	pool_size=(2,2), strides=(2,2)	0.3
Fourth Layer	filters = 128, kernel_size = (2,2), padding = 'Same', activation ='relu'	pool_size=(2,2), strides=(2,2)	0.3
Fifth Layer	filters = 256, kernel_size = (2,2), padding = 'Same', activation ='relu'	pool_size=(2,2), strides=(2,2)	0.3

Parameter	Value
Batch Size	40
Learning Rate	0.001
Optimizer	Adam
No. of Epochs	100
Total Parameters	4,619,524
Trainable Parameters	4,619,524
Non-Trainable Parameters	0

Figure 3: *Layers and parameter details of BCDNet*

As shown in Figure 3, our model makes use of 2D convolutional layers, with the first block's kernel size being 5 × 5, and the second and third blocks' kernel sizes being 3 × 3. Also, we use 2 × 2 for the last two blocks. Every block is activated using the ReLU function; Batch Normalization (BN) is not utilized. The second convolutional layer in each block performed downsampling with a stride of two. Each subsequent block has twice as many filters as the preceding block, which had 64 filters. Following the last convolutional layer, a dropout layer (p = 0.3) was added, and it was connected to a single FC dense layer with ReLU activation values of 1024. A dropout layer (p = 0.3) was also seen, situated between those thick layers. Finally, a multi-dense neuron with softmax activation produced the model output. Training was done for a maximum of 100 epochs at a learning rate of 0.001, using a batch size of 40 and the Adam optimizer to estimate model parameters. The loss function utilized was the categorical-cross-entropy one,

which is frequently applied to multiclass classification issues. Using the categorical-cross entropy definition as H (p, q) =-$\sum_x p(x)\log(q(x))$, where q represents the calculated distribution and p represents the genuine distribution. All of the parameters for Table 1 compiles the potential deep learning pipeline.

5.4 Dataset Details

Dataset is collected from [42] which has Hematoxylin and eosin stained histology images suitable for early detection of bone cancer. The dataset distribution dynamics are presented in Figure 4. The dataset has different classes of images. We made two versions of dataset, one for binary classification with labels such as BONE CANCER and BENIGN and other for multi-class classification with labels such as NON-TUMOR, NECROSIS and VIABLE-TUMOR. The dataset was originally created by a group of experts from the Dallas-based University of Texas Southwestern Medical Center. The data was created based on treatment archives of 50 bone cancer patients. The images are of 1024x1024 size with 10X resolution. Dataset has a total of 1144 histology images.

5.3 Evaluation Methodology

The suggested algorithm's assessment is contrasted with the state of the art using the confusion matrix as a basis. The several measures included in the assessment process are displayed in Table 1. The metrics such as true positive (TP), false positive (FP), false negative (FN), and true negative (TN) are displayed in the confusion matrix, which is seen in Figure 5. Their determination involves contrasting the output of the machine learning system with the actual data. True positive rate is referred to as recall, whereas positive predictive value is related to precision. A metric that does not exhibit imbalance, unlike accuracy measures, is the F1-score, which is calculated as the harmonic mean of recall and precision.

4. Experimental Results

This section presents results of our empirical study with BCDNet and the results are compared with existing baseline models such as CNN [12], MobileNet [43] and UNet [44]. Experiments are made with binomial classification and also multi-class classification. Empirical study has revealed that BCDNet has potential for better learning process and that is reflected in the results of the

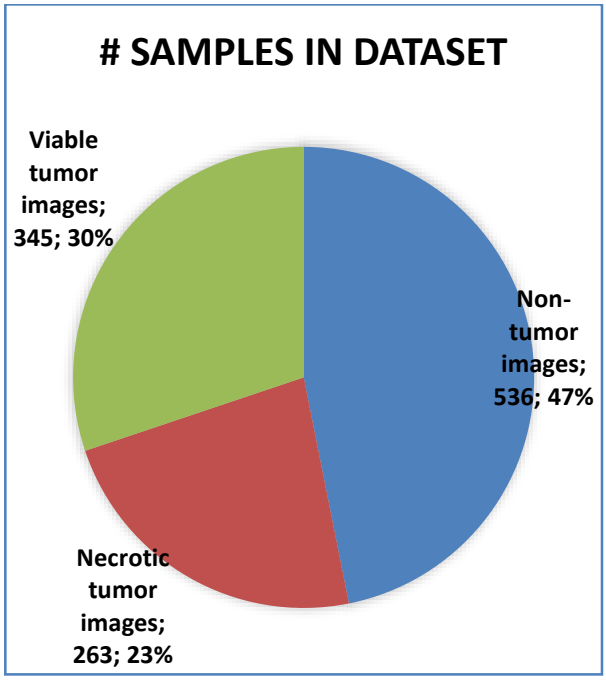

Figure 4: *Dataset distribution dynamics*

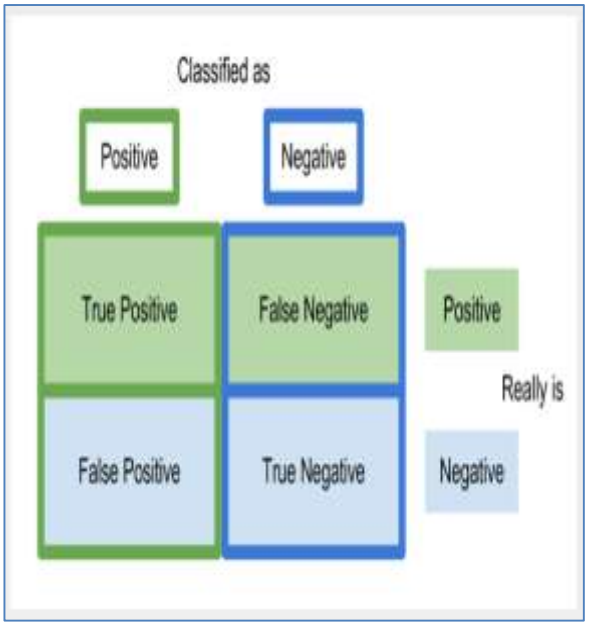

Figure 5: *Confusion matrix*

Table 1: *Performance metrics used for evaluation*

Metric	Formula	Value range	Best Value
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$	[0; 1]	1
Precision (p)	$\frac{TP}{TP+FP}$	[0; 1]	1
Recall (r)	$\frac{TP}{TP+FN}$	[0; 1]	1
F1-Score	$2*\frac{(p*r)}{(p+r)}$	[0; 1]	1

study. Empirical study is made with the histology dataset obtained from [42]. The data is used in this research with two versions created. The binary classification dataset has two labels TUMOR and BENIGN. Figure 6 shows an excerpt non-tumor samples from dataset.

The data is used in this research with two versions created. The binary classification dataset has two labels TUMOR and BENIGN. Figure 7 shows an excerpt tumor samples from dataset. The dataset version which has three classes for multi-class classification contains non-tumor, non-viable tumor and viable-tumor. Figure 8 show an excerpt of non-tumor samples from multi-class dataset.

The dataset version which has three classes for multi-class classification contains non-tumor, non-viable tumor and viable-tumor. Figure 9 show an excerpt of non-viable tumor samples from multi-class dataset. The dataset version which has three classes for multi-class classification contains non-tumor, non-viable tumor and viable-tumor. Figure 10 show an excerpt of viable tumor samples from multi-class dataset. Binomial classification results in finding whether the given test sample has bone cancer or not without classifying it further. Table 2 shows the results of binary classification. Multi-class classification models classify given test samples into three classes. Table 3 shows the results of multi-class classification.

Table 2: *Performance comparison of models for binary classification*

Binomial Classification Model	**Precision**	**Recall**	**F1-Score**	**Accuracy**
CNN	94.85	96.29	95.56	87.54
MobileNet	92.74	91.29	92	91.67
UNet	94.56	82.56	88.15	93.54
Proposed (BCDNet)	95.97	96.3	96.13	96.29

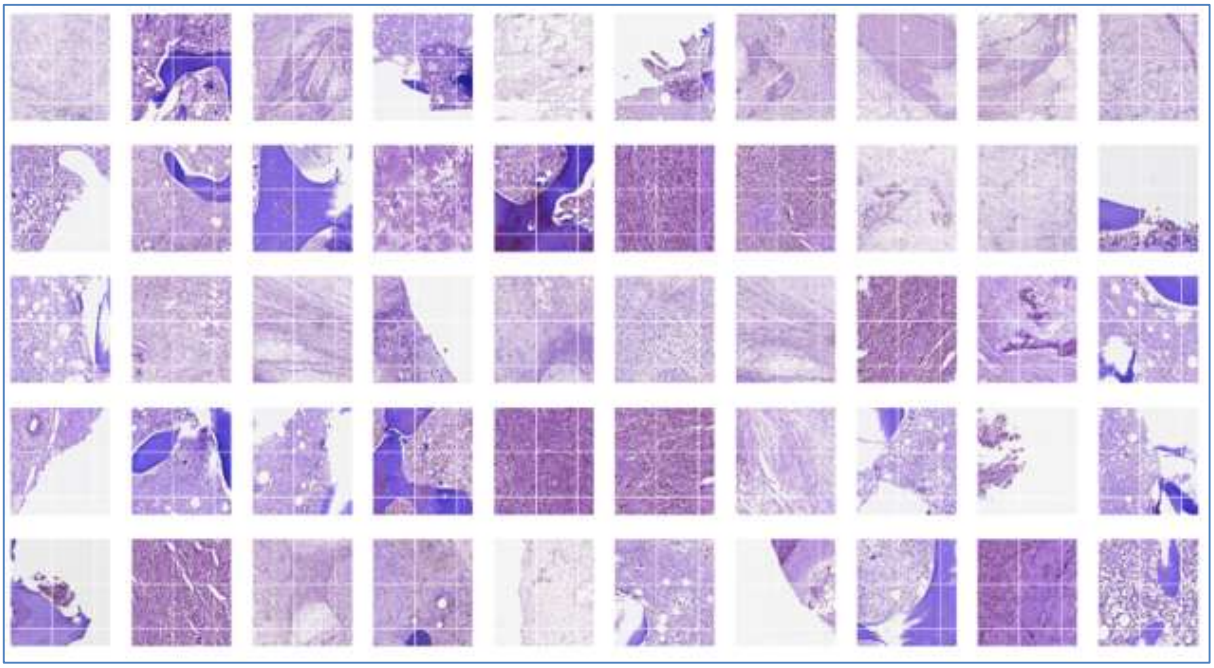

Figure 7: *An excerpt of tumor samples from dataset*

Figure 8: *An excerpt of non-tumor samples from multi-class dataset*

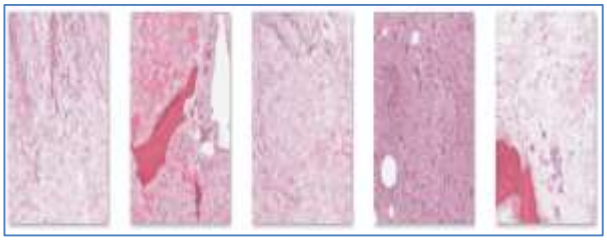

Figure 9: *An excerpt of non-viable tumor samples from multi-class dataset*

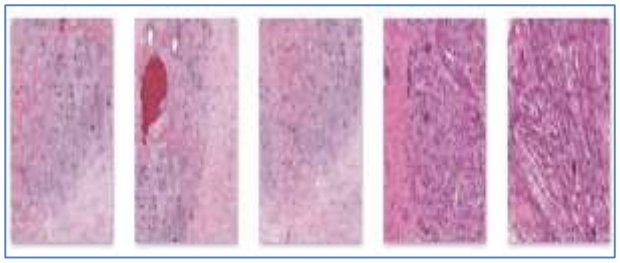

Figure 10: *An excerpt of viable tumor samples from multi-class dataset*

Table 3: *Performance comparison of models for binary classification*

Multi-Class Classification Model	Precision	Recall	F1-Score	Accuracy
CNN	90.89	71.54	80.06	78.48
MobileNet	83.74	74.67	78.94	86.63
UNet	94.56	82.56	88.15	89.75
Proposed (BCDNet)	97.98	93.86	95.88	94.69

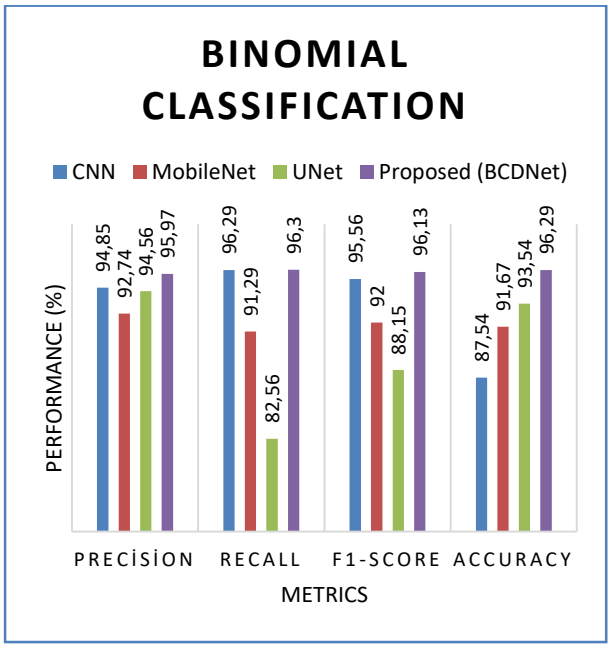

Figure 11: *Results of bone cancer detection models with binomial classification*

Binary classification results with different deep learning models including the proposed BCDNet are presented in Figure 11. Observations are made in terms of their performance in bone cancer detection. CNN model achieved 94.85% precision, MobileNet 92.74%, UNet 94.56% and the proposed BCDNet 95.97% precision. With regard to recall measure, CNN model achieved 96.29%, MobileNet 91.29%, UNet 82.56% and the proposed BCDNet 96.30%. With respect to F1-score measure, CNN model achieved 95.56%, MobileNet 92%, UNet 88.15% and the proposed BCDNet 96.13% F1-score. CNN model achieved 87.54% accuracy, MobileNet 91.67%, UNet 93.54% and the proposed BCDNet 96.29% accuracy. With binary classification, highest accuracy is achieved by BCDNet with 96.29%.

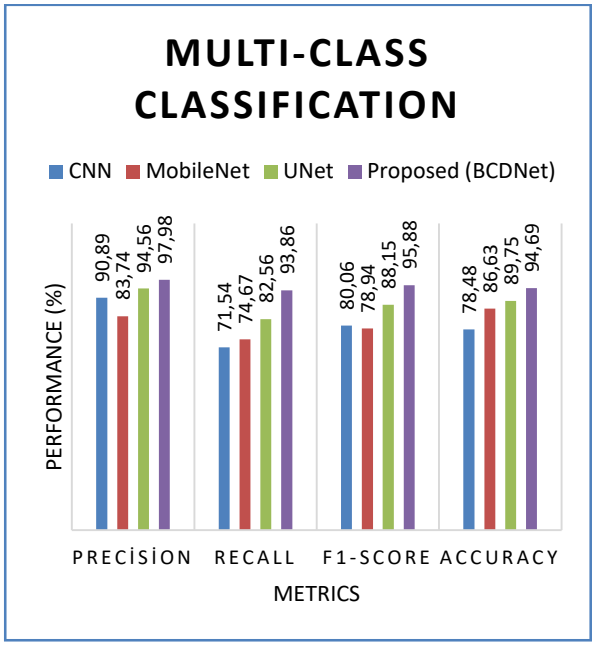

Figure 12: *Results of bone cancer detection models with multi-class classification*

Multi-class classification results with different deep learning models including the proposed BCDNet are presented in Figure 12. Observations are made in terms of their performance in bone cancer detection. CNN model achieved 90.89% precision, MobileNet 83.74%, UNet 94.56% and the proposed BCDNet 97.98% precision. With regard to recall measure, CNN model achieved 71.54%, MobileNet 74.67%, UNet 82.56% and the proposed BCDNet 93.86%. With respect to F1-score measure, CNN model achieved 80.06%, MobileNet 78.94%, UNet 88.15% and the proposed BCDNet 95.88% F1-score. CNN model achieved 78.48% accuracy, MobileNet 86.63%, UNet 89.75% and the proposed BCDNet 94.69% accuracy. With multi-class classification, highest accuracy is achieved by BCDNet with 94.69%.

5. Discussion

In this study, we suggested an autonomous method for bone cancer diagnosis based on deep learning. It is predicated on CNN model as it is found superior towards medical image processing. We proposed a CNN variant known as BCDNet for improving performance in bone cancer detection. Many

medical imaging modalities such as histology, histopathology, radiology, X-rays, MRIs, CT scans, phototherapy, PET and ultrasounds are being used in bone cancer detection research. However, hematoxylin and eosin stained histology images are found crucial for early diagnosis of bone cancer. An algorithm known as Learning based Osteosarcoma Detection (LbOD). It exploits BCDNet model for both binomial and multi-class classification. Osteosarcoma-Tumor-Assessment is the histology dataset used for our empirical study. These models offer a deeper differentiation between the representations of each class since CNNs operate internally using convolutions in numerous sliding windows, which allows them to discern patterns locally. BCDNet can serve as part of a Clinical Decision Support System (CDSS) in healthcare units for bone cancer diagnosis and correlation of facts by doctors.

5.1 Limitations

The proposed system in this research has certain limitations. First, the dataset has limited samples and those are taken from only 50 patients. Second, this research is confined to histology dataset and does not explore other medical image modalities. Though the proposed model BCDNet outperforms existing base models, the observations cannot be generalized as the model is only trained with histology imagery with limited training samples.

4. Conclusions and Future work

We suggested a system for automated bone cancer screening based on deep learning. The framework includes resizing, normalization and data augmentation techniques as part of pre-processing for improving quality of training. Histology imaging model is preferred as it has potential for early detection of bone cancer probability. As deep learning models such as CNN could offer promising results in medical image analytics, we proposed a CNN variant known as Bone Cancer Detection Network (BCDNet) which is configured and optimized for detection of a common kind of bone cancer named Osteosarcoma. BCDNet model is found efficient in capturing pattern and spatial dependencies with the help of local receptive fields. Its architecture is designed with empirical study for leveraging learning process using histology imagery. An algorithm known as Learning based Osteosarcoma Detection (LbOD). It exploits BCDNet model for both binomial and multi-class classification. Osteosarcoma-Tumor-Assessment is the histology dataset utilized in our investigation of the empirical data. Our the outcomes of the trial showed that BCDNet outperforms baseline models with 96.29% accuracy in binary classification and 94.69% accuracy in multi-class classification. In future, we explore other deep learning models such as Long Short Term Memory (LSTM) with optimizations for further improving bone cancer detection process. There are a number of works done on this subject and reported in literature [45-49].

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
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