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Bone Fracture Detection and Classification using Deep Learning Approach

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ABSTRACT: Bone Fractures are a prevalent clinical condition that necessitates and timely diagnosis. Conventional manual identification of fractures from X-ray images is slow and error-prone. In response to these issues, this paper introduces a deep learning approach for automated detection and classification of bone fractures. A Convolutional Neural Network (CNN) model was implemented and trained on an X-ray image dataset, using data augmentation methods to improve generalization and avoid overfitting. The suggested model was tested with various experimental configurations, such as cross-validation and showed better performance than current state-of-the-art techniques. Adam optimizer helped achieve better classification accuracy than traditional methods. Additional improvements, including sophisticated augmentation methods, transfer learning and ensemble models, may enhance predication accuracy. This research underscores the potential of deep learning in medical imaging for precise and computerized fracture identification, lowering diagnosis time and enhancing patient outcomes.

KEYWORDS: Bone fracture, Deep Learning, Fracture detection, Fracture classification

I. INTRODUCTION

The human body consists of many types of bone. Bone fractures are mostly caused by the automobile accident or bad fall. The bone fractured risk is high in aged people due to the weaker bone [1]. The fracture bone heals by giving proper treatment to the patient. The doctor uses x-ray or MRI (Magnetic Resonance Imaging) image to diagnose the fractured bone [2]. The small fracture in the bone becomes difficult to analyze by the doctor. The manual process for the diagnosis of the fractured bone is time consuming and the error probability is also high. Therefore, it is a necessity to develop a computer based system to reduce the time and the error probability for the fracture bone diagnosis [3]. The recent emerging machine learning technologies are widely used in medical imaging as well as in the power electronics fields. The x-ray or MRI image is used in the computer based system to perform the fracture bone diagnosis [4]. The bone image contains noise. Therefore, a suitable preprocessing algorithm is used to remove noise and edges in the image. . Finally, system is trained with the features and classification is performed by the ML (Mechine learing) algorithms.

Bone fracture detection and classification has been developed in the past. Dimililer and Kamil [5] have used ANN (Artificial Neural Network) to classify fracture bone but authors have not classified the bone into the healthy and the fracture. Yang et al. [6] have used a contour feature of the x-ray image to detect the fractured bone. The accuracy of the system is 85%, which need to improve. In the paper of the Chai et al.[7] Gray-Level Co-occurrence Matrix (GLCM) was used to extract the texture feature to classify the bone into the fracture and the non-fracture. The features are extracted from the image of the size 410×500 resolution. The classification accuracy of their system is 86.67%. In the present work, we have developed a deep neural network for the identification and the classification of the healthy and the fractured bone. The data set consists of 100 images of different types of human bone. The deep neural network gets

over fitted due to a small data set. Therefore, a image augmentation technique was has applied on the data set. The classification accuracy of the proposed model is 92.44% for the healthy and the fractured bone using 5 fold cross validation. The classification accuracy on 10% and 20% test data is more than 95% and 93% respectively. The proposed model performs much better than [8] of the 84.7% and 86% of the [9].The proposed paper consists of five sections as follows: Section 2 contains the proposed work with details of data set. Section 3 describes the results and section 4 represents the conclusion and future scope of the proposed scheme.

II. PROPOSED WORK

This section includes data collection, augmentation of data using transformations of the image and finally classification of healthy and cancerous bone using deep CNN. The experiment has been performed on the bone X-ray image data sets, collected from different sources publicly available for research such as the Cancer Imaging Archive(TCIA) and Indian Institute of Engineering Science and Technology, Shibpur (IEST) [10].The fracture and the healthy bone is shown in figure1.



Fig. 1.The fracture and the healthy bone

Data Augmentation: In a deep learning approach, the size of the data set is an important component. If the data set size is small, then the possibilities of over fitting may arise [11]. To overcome this problem, data augmentation technique is used to increase the size of the data set. Keras module provides Image Data Generator method to augment image [12]. We have applied an image transformation technique flipping and shifting to generate a new image from the available data set. The more generalize capability of a machine learning model can be achieved by training with the original image and with the augmented image. In the past several researchers have used data augmentation technique to reduce the error rate of the machine learning model [13].In the present study data set is a collection of the different types of the human bone. The data set size is small due to this memorization of the algorithm may arise. Therefore, we have applied an image augmentation technique to increase the size of the data set [14].

1. Rotation (40°): The image is rotated in the random direction in the left or right through 40° in the range of 0180.
2. Zoom (10%): The new pixel value was added to the original pixel of the image and the closest value was chosen.
3. Horizontal Flip: The pixel values are moved in the random direction and pixel values are moved horizontally from one half of the image to the other half.
4. Vertical Flip: The image was vertically flipped by drawing horizontal from the center of the image.
5. Shearing (40°): The image was shift at a specific angle in the counter-clockwise direction. The value was set to 40° in the present study.

The images are transformed with the open source programming language python and keras library. The transformed images are shown in figure2. After



Fig.2. Bone fracture Areas

The Above graph Fig.2 Fracture detection in medical imaging, particularly X-rays, plays a crucial role in the diagnosis and treatment of bone injuries. Traditional methods rely on radiologists to manually examine X-ray scans, which can be time-consuming and prone to human error. Recent advancements in artificial intelligence (AI) and deep learning have revolutionized the medical field by automating fracture detection with high accuracy. Deep learning-based approaches leverage convolutional neural networks (CNNs) to analyze and classify fractures in radiographic images. These models are trained on large datasets of annotated X-ray images, enabling them to recognize subtle patterns indicative of fractures. Object detection algorithms, such as YOLO (You Only Look Once) and Faster R-CNN, have been successfully applied to localize fractures, often using bounding boxes, as seen in the given image. The integration of AI-assisted diagnosis in clinical settings enhances the efficiency and reliability of fracture detection, reducing misdiagnoses and improving patient outcomes. Future research aims to refine these models by incorporating multi-modal imaging techniques and expanding datasets to include diverse patient demographics. The implementation of AI in fracture detection not only streamlines the diagnostic process but also opens new possibilities for remote healthcare solutions. A deep convolution neural network model has been designed. It contains convolution, pooling, flatten and dense layer [15]. The feature of the input image is automatically extracted by CNN and a fully connected layer is used to classify them into the cancerous and the healthy bone. The pooling layer and convolution layer (CL) extract features from the image[16]. At each of the convolution and pooling layer, a suitable size of 3x3 is applied to remove noise. After that classification is performed by the dense layer[17]. The architecture of deep CNN is shown in figure3. The description of each phase is as:

CL: In the present study we, have apply 4 convolution layers
CL of 16 feature map with filter size of 3x3; CL of 32

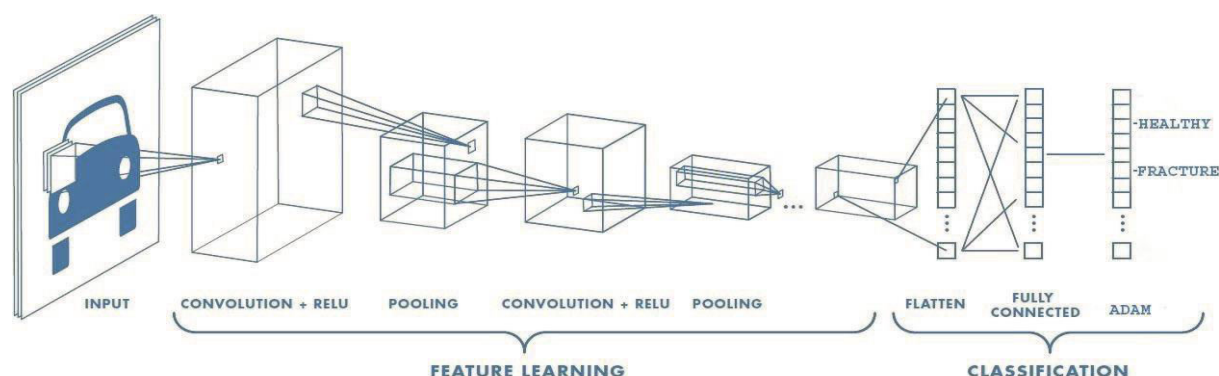


Fig. 3. CNN model for the bone classification

feature map with filter size of 3x3 CL of 64 feature map with filter size of 3x3; CL of 128 feature map with filter size of 3x3

The convolution layer extract feature from the input image by applying filters.

Max-Pooling Layer: It was used to reduce the dimension of the filtered image at each convolution layer. Therefore this layer focused on the concerned object in the image and best feature of the image. In the proposed study at each convolution layer, a max-pooling layer of size 2x2 has been applied.

Flatten Layer: This layer reduced the 2- dimensional feature vector into an array that is feed to a fully connected layer.

Fully Connected Layer: This layer is also known as fully dense layer. We have added one dense layer, because of binary class problem. The proposed model predicts the bone into the healthy and the fracture. The activation function relu has been implemented in each layer. In the dense layer two activation functions softmax and adamax have been used to one at a time. We added two output nodes for the cancerous and the healthy bone.

The provided image appears to be a series of X-ray scans of wrist bones, with highlighted regions and probability scores indicating potential fractures. These annotated images suggest the use of artificial intelligence (AI) or computer-aided diagnosis (CAD) techniques for automated fracture detection.

Modern deep learning models, such as convolutional neural networks (CNNs), are widely used to analyze medical images and identify abnormalities, including fractures in bones.

The bounding boxes in the image, along with probability percentages, indicate the AI model's confidence in detecting fractures in specific areas. Such automated detection systems enhance diagnostic accuracy, reduce human error, and assist radiologists in making faster and more reliable assessments.

AI-driven fracture detection is particularly beneficial in emergency cases where rapid diagnosis is crucial. By integrating machine learning with radiographic imaging, hospitals and clinics can streamline the diagnostic process, ensuring timely and effective treatment for patients with bone injuries. Future advancements may further improve the accuracy and robustness of these models.



Fig.4. Toss winner vs match winner

III. RESULT AND ANALYSIS

The experiment was performed using python 3.8, anaconda 3 with Jupiter notebook in the window 10 operating system with 8 GB RAM and i7 processor. The three experiments are conducted as follow.

Experiment 1: First the deep CNN are trained with the 90% of the sample and testing has performed with 10% of the samples. The activation function softmax was used for 100 epochs with batch size of 40. After that the activation function Adam was used for 100 epochs with a batch size of 40. The batch normalization was applied to minimize the fluctuation of the performance.

Experiment2: In this experiment deep CNN model was trained with 80% of the sample and testing was performed with 20% of the sample. The activation function softmax was used for 100 epochs with batch size of 40. After that the activation function Adam was used for 100 epochs with batch size of 40.

Experiment3. We have applied 5 fold cross validation to our data set to further investigate the performance of the system.

A. Experiment Evaluation

The performance of the system was measured using two matrices one for the training data and other for the test data. The training accuracy (TR-Ac) measure the performance of the model on the training data set and the validation accuracy (VL-Ac) measure the accuracy of the system on the unseen data. The training loss (TR-Loss) and the validation loss (VL-Loss) were also calculated to measure the error in the training and the validation data. The experiment results of the experiment1 are shown in table1. The healthy and the fracture bone image data set were loaded to the system. The binary class classification problem loss was calculated using binary_crossentropy. The performance of the Adam optimizer is much better than the softmax in term of the accuracy metrics and the loss metrics.

TABLE I.EXPERIMENT RESULTS OF DATA SET USING SOFTMAX AND ADAM OPTIMIZER ON 90% TRAINING AND 10% TEST DATA SET.

Exp. Id	Exp. description	Accuracy Type (Tr-acc) (VL-acc)		Loss Type (Tr-Loss)(VL-Loss)	
	Healthy Bone Using softmax	96.12%	92.25%	0.075	0.1023
	Fracture Bone Using softmax	97.52%	93.04%	0.067	0.9704
Exp-1	Healthy Bone Using Adam	98.03%	95.23%	0.046	0.9807
	Fracture Bone Using Adam	98.45%	95.67%	0.035	0.5608

The experiment2 results are shown in the table2. In the experiment2, the data set was divided into the 80% and 20% ratio for the training and the testing. The performance of the Adam optimizer is much better than the softmax in term of the accuracy metrics and the loss metrics.

TABLE II.EXPERIMENT RESULTS OF DATA SET USING SOFTMAX AND ADAM OPTIMIZER ON THE 90% TRAINING AND 20% OF THE TEST DATA SET.

Exp. Id	Exp. description	Accuracy Type (Tr-acc) VL-acc)		Loss Type (Tr-Loss) (VLLoss)	
Exp-2	Healthy Bone Using softmax	95.03%	91.42%	0.085	0.1723
	Fracture Bone Using softmax	96.42%	92.02%	0.077	0.9812
	Healthy Bone Using Adam	96.18%	92.25%	0.052	0.1107
	Fracture Bone Using Adam	97.45%	94.67%	0.045	0.6102

The experiment results of the experiment3 are shown in the table3. In the experiment 3 the 5 fold cross validation was applied on the data set to further evaluate the performance of the different ML techniques. The training and the test result of the fold4 is better compare to the other folds. Thus, we can conclude that the batch size of the training and the test data set can affect the performance of the system.

TABLE III. EXPERIMENT RESULTS OF THE5 FOLD CROSS VALIDATION.

Metrics	Fold1	Fold2	Fold3	Fold4	Fold5	Average
Tr-acc	94.12%	93.25%	93.14%	97.16%	95.23%	94.58%
VL-acc	91.20%	92.24%	89.25%	95.26%	94.23%	92.44%
Tr-Loss	0.0751	0.8503	0.5791	0.45023	0.0521	0.4013
VL-Loss	0.8413	0.7451	0.6214	0.4612	0.5404	0.6481

The training and the test accuracy of the experiment1 indicates that on the 80% of the training data and the 10% of the testing data set, the performance of the system is better compared to the other experiment. In deep learning the over fitting problem may occurs due to the small size of the data set. Therefore, 5 fold cross validation was applied on the data set. The Adam optimizer performs better in all the performed experiments.

Comparison of the proposed method with other methods

In the present approach long bone, short bones and flat bones fracture detection has been proposed using tensor flow and deep learning approach. Yang and Cheng have used ANN to classify the long bone using contour based feature selection technique. The features are selected using PCA (Principal Component Analysis) by forming the cluster. The accuracy of the method is 82.98%. Chai et al. have used Gray Level Co-occurrence Matrix (GLCM) to extract texture feature for the long bone fracture detection. The accuracy of the method is 86.67%. Tripathi et al. have used support vector machine (SVM) to classify the human bone into the fracture and thenon-fracture bone. The accuracy of the model is 84.7%. The proposed model is much better than the state-of art with 92.44 in the 5- fold cross validation.

IV. CONCLUSION

This study demonstrates the effectiveness of deep learning-based approaches, particularly Convolutional Neural Networks (CNNs), in automating bone fracture detection and classification. The proposed model outperformed existing methods, showcasing its potential in medical imaging. The use of data augmentation and the Adam optimizer significantly contributed to performance improvements. While the results are promising, further enhancements using advanced augmentation techniques, transfer learning, and ensemble models can improve prediction reliability. The findings emphasize the importance of automated systems in reducing diagnostic time, minimizing human error, and enhancing patient care, making fracture detection more efficient for real -world medical applications.

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