Scalable Computing: Practice and Experience, ISSN 1895-1767, http://www.scpe.org

Volume 24, Issues 2, pp. 161–171, DOI 10.12694/scpe.v24i2.2081

A BONE FRACTURE DETECTION USING AI-BASED TECHNIQUES

RUSHABH MEHTA,* PREKSHA PAREEK,† RUCHI JAYASWAL,‡ SHRUTI PATIL,§ AND KISHAN VYAS¶

Abstract. The medical field in itself is a complex term where the diagnosis is of the most importance. If there is a correct diagnosis made on time in the appropriate time duration then the treatment can be started in a timely manner and this treatment will be beneficial in curing the patient. There are many different techniques that are available to find the abnormalities in an image given but we will review some of them which are most recently developed and will compare the results of each of them. A detailed study is done at the end of this paper which gives insights into fractures and their types. The dataset which we would consider is the MURA dataset. Discussion about further research in this area is also done to help researchers in exploring new dimensions in this field.

Key words: Machine Learning, Artificial intelligence, Bone Fractures, Medical Images, X-Rays, CAD.

1. Introduction. The adult human body consists of 206 bones, these include different types of bones which are different in shape, size, structure and morphology. There are many causes of fracture in human bone these may be due to old age, accident, or falling. The risk of getting a bone fracture mostly increases in such cases when the bones are weak and there are deficiencies of required vitamins, minerals and calcium [32]. The most used method for the interpretation of fracture in humans is an x-ray or medical resonance imaging [37]. Sometimes there are cases when the cracks in a bone are very small and doctors cannot detect them easily so there is a need for enhancement in the diagnosis of bone fracture detection with the help of computer-aided diagnosis or machine learning coupled with different methods [4].

The normally or usually used method which is used to find fracture in a bone is by viewing it by a radiologist who must use his experience in inspecting the X-ray image and giving the results after visually inspecting it. Most of the time technicians have to take x-ray images in different poses like anterior view, posterior view and lateral view as many times it happens that there are cases where by viewing different views like anterior view or posterior view radiologist cannot come to one given results in such cases, he has to use different views of x-rays so that he can give a result if a bone is a fracture or not. But this is not sufficient in diagnosis as sometimes a doctor may miss a diagnosis and, in such cases, there may be chances that the patient may have to undergo a prolonged treatment.

In some cases, there are many times patient ignores some symptoms and the diagnosis by a doctor is done based on their complaints as many times the patient gives incomplete information about his/her health condition. Sometimes there are cases where there may be chances that the x-ray image is not taken properly in such cases also there are chances of missing the diagnosis. These are the cases of bone fracture. But in complex cases where there is a need for a CT scan the whole diagnosis is mostly based on the complaints. Thus, in this survey, the main motive is to help the medical fraternity in diagnosing x-ray images.

This paper could further help- researchers to improve the given technology and will motivate them in finding

*Department of Artificial Intelligence and Machine Learning, Symbiosis Institute of Technology, Pune, India (rushabh.mehta.mtech2021@sitpune.edu.in)

†Department of Artificial Intelligence and Machine Learning, Symbiosis Institute of Technology, Pune, India (preksha.pareek@sitpune.edu.in)

‡Department of Artificial Intelligence and Machine Learning, Symbiosis Institute of Technology, Pune, India (ruchi.jayaswal@sitpune.edu.in)

§Department of Artificial Intelligence and Machine Learning, Symbiosis Institute of Technology, Pune, India (shruti.patil@sitpune.edu.in)

¶Department of Artificial Intelligence and Machine Learning, Symbiosis Institute of Technology, Pune, India (kishan.vyas.mtech2021@sitpune.edu.in)

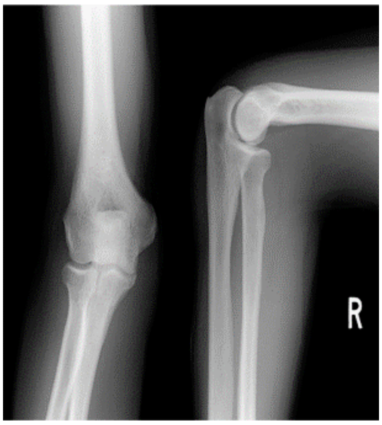

Fig. 1.1: Sample X-Ray Image

new ways in forming more accurate systems. X-ray images which are considered by different authors are from different sources and the accuracy is mentioned in the cases where results were available. Further, there is a model which is proposed which could give more accurate results. These technologies of machine learning and computer-aided diagnosis can be further used in more complex diagnoses like CT scans or MRIs.

The process of first diagnosing the fracture is time-consuming with there being the difficulty of radiologist experts present in villages or remote areas. Thus, with the help of machine learning there can be adverse changes that can be made for effective diagnosis of x-rays [10, 12]. In the past decade, there has been an increasing application of convolution neural network models for the detection of bone fractures, these methods have demonstrated that the use of deep learning has also proved to be beneficial and has added advantage for this purpose [27, 40]. Figure 1.1 represent sample of X-Ray image.

2. Motivation. X-ray with auto-report generation by the machine itself, the day is not far when there would be ultrasound and these reports would be analyzed by the machine itself based on the data by which it is trained. There can be a machine learning model by which the machines are trained and they could be trained to such an extent that they could predict far better than doctors. The radiologist would visit only twice or thrice a week, and ultrasound, X-ray reporting and MRI could be performed on these days. For any critical illness, this type of infrastructure would be dangerous and if these types of machines come up then a technician could perform X-rays and reports would be analyzed by the machine itself (maybe the patient could act faster). This could not only be beneficial to rural areas but also could be faster and more precise in the detection of diseases.

Bone is an important part of the human body, without bones, we would not be able to walk, run, jump, climb stairs, or do any physical activity. bones also help us to carry out our daily activities. when a person falls down, he/she can break his/her bones. to make a diagnosis, they must know how to read these images. they then compare them to previous ones to see if the same injury has happened before. for example, if a patient had a broken arm last year, the doctor might ask about the location of the injury. he/she might also ask about the type of injury (fracture vs. dislocation).

Finally, the doctor will check whether the injury was caused by a fall or by something else. hence our main goal is to make a robust system that can help medical professionals in interpreting x-ray images and help them identify bone fractures. There are mainly two methods that we can use to primarily develop a model these include machine learning and deep learning.

2.1. Contribution of the work. A contribution of this review paper as follows:

- X-ray images of the bone are taken with medical instruments, x-ray is mostly used for the detection of bone fractures. Bone fractures are those abnormalities that are caused when a given bone cannot withstand the given pressure from outside and due to this, there is the development of cracks in bones.

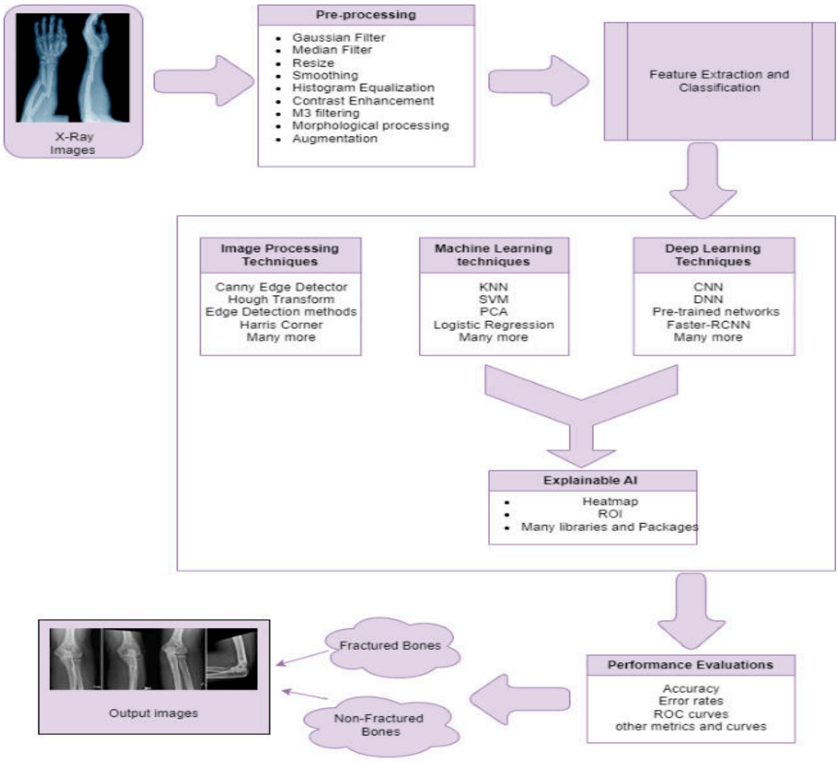

Fig. 3.1: Block Diagram of Bone Fracture Detection

- It is of utmost importance for doctors to detect bone fractures in time to ensure timely treatment is provided to the patient.
- Thus, new technologies and advancements in artificial intelligence and machine learning there have new reasonable ways to detect bone fractures on different types of bones.

2.2. *Organization of the paper***.** Section 2 defines the related work carried out previously by different researchers. Section 3 defines the different datasets which are openly available for this research. Section 4 defines the evaluation metrics. The further part section 5 details the challenges which have to be addressed. Section 6 gives a conclusion about our learnings from this paper. Section 7 narrates the further scope of this research and the further enhancement of this field.

3. Background Work. In the proposed model we acquire the images from the MURA dataset and select one category of x-ray from the seven types of bone X-rays such as the forearm, elbow, wrist, humerus, hand, fingers, and shoulder. The next step involves the pre-processing of these images, these methods include some of the mentioned as a gaussian filter, median filter, smoothing, resizing, contrast enhancement, histogram equalization and augmentation. After the pre-processing is done, we move towards feature extraction and classification. There are machine learning techniques as well as deep learning techniques which are involved, we may use any one of them which fetches better performance. Machine learning technique involves the use of SVM, KNN, Logistic Regression, etc. While deep learning techniques involve CNN, Faster R-CNN, DNN, etc. with the use of these techniques our model will classify x-ray image as fractured and normal images with a certain accuracy level. We now will use techniques like ROI, and heatmap to find and explain the behaviours of our model. We move towards performance evaluation of our model, these include accuracy, precision, recall, AUC, ROC, etc. after the performance is evaluated, we try to change parameters and fine tune it in order to get better performance.

The study from [4] uses primitive machine learning techniques such as feature extraction and pre-processing.

Developed the RDSS method to recover incorrect parameters to overcome errors in contour segmentation [5]. The same author has developed in [6] a fracture diagnosis model based on machine learning techniques. Initially, the gaussian filter is used to enhance the quality of the given X-ray image. The corners and edges are then identified using the Canny Edge algorithm. Lastly, the Harris corner detection method is used to detect the fractured areas. The method can classify fractured bones with 92% accuracy. Feature extraction is enhanced by various image processing techniques, such as pixel density, controllable filters, and image projection integration [17].

All of the above-mentioned methods do an excellent job of diagnosing the skeletal system. However, the performance of these techniques is not satisfactory due to the handmade features used to train the model. Recently, some authors reported that adding deep convolution neural network models to a set of, features gave improved classification performance. More recently, the authors of [26] developed the Regional Convolutional Neural Network (R-CNN) for the detection of skull fractures. They leveraged the prior clinical knowledge of the fastest R-CNN to improve the classification performance.

The authors of the paper [22] have developed a deep-ensembled-based convolution neural network(CNN) model for ankle fracture detection. Their methods include ResNet and InceptionV3 for feature extraction. The cluster-based model classified healthy and fractured individuals with 81% accuracy. Among transfer-based learning methods, the authors of [11] have also used the YOLOV3 model was used to identify skull fractures which had a sensitivity of 91.7%. In, subsequent research [21], pre-trained InceptionV3 and DenseNet-121 models were used for bone diagnosis. The methods mentioned in the paper [21] achieved an accuracy of 95%, while the method described in the paper [20] achieved an accuracy of 95.4%. Some studies reported that they first trained the models on a dataset of skeletal images before classification.

The authors of [45] have developed two deep convolutions neural network(CNN) models for the identification and segmentation of intertrochanteric fractures. The dataset is divided into two parts, training, and testing, with 32,045 and 11,465 images, respectively. First, a region of interest (ROI) is identified using a CNN based on a cascade structure. Another CNN is then used for segmentation and recognition. In other studies, of paper considered the researchers of the paper [45] have pre-processed rib fracture images, and resized the image from 128 x 128 x 333 pixels. The semantic segmentation technique was later used to locate the fractured regions of the ribs. Finally, a UNet model is used to classify the CT images with an accuracy of 88.5%. in the paper [33] the authors have used YOLO Model for bone localization of fractures. Data augmentation techniques are also applied and the performance of their models is compared with the original datasets. In the original dataset, the method can classify fractured and non-fractured regions with an accuracy of 81.9

In the paper [42] researchers have designed a hierarchical network and compared it to orthopedic diagnoses. They trained hierarchical matrices on X-ray images. Their method achieved a classification accuracy of 88.7%. In the research paper [30] use fractures were identified in two stages; In the initial step, the fastest R-CNN was used to locate 20 fracture regions, and in the next step, the new CrackNet network was used to classify the fractures. Their method classified healthy bones and, fractured bones with a classification accuracy of 90.1%. In a similar study, a new method was proposed to classify the parallel net fraction using the two-scale method proposed by [41].

The authors of [44, 3] used pre-trained R-CNN was applied to the small dataset and achieved 96% and 97% accuracy, respectively. The authors of [29] have applied their experiences and designed a decision tree for the identification of fractures. Their method achieved a classification accuracy of, of 86.57%. The researchers of [8, 19] have used deep CNN applications to extract features from skeletal images. The validation accuracy of their method is 83% and 97.4%, respectively. The authors of [14] and Rayvolve model was designed to detect, fractures in children. Externally validated methods classified healthy and broken bones with 95% accuracy.

In 2022 the authors of [16] used a deep CNN model based on clusters was applied to determine wrist fractures. Their method isolated, broken, and healthy wrist bones with 86.39% accuracy. The authors of [34] have used in 2019 classified bone fractures by combining, depth lines and SURF features. They compared the performance of ResNet and VGG16 among which, deep CNN models have been previously trained. Of the two models considered the ResNet model has the highest classification accuracy of 98%.

In 2020 the researchers of [31] have used techniques like Generative Adversarial Networks and Digitally Reconstructed Radiographs. The image dataset was generated using GAN and a deep CNN model was used to

Table 3.1: Literature Review of Bone Fracture Detection by Computer Vision Techniques

Year	Methods	Pros	Cons	Datasets	Performance
2021 [35]	KNN classification	Accuracy is good to rely on for the detection of osteoporosis.	As the feature dimension increases. the accuracy suffers. Has been implemented for the lumbar spine only.	Self-synthesized dataset.	97.22% Accuracy
2019 [36]	Image Pre-Processing: 1)Smoothing 2)Histogram equalizer 3)Edge detection 4)Segmentation 5)Contrast enhancement	The theory of enhancement of images and then identifying the focus area using computer vision is used In this paper.	The dataset is not well defined. Accuracy is not declared in this paper.	The dataset is collected from different medical institutes and one dataset is formed from the obtained data.	Not Available
2020 [37]	Harris Corner method is used for the detection of fracture and for image pre-processing M3 filtering is used as it gives good PSNR(peak signal noise ratio) compared to mean filtering and . median filtering.	It gives us new direction for us in this field as these new methods can be used for fracture detection rather than using CNN or Deep learning.	The dataset is self-synthesized so it is difficult to procure this dataset.	Self-synthesized dataset.	94% Accuracy
2018	Morphological operations, Special Bone Feature, Extraction, Sobel Edge Detection	Hand fingers are only used thus which helps in increasing the accuracy.	Hand fingers are only used but it does not specify properly which finger is used like the thumb,index, etc.	Self-synthesized dataset(155 images (100 fractures images, 30 hands finger images, 25 normal images)	92% for general fracture, 93.33% for finger
2018 [38]	Gaussian filter, canny edge detector, Sobel Threshold	It uses the technique of the Gaussian filter which has given accurate results.	The dataset is self-synthesized so it is difficult to procure this dataset.	Self-synthesized dataset.	Not Defined
2017 [39]	Canny edge detector, Hough Transform	New methods of the Hough transform are used for bone fracture detection.	A small dataset of only 10 images is used due to which . there is a lack of training in the model.	10images	80% Accuracy
2017 [40]	Gaussian Filter, Gradient Magnitude, Canny Detector	Methods of computer vision give new direction to this work.	A very small dataset of only 12 images is used for training the model.	12images	Not Defined
2016 [41]	Canny detector.	It only focuses on one technique to detect fractured images thus gaining a good amount of accuracy.	The dataset used is an imbalanced dataset thus it should first balance the dataset.	Self-synthesized dataset. 21 images (16 images are normal 5 images are fractured)	87.5% Accuracy
2016 [42]	Morphological Gradient, Smoothing, Canny Detector	Methods of gradient and canny detector are used which gives new direction to research.	The dataset used is not mentioned. The accuracy or any other metric to evaluate is not defined.	Not defined.	Not defined.
2015 [43]	Laplacian Gradient, K means clustering	Techniques used are based on computer vision thus making new methods available for the purpose of bone fracture detection.	The dataset used is not defined.	Not defined.	85%
2013 [44]	Edge detection, texture detection, parallel edges	Edge detection along with parallel edges is used.	The dataset used is an imbalanced dataset thus it needs to be first balanced and then used so that training would give accurate results.	Self-synthesized dataset 300 (200 normal, 100 fractures images)	83%

perform the classification. The researchers of [43] have applied a CNN model based on deep learning, obtaining an accuracy of 90.2% to identify rib fractures. The authors of [38] have used the InceptionV3 model to classify radiographs of the proximal femur. Their method classified, images of healthy and broken bones with 86 percent accuracy. In a similar study, the researchers of [28] have uses DenseNet to classify femoral fractures with 89% accuracy.

3.1. Bone Fracture Detection using Computer Vision. Generally used methods are based on concepts of computer vision and image processing. Computer vision has an immense application in the area of the medical field and has been proven helpful with reasonable performance levels. Some of these methods also use concepts of computer vision along with machine learning or deep learning. The use of computer vision in x-ray bone fracture detection is used for more than a decade and researchers are continuously enhancing and introducing new methods for better performances.

Table 3.1 compares some different other methods and their application for the purpose of bone fracture detection. These papers included are from 2012 to the present.

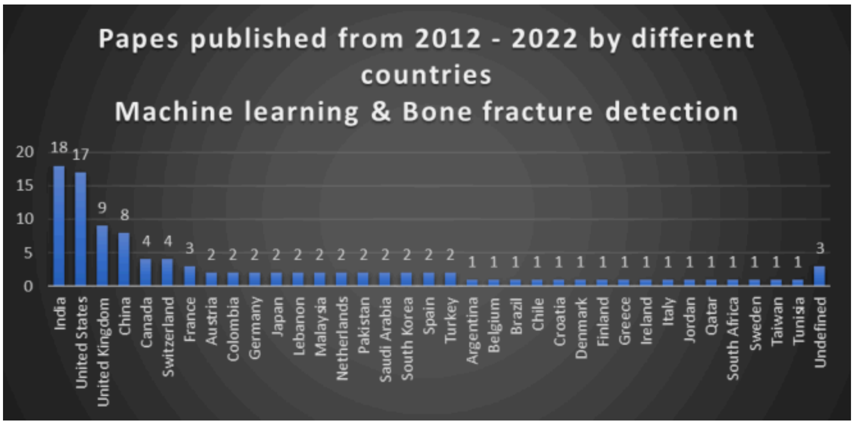

Fig. 3.2: Country-wise papers for ML and bone fracture detection

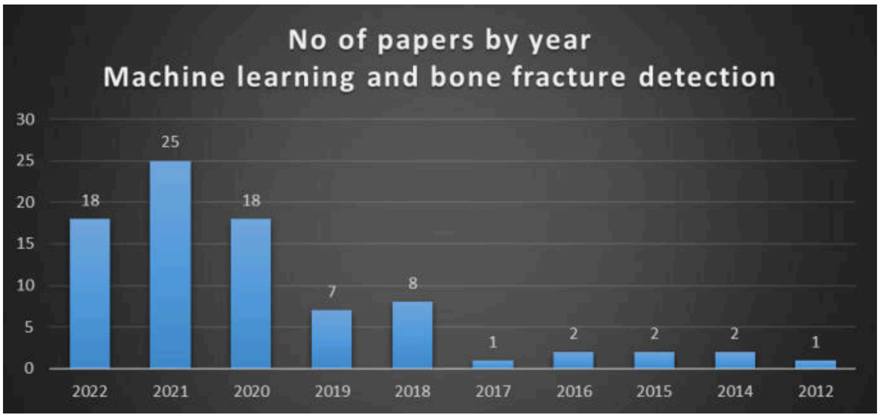

Fig. 3.3: Year-wise paper for ML and bone fracture detection

3.2. Bone Fracture Detection using Machine Learning. Bone fracture using machine learning in itself has a very wide scope due variety of methodologies available for this purpose. There is a variety of different classification algorithms which can be used in order to classify healthy bone and fractured bone. Different classification methods involve KNN [7], SVM [7], Logistic Regression [23], Naïve Bayes, etc are few to mention. Machine learning methods have proven to give acceptable accuracy levels for purpose of bone fracture detection. From the graphs and the data collected from different data sources, it can be seen that the use of machine learning applied for the purpose of bone fracture detection has seen a declining trend after 2020 and 2021 as the concept and use of deep learning methods have been proving more advantages in both simple computations, less computation time as well as a higher level of accuracy.

Figure 3.2 depicts and gives insight into the number of papers published for bone fracture detection using machine learning from 2012 to 2022 by different countries. The data are collected from Scopus.

Figure 3.3 depicts and gives insight into the number of papers published for bone fracture detection using machine learning in the last decade. The data are collected from Scopus.

3.3. Bone Fracture Detection using Deep Learning. Bone fracture detection using deep learning involves different techniques such as Convolution Neural Networks [36], Artificial Neural Networks, Deep Neural Networks [36], Deep Convolution Neural Networks [27], Inception V3 [39], R-CNN, etc few to mention. The concept of use and application of deep learning towards the use of bone fracture detection has taken momentum after 2019 as these methods or techniques once tried have given very interesting and useful results. The drawbacks of previously used different methods have been overcome using the concept of deep learning. There was a problem with analysing images from only one anatomical position and due to this, there are some cases where there is missed diagnosis. Due to this deep learning method and the use of faster R-CNN and customized cracknet [30] the minute cracks in the x-rays were been able to be detected.

3.4. Bone fracture detection using Explainable AI. Explainable AI(XAI) [46] refers to a technique in which we try to explain why a machine learning algorithm or deep learning algorithm has reached a solution. In our case, we consider some papers which try to explain why the model has predicted the outcome as normal bone or fractured bone. The XAI has been in use for the explainability of the model and the research on why the model has reached some definite conclusion.

In the paper [18] authors have used classification techniques for finding fractured and normal bones. They have used full radiographs as well as the manually defined region of interest to help classify better. In these cases, the accuracy of full radiographs was 835 whereas the accuracy level of manually decided regions of interest the accuracy level was 93%. The accuracy level was the same for automatic localized x-ray images 93%. In the paper [46] researchers used binary classification on the whole dataset and managed to get 96.9% accuracy, use of the CNN algorithm fetched different results for different bone types. The authors of [9] have used deep learning systems for the purpose of bone fracture classification and have achieved an AUC OF 0.93 and a 95% confidence interval. It was found that in around 90% of x-ray images the model prediction was in line with radiologist annotation. The authors of [24] have used densely connected convolution neural networks and have achieved an accuracy of 95 .8%, they have further used binary classification for the femoral neck (displaced and non-displaced), and intertrochanteric fracture. In the paper [27] authors have used deep learning algorithms with aided and unaided diagnosis and have found an AUC of 0.967. Explainable AI tries to answer some of the most important questions such as what are the model's weaknesses and model strengths, the criteria by which the model has chosen to arrive at a specific conclusion, the most important why has model chosen this approach and given particular solution as opposed to other, what are the errors that may be faced by certain models and how to correct these errors is all that explainable AI explains.

4. Datasets. The most openly available and free-access datasets for this research are as follows:

MURA Dataset. MURA [35] dataset is a large collection of x-ray images from a huge number of patients collected over a large period of time. The samples which are collected include one of the seven types of bones such as forearm, elbow, wrist, humerus, hand, fingers, and shoulder. This huge dataset is collected from 12,173 patients which contains a total of 14,863 x-ray images of bone with a total multi-view of the different anatomical positions of 40,561 x-ray images.

Medpix Dataset. Medpix [25] is an open-source database that is available to the public. It has a vast variety of data including cases in every vertical. The database collected is from nearly about 12,000 patients and it has around 59,000 images in 9000 topics.

Imaging Archive (TCIA). TCIA [13] is a dataset of a collection of cancer images. The cancer imaging archive has a very large and free source of the dataset which is available to the public. It is mainly funded by CIP a part of the National cancer institute which is managed by FNLCR. Figure 10 is a sample image from TCIA which indicates both the chest x-ray as well as CT image of the chest of the same patient.

Radiopedia Dataset. Radiopedia [2] started in 2007 has been the most trusted and reliable source of datasets for radiology which is available for free to the public. In 2021 radiopedia has achieved to serve and provide data to almost 41 million people. Every single country on earth has in some or another other way been provided data from radiopedia. Figure 4.1 shows the frontal and lateral view of the right hand having an intra-articular radial styloid fracture.

Alyward Dataset. Alyward.org [1] has a dataset of chest x-ray images. There is a vast collection of 10,000 chest x-ray images along with the diagnosis.

Diagnostic Imaging Dataset (DID). The dataset [15] is a central collection of imaging that is carried out every month on NHS patients, and it is then extracted locally from the radiology information center. The diagnostic imaging dataset is only available through the data access request service. Other datasets which are available are Dataset by the Institute of Engineering Science and Technology, Shibpur (IIEST).

Fig. 4.1: Sample Image from Radiopedia Dataset

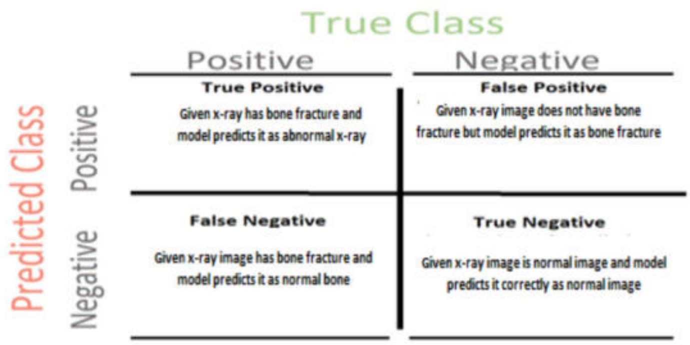

Fig. 5.1: Confusion matrix for bone fracture detection

5. Evaluation Metrics. The evaluation measures of the models are calculated using accuracy, recall, precision and F1 score. These metrics are evaluated based on the confusion matrix of each model using the mathematical formula.

Confusion matrix it is used to give details of the total performance of the classifier model. Accuracy can sometimes portray wrong or false results in cases where the dataset is considered to be imbalanced or uneven dataset. An uneven dataset is a dataset where there are an unequal number of samples for each category. Sometimes classification accuracy can give false results when there are more than two categories being considered. By evaluating the confusion matrix researchers get to understand better what is true and what is false in the model. In the confusion matrix, the correct and incorrect cases are grouped together and their total number of counts is divided by a particular category. The confusion matrix basically tries to portray how confused the classifier is when classifying the datasets. It tries to identify the errors which the classifier makes and also helps in identifying types of errors made by the classifier. Figure 5.1 defines the different aspects of true positive, true negative, false positivea and false negative in respect of bone fracture detection.

Accuracy can be defined as the ratio of total correct predictions to the total no of samples considered.

Accuracy = (TP+TN)/ (TP+TN+FP+FN) (1)

Precision can be defined as the ratio of actual results obtained to that of positive samples.

Precision = TP/(TP+FP) (2)

Recall can be defined as the ratio of the total number of positive cases to the total number of predictions done.

Recall = TP/ (TP+FN) (3)

F1-Score measures the harmonic mean of the model performance.

F1 − Score = (2 × (Precision × Recall)) / (Precision + Recall) (4)

6. Challenges. There have been various challenges which are faced while working on research related to the medical field, as there has been a huge number of problems related to the acceptance of new systems and public acceptance is of most importance as they decide the fate of the success of the research. Some of the challenges are mentioned below:

Generalized model: In general, an adult human has 206 bones. Every bone in the human body has a different shape, size, structure and different morphological features. To generalize and form a model which is a general model which can classify between fractured and non-fractured images for any given bone is practically not possible as in such cases for every type of bone there must be training and the accuracy level would also differ for every type of bone.

To form a model which can generalize every bone would take a huge amount of dataset and the challenge would be to gather a huge amount of dataset as for specific types of bone finding both fractured and normal images is difficult and these datasets are most of the time, not open source.

Time complexity and large dataset: If one gets all images by collaborating with an imaging center or hospital the training of such models will also take a huge amount of time and computation complexity would also be very large.

Integration with machines: Integrating these models with x-ray machines for spot diagnosis is also a key challenge as it requires a change of the whole system.

Acceptance by the general public is a key challenge as in cities there are adequate amounts of resources and doctors available for diagnosis but in villages, there is a lack of resources and doctors thus there these types of models can be proved to be a boon to mankind for its spot diagnosis as well as lower cost of diagnosis.

7. Conclusion. This paper contains a full end-to-end analysis of the considered papers and the techniques used in this paper. Methodologies used in these papers and detailed pros and cons have been discussed. The paper also discusses and compares the accuracy level of the considered papers. In the results and discussion, the new age problems related to these technologies and methodologies have been discussed in detail. Thus, the advancement in the field of medical science due to the extensive use of machine learning can be seen in the above learnings. It can be often learned that the use of machine learning towards such a humanitarian cause can be very useful in developing a stronger healthcare infrastructure in the country. It has been seen that the use of machine learning has become obsolete after the introduction of the use of deep learning for the purpose of bone fracture detection as the level of accuracy being achieved by deep learning is commendable and has seen practical life applications. The use of such technology and integration with the medical field should be encouraged at a national level for the technology to reach remote areas as well as encourage new researchers to enhance these types of projects. Further direction to this work is that researchers have used different techniques to develop models and to classify if a given x-ray image is a fractured or normal image. This work can be further given more impact by classifying the types of fractures i.e., stress fracture, oblique fracture, open fracture, close fracture, compression fracture, etc. In this further work, researchers can try to combine different methodologies from the referred papers and try to form a model which can give the highest level of accuracy and can be used by medical professionals in their routine. The other aspect that researchers can try to achieve is to integrate their formed model with X-Ray machines.

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Edited by: Katarzyna Wasielewska
Received: Dec 10, 2023
Accepted: Jun 11, 2023