Detection and Meta-Analysis of Human Bone Fractures using CNN

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***Abstract-*** **To find studies that used machine learning techniques and algorithms to estimate the risk of fractures, a thorough literature search was done. A total of 15 research articles that were published over the last two to three years were used to compile the statistical findings. This review looks at protracted fracture injuries that cause early mortality, significant rates of morbidity, or diminished quality of life. Our objective was to determine whether there was a constant need to improve the factors that could reduce the likelihood of suffering fractures and the problems that go along with them. Decreased bone density, epidemiological risk factors, collagen structure and bone proteins, pre-existing medical disorders, smoking, and immobility are the most crucial elements that were taken into consideration after reading publications. In order to convey the survey results, we summarise the authors' arguments by highlighting the key machine learning methods discussed in the papers and the precision of their predicted performance.**

***Keywords: Fracture detection, radiography, X-rays, MRI scans, YOLO, BMD, THR.***

# INTRODUCTION

Anyone can sustain a fracture at any age, and they are very common. The term "broken bone" in medical terminology refers to a bone fracture. Traumas like falls, auto accidents, or sports injuries frequently result in fractures. The kind and position of the fracture, however, differ from person to person. Globally, there were 178 million (95% UI 162-196) new fractures in 2019 (an increase of 34% [30-13.7] since 1990), 455 million (428-484) cases of prevalent acute or chronic fracture symptoms since 1990 (an increase of 71% [67-72.5] since 1990), and 25.8 million (17.8-35.8) YLDs since 1990 (an increase of 65.3% [62-48.0]). Doctors who must assess dozens of X-ray images each day bear a heavy burden.

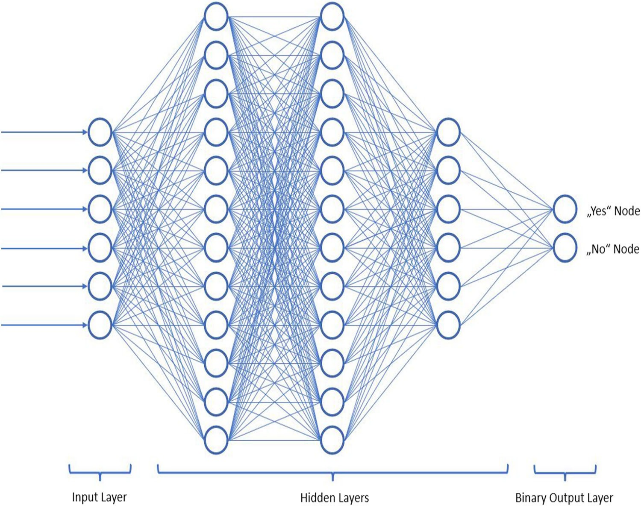
Tasks like the one we have at hand, hip fracture detection, can be handled easily with the application of ML models. The use of AI in this type of problem incorporates machine learning and deep learning concepts which greatly reduce the time required for diagnosing these issues and can provide almost accurate results consistently.

1. BACKGROUND

The topic of hip fracture detection is centred around the best possible algorithm for image processing using CNN to diagnose various kinds of osteoporosis based on the muscle density of the surrounding area of the hip. A huge requirement and dependence of this type of model is X-rays generated through X-ray machines scanning multiple people's hips. In order to create the dataset of these images, both training and testing dataset must be accounted for and these must also include X-rays of healthy hips, i.e. without fractures.

We've decided to write and research on this topic so as to understand the intricacies and complications in the designing of such models. Moreover, the issue being handled is of great public value, ensuring a cheaper and reliable method of hip fracture detection. A single X-ray image will be sufficient for the diagnosis and can even provide the direction of treatment based upon the severity of the fracture. This saves time and money which would've been consumed by an actual physician.

The need of such models in the modern day just proves how far we've come in terms of technology and shows how efficiently we can combine the field of AI and medicine to make lives easier. Accuracy is forever a priority and machines are consistent with their accuracy in most cases. Tasks like the one we have at hand, hip fracture detection, can be handled easily with the application of ML models.

The application of AI to this kind of issue involves machine learning and deep learning ideas, which significantly shorten the time needed for diagnosing these problems and can regularly deliver answers that are almost accurate. The performance of artificial intelligence is not yet excellent enough to replace people, despite the fact that training it takes far less time than training doctors. Training datasets that are too small and have heterogeneous picture data make up the majority of the limiting constraints. We see the current value of this technology in pre-screening patient data, assisting clinicians in workflow prioritisation (for example, identifying highly displaced fractures with potential nerve compression or lesion and notifying the attending emergency room physician), or background double-checking the diagnosis.****

Simplified schematic pattern of an artificial neural network (ANN)

1. MOTIVATION

Fractures are a common and debilitating injury that can result in health issues and long-term pain and other serious consequences. To prevent these injuries accurate precisions are necessary, but the traditional methods are not so effective or accurate enough and they are very time consuming.

In recent years, machine learning as a tool has become so powerful that it has improved the fracture risk prediction. In machine learning we use large datasets and complex algorithms that can identify the key features and predict the likelihood of fracture with high accuracy. This approach can help healthcare professionals make more informed decisions and revolutionize fracture management system.

As young children, we have all witnessed our grandparents struggle with the effects of hip fracture. So now as students pursuing a degree in computer science, we became interested in the potential applications of machine learning in healthcare. When it was time to choose a minor project, this seemed to be the most promising one. Our goal is to develop a comprehensive and robust prediction model that incorporates a wide range of factors, including demographic information, medical history, and lifestyle factors.

1. CONTRIBUTION

Author's contributions in this paper includes providing a comprehensive analysis of existing research on machine learning fracture detection, to synthesize and organize the existing literature to provide a new perspective or insight into the topic and identifying gaps and suggesting future research directions.

While deep learning models have shown promising results in detecting bone fractures, they can be difficult to interpret. Future work could focus on developing more interpretable models or methods for visualizing and explaining the features that are used to identify fractures.

Combining multiple imaging modalities, such as X-ray, CT, and MRI, could improve the accuracy of fracture detection. Future work could explore how to integrate different modalities in a way that improves diagnostic performance.

# V. LITERATURE SURVEY

**Hardalaç F. et al** in this paper **[1]** aimed to diagnose wrist fractures using deep learning-based object detection algorithms. The study improved the fracture identification processes on wrist X-ray images by using a variety of models, including SABL, RegNet, RetinaNet, PAA, Libra R-CNN, FSAF, and more. In the special detection model, WFD-C, the highest detection result was 0.8639 average precision (AP50). As a part of an ongoing collaboration initiative between Gazi University, Huawei, and Medskor, the study was funded by Huawei Turkey R&D Centre. The study's findings generally point to the use of deep learning-based object detection models for fracture detection in X-ray pictures as a promising method to assist doctors in the diagnosis of fractures, particularly in emergency services. On both typical and abnormal (fracture) image datasets, it is feasible to implement classification, fracture detection, and segmentation procedures in a mobile application. Doctors can utilise such an app on their portable devices.

**Michel D. et al** in this paper **[2]** sought to test the effectiveness of Rayvolve, a deep learning system, in identifying fractures in paediatric patients. 2634 sets of digital radiographs from 2549 kids were used in the investigation. The algorithm's performance was assessed using three different methods: detection (presence or absence of a fracture), enumeration (number of fractures), and localization (accurately identifying the location of fractures). For each set, the radiologist's diagnosis and the algorithm's diagnosis were recorded.The findings demonstrated that the algorithm had a high accuracy of 92.6% and high sensitivity (95.7%) and specificity (91.2%) in detecting fractures utilising the detection strategy. The algorithm's sensitivity for the enumeration and localization methods was 94.1%, its specificity was 88.8%, and its accuracy was 90.4%.

**Zhang B. et al.** in this paper **[3]** looked into how deep learning (DL) affected the effectiveness of reading and detecting rib fractures on CT images. 198 individuals with acute chest injuries who obtained CT scans were included in the study. In three sessions, two radiologists read the CT images independently, with assistance from DL as the contemporaneous reader, and with DL acting as the second reader. An expert group decided on the reference standard for rib fractures.Out of a total of 4752 ribs, the reference standard found 865 actual fractures in 713 ribs. For radiologist 1 and radiologist 2, respectively, the sensitivity of the unsupported reading session was 68.7% and 66.9%. Both radiologists' sensitivity significantly increased throughout DL-assisted reading sessions, with radiologist 1's sensitivity increasing to 81.3% and radiologist 2's to 81.6%. The radiologists assessed the scans in the second reader session after DL had identified the fractures, and their sensitivity was 87.1% for radiologist 1 and 88.5% for radiologist 2.

With 86 false-positive findings, DL discovered 687 (79.4%) of the 865 actual fractures, yielding a false-positive rate of 0.43 per scan. In comparison to non-displaced, buckle, and callus fractures, DL found a higher percentage of dislocated fractures.

The study came to the conclusion that reading sessions with DL assistance increased the efficiency and accuracy of finding rib fractures on CT scans. Clinical judgements for patients who have suffered severe trauma may be affected by the increased sensitivity of fracture diagnosis using DL-assisted reading, which may also be utilised as a signpost for additional research like contrast-enhanced CT. As these conditions were linked to a higher risk of surgical fixation in rib fracture patients, the study emphasises the significance of identifying flail chest and non-flail fractures involving more than three ribs.

**Harinath B. et al** in this paper **[4]** discuss a method for image processing that can be used to identify bone fractures in X-ray pictures. The authors present a more effective and accurate method to diagnose bone fractures and draw attention to the drawbacks of conventional diagnostic techniques including CT, MRI, and X-ray.

The approach for identifying fractures from X-ray pictures is described in the publication. It starts off by talking about the problem of salt and pepper noise in X-ray images, which can be brought on by a failure in capture or transmission and manifest as light and dark spots. The authors suggest a technique for eliminating this noise and enhancing the image quality by smoothing it.The method of edge detection, a crucial stage in image processing that minimises the amount of pixels while identifying the borders of objects in the image, is then described. The Canny edge detector, a well-liked technique for spotting edges in medical pictures, is covered by the authors.

The proposed system for identifying bone fractures in X-ray pictures is then presented in the publication. The system makes use of MATLAB-created image processing algorithms for noise removal, image enhancement, and feature extraction. Three fracture images and one non-fracture image were provided as results of the system's testing on 12 X-ray images by the authors.The outcomes show how well the suggested approach works in spotting bone fractures. The accuracy, recall, F-measure, and area under the ROC curve precision measures used to assess the system's performance are also included in this study.

Overall, the work offers a thorough review of how image processing methods might be used to identify bone fractures in X-ray pictures. The authors point out the drawbacks of conventional diagnostic methods and suggest a quicker and more precise method that may also reduce diagnostic errors. They also recommend that future studies concentrate on identifying fractures in smaller bones and other body areas.

**Susan C. et al** in this paper **[5]** sought to employ artificial intelligence and computer assisted approaches for paediatric appendicular fracture identification. This review is primarily based on radiological interpretation, with limb fractures being the most frequent type of fracture. Along with the Retina Net, Xception, and ResNet-50 architectures, the neural network architecture will also be used in this study. When the performance of an AI tool was compared to that of human readers, the algorithms showed equal diagnostic accuracy rates and, in some circumstances, even outperformed radiologists in terms of diagnostic performance. Most studies employ data from a single dataset for training, testing, and validation. This paper has given a summary of the most recent data on AI applications for imaging evaluation of paediatric appendicular fractures. It is essential to improve research methods by using a multi-centric dataset for algorithm training, as well as carrying out external validation and real-world evaluation, in order to better comprehend the effect of these tools on paediatric healthcare.

**Johnathan R. et a**l in this paper **[6]** seek to create machine learning (ML) models for the detection of hip fractures from pelvic or hip radiographs or to forecast any postoperative patient outcome following hip fracture surgery. Comparing classical statistical models (multivariable linear or logistic regression) versus machine learning (ML) models' areas under the curve for postoperative outcome prediction. MEDLINE, Embase, and the Cochrane Libraries were used in this investigation. This review was divided into two groups: (1) studies that created any machine learning (ML) or deep learning models for identifying hip fractures through the use of medical imaging, and (2) research that created models to forecast any postoperative patient outcomes after hip fracture surgery. A pooled 95% CI around the mean was used to plot and compare the diagnostic AI model's performance's sensitivity and specificity to that of medical specialists. The mean (SD) sensitivity, specificity, and F1 score for the included AI models were 89.3% (8.5%), 87.5% (9.9%), and 0.90 (0.06), respectively. Studies found that specificity varied from 70.0% to 98.7% and sensitivity varied from 67.0% to 98.0%. The most often used parameters were age and sex, but all other input features differed greatly between research and databases. The use of AI to assist in diagnosis using radiographs of the hip and pelvis holds a lot of promise. However, using AI does not appear to offer a significant advantage over multivariable predictive statistics.

**Nattaphon T. et al** in this paper **[7]** used AI model You-Only-Look-Once (YOLO), which is a deep convolutional neural network (DCNN) capable of performing image detection tasks (such as drawing a bounding box around a fracture) and classification tasks (such as identifying normal, femoral neck, intertrochanteric, and subtrochanteric fracture class types. In comparison to the previous regional convolutional neural network (R-CNN), it uses multi-layer image detection, applies single neural network techniques to a complete image faster, and uses fewer resources. YOLO is a supervised learning model that utilises fewer training photos than unsupervised machine learning while producing results with a high degree of probability. The cutting-edge AI model YOLO-v4-tiny, which could recognise objects with high accuracy and required little training time, was employed in this work. In our environment, we did our best to prepare the ground truth photos. Postoperative films were used to confirm all fracture instances. Review of all hip CT and MRI scans that were connected to the chosen PACS radiographs. It is thought that if a solid dataset is provided, good AI results can be obtained, just like with human brain training. Good dataset preparation must, however, be exchanged for time. So, for the purpose of this study, only 1000 X-ray images were found.

367 men and 633 women made up the 1000 patients corresponding to the radiography used for this study, as shown in Table 1. In comparison to the overall mean age of 60.73 years, the mean age of patients with hip fractures was 68.54 years old. Care should be taken to remove external artefacts, such as diapers, clothing, or other exterior things that may produce artefacts, from X-ray images, whether AI is present or not. Additionally, it is important to follow the fundamentals of positioning so that hip radiographs are taken with an internal hip rotation of 15-20 for proper femoral neck access.

In order to discriminate between fractured and healthy hips, the deep learning CNN model obtained a sensitivity of 96.2% (86.8-99.5%) and a specificity of 94.6% (89.6-97.6%). The model performed with an accuracy of 0.950, a precision of 0.862, and an F1 score of 0.909.

There was no statistically significant difference between the model's performance and that of the attending and chief residents of radiology and orthopaedics.

**Marco K. et al** in this paper **[8]** carried out a thorough literature search in the MEDLINE/PubMed and Cochrane Collaboration libraries. An emphasis was placed on automated image analysis of anatomical structures utilising mathematical models. A retrospective analysis of 300 radiographic scaphoid series revealed 150 fractures (127 visible on radiographs and 23 only apparent on MRI) and 150 non-fractures. For each imaging series, a matched CT or MRI was used to determine if a fracture existed or not. The Visual Geometry Group, Oxford, United Kingdom, uses an open source pretrained CNN. An AUC of 0.77, 72% accuracy, 84% sensitivity, and 60% specificity were displayed by the algorithm. Although all orthopaedic surgeons missed five of the six occult scaphoid fractures that the CNN was able to identify, it also generated thirteen false positive suggestions. The availability of a bigger dataset was the key area of improvement. Despite great performances from a number of prospective artificial intelligence applications in hand surgery and rehabilitation, these applications are typically only used in experimental investigations. Consequently, their use in routine clinical practise is still restricted.

**Justin D. et al** in this paper **[9]** developed a deep learning model for identifying and categorising hip fractures in radiographs. The model's accuracy for identifying fractures was 93.7%, with a sensitivity of 93.2% and a specificity of 94.2%, after being trained on a dataset of 1118 studies. When comparing the model's performance to that of human observers, the findings revealed that the model consistently classified objects at the expert level. Human performance increased when the model was employed as a tool, and assisted resident performance came close to that of unaided fellowship-trained experts.

According to the study's findings, the deep learning model has the ability to reduce diagnostic blunders, the utilisation of advanced imaging, and the time between diagnosis and eventual surgery, all of which may have an effect on the morbidity and recovery of patients. Patients who were a part of the study had an average age of 75.2 years, and 62% of them were female. The time to radiological reading was also recorded; on average, it took 238 minutes from the end of the exam to produce the preliminary radiology report and 767 minutes to provide the complete report. This is the first report of deep learning-based hip fracture subclassification in the literature.

**Alireza B. et al** in this paper **[10]** sought to examine the feasibility of training a deep convolutional neural network (CNN) to automatically identify total hip replacement (THR) implant designs from radiographic pictures. They looked at 252 primary THR patients' post-surgery anteroposterior (AP) hip X-rays with three distinct widely utilised implant types. The ground truth label for the X-ray images was the stem design described in the primary surgery operating note. The premise that a CNN may be taught to offer automatic detection of THR implant designs from radiographic images was demonstrated by the retrained CNN, which correctly classified all of the X-rays in the test subset with 100% accuracy. The saliency maps demonstrated that, depending on the type of implant, the retrained CNN recognised the implant design by "looking" at various places. This work demonstrates the potential for CNN integration in orthopaedic care, where it may be used to quickly and accurately determine the design of THR implants, saving time and enhancing practitioner detection accuracy. By determining the appropriate components to replace, this may significantly affect the patient's health and lower the overall cost of revision THR surgeries.

**Fahad A. et al** in this paper **[11]** concluded that osteoporosis frequently jeopardises the success of utilising orthopaedic devices because of the impact of decreased bone quality on stability and secondary fractures. This review's three sections on biomechanical features, implant optimisation, and drug-infused hydrogels focus on the issues connected to osteoporosis and total hip arthroplasty. By examining the femoral neck on the unaffected side of a straightforward anterior-posterior X-ray, osteoporotic bones can be seen. The severity of osteoporosis can be categorised into one of six grades, known as the Singh Index. The results of this study show that gender is one of the factors that should be taken into account when developing a treatment plan for an osteoporotic patient. The CT scans used to build the models have a significant impact on the accuracy of the data generated by FEA. According to Rieger et al., other academics have used their method to examine and evaluate the macro- and microstructure of bone. Using impregnated hydrogels to treat osteoporosis has shown encouraging outcomes in terms of enhancing osteointegration and reducing excessive osteoclastic activity. One of the most significant indicators of bone quality is BMD, and DEXA scans are the most reliable method for measuring BMD.

**Leonardo T. et al.** in this study **[12]** used a variety of deep learning methods to categorise bone fractures, determine each algorithm's advantages, and attempt to define a generalised approach. A radar graph with six values—area under the curve (AUC), test accuracy, sensitivity, specificity, dataset size, and labelling reliability—is used to summarise and assess each investigation. The authors classified whether or not the fracture is present and then determined the fracture's location using Faster R-CNN. When region of interest focusing was used, the model's accuracy increased, attaining an AUC of 0.978 as opposed to an AUC of 0.954 without region of interest. The findings for specificity and sensitivity were 94% and 96%, respectively. The X-ray images come in a variety of shapes, and all of the input images are reshaped to fit the input size that the network in use has asked. For the classification job, the author tested the pre-trained VGG19, ResNet50, and InceptionV3 architectures using ImageNet. The average accuracy for VGG19, InceptionV3, and ResNet50 utilising five-fold cross validation and a completely automated technique was 82.7%, 89.4%, and 90.5%, respectively. For VGG19, Inception, and ResNet50, respectively, using the interactive approach increased accuracy by 92.2%, 93.4%, and 94.4%. The ultimate goal of this study is to demonstrate how the CAD system efficiently aids physicians in their diagnoses. It is also crucial to assess how well the experts work both with and without the assistance of the CAD system.

**Genoveffa R. Morway et al** in this study **[13]** uses retrograde headless intramedullary screw (RIS) fixation whish is a more recent approach that was first published in 2016. Reduced operating time, little to no postoperative immobilisation needed, early range of motion, and low complication rates are some of the benefits of RIS that have been touted. However, many things, including specific indications, contraindications, and long-term outcomes, are still unknown due to the novelty of this technique. This review's objectives are to:

1) objectively assess the clinical and biomechanical results of RIS fixation for metacarpal fractures; and

2) assemble a complication profile for this technique from recently published material.

Numerous studies have mentioned broken and bent screws following metacarpal refracture, but the complication rate shown here does not account for these cases. However, people voiced concerns about how challenging it was to remove the screws. Numerous studies have mentioned broken and bent screws following metacarpal refracture, but the complication rate shown here does not account for these cases. However, people voiced concerns about how challenging it was to remove the screws.

**Yangling Ma et al** in this research **[14]** proposed a system that implements the notion of employing Faster R-CNN and Crack-Sensitive Convolutional Neural Network (CrackNet) to detect bone fracture. It is crucial for clinicians to use X-ray pictures to pinpoint the exact location of bone fractures. As stated, they extracted features from the pelvic CT images using adaptive windowing, boundary tracing, and wavelet transform, and then utilised a registered active shape model to diagnose fracture. Or Yu et al. employed feature-fusion-based stacked random forests to identify fracture in X-ray images. Several classifiers, including Back Propagation Neural Network, K-Nearest Neighbour, Support Vector Machine, Max/Min Rule, and Product Rule, are combined to design a combining classifier to detect fracture after edge and shape features of the bone have been extracted. Among other things, the identification of bone fractures has made extensive use of mathematical morphology. These techniques rely on the entire image to determine whether it is fractured, but they are unable to identify the specific bone region that is broken. There are numerous detection frameworks as a result of the advancement of object detection in recent years. The R-CNNs known as Fast and Faster R-CNN are based on the region proposal method. Among these frameworks, faster R-CNN that is based on R-CNN exhibits the best recognition accuracy. To increase the resistance of deep learnt features to changes in orientation and scale, they proposed Gabor Convolutional Networks (GCNs or Gabor CNNs), which incorporate the Gabor filter into Deep Convolutional Neutral Network. In this study, we apply the Schmid filter to the convolution and, during training, change the values of two super parameters using the chain rule. We suggest CrackNet, a new deep model for bone fracture diagnosis that starts with the Schmid convolutional layer and connects to standard convolutional layers. Faster R-CNN and Crack-Sensitive CNN with greater than 90% accuracy and greater than 90% F-measure on X-ray pictures. Instead of training in two stages, R-CNN and CrackNet, which are faster, are trained simultaneously.

**Anu T C et al.** in this paper **[15]** provides lower Mean Absolute Error (MAE) and greater Peak Signal-to-Noise Ratio (PSNR) when compared to other filtering algorithms including mean, alpha-trimmed mean, Wiener, K-means, bilateral, and trilateral. The automatic categorization of bone fracture using image processing techniques based on data from X-ray and CT images is attempted in this study with reasonable accuracy and for the first time is attempted for all types of bone fracture without focusing on any particular type of fracture. And with some restrictions, they also tried for CT images. The process of edge detection involves locating regions in a digital image where the brightness of the image abruptly changes or, more technically, where there are discontinuities.

The accuracy of the neural network (NN) and decision tree (DT) classifiers is 50% and 53.25%, respectively. As a result, the accuracy, precision, sensitivity, and specificity of the metaclassifier created by combining the aforementioned classifiers are 85%, 100%, 76.9%, and 70%, respectively. A selection of iGLCM features have been used to test the approach. Analysis revealed that this procedure had an accuracy of 85% and that the results were satisfactory. This method's shortcoming is that it might be quite challenging to locate the fracture in CT and some X-ray pictures. Future research must completely utilise CT imaging and categorise the type of fracture that occurs.

**D. P. Yadav et al.** in this study **[16]** use the flipping and shifting image modification technique to create a new image from the current data set. By training on both the original and augmented images, a machine learning model can develop more generic capabilities. Several researchers have used data augmentation techniques in the past to lower the machine learning model's error rate. CNN uses a fully connected layer to automatically extract the features from the input image and identify them as either malignant or healthy bone. Features are taken out of the image via the convolution layer (CL) and pooling layer. The current method uses tensor flow and deep learning to suggest fracture diagnosis for long bones, short bones, and flat bones. Yang and Cheng have employed contour-based feature selection and ANN to categorise the long bone. By establishing the cluster, the features are chosen using PCA (Principal Component Analysis). The method's accuracy is 82.98%. Grey Level Co-occurrence Matrix (GLCM) was utilised by Chai et al. to extract textural features for the identification of long bone fractures. The method's accuracy is 86.67%. Support vector machine (SVM) was utilised by Tripathi et al. to categorise human bone into fracture-prone and non-fracture-prone categories. The model's accuracy is 84.7%. The suggested model outperformed the state-of-the-art with a 5-fold cross validation score of 92.44. The model's classification accuracy for both healthy and damaged bones is 92.44%. The projected accuracy outperforms 82.89% and 84.7% by a wide margin. The use of another deep learning model can increase the model's accuracy even more. To more thoroughly examine the performance, the system requires validation on the bigger data set.

VI. CONCLUSION

It is no small task to implement and accurately determine fractures in any part of the human body using machine learning algorithms coupled with deep learning and neural networks. All the papers that we reviewed utilised one or more of these approaches to fulfil their goal and that too with an average of 90% accuracy in the top cases. The scope of improvement is also addressed with better training datasets and even more complex neural networks accompanied by deep learning. The widely used models were CNN and SVM which are quite popular themselves. We believe this field of study to be immensely fruitful in the future as well as in the present.

VII. CHALLENGES

1. In the creation of the bone fracture image data set, there are standardisation problems which lead to no fixed protocol for its advancement.
2. When creating the model for fracture detection on the training dataset there are high chances of overfitting or poor generalisation. This may be caused due to the presence of multiple cases without fractures and very few cases with fractures, leading to a bias in the model.
3. The different bone fractures can vary significantly when presented in an X-ray format which is harder to process and apply the machine learning models upon. A better type of dataset with MRI images can be much more helpful and accurate but is difficult to get hands-on.
4. There could exist ethical discrepancies arising from poor control of the patient’s privacy by the organisation issuing the X-rays.
5. It is very complex to understand the background processes of the machine learning models for fracture detection for clinicians.
6. The implementation of these kinds of machine learning and deep learning models for fracture detection in clinical settings can be cumbersome due to the inconsistency in imaging equipment, patient demographics and clinical workflows.

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