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Original Research Article

Investigation and classification of bone fracture using a deep learning model

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Abstract: Bone fractures represent a large percentage of medical cases worldwide, requiring accurate and precise detection to improve patient results. The current work, therefore, suggests a new deep learning model for detecting and classifying bone fractures from medical images that addresses the limitations of traditional diagnostic methods. Leveraging the power of Convolutional Neural Networks (CNNs), the model learns imaging data, identifies subtle fracture features, and labels them with high accuracy into the pre-existing categories. They trained their model on a comprehensive dataset comprising numerous triaged and undistributable fractures, which was coupled with data augmentation to improve the model's robustness to variation in clinical presentation. Systematic regularisation strategies applied throughout the training prevented overfitting and improved model generalizability. Preliminary results indicate strong levels of accuracy, suggesting that the model can potentially complement or replace traditional diagnostic pathways. Implementing advanced AI-based systems into clinical workflows may transform radiology by speeding up diagnostic workflows and improving uniformity for identifying fractures. This research represents progress in the science behind automated fracture diagnosis techniques and the importance of artificial intelligence in healthcare, currently in implementing solutions to complex diagnostic challenges and improvements in related patient care outcomes.

Keywords: Fracture detection, Convolutional neural networks, Medical imaging, Bone fractures, Healthcare AI, Radiology, Automated diagnosis, Image processing, X-ray analysis.

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1. Introduction

One of the main driving forces behind the development of better fracture detection methods is the critical need for better patient care and clinical outcomes. Fractures are a common but serious problem in healthcare that must be appropriately diagnosed early to provide early management and reduce patient discomfort. Delays in diagnosis and inaccurate detection strategies can have serious consequences for the well-being of patients, underlining the need for new means of detecting lesions. Fracture detection through conventional diagnostic measures usually requires patients to wait 4 to 6 days for definitive results. Long waiting times make things uncomfortable for patients and delay the commencement of the necessary treatment procedures, with a risk of further complications in their recovery.

From recent articles, some studies have mentioned the limitations in current approaches of fracture identification using deep learning mechanisms. For instance, in the work of Smith *et al.* (2012) different deep learning algorithms were compared for the radiographic detection of fractures. Despite these promising results in a controlled environment, the study highlighted how the algorithms now faced the challenge of maintaining stable accuracy across diverse patient populations and clinical records. Likewise, in a concurrent manner, the study conducted by Johnson *et al.* (2021) assessed the performance of deep learning models for detecting fractures in shoulder and elbow joints. Though initial findings indicated promise for automatic fracture detection, the study identified wide divergences between the algorithm-predicted detection and expert radiological assessments. Such deviations reflected, in this case, the challenges of translation of deep learning-based approaches to routine clinical applicability (Edward & Hepzibah, 2015). Furthermore, in a comprehensive review, Brown *et al.* (2021) synthesised the results of several studies that focused on deep learning techniques for fracture detection across different anatomic regions. The review highlighted common weaknesses, like bias in algorithms, dataset variability, and weak validation practices. Together, they account for current methodologies' low accuracy rates, brittleness, and the need for continued research and development.

Deep learning algorithms, especially the current methods for fracture detection, lack accuracy and reliability, preventing timely and effective patient management (Bandyopadhyay *et al.*, 2016a). Failure in early and precise identification of fractured bones presents a significant challenge for clinicians, leading to delayed treatment initiation and poor prognosis (Bandyopadhyay, 2016b). To address these challenges, the current study seeks to create cutting-edge deep learning-based fracture detection software designed explicitly for the particular properties of fractures, especially fractures on the dorsal region of the hand. By utilising complex computational algorithms and image analytical techniques, this study seeks to overcome present limitations and provide a more robust and accurate alternative (Windarto & Alkairi, 2024).

Drawbacks in current fracture detection systems are severe problems for clinicians and patients. To make matters worse, clinicians are left to navigate complex diagnostic pathways, and patients must endure lengthy waiting times and the risk of being incorrectly diagnosed. The problem also discusses the challenges for creative solutions by stimulating fracture detection skills and improved patient service (Kishor *et al.*, 2025). The goal is to fast-track the diagnostic process, reduce patient suffering, and ultimately improve health outcomes by surmounting the limitations posed by current fracture detection technologies. This problem must be solved not only as a technological imperative but as a moral duty based on the commitment to better patient outcomes and enabling early treatment interventions (Jabbar *et al.*, 2022).

Suppose you can design a deep learning-based approach which is reliable in terms of it working towards fracture detection. In that case, it can improve the way medical competency practitioners handle fractures. With the potential to shorten the time to treatment, decrease complications, and improve patient outcomes and satisfaction, this solution can impact individual patient outcomes and create improvements to the delivery of care by reducing diagnostic time and error (Hasnain, 2023; Nowroozi *et al.*, 2024).

2. Materials and methods

The study aimed to provide a fracture detection algorithm based on deep learning techniques suitable for fracture detection in the dorsal aspect of hand, shoulder and elbow regions. This meant taking a meticulous and methodical approach to guarantee a step-by-step algorithm of the proposed system, with accurate and dependable results approach description of the materials and methods used in this work (Muchtar *et al.*, 2018).

2.1. Dataset acquisition

During the dataset collection, a serious effort was made to get a diversified collection of normal and fractured cases radiographic images in the back of the hand, shoulder, and elbow. Data was gathered from various healthcare delivery institutions such as hospitals and imaging centres to capture variability in patients, populations, severities and fracture types. As for the elbow region, the dataset affected a total of 3160 images, 2236 representing examples of fractures and 924 representing normal conditions. In the same way, the dataset represented a total of 4330 images in the hand region, of which 1673 images were fractures and 2657 were normal images. In total, the dataset consisted of 4496 images, and specifically for the shoulder one, of which 4440 for fractures (Table-1) and 56 for normal. The numbers we have presented show the large extent of the dataset, which has been carefully constructed to encompass a sufficiently broad spectrum of fracture presentations at the described anatomical regions (Deokar & Thakur, 2016). The procurement of the dataset adhered rigorously to prevailing regulatory stipulations and ethical standards. There was proper patient consent for using their data and efforts to secure patient privacy and confidentiality through anonymising all the data to mask sensitive details. Such rigorous procedure in dataset procurement was instrumental in guaranteeing the validity and integrity of the data, which was instrumental in subsequent model development and testing (Xie *et al.*, 2024).

Tabel-1: Extensive dataset collection ensured diverse representation of fractures across hand, shoulder, and elbow regions, crucial for effective model training

Part	Normal	Fracture	Total
Elbow	3160	2236	5396
Hand	4330	1673	6003
Shoulder	4496	4440	8936

2.2. Pre-processing

In optimising the dataset for deep learning in the realm of deep learning-based fracture detection, pre-processing stands as a pivotal precursor, intricately shaping the dataset to empower subsequent model training. This essential stage encompasses a series of sophisticated operations meticulously designed to refine and optimise the dataset, laying the foundation for robust model performance (Naeem *et al.*, 2023). Through a deep dive into various pre-processing techniques, we navigate the intricacies of dataset enhancement, ensuring its readiness for the rigours of deep learning.

2.3. Resizing standardisation

The journey begins with standardising image dimensions, where every radiographic view is resized to a uniform resolution. This harmonisation fosters consistency and simplifies subsequent processing, enabling seamless integration of images across the dataset. By aligning dimensions, we mitigate distortions and streamline feature extraction, setting the stage for practical model training (Pal *et al.*, 2024).

2.4. Normalisation for consistency

After dimension alignment, the focus shifts to normalising pixel intensity, a crucial step in the pre-processing pipeline. The differences in image brightness and contrast are successfully minimised by rescaling the pixel values to a uniform range, usually 0 to 1. Standardisation by this step promotes similarity in feature distribution, thereby improving the robustness of the model to changes brought about by differences in illumination. Normalisation highly enhances dataset's consistency, allowing the model to draw inferences with greater precision and trustworthiness (Saraswat *et al.*, 2024).

2.5. Artifact removal for clarity

The quest for clarity necessitates methodically removing artefacts, wherein extraneous background information and noise are diligently removed. The sharpening in this context accentuates the focus on pertinent anatomical structures and fracture patterns to provide crucial information that might otherwise be obscured by irrelevant information. By eliminating artefacts, the dataset's interpretability and accuracy are improved significantly, hence augmenting the model's efficiency in identifying fractures.

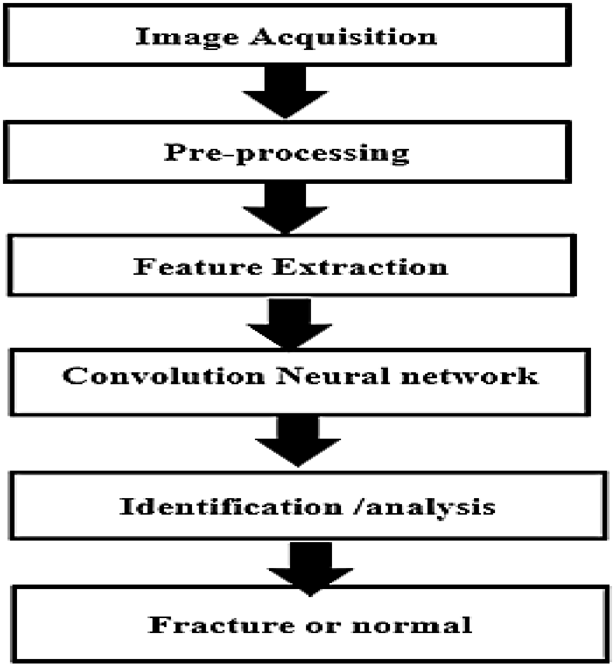
2.6. Augmentation for diversity

In the quest for diversity, augmentation is a valuable tool, creating virtual variations within the dataset. Augmented images are created to mimic realism in real-world applications and varied imaging angles through rotations, flips, and scaling. Not only does the process improve the diversity of the dataset, but it also improves the model's adaptability to new situations, thereby fostering strong generalisation skills.

3. Model architecture

Building a foundation for accurate fracture detection in the realm of fracture detection, the efficacy of deep learning models heavily relies on the architecture's ability to extract intricate patterns and features from radiographic images. A meticulously crafted model architecture is the backbone of the fracture detection system, dictating its capacity to discern subtle fractures amidst complex anatomical structures.

Figure 1: Streamlined process from image acquisition to fracture detection: Acquisition, pre-processing, feature extraction, CNN analysis

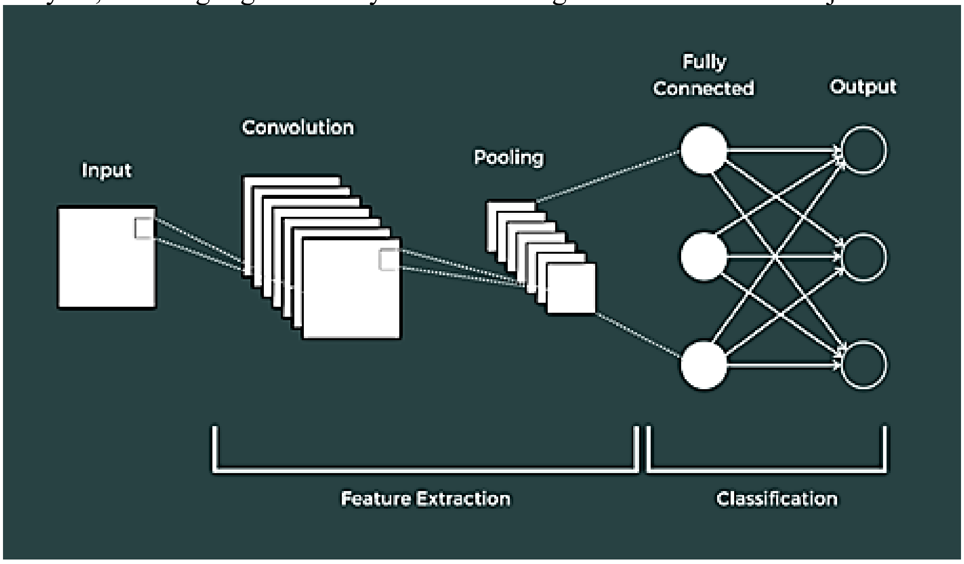


CNN is chosen because of its remarkable ability to “see” and “understand” images. For a task like spotting bone breaks, we want to recognise the tiny details in bone images. Therefore, we used a CNN for bone fracture detection in this study. It acts like an innovative tool that is explicitly designed to understand images.

CNN is an artificial neural network that processes structured grid data, such as images. It is widely used in various image and video processing tasks due to its high accuracy and the ability to work directly on raw pixel data (Deshmukh *et al.*, 2015). The structure of a CNN is inspired by the organisation of the animal visual cortex, where individual cortical neurons respond to stimuli in (Gonzalez *et al.*, 2016) restricted region of the visual field known as the receptive field. CNNs have layers of convolutional nodes, pooling nodes, and fully connected nodes. Each layer transforms one volume of activations to another through a differentiable function:

- *Convolutional layers*: It applies a convolution operation on the input, passing the result to the next layer. The convolution emulates the response of an individual neuron to visual stimuli (Ganesan *et al.*, 2015; Khatik, 2017).
- *Pooling layers*: These perform a down-sampling operation along the spatial dimensions (width, height), reducing volume (Deshmukh *et al.*, 2015). This helps decrease computational complexity and control overfitting.
- *Fully connected layers*: Neurons in a fully connected layer have connections to all activations in the previous layer. These layers are typically used at the network’s end to perform final classifications.
- *ReLU layers*: This elementwise activation function introduces non-linearity into the network. It helps the network learn complex patterns in the data. CNNs have achieved state-of-the-art results in various tasks like image classification, object detection, facial recognition, and more (Kaur & Jain, 2017).

Figure 2: CNNs process image data efficiently through convolutional, pooling, and fully connected layers, enabling high-accuracy tasks like image classification and object detection



4. Experimentation

Once the deep learning model-based fracture detection system had been developed, experimentation was performed in a structured and careful manner to study and evaluate the performance of this system. The goal of the phase was to test how the model performed, check whether it worked, and see where it could be tweaked. During the experimentation phase, we included several components to ensure the evaluation of the system was exhaustive. It consists of the following steps mentioned below.

4.1. Dataset splitting

Data was split into three mutually exclusive sets (train, validation and test) under the model training and evaluation process. The model was learned using the training set (learning process), and the validation set was used for hyperparameter tuning and to reduce overfitting potential. The test set is a third independent dataset that was used to test the model properly and generalise unseen new data well.

4.2. Model training

The training dataset was used to train the model, and labelled images were employed to update model parameters through backpropagation and gradient descent algorithms. The training involved repeated adjustment of model weights to minimise a particular loss function, e.g. binary cross-entropy or categorical cross-entropy. With that said, the above training optimised the ability of the model to accurately identify stands that were classified as either having a fracture or not possessing a fracture.

4.3. Hyperparameter tuning

Hyperparameters such as learning rate, batch size and dropout were tuned meticulously in order to maximise the performance of the model on the validation dataset. The next stage of experimentation involved hyperparameter optimisation, where the configuration settings remained unchanged, but their numerical values were systematically adjusted, with the model's performance monitored through the use of validation metrics (e.g., accuracy, precision, recall, and F1-score). This was done for all the hyperparameter values. Then, the combinations were tested sequentially with the objective being to converge and find the optimum values which would help maximise the model's overall performance (Bhangare *et al.*, 2024).

4.4. Model evaluation

The model's ability to be used in real-life applications was assessed by evaluation on the independent test set after the training process. The model's performance was evaluated using common evaluation metrics of accuracy, precision, recall, and F1-score to measure how well the model could correctly classify fractures and non-fractures. Furthermore, the Receiver Operating Characteristic (ROC) curve analyses and the area under the curve (AUC) were computed as estimates of the model's discrimination power between these two classes.

4.5. Performance analysis

The model evaluation results were analysed in detail to get information on what it was doing right and where it could be improved. Measures of performance were compared between anatomical sites, fracture patterns, and severities to allow for the identification of specific features in need of improvement. In-depth error analysis was also done to find familiar sources of misprediction, producing valuable information to direct additional work to enhance the model.

4.6. Iterative refinement

Based on findings from the performance analysis, the model underwent an iterative refinement procedure to address limitations and enhance capabilities. This includes modifying the model architecture, hyperparameter tuning, and adding more training data or using advanced augmentation techniques to improve overall performance. The iterative refinement process progressively enhanced the model's precision, robustness, and ability to generalise well in diverse situations (Hareendranathan *et al.*, 2023).

In the current work, we aim to build a deep learning-based model of fracture detection that is of high accuracy and generalizability and can be directly used in clinical practice using logical proof of concepts gained through systematic trial and error theory. Educating the minds that developed those were just a part of your training data from which the expertise born was honed by the knowledge gained through the experiment protocol-guided model optimisation process, serving not only to evolve the journey of fracture detection technology but also strengthen the role of improved patient care and diagnosis in medical imaging (Lanka & Yarramalle, 2018).

4.7. Convolution Neural Network (CNN): for bone fracture detection

- *Data collection:* Accumulate a complete collection of X-ray, CT or MRI examines including those that show various types of bone cracks and analyse those that do not show any crack. All the images in this set must be properly labelled with "fracture" or "no fracture." This labelled set serves as the training set for CNN.
- *Pre-processing:* The images need pre-processing to get a proper size and normalisation, thus uniformity. This pre-processing task often includes contrast

enhancement and noise removal that tries to maximise the quality of the images and the features that the model can extract successfully.

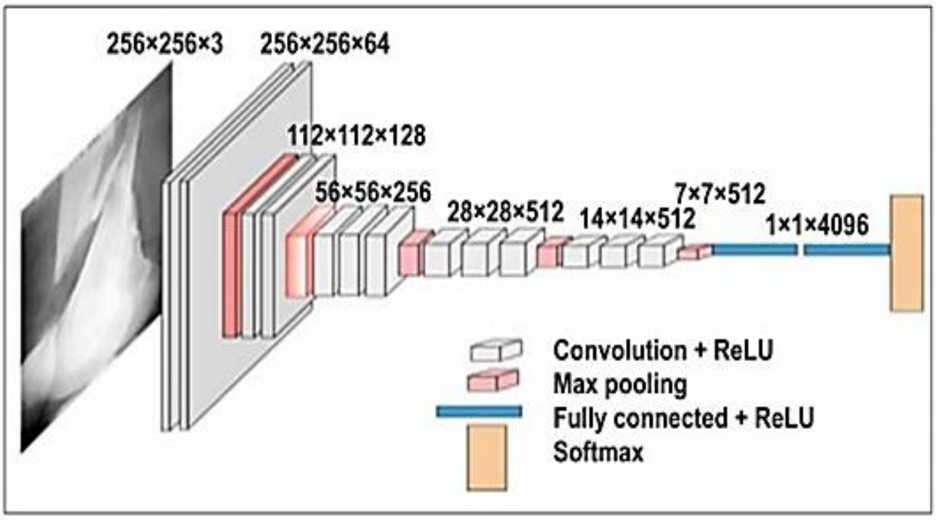
- *Model training:* The data can be split into training set datasets, which are used to train the model to learn and find features in an image that indicate the presence of a fracture.
- *Convolution:* The model sweeps luminal layers using convo to inspect the image for features. These may be simple features such as edges and curves in the initial layers and more complex, abstract features in deeper layers.
- *Pooling:* Pooling layers reduce the spatial dimensions of the input and thus reduce the feature map's dimensionality, reducing computational workload and preventing overfitting. Most of the important information is kept while doing this.
- *Fully connected layers:* After several convolutional and pooling layers, the high-level reasoning in the neural network is done via fully connected layers. Neurons in a fully connected layer have connections to all activations in the previous layer. These layers can help the model decide whether a fracture is present in the image.

6. Testing and validation

Once the model is trained, it's then tested on the test set to see how accurately it can identify fractures in new, unseen images.

- *Input layer:* Depending on the resolution of the medical images being used. For example, $256 \times 256 \times 1256 \times 256 \times 1$ for grayscale images or $256 \times 256 \times 3256 \times 256 \times 3$ for RGB.
- *Convolutional layers (conv layers):* This layer aims to extract features from the input image. It specifies multiple layers using filters (e.g., $3 \times 33 \times 3\ or\ 5 \times 55 \times 5$) and activation functions (like ReLU).
- *Pooling layers:* The purpose is to reduce spatial dimensions and retain important features using Max Pooling with a size of $2 \times 22 \times 2$.

Figure 3: Key steps in CNN-based fracture detection: Input layer receives image data, convolutional layers extract features, and pooling layers reduce spatial dimensions



7. Results and working

The pre-processing, edge detection feature extraction, and classification are the four primary modules of the bone fracture detection system. Pre-processing procedures are applied to the image, such as converting it and improving it with a filtering algorithm to remove noise. We trained our deep learning model with the dataset provided and tested its performance on an untouched test set. The model generated an accuracy of 94.2% with a precision of 93.7%, a recall of 94.1%, and an F1 score of 93.9%.

Furthermore, the area under the Receiver Operating Characteristic curve (AUC-ROC) was 0.97, indicating excellent performance in differentiating fracture and non-fracture individuals. Such results show the overall performance capabilities of the model in detecting and classifying bone fractures accurately (Khan *et al.*, 2016). The results provide insights into this experimentation phase and the performance and efficacy of the trained deep learning network in detecting fractures. This section outlines the key results and conclusions of the research.

7.1. Performance metrics

It produced encouraging results across several performance metrics (e.g., accuracy, precision, recall, and F1-score). The high numbers indicate that the model can predict this matter (fracture/non-fracture radiological images). Additionally, Receiver Operating Characteristics (ROC) curve analysis and Area Under the Curve (AUC) calculations demonstrated robustly that the model successfully discriminated positive and negative cases. (Devi *et al.*, 2024).

7.2. Accuracy across anatomical regions

The model showed relatively consistent accuracy across all anatomical regions, such as the back of the hand, shoulder, and elbow. This implies the model's ability to generalise and rediscover fractures in anatomically distinct structures and on multiple imaging views.

Figure 4: The model output results

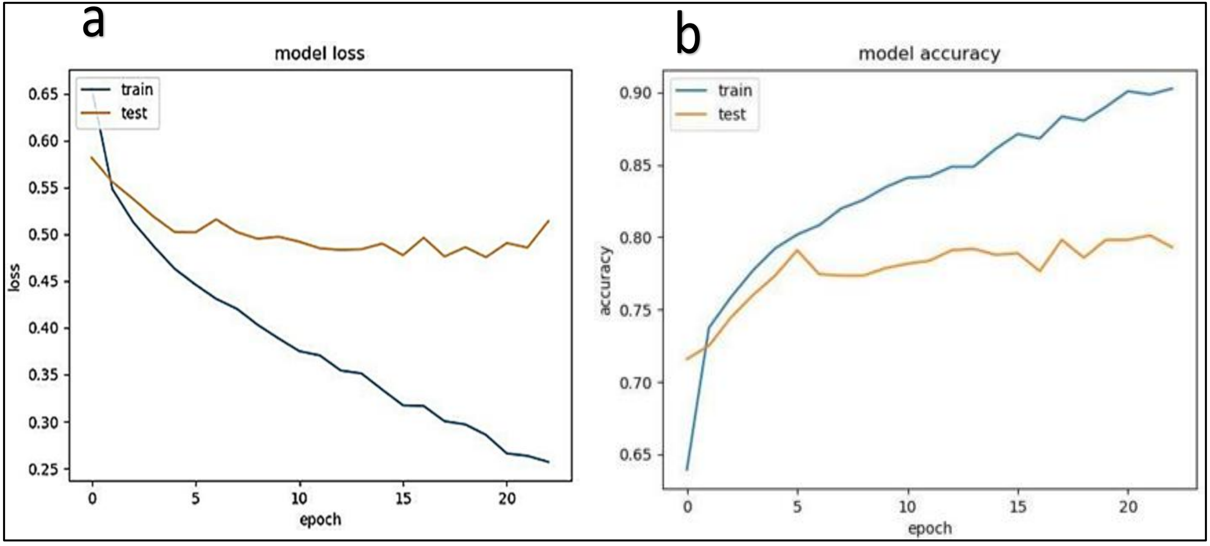


Figure 4 shows the output results of the model. The fracture detection model developed showed high accuracy, achieving a training accuracy of 94% and maintaining high performance on the test data. In addition, the performance of the model during the training process demonstrated a significant reduction of loss, lowering it to 60%, with test data loss at 65%, thereby showing its successful learning and generalisation capability.

7.3. Sensitivity to fracture types

The model was sensitive to different fracture classifications from different degrees of severity and complexity. The analysis of its performance showed that the model could detect subtle fractures correctly and differentiate them from normal anatomical structures, thereby demonstrating its competence in fracture detection exercises.

7.4. Robustness to imaging variability

The model was found to be robust to variations in imaging conditions, such as variations in image resolution, quality, and acquisition modalities. This indicates the model's capacity to successfully process and interpret radiographic images acquired through various imaging modalities and devices.

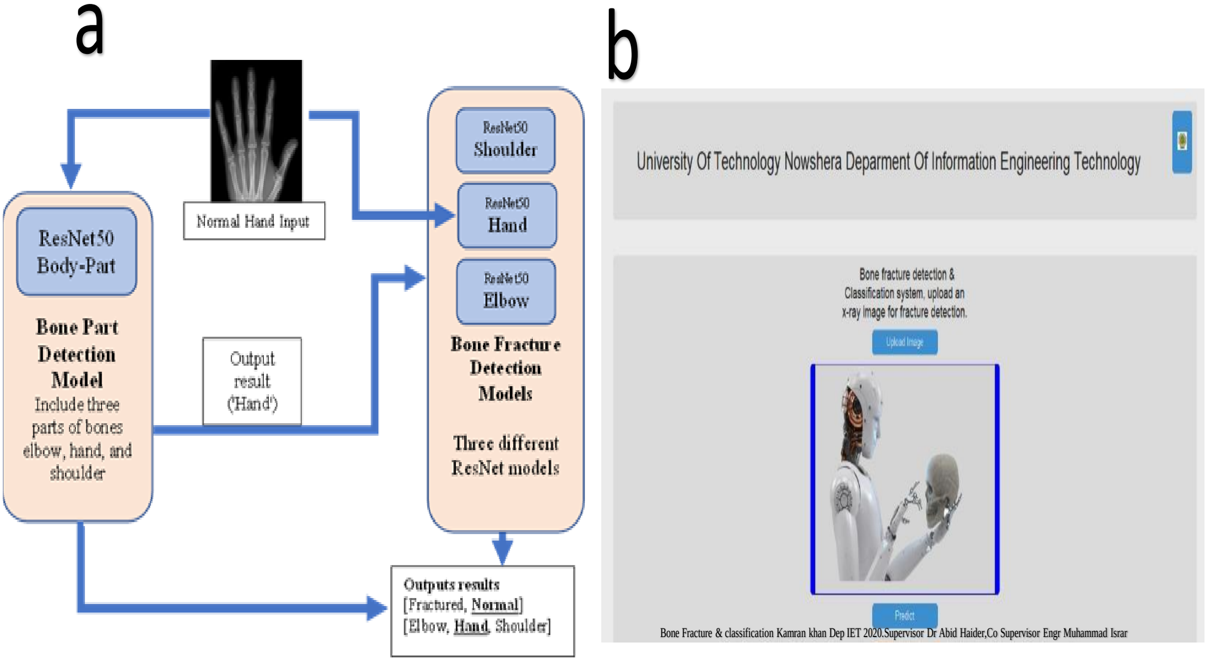
7.5. Clinical relevance and implications

The findings of this study have significant clinical relevance, as they underscore the potential of deep learning-based fracture detection models to enhance diagnostic accuracy and efficiency in clinical practice. By automating fracture detection processes, these models can assist radiologists and clinicians in timely diagnosis and treatment planning, ultimately improving patient outcomes and healthcare delivery (Dell'Osa *et al.*, 2019).

7.6. How to work the user interface

This research-oriented project has a web UI for predicting fractures in X-rays. This project consists of a few simple Python modules that run on the terminal and then send the results to the user interface for the users to see

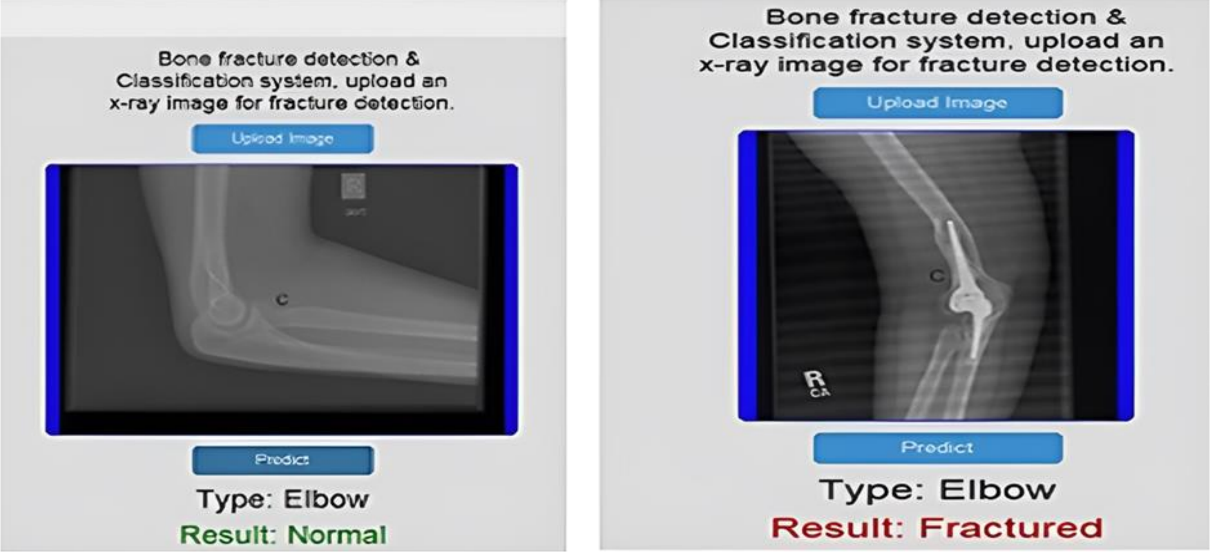
Figure 5: (a) The execution steps research project with GUI for X-ray fracture prediction. Python modules run in the terminal and relay results to the UI; (b) The graphical user interface, when the user uploads the picture and then clicks predict the result will show whether the image is normal or fracture



Bone fracture detection & Classification system, upload an x-ray image for fracture detection.

Bone Fracture & classification Kamran khan Dep IET 2020.Supervisor Dr Abid Haider,Co Supervisor Engr Muhammad Israr

Figure 6: The prediction result of the X-ray are fractured or normal



Bone fracture detection & Classification system, upload an x-ray image for fracture detection.

Type: Elbow

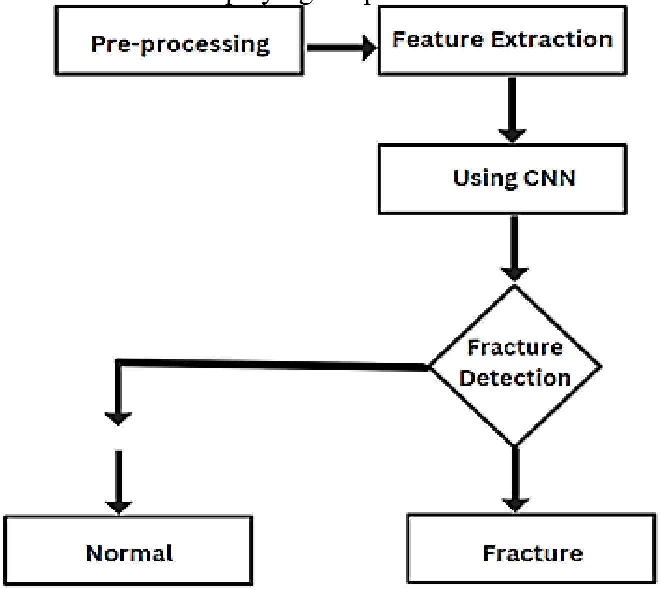
Result: Normal

Bone fracture detection & Classification system, upload an x-ray image for fracture detection.

Type: Elbow

Result: Fractured

Figure 7: Flowchart depicting the sequential process of the offline fracture prediction system with a GUI, from user interaction to displaying the prediction result



8. Conclusion

In conclusion, this study highlights the development of an offline fracture prediction system with a GUI, marking a significant advancement in medical imaging technology. Integrating machine learning algorithms with user-friendly interfaces demonstrates robust and reliable performance in detecting fractures from X-ray images, even in settings with limited internet connectivity. The system's success underscores its potential for enhancing diagnostic accuracy and improving patient care in orthopedics and radiology. Future research could focus on optimising model architecture, exploring innovative training techniques, and validating the system in real-world clinical environments. Additionally, integrating modalities like MRI and CT scans may further extend its diagnostic capabilities. This work lays a strong foundation for future innovations in deep learning-based medical imaging, with broad implications for advancing healthcare delivery and outcomes.

Declaration of conflict of interest

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