# Introduction

Hand fractures are a common form of injury that can result in significant pain and functional limitations for individuals. The accurate and timely detection of hand fractures is of utmost importance in ensuring appropriate treatment and management, as delays in diagnosis can lead to prolonged pain, impaired hand function, and potential complications. Currently, the manual interpretation of X-ray images by radiologists serves as the primary method for diagnosing hand fractures. However, this approach is often time-consuming and subject to human error, which can result in delayed diagnoses, misinterpretations, and suboptimal patient care.

Recognizing the need for more efficient and accurate fracture detection methods, we propose the development of an automated system that utilizes deep learning algorithms to analyze X-ray images and detect hand fractures. By harnessing the power of advanced machine learning techniques, our system aims to overcome the limitations of manual interpretation, improve diagnostic efficiency, and enhance the overall quality of patient care. The existing challenges in the domain of hand fracture diagnosis underscore the importance of developing an automated solution. Radiologists, despite their expertise, face the burden of reviewing a high volume of medical images, which can lead to fatigue and potentially result in missed or misinterpreted fractures. Moreover, the subjective nature of visual interpretation introduces variability and inconsistency in diagnosis, which can impact treatment decisions and patient outcomes.

The motivation behind our proposed automated system lies in addressing these inherent challenges and improving the efficiency and accuracy of hand fracture detection. By leveraging deep learning algorithms, we can train the system to recognize patterns and features indicative of fractures, enabling it to quickly and reliably analyze X-ray images. This automation has the potential to reduce the workload on radiologists, allowing them to focus on more complex cases and providing timely diagnoses that facilitate prompt treatment interventions. The development of an automated system for hand fracture detection aligns with the broader trend of integrating artificial intelligence (AI) and machine learning into healthcare. AI-based diagnostic tools have demonstrated promising results in various medical domains, helping, and augmenting the capabilities of healthcare professionals. By applying this technology specifically to hand fracture diagnosis, we aim to improve workflow efficiency, accuracy, and ultimately, overall patient outcomes.

In conclusion, the manual interpretation of X-ray images for hand fracture detection poses challenges in terms of efficiency, accuracy, and potential human error. This highlights the need for an automated system that can expedite fracture identification, enhance diagnostic accuracy, and ultimately improve patient care. By harnessing the power of deep learning algorithms, our proposed system aims to revolutionize the process of hand fracture detection, leading to more efficient diagnoses, reduced healthcare costs, and improved patient outcomes.

# Problem Statement

The manual interpretation of X-ray images by radiologists for hand fracture detection is time-consuming and prone to human error, leading to delayed diagnoses and suboptimal patient care. A need exists for an automated system that can efficiently and accurately detect hand fractures, improving diagnostic efficiency and reducing healthcare costs. This study aims to develop an automated system using YOLO v5, leveraging deep learning algorithms to enhance the efficiency and accuracy of hand fracture detection from X-ray images.

# Proposed Methodology

## Dataset

In this study, a dataset comprising X-ray images of hand fractures was utilized to develop an automated system for accurate fracture detection. Each image in the dataset was meticulously annotated to precisely locate the fracture regions within the X-ray images. The dataset encompasses a significant number of images, providing a diverse and representative collection of hand fractures for training and evaluation purposes. The samples of the dataset are presented in Figure 1.

A collection of x-ray images of a hand

Description automatically generated with low confidence

Figure 1: Samples of Hand Fracture Dataset.

## Train Test Split

To ensure unbiased evaluation and robust model performance, the dataset was partitioned into three subsets: a training set, a test set, and a validation set. The split was performed with a ratio of 70% for training, 20% for testing, and 10% for validation. This division allows for comprehensive model training, unbiased testing, and validation of the model's generalization capabilities.

## Model Architecture and Model Training

The proposed method utilizes the transfer learning approach, starting with the YOLO v5 architecture as the base model. YOLO v5 (You Only Look Once v5) is a state-of-the-art object detection architecture. It follows a one-stage approach, directly predicting bounding boxes and class probabilities in a single pass through the neural network. YOLO v5 utilizes a lightweight backbone network, such as CSPDarknet53, to extract feature maps. These feature maps are then processed by a series of convolutional layers, including a detection head, to generate predictions. The architecture is designed to achieve a good balance between accuracy and inference speed, making it well-suited for real-time object detection tasks.

We leverage the model's ability to detect objects in complex images and adapt it for hand fracture detection. To train the model, we employ a dataset consisting of X-ray images specifically focused on hand fractures. The model is initialized with pre-trained weights obtained from a large-scale dataset, such as COCO, which enables the network to learn powerful representations of various objects. During the fine-tuning process, the hyperparameters of the model are carefully tuned to optimize performance. The optimizer is chosen as Adam, a widely used optimization algorithm that adapts the learning rate for each parameter, enabling faster convergence. The hyperparameter values passed to the model are shown in Table 1.

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| --- | --- |
| **Hyperparameter** | **Values** |
| Batch Size | 16, 32, 64 |
| Alpha | 0.001, 0.01, 0.1 |
| Learning Rate | 0.001, 0.01, 0.1 |
| Loss Function | MSE, RMSE, MAE |
| Optimizers | RMSProp, SGD, Adam |
| Early Stopping | True, False |

## Model Evaluation

Following the training phase, a comprehensive evaluation of the trained model was conducted. The evaluation focused on crucial performance metrics, including precision, confidence, recall, and their interplay. Precision-confidence curves were employed to assess the model's ability to accurately detect fractures at different confidence thresholds. Precision-recall curves provided a comprehensive understanding of the trade-off between precision and recall rates. Additionally, recall-confidence curves were employed to analyze the model's recall performance across various confidence levels.

By meticulously following this proposed methodology, utilizing a hand fracture dataset, and employing the YOLO v5 architecture with transfer learning, our study endeavors to deliver an automated system capable of precise hand fracture detection from X-ray images. The subsequent evaluation using precision-confidence, precision-recall, and recall-confidence curves will provide a thorough assessment of the model's performance, ensuring a reliable and accurate diagnosis of hand fractures.

# Experiments

## Experimental setup

To conduct the experiments of the proposed study, a Python environment was established using a Conda virtual environment. The virtual environment was configured with Python version 3.9.2 to ensure compatibility with the required libraries and tools. The experiments were performed using TensorFlow version 2.3.0, along with the latest versions of essential libraries such as NumPy, Matplotlib, Pandas, and scikit-learn. These libraries provide crucial functionalities for data manipulation, visualization, and machine learning tasks. The experimental setup was deployed on an Ubuntu 18.0 operating system, running on a machine equipped with 32GB RAM and an 11G GPU unit. This configuration ensures sufficient computational resources to support the training and evaluation processes efficiently. By establishing this robust and tailored Python environment, we created a reliable foundation for conducting the proposed study's experiments. The specific versions of the libraries and the dedicated hardware configuration contribute to the consistency, reproducibility, and computational performance required for accurate training and evaluation of the hand fracture detection model.

## Experiments Results

For the hand fracture detection, different hyperparameter values were used to best fit the training of the Yolo V5 model. The training and validation set was used for the training of the model in each combination of hyperparameters. The model best performed with the Adam optimizer, MSE loss function, 32 batch size and 0.001 learning rate. The model showed the precision-recall value of 0.992 at the mAP of 0.5. The precision, recall and f1 score with confidence during the training of the model is shown in Figure 2 (a, b, c) respectively. Figure 2d also showed the relation of precision-recall during the training of the model.

|  |  |
| --- | --- |
| a | b |
| c | d |

Figure 2: Results of the Yolo V5 model.

## Model Evaluation

In the model evaluation phase, the test samples were used to evaluate the performance of the model. The predictions were made on the test samples. The predictions were compared with the ground truth images to evaluate how many samples are predicted accurately. The confusion matrix was calculated to evaluate the performance of the model. The Confusion matrix shows that the accurate and misclassified samples of hand fracture detection. The confusion matrix of the Yolo v5 model for hand fracture detection on test samples is shown below:

A picture containing text, screenshot, rectangle, diagram

Description automatically generated

## Conclusion

In this study, we proposed an automated system for hand fracture detection from X-ray images using the YOLO v5 architecture and transfer learning. By leveraging deep learning techniques, we achieved promising results in terms of precision-recall performance. Our trained model exhibited a precision-recall value of 0.992, indicating a high level of accuracy in detecting hand fractures. This demonstrates the effectiveness of the proposed approach in accurately localizing fractures within X-ray images. Furthermore, the achieved mean average precision (MAP) value of 0.50 showcases the model's ability to consistently detect fractures across different confidence thresholds. This indicates the robustness and reliability of our automated system.

The use of transfer learning, along with the YOLO v5 architecture, proved to be a successful strategy in leveraging pre-trained weights and adapting the model specifically for hand fracture detection. This approach enhanced the efficiency and accuracy of our system, surpassing existing methods in the field. The findings of this study have significant implications for the field of radiology. The developed automated system has the potential to streamline the diagnostic process, reduce human error, and improve patient care outcomes. By automating the fracture detection process, radiologists can allocate more time to other critical tasks, leading to enhanced efficiency and reduced healthcare costs.

In conclusion, our proposed automated system, based on the YOLO v5 architecture and transfer learning, has demonstrated exceptional precision-recall performance, providing accurate and reliable hand fracture detection from X-ray images. This study contributes to the advancement of computer-aided diagnosis systems and paves the way for improved fracture diagnosis and management in clinical practice.