Progress Report 1

Group 9

Members: Frederick Damptey And Cletus Ngwerume

FRACTURE DETECTION ON WRIST X-RAY USING CONVOLUTIONAL NEURAL NETWORKS

Introduction

The wrist is a distinct anatomical area of the upper limbs consisting of complex articulations of multiple bones. It comprises the distal radioulna bones, eight carpal bones, and five proximal metacarpal bones. The radius and ulna articulate distally to form the distal radioulna joint. The carpal bones articulate with the radius and ulna, adjoining carpal bones, and the proximal metacarpal bones. These bones are connected by ligaments and tendons, and surrounded by fibrous capsules and muscles, allowing a varied range of movements, including flexion, extension, deviations from the central axis, and adduction and abduction of the fingers. Together with the forearm, the wrist enables rotations to pronate or supinate the hand and wrist. It is one of the most used joints of the body, enabling critical functions to be performed while maintaining joint integrity (Raisuddin et al., 2021).

Several imaging modalities can be used to assess the wrist, including MRI, ultrasound, nuclear medicine, fluoroscopy, CT scans, and plain (general) X-rays. The choice of modality depends on the clinical indication or suspected pathology. MRI and ultrasound are radiation-free and pose no risk from ionizing radiation. In contrast, other modalities, such as fluoroscopy and CT scans, use X-rays, exposing the body to some level of radiation. Among these, plain wrist X-rays involve the smallest dose of radiation, making them the safest option for imaging that requires ionizing radiation. They are particularly effective for evaluating wrist bones and surrounding soft tissues, especially in cases of fractures and dislocations (Xu et al., 2023).

The wrist joint, due to its extensive use, is highly susceptible to acute injuries, including fractures. Wrist fractures are among the most common injuries encountered in emergency departments, with an estimated prevalence of 12.8% among adult Americans aged 50 years and above from 2017 to 2020 (Karzon et al., 2024). The preferred imaging modality for diagnosing wrist fractures is the plain wrist X-ray due to its cost-effectiveness, accessibility, and efficiency in fracture classification. However, despite its advantages, the accuracy of wrist X-ray interpretation depends on the expertise of the reader, making subtle fractures susceptible to being overlooked (Thorat et al., 2023).

Literature Review

The application of artificial intelligence (AI) in medical imaging has been widely explored, particularly in musculoskeletal radiography. AI-based diagnostic tools, including convolutional neural networks (CNNs), have demonstrated remarkable potential in detecting fractures with accuracy comparable to human experts. Studies have investigated the effectiveness of CNNs in fracture detection, highlighting their ability to reduce inter-observer variability, improve diagnostic accuracy, and enhance workflow efficiency (Ali, 2025).

Recent advancements in AI have led to the development of sophisticated deep learning models trained on large-scale radiographic datasets. These models employ various feature extraction techniques, such as attention mechanisms and transfer learning, to improve diagnostic performance. For instance, Husarek et al. (2024) conducted a systematic review on AI-assisted fracture detection, concluding that AI models achieved a pooled sensitivity and specificity of approximately 90%, which was comparable to expert radiologists.

Furthermore, Suen et al. (2024) evaluated the performance of AI-based systems in wrist fracture detection, reporting a sensitivity of 92% and specificity of 89%. These findings reinforce the efficacy of AI in identifying fractures accurately and reliably. Similarly, Yee et al. (2019) employed Inception-ResNet v2 and Faster R-CNN architectures for wrist fracture detection and localization, achieving an area under the receiver operating characteristic curve (AUC) of 0.895.

Despite the promising performance of AI in fracture detection, challenges persist regarding dataset quality, ethical considerations, and clinical integration. Concerns related to data privacy, algorithmic bias, and generalizability remain significant obstacles to AI adoption in clinical practice (Sharma, 2023). Nevertheless, ongoing research aims to address these limitations by enhancing AI transparency, improving interpretability, and optimizing training methodologies.

Methodology

The study follows a systematic approach to developing a deep learning model for wrist fracture detection using transfer learning. The key stages include dataset acquisition, preprocessing, model selection, training, performance evaluation, and interpretability.

1. Dataset Acquisition:
   - The dataset for this study is the MURA (Musculoskeletal Radiographs) dataset, sourced from Kaggle. Link: https://www.kaggle.com/datasets/cjinny/mura-v11
   - It consists of over 3,000 wrist X-ray images, labeled as either fractured or normal.
   - Images are captured from multiple angles, including posteroanterior (PA), anteroposterior (AP), and lateral views (Raisuddin et al., 2021).
2. Preprocessing:
   - Images will be resized to a standard input size suitable for deep learning models (e.g., 224×224 for ResNet50 or EfficientNet input dimensions) (Tan & Le, 2019).
   - Data augmentation techniques such as rotation, flipping, contrast normalization, and noise reduction will be applied to improve model generalization (Kalmet et al., 2020).
   - Pixel values will be normalized to ensure uniform input distributions (Thian et al., 2019).
3. Model Selection & Training:
   - This study employs transfer learning by fine-tuning a ResNet50 (He et al., 2016) or EfficientNet (Tan & Le, 2019), both of which are pre-trained on ImageNet.
   - Transfer learning helps leverage pre-existing feature extraction capabilities while fine-tuning on the wrist fracture dataset (Suen et al., 2024).
   - A stratified K-fold cross-validation approach will be used to ensure robust model evaluation (Husarek et al., 2024).
   - Grad-CAM (Gradient-weighted Class Activation Mapping) will be utilized for fracture localization, enhancing interpretability (Selvaraju et al., 2017).
   - Hyperparameters such as learning rate, batch size, and optimizer will be tuned to optimize performance.
4. Performance Evaluation:
   - The model will be evaluated using metrics such as accuracy, sensitivity, specificity, F1-score, and AUC-ROC (Thian et al., 2019).
   - A confusion matrix will be generated to analyze misclassification patterns (Suen et al., 2024).
   - The model's diagnostic performance will be compared against expert radiologists to assess its clinical applicability (Husarek et al., 2024).

Future Work

- Further model optimization by fine-tuning hyperparameters and evaluating different CNN architectures.
- Expanding the dataset by including additional wrist X-ray images from diverse sources to improve model generalizability.
- Conducting external validation on independent datasets to ensure clinical applicability.
- Exploring the integration of AI-assisted diagnosis into clinical workflows to assess real-world usability.

References

- Ali, M. (2025). 8 Top AI Tools For Medical Diagnosis in 2025. aimojo.io. Retrieved from https://aimojo.io/ai-tools-medical-diagnosis/
- He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 770–778.
- Husarek, J., Hess, S., Razaeian, S., et al. (2024). Artificial intelligence in commercial fracture detection products: a systematic review and meta-analysis of diagnostic test accuracy. *Scientific Reports, 14*, 23053. https://doi.org/10.1038/s41598-024-73058-8
- Kalmet, PHS, Sanduleanu, S., Primakov, S., et al. (2020). Deep learning in fracture detection: a narrative review. *Acta Orthop, 91*(2), 215-220. https://doi.org/10.1080/17453674.2019.1711323
- Raisuddin, A.M., Vaattovaara, E., Nevalainen, M., et al. (2021). Critical evaluation of deep neural networks for wrist fracture detection. *Scientific Reports, 11*, 6006. https://doi.org/10.1038/s41598-021-85570-2
- Selvaraju, R. R., Cogswell, M., Das, A., et al. (2017). Grad-CAM: Visual explanations from deep networks via gradient-based localization. *Proceedings of the IEEE International Conference on Computer Vision (ICCV)*, 618–626.
- Suen, K., Zhang, R., & Kutaiba, N. (2024). Accuracy of wrist fracture detection on radiographs by artificial intelligence compared to human clinicians. *European Journal of Radiology, 178*, 111593. https://doi.org/10.1016/j.ejrad.2024.111593
- Tan, M., & Le, Q. (2019). EfficientNet: Rethinking model scaling for convolutional neural networks. *Proceedings of the 36th International Conference on Machine Learning (ICML)*.
- Thian, Y.L., Li, Y., Jagmohan, P., et al. (2019). Convolutional Neural Networks for Automated Fracture Detection and Localization on Wrist Radiographs. *Radiology: Artificial Intelligence, 1*(1), e180001. https://doi.org/10.1148/ryai.2019180001