Utilization of the a 2D Convolutional Neural Network for Computer Assisted Detection of Stress Fractures of the Ankle and Foot

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Curated Datasets

An IRB approved protocol at Lovell FHCC, a combined VA/DoD site, which has been in use since 2018, outlining an approved set of methods and information security practices for the acquisition, deidentification, pre-processing, and sharing of imaging and clinical data for use in the production of predictive models using imaging and clinical data using machine learning methods. All datasets are minimal-risk retrospective chart reviews obtained with a consent waiver.

Background

Artificial Intelligence (AI) use in medicine is becoming increasingly popular. It allows more time for physicians to interact with patients, strengthening both the emotional bond between them, as well as the information shared about their care (1). Specifically, significant progress has been made by AI/deep learning in revolutionizing image-based tasks in radiology. AI methods excel at automated pattern recognition, offering quantitative assessments of radiographic characteristics, thereby enhancing diagnostic precision. The shift from qualitative to quantitative evaluations represents a notable advancement in the field. However, AI is currently limited in its capabilities, and the healthcare system needs to help develop the expanding role of radiologists alongside AI, open-source deep learning platforms, the shift from processed to raw data, discerning signal from noise, and a globally interconnected network of deidentified patient data (2).

Convolutional Neural Networks are a subclass of Artificial Intelligence neural networks with the explicit assumption that inputs to the function will be images. Akin to visual processing in the Visual Cortex, multiple layers of processing are performed that begin with simple binary outputs that allow complexity to be added in each layer of processing (binary presence of object in location -> orientation/edge recognition -> complex shapes -> etc). The ultimate layer is able to detect and identify, classify, or even segment an object as the weighted summation of these inputs (3, 4, 5, 6).

Current trends in musculoskeletal radiology indicate CNNs mostly being developed for bone density and bone aging studies (3). Additionally, CNNs have been increasingly applied towards evaluating fractures (7, 8, 9, 10) and to assist both radiologists and non-radiologist clinicians in increasing the speed and accuracy of interpreting imaging studies (11, 12). These advancements have the potential to help bridge the gap in rural and lower socioeconomic areas where access to trained specialists is limited and increase the total number of studies clinicians can read per day allowing for overall improved health outcomes (1, 2).

Number of Patients (JPEG): 34			
	Total Number	Healthy	Unhealthy
Train (1)	579	388	191
Val (1)	276	189	87
All	855	577	278
Train (2)	412	222	190
Val (2)	191	107	85
All	604	329	275

Table 1: Number of Images

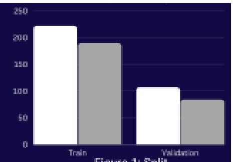


Figure 1: Split

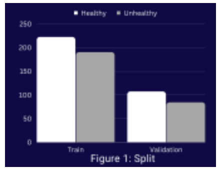
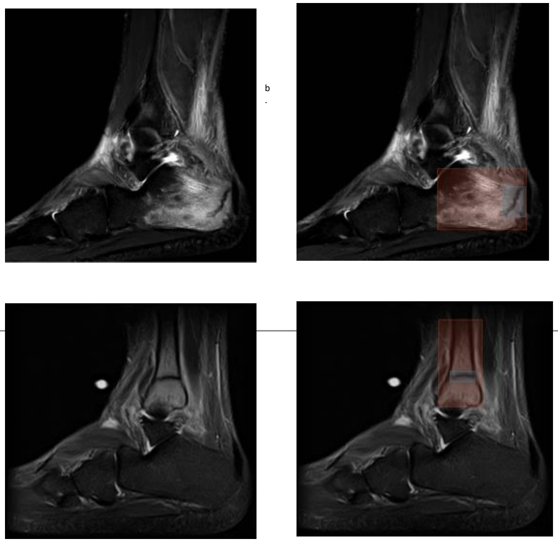


Figure 1: Split

2D CNN on MRI		Predicted	
		Healthy	Unhealthy
Actual	Healthy	74	33
	Unhealthy	28	57

Table 3: Confusion Matrix



Sagittal short tau inversion recovery images demonstrating edema and fracture lines in the calcaneus and distal fibula, with and without bounding box labels.

The Dataset

A dataset consisting of MRI imaging data on patients diagnosed with acute stress fractures since the merger of the Great Lakes Naval Hospital and the North Chicago VA Medical Center into Lovell FHCC in 2010. Current dataset collected this summer consists of approximately 120 MRI studies of the ankle reported positive for acute stress fracture between 2018 and 2023. Bone marrow edema and stress fracture lines were labeled using bounding boxes by a team of medical student RA's Labeled sagittal T1 weighted and short tau inversion recovery images have been shared with the DePaul Data Science Center and shared with Dr. Jacob Furst and his team.

Algorithm Architecture and Results

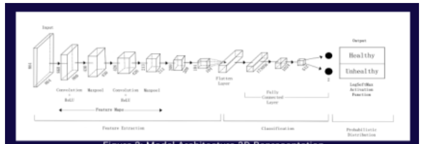


Figure 2: Model Architecture 3D Representation

A 2D convoluted neural network algorithm was utilized , with normalization using z-score and mean intensity filtration. A binary classifier was applied, using images, trained to discriminate between images where edema and fracture lines were labeled using the images without labels as controls. Results listed in center column.

Future Directions

Future directions include collection of the remaining available MRI ankle data, MRI studies of the knee, tibia/fibula, femur, and hip. A planned second phase of this study would involve retrospectively collecting radiographs of the positive stress fracture cases identified in phase I and attempt to produce a predictive model capable of detecting the fractures. The goal would be to produce a model with potentially higher sensitivity than achievable by conventional radiograph interpretation

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