**Supplementary Digital Content 1.** Supplementary methods and results

*Deep Learning System*

The deep learning system was trained on a development dataset consisting of 715,343 deidentified radiographs from 314,866 patients collected across 15 hospitals and outpatient care centers in the United States. There were 18 US board-certified orthopaedic surgeons and 11 US board-certified radiologists who manually annotated the radiographs by drawing a bounding box around the site of any fracture or noting that the radiograph contained no visible fractures as per specifications in a comprehensive fracture taxonomy. The deep learning system was created using an ensemble of 10 convolutional neural networks that identify and localize fractures from their appearance on radiographs.

*HIPAA Compliance*

All protected health information used in the training and testing of the deep learning system was deidentified in compliance with the Healthcare Information Portability and Accountability Act of 1996 (HIPAA)’s Expert Determination method. The level of reidentification risk was very small and acceptable by HIPAA Expert Determination methods. The study complied with all relevant ethical regulations and the protocol was approved by the New England Independent Review Board. A patient waiver of consent was granted because the study design and use of deidentified patient radiographs presented minimal risk to patients.

*Estimating Missed Fractures Across the Medicare-age Population*

To illustrate the deep learning system’s potential impact on the US healthcare system, we estimated the total number of missed fractures across the Medicare-age population with and without assistance from the deep learning system. We estimated the total number of fractures across all Medicare enrollees in 2018 by multiplying a previously published fracture incidence rate of 19.63 fractures per 1000 person-years in adults ages 65 and older [28] by the total number of Medicare enrollees in 2018 (38,655,082) [5]. To account for the large variation in volumes of radiographs interpreted by each clinician type, we multiplied the estimated total number of fractures across the Medicare-age population by the proportion of radiograph volume interpreted by the clinician types in our study. Finally, to estimate the total number of fractures missed by clinicians when unaided and aided by the deep learning system, we multiplied the number of radiographs interpreted as showing possible fractures by the miss rate for clinicians with or without extensive training in musculoskeletal imaging found in our study.

**Supplementary Results**

*Deep Learning System’s Potential Impact on Missed Fractures Across the Medicare-age Population*

Across the Medicare-age population, we estimated that clinician types included in the clinical study may miss 18% (121,393 of 675,021) of fractures per year without the assistance of the deep learning system (Supplementary Table 7). However, if aided by the deep learning system, these clinicians would miss 10% (69,047 of 675,021) of fractures per year across the Medicare-age population, resulting in a 43% (52,346 of 121,393) reduction in missed fractures.