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# No code machine learning: validating the approach on use-case for classifying clavicle fractures

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ABSTRACT

*Purpose:* We created an infrastructure for no code machine learning (NML) platform for non-programming physicians to create NML model. We tested the platform by creating an NML model for classifying radiographs for the presence and absence of clavicle fractures.

*Methods:* Our IRB-approved retrospective study included 4135 clavicle radiographs from 2039 patients (mean age 52 ± 20 years, F:M 1022:1017) from 13 hospitals. Each patient had two-view clavicle radiographs with axial and anterior-posterior projections. The positive radiographs had either displaced or non-displaced clavicle fractures. We configured the NML platform to automatically retrieve the eligible exams using the series' unique identification from the hospital virtual network archive via web access to DICOM Objects. The platform trained a model until the validation loss plateaus. Once the testing was complete, the platform provided the receiver operating characteristics curve and confusion matrix for estimating sensitivity, specificity, and accuracy.

*Results:* The NML platform successfully retrieved 3917 radiographs (3917/4135, 94.7 %) and parsed them for creating a ML classifier with 2151 radiographs in the training, 100 radiographs for validation, and 1666 radiographs in testing datasets (772 radiographs with clavicle fracture, 894 without clavicle fracture). The network identified clavicle fracture with 90 % sensitivity, 87 % specificity, and 88 % accuracy with AUC of 0.95 (confidence interval 0.94–0.96).

*Conclusion:* A NML platform can help physicians create and test machine learning models from multicenter imaging datasets such as the one in our study for classifying radiographs based on the presence of clavicle fracture.

## 1. Introduction

The healthcare industry now generates 30 % of the entire global data by volume, which is expected to increase exponentially in the coming years.[1,2] Digital data from radiology contributes to a huge proportion of healthcare data. Technological and fundamental advancements in artificial intelligence (AI) applications have helped translate these enormous health datasets into practical and actionable health systems. Breakthroughs in graphics processing units (GPU), data architecture, and deep neural networks enable the creation of numerous AI algorithms in healthcare practices, radiology in particular.[3] However, the process of creating large, labeled training data sets, selecting suitable algorithms, choosing appropriate hyperparameter values, as well as testing and validating the trained model is a complex and labor-intensive process that requires advanced knowledge of computational sciences and neural networks as well as inputs from radiologists during the training and testing steps.[4] The need for human intervention for training and/or testing at several stages can limit or slow down AI development and/or application. Automation at one or more process steps can expedite development and reduce human efforts.

No code machine learning (NML) technology supports automation and efficiency in developing AI models. Unlike traditional machine

*Abbreviations:* AI, Artificial intelligence; GPU, Graphics processing units; NML, No code machine learning; VNA, Virtual network archive; UID, Unique identification; JSON, Java Script Object Notation; CSV, Comma-separated value; WADO, Web Access to DICOM Objects.

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learning programs, NML is a highly calculative, self-reliant process that executes actions in an accelerated, efficient, and effective manner for generating expected outcomes with minimal human intervention at each stage of AI development.[5] We created an infrastructure for No code machine learning (NML) platform for non-programming physicians to create NML models. A fully integrated NML system allows radiologists to leverage in-house data to train ML models that can be used for diagnosis, worklist prioritization, and automation of time-consuming tasks such as the segmentation of anatomical structures. We assessed the performance of an NML platform for classifying radiographs based on presence and absence of clavicle fractures.

## 2. Methods

Our institution review board (IRB) waived the written consent requirement for our retrospective, Health Insurance Portability and Accountability Act (HIPAA) compliant study. The study details are presented in conformance with the CLAIM checklist.[6]

### 2.1. Study design and data sources

The study data included clavicle radiographs of 2039 adult patients (age >18 years) from 13 hospitals (1 urgent care center, 10 community/cottage, and two quaternary care hospitals).

To identify the eligible radiographs for our study, we used Nuance mPower Clinical Analytics Search (Microsoft Inc.), a cloud-based, commercial radiology reports search engine that integrates radiology reports data from the sites included in our study. The search key terms for identifying consecutive radiology reports and radiographs with and without clavicle fractures were “acute fracture” OR “no fracture” OR “displaced fracture” AND “clavicle X-ray”. The search was limited to clavicle radiographs performed between January 2016 and December 2022. Both right and left clavicle radiographs were included in the study. A post-doctoral radiology research fellow (2 years of experience) reviewed all radiology reports and radiographs to exclude clavicle radiographs with incomplete anatomic coverage of clavicles, metal-related artifact, prosthesis, or evidence of open reduction with internal fixation ($n = 267$). Non-clavicle radiographs (such as shoulder and chest radiographs) with or without clavicle fractures were not included in the study. Flowchart of the inclusion and exclusion with training and test data has been represented in Fig. 1.

### 2.2. Ground truth

We exported radiology reports of the eligible radiographs from the radiology report search engine with the following data elements: radiology findings text, radiology impression text, date of examination, name of the radiographic procedure, site of radiographic acquisition, as well as patients' age and gender. We reviewed the radiology reports and recorded the details of the presence of fracture to establish the ground truth. Since the models were trained on an autonomous learning platform, there was no need to perform pixel-level annotations (e.g., bounding boxes) at the location of the fractures.

### 2.3. Data partitioning

To avoid selection bias, all consecutive clavicle radiographs were included regardless of patients' age, race, and sex as well as radiographic equipment and site of acquisition. Although the power analysis was not performed to determine the sample size, our sample size was larger than most prior publications in this domain.[7–17] The radiographs were divided at the site level to create distinct training, testing, and validation datasets. Clavicle radiographs from three sites were set aside as external test datasets. The remaining radiographs were used for training and validation of the model.

### 2.4. Model

The automated classifier training system runs on the PyTorch ML framework. For inputs, the system takes in a configuration file in Java Script Object Notation (JSON) format and a dataset list with labels and optional splitting (into training, validation, and test datasets) in the comma-separated value (CSV) format. The system pulls the training examples listed in the dataset list from the hospital virtual network archives (VNA) using Web Access to DICOM Objects (WADO) and feeds them to the training process after applying windowing and leveling, normalizing, resizing, and applying data augmentations as specified in the configuration JSON.

We used a pretrained DenseNet201 architecture (20.1 M parameters), but the system supports many models which are available from

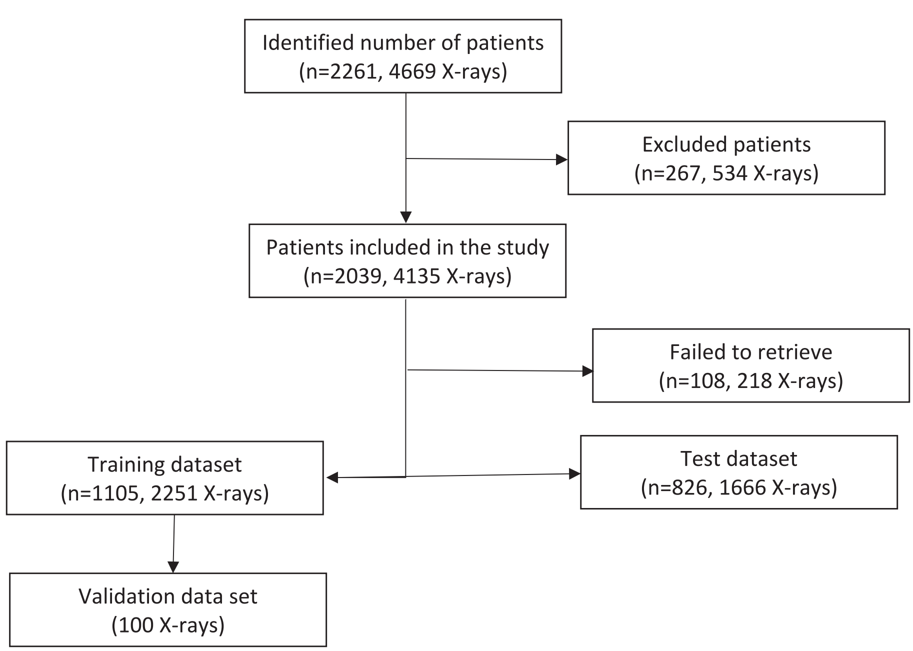


**Fig. 1.** Flowchart of the inclusion and exclusion criteria for the training and test dataset.

MONAI, such as EfficientNet models, which use less compute.[18–19] The user must specify the number of classes and whether they are doing exclusive classification, non-exclusive classification, or regression. By default both drop-connect (Wan et al., 2013)[20] and dropout are used with a conservative rate of 0.2 and the following types of data augmentation are implemented - random rotations (−10 to +10 degrees), random zooms/crops (0.9–1.25×), random flipping, and random elastic deformations. The amount of elastic deformation is kept small as large deformations may not be suitable for all applications. Several options for data normalization are provided (clipping, rescaling, etc.). Models are trained using the Adamax optimizer algorithm, (Kingma and Ba, 2015) with weighted random sampling to improve performance in the case of unbalanced training labels. The default batch size is 6 and the default learning rate is set low at 0.0005 to avoid training instabilities. We use the well-known "reduce on plateau" learning rate schedule, which reduces the learning rate by a factor of 0.5 when the validation loss plateaus for 5 steps. A key challenge in no-code ML is determining the criteria for stopping training. If the model is trained too long it will overfit, whereas if training is stopped too early the model's accuracy may not have reached the best possible value. Since the validation loss can be very noisy we smooth the validation loss using a moving average of width 5 iterations. We stop the training when the smoothed validation loss no longer decreases for 1500 iterations. The maximum number of epochs is set to 400. The trained model was saved in a designated output directory alongside training logs and the configuration in JSON.

Normalization, learning rate, and early stopping criteria were adjustable by modifying the JSON config file. While nearly all options of the training system were configurable, we used the abovementioned default values across multiple tasks.

### 2.5. Preprocessing and training

A total of 2151 clavicle radiographs were used in the training dataset, and 100 radiographs from the same institutions were automatically separated by the model as the validation dataset. All radiographs were resampled to a size of 512 × 512 and normalized to have a mean of zero and standard deviation of one.

A key challenge in NML is determining criteria for stopping training. If the model is trained too long, it will overfit, whereas if the training is stopped too early the accuracy may not have reached the maximum value. We smooth the validation loss using a moving average of width 5 and stop the training when the smoothed validation loss no longer decreases for 10 steps. We use the well-known "reduce on plateau" learning rate schedule, which reduces the learning rate by a factor of 0.5 when the validation loss plateaus for 5 steps.

The model was trained using the Adamax optimizer algorithm, with weighted random sampling used on the dataset to improve performance on unbalanced training datasets. The Adam algorithm uses a first-order gradient-based stochastic optimization approach based on adaptive estimations from first- and second-order moments of the gradient.[21] We used dropout and the following types of data augmentation - random rotation, random zoom, random horizontal flipping, and a small amount of elastic deformation.

### 2.6. Statistical analysis

After the model training, testing, and validation, the platform generated the statistics for the performance of the AI model. For analysis, we classified the AI output as true positive (both the ground truth and AI model agreed on the presence of fracture), true negative (both the ground truth and AI agreed on the absence of fracture), false positive (AI falsely called a fracture which was not present in the ground truth), and false negative (AI did not find the fracture reported in the ground truth). The platform also generated the confusion matrix represented in Fig. 2.

The performance of AI models for the presence and absence of fracture was estimated by calculating sensitivity, specificity, accuracy, and area under the receiver operating characteristic curve (AUC) with 95 % confidence intervals (CI). All statistical analyses were performed with SPSS (IBM Inc., Version 13).

## 3. Results

### 3.1. Data

The mean age (± standard deviation) of 2039 adult patients included in our study was 52 ± 20 years. There were 1022 female patients and 1017 males. Site-wise distribution of patients was Site 1 ($n$ = 621 patients), Site 2 ($n$ = 651), Site 3 ($n$ = 166), Site 4 ($n$ = 40), Site 5 ($n$ = 223), Site 6 ($n$ = 167), Site 7 ($n$ = 43), Site 8 ($n$ = 11), Site 9 (n = 6), Site 10 ($n$ = 36), Site 11 ($n$ = 37), Site 12 ($n$ = 7), and Site 13 ($n$ = 31).

Of the 2039 X-rays, there were 1225 radiographs of the right clavicle and 814 left clavicle radiographs. Most patients were either outpatients ($n$ = 1066) or in the emergency department ($n$ = 828), with only 145 inpatients.

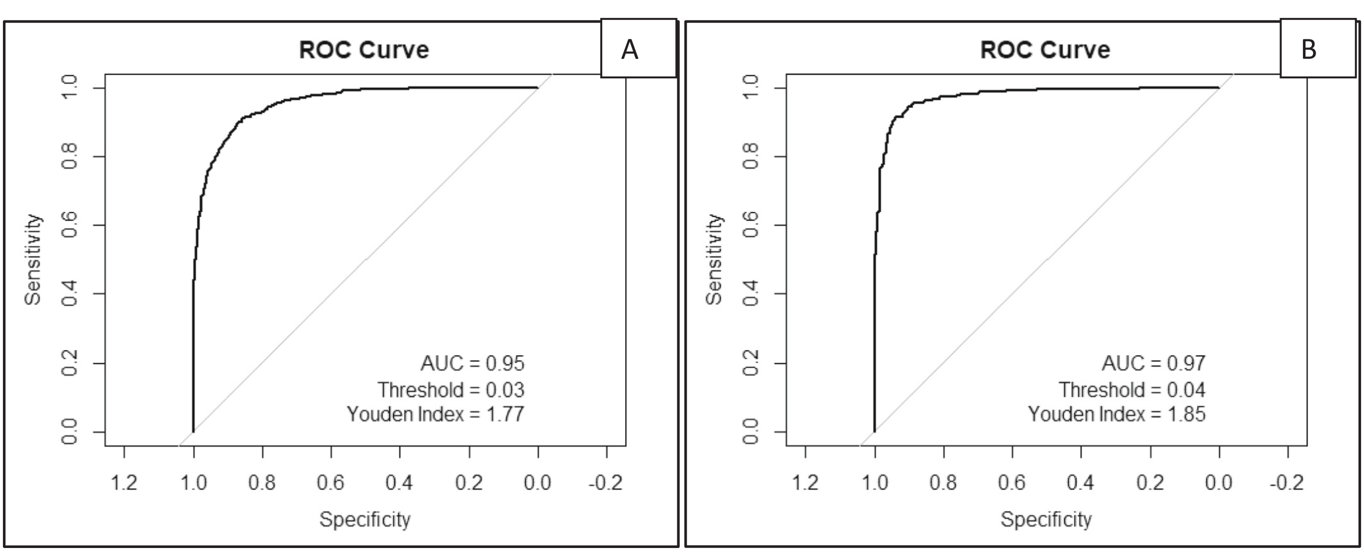


**Fig. 2.** ROC AUC for per X-ray (A) and per patient (B) analysis by the no code machine learning models for identifying clavicle fracture.

### 3.2. Model performance for validation dataset

A total of 100 radiographs from were automatically split to comprise the validation dataset. The performance in this dataset was 80 % sensitivity, 98 % specificity, 89 % accuracy, 97.6 % precision and F1 of 0.87 %.

### 3.3. Model performance per X-ray

To protect data privacy, the model was built on a secure platform within the hospital firewall. Radiographs of 108 patients who could not be automatically deidentified were excluded. The 1666 radiographs used for model testing (772 radiographs with clavicle fracture and 894 radiographs without clavicle fracture) belonged to two sites that did not contribute to the training datasets.

The model was a simple classifier of clavicle radiographs into those with and without fractures. The model had 90 % sensitivity, 87 % specificity, 88 % accuracy, and an AUC of 0.95 for detecting clavicle fractures. The distribution and example of true positive, true negative, false positive, and false negative outputs is summarized in Figs. 2 and 3, respectively. There was no significant difference in model performance in male or female patients and among patients in different locations at the time of their radiography ($p > 0.05$). On analyzing the performance of the AI model in our study, false positive findings were noted in X-rays when clavicle had degenerative changes, skin folds, artifacts, and foreign bodies such as post catheter overlying the clavicle. False negative findings were present in both displaced and non-displaced clavicle fractures.

### 3.4. Model performance per patient

The model performance was evaluated per patient by using the absolute value of AI model prediction. The test set included 826 patients with 384 in positive group (with fracture) and 442 in the negative group (without fracture). The model had sensitivity of 91 %, specificity of 94 %, accuracy of 93 % with AUC of 0.97 (95 % CI 0.96–0.98) for classifying the patients with fracture.

## 4. Discussion

Our study demonstrates that the NML platform can help develop simple image features-classifying AI models in a fast and efficient manner to achieve the expected outcome. Although the AI development process required human involvement in several steps such as in defining

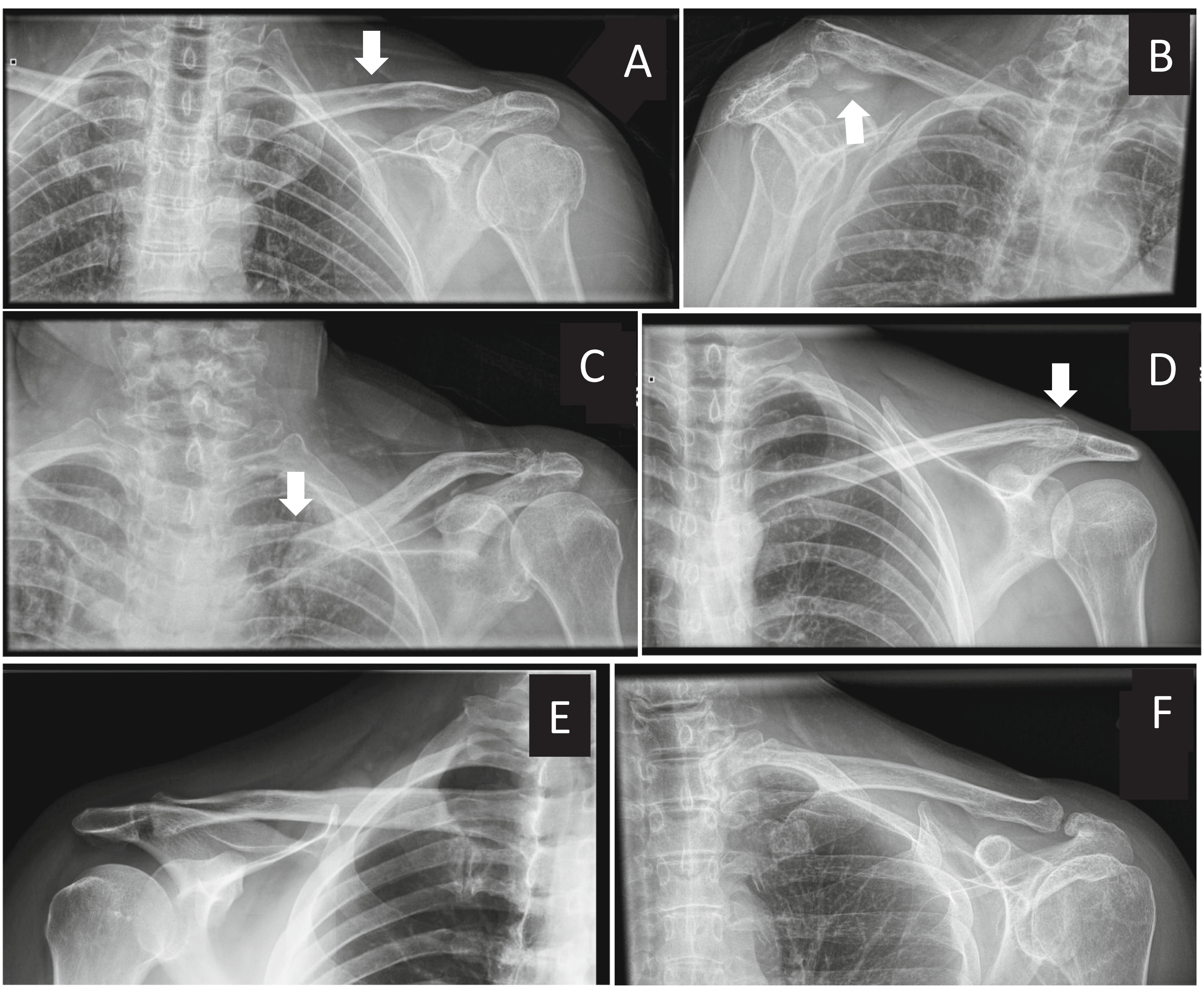


**Fig. 3.** Model performance examples on frontal projection radiographs of clavicles with AI-detected (true positive: A, B), AI-missed (false negative: C, D), and AI-false positive (E, F) clavicle fractures.

the problem of interest and the creation of training datasets, the platform required no programming or fine-tuning steps for creating the AI model.

Performance of our NML platform-developed AI model was similar to the conventional AI models. For example, Guermazi et al. reported the stand-alone performance of their AI model for identifying shoulder and clavicle fractures with an 84 % sensitivity, 83 % specificity, and AUC of 0.90 (95 % CI 0.79–0.96).[22] Jones et al. reported on a deep learning system, an ensemble of 10 convolutional networks, for identifying clavicle fractures with a 90 % sensitivity, 91 % specificity and an AUC of 0.96.[23] Ma et al. reported the model performance with an average precision of 0.90.[24] Studies by Lindsey et al. and Reichert et al. have reported also reported similar performance for fracture detection with the aid of AI models.[25,26] Versus some other models, our model does not produce heat maps or mark-up the regions of radiographs with clavicle fractures. Prior studies have reported on identifying fractures with AI models developed with conventional training methods (Table 1) instead of the NML platform used in our study.[7–17]

The main clinical implication of our study pertains to the use of NML platform to simplify the creation of an AI tool for classifying radiographs based on the presence of clavicle fractures. A radiology report search engine, preferably with a multi-site report database such as the one used in our study, can help identify a large volume of eligible cases. Auto-retrieval and de-identification of image datasets from the site VNA to the NML platform require upfront efforts and infrastructure but can expedite the development efforts. For simple classification models, such NML-trained models can help improve the diagnostic accuracy of fracture detection, especially in clavicle fractures without displacement that can challenge the interpreting physician. Third, our study documents the feasibility of utilizing NML platform for building AI models, particularly those targeting classification of radiographic findings without the need for an image level annotation, which is a time-consuming and expensive process. Fourth, the NML platform offers various data augmentation options for training AI models with limited training datasets such as random rotation, random zoom, and random elastic deformation. Finally, it is important to understand that the classification task on two-dimensional projectional radiography is likely a less complex task for NML platforms than lesion detection or characterization on radiography or a classification task on cross-sectional imaging modalities such as CT or MR.

Our study has limitations. First, there was an asymmetric distribution of radiographs across different institutions and between the radiographs with and without clavicle fractures. Second, despite variable practice types and radiographic equipment, all clavicle radiographs belonged to a common healthcare system in the same geographic location in the Northeast part of the United States. Third, we did not assess variations in the model performance across patients' size, racial, or ethnic groups. Fourth, as stated above, the successful creation of a classification model for clavicle fractures does not imply that the same NML platform will be successful at building sophisticated models or those for cross-sectional imaging modalities. Furthermore, model performance on different radiography techniques (computerized versus digital radiography) was not assessed; however, considering variations in equipment across the 14 hospitals, the model was trained and tested on radiographs from several different vendors.

Another limitation of our study pertains to the use of clavicle radiographs only. In clinical practice, clavicle fractures are also identified on chest radiographs; our model was not trained or tested on chest radiographs. With greater anatomic coverage, variable radiographic quality, and distracting or overlapping abnormalities on chest radiography, a separate AI model will likely be necessary to expand clavicle fracture detection on chest radiographs. Likewise, due to the exclusion of radiographs with incomplete anatomic coverage, artifacts, and prior open reduction and internal fixation, we cannot comment on the model performance on such radiographs. Another limitation of our study pertains to the ease of detecting clavicle fractures with the NLM platform. It is possible that the platform might not work on other more complex or subtle fractures or lesions. Likewise, the results might also not transfer with similar NLM performance from 2D radiographs to 3D imaging datasets such as from CT and MRI. Finally, we also did not assess the model's performance in non-displaced versus displaced fractures and for patients with chronic or non-healed clavicle fractures.

In conclusion, the No code ML platform can help develop AI models with sparse data and data labeling, thus simplifying and expediting the development of a certain class of AI models such as for fracture classification models. Such No code ML platforms can help data scientists and physicians to create and test successful machine learning models from multicenter imaging datasets such as the one in our study for classifying radiographs based on the presence of clavicle fracture.


## Funding information

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## Data sharing statement

All data generated or analyzed during the study are included in the published paper.

## CRediT authorship contribution statement

**Giridhar Dasegowda:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Validation, Visualization, Writing – original draft, Writing – review & editing, Supervision. **James Yuichi Sato:** Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Daniel C. Elton:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Emiliano Garza-Frias:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology,

**Table 1**
Tabular summary on model performance for detection of radiographic detection of fractures from previous studies[7–17] (NS - Not specified).

| Authors | Year | Fracture | Sensitivity | Specificity | AUC | 95 % CI |
|---|---|---|---|---|---|---|
| Current study | 2022 | Clavicle | 91 % | 94 % | 0.97 | 0.96–0.98 |
| Dupuis[7] | 2022 | All fractures | 96 % | 91 % | NS | NS |
| Hayashi[8] | 2022 | All fractures | 91 % | 90 % | 0.93 | 0.88–0.97 |
| Ashkani-Esfahani[9] | 2022 | Ankle | 99 % | 99 % | 0.99 | NS |
| Raisuddin[10] | 2021 | Wrist | NS | NS | 0.98–0.99 | 0.97–0.99 |
| Yoon[11] | 2021 | Scaphoid | 87 % | 92 % | 0.96 | NS |
| Murata[12] | 2020 | Spine | 85 % | 87 % | 0.91 | 0.96–1.00 |
| Mawatari[13] | 2020 | hip | 88 % | 72 % | 0.90 | NS |
| Bluthgen[14] | 2020 | Distal radius | 64 % | 60 % | 0.80 | NS |
| Cheng[15] | 2020 | Hip fracture | 98 % | 84 % | NS | NS |
| Starosolski[16] | 2019 | Tibial | 96 % | 100 % | 0.995 | NS |
| Chung[17] | 2018 | Proximal humerus | 99 % | 97 % | 0.97 | 0.96–0.97 |

Project administration, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Thomas Schultz:** Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Christopher P. Bridge:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Bernardo C. Bizzo:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Mannudeep K. Kalra:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Keith J. Dreyer:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing.

## Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Mannudeep K. Kalra reports a relationship with Siemens Healthineers that includes: funding grants.

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