Supplementary Online Content

Lex JR, Di Michele J, Koucheki R, Pincus D, Whyne C, Ravi B. Artificial intelligence for hip fracture detection and outcome prediction: a systematic review and meta-analysis. *JAMA Netw Open*. 2023;6(3):e233391. doi:10.1001/jamanetworkopen.2023.3391

eFigure 1. PRISMA Flowchart of Included Studies

eFigure 2. Depiction of Typical Machine Learning Models Used for Diagnosing Hip Fractures From Medical Imaging, Representing a Convolutional Neural Network (A), and for Predicting Postoperative Patient Clinical Outcomes From a Multilayer Perceptron (B)

eTable 1. Machine Learning Algorithm Properties of Studies on Hip Fracture Diagnosis Using Plain Radiographs

eTable 2. Databases Used for Outcome Prediction With Availability

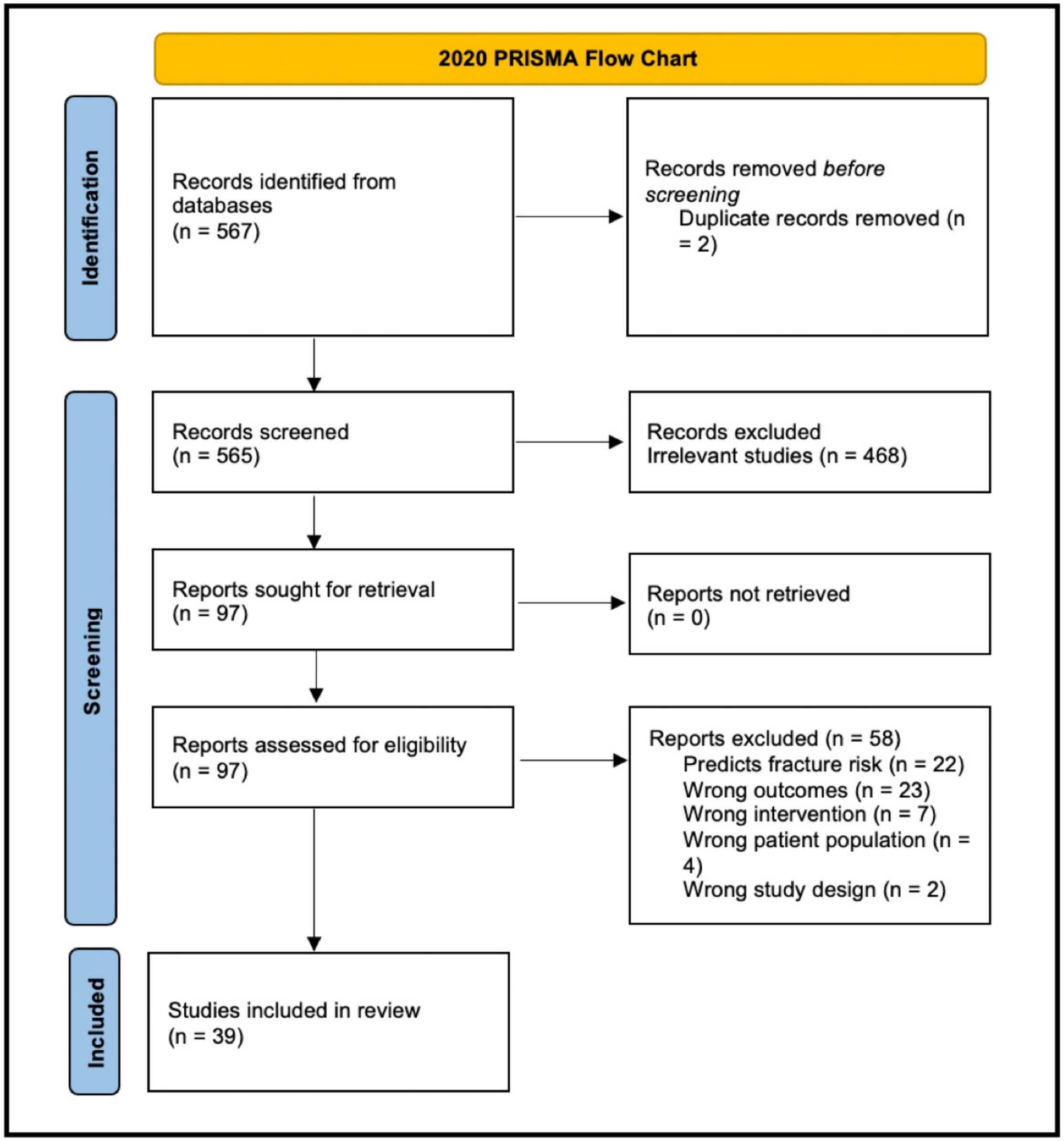
eTable 3. Summary of Outcome Performance of Artificial Intelligence Models for Diagnosing Hip Fractures Based on Plain-Film Radiographs

eTable 4. Common Features Used for Postoperative Outcome Prediction by Each Study

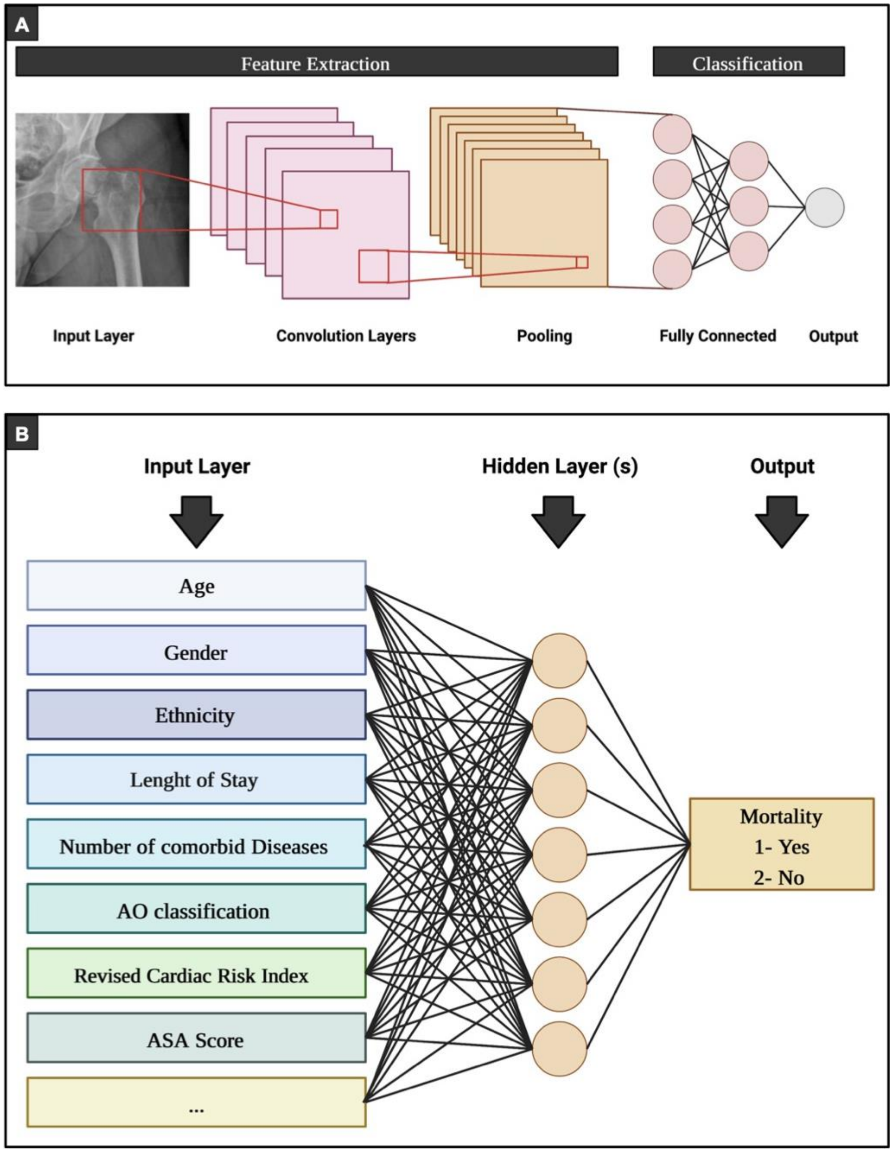
eTable 5. Comparison of Area Under the Curve Values Between Machine Learning Models and Traditional Statistical (multivariable logistic or linear regression) Prediction Models

This supplementary material has been provided by the authors to give readers additional information about their work.

eFigure 1 – PRISMA flow chart of included studies.



eFigure 2 – Depiction of typical machine learning models used for diagnosing hip fractures from medical imaging, representing a convolutional neural network (A), and for predicting post-operative patient clinical outcomes from a multilayer perceptron (B).



eTable 1 – Machine learning algorithm properties of studies on hip fracture diagnosis using plain radiographs.

FCV = Fold cross validation

Study	# Epochs used to train the Model Trained	Was Augmentation utilized?	# Fold Cross Validation
Cheng, 2019[29]	60	Yes	-
Urakawa, 2019[30]	-	Yes	-
Adams, 2019[31]	50	Yes	-
Mawatari, 2020[32]	-	Yes	-
Jimenez-Sanchez, 2020[33]	80 or 200	Yes	-
Yu, 2020[34]	200	Yes	20-FCV
Kitamura, 2020[35]	400	Yes	-
Krogue, 2020[36]	10	Yes	-
Yamada, 2020[37]	100	Yes	-
Mutasa, 2020[38]	200	Yes	-
Beyaz, 2020[39]	50	Yes	5-FCV
Acici 2021[40]	50	No	5-FCV
Bae, 2021[41]	-	Yes	-
Cheng, 2021[42]	100	Yes	5-FCV
Guy, 2021[43]	-	Yes	8-FCV
Twinprai, 2022[44]	60	Yes	-
Murphy, 2022[45]	-	Yes	-
Liu, 2022[46]	-	No	-

eTable 2– Databases used for outcome prediction with availability.

Study	Database	Data Availability
Ottenbacher, 2004[47]	1- Uniform Data System for Medical Rehabilitation (UDSMR) 2- National Follow-up Services (NFS)	Private. Available for purchase.
Sund, 2009[48]	Finnish Health Care Register	Available with Permission.
Lin, 2010[49]	Department of Orthopedics, National Taiwan University Hospital Yun-Lin Branch Database	Hospital owned.
Shi, 2013[50]	Department of Orthopedics, First Affiliated Hospital, Liaoning Medical University Database	Hospital owned.
Karnuta, 2019[51]	New York Statewide Planning and Research Cooperative System Database	Available with Permission.
Chen, 2020[52]	National Health Insurance Research Database - Taiwan	Available with Permission.
DeBaun, 2020[53]	National Surgical Quality Improvement Program	Available with Permission.
Zhang, 2020[54]	A hospital-owned patient management database	Hospital owned.
Cao, 2021[55]	Swedish National Quality Registry	Available with Permission.
Cowling, 2021[56]	National datasets of routinely collected hospital data and official death records from England	Available with Permission.
Forssten, 2021[57]	Swedish National Quality Registry	Available with Permission.
Oosterhoff, 2021[58]	National Surgical Quality Improvement Program	Available with Permission.
Li, 2021[59]	Chinese PLA General Hospital Hip Fracture Study Database	Hospital owned.
Cary Jr, 2021[60]	1- Inpatient Rehabilitation Facility–Patient Assessment Instrument (IRF-PAI) 2- The Medicare Provider Analysis and Review (MedPAR) 3- Master Beneficiary Summary Files	Available for purchase.
Shtar, 2021[61]	Petach Tikva, Israel Geriatric Rehabilitation Center Database	Hospital owned.
Zhong, 2021[62]	Tianjin Medical University General Hospital Database	Hospital owned.
Xing, 2022[63]	West China Hospital	Hospital owned.
Harris, 2022[64]	National Surgical Quality Improvement Program	Available with Permission.
Oosterhoff, 2022[65]	Multiple hospitals in the USA	Hospital owned.
Lei, 2022[66]	Medical Information Mart for Intensive Care-III	Available with Permission.
Kitcharanant, 2022[67]	Siriraj Hospital Database	Hospital owned.

eTable 3 – Summary of outcome performance of artificial intelligence models for diagnosing hip fractures based on plain-film radiographs.

Study	Sensitivity	Specificity	F1-score	Kappa Score	Youden Index
Cheng, 2019[29]	98%	84%	0.916	-	0.82
Urakawa, 2019[30]	93.90%	97.4%	-	-	0.91
Adams, 2019[31]	-	-	-	-	-
Mawatari, 2020[32]	88%	72%	-	-	0.60
Jimenez-Sanchez, 2020[33]	-	-	0.94	-	-
Yu, 2020[34]	97.10%	96.70%	-	-	0.94
Kitamura, 2020[35]	86.0%	90.0%	-	-	0.76
	-	-	-	-	-
Krogue, 2020[36]	-	-	-	-	-
	93.20%	94.20%	-	-	0.87
Yamada, 2020[37]	-	-	0.98	-	-
Mutasa, 2020[38]	91%	93%	-	-	0.84
Beyaz, 2020[39]	82.9%	72.9%	0.836	0.554	0.56
Acici 2021[40]	79.5%	81.4%	0.803	0.609	0.61
Bae, 2021[41]	97.3%	98.7%	-	-	0.96
Cheng, 2021[42]	90.8%	93.2%	-	-	0.84
Guy, 2021[43]	67%	70%	-	-	0.37
Twinprai, 2022[44]	96.2%	94.6%	0.909	-	0.91
Murphy, 2022[45]	-	-	0.91	0.87	-
Liu, 2022[46]	89.0%	87.0%	-	-	0.76

eTable 4 – Common features used for post-operative outcome prediction by each study.
LOS = Length of stay; ASA = American Society of Anaesthesiologists Score; CCI = Charlson Comorbidity Index; RCRI = Revised Cardiac Risk Index; DM = Diabetes mellitus; HTN = Hypertension; OA = Osteoarthritis; CVD = Cardiovascular disease; CHF = Congestive heart failure; CVA = Cerebrovascular accident; COPD = Chronic obstructive pulmonary disease; PNA = Pneumonia; CKD = Chronic kidney disease; SES = Socioeconomic status.

Study	Outcome Predicted	Fracture Type / Fracture pattern	Age	Sex	Ethnicity / Race	LOS	ASA	CCI score	RCRI score	DM	HTN	OA	CVD / CHF	CVA	COPD	PNA	CKD / Dialysis	Anemia / Hb	Dementia / Cognitive impairment	Cancer	SES	Functional status
Lin, 2010[49]	Mortality	✓	✓	✓			✓			✓	✓		✓	✓					✓			
Shi, 2013[50]	Mortality		✓	✓						✓			✓						✓	✓		
Chen, 2020[52]	Mortality	✓	✓	✓																	✓	
DeBaun, 2020[53]	Mortality												✓		✓	✓	✓			✓		
Zhang, 2020[54]	Mortality	✓	✓	✓			✓											✓				
Cao, 2021[55]	Mortality		✓	✓			✓		✓		✓								✓			
Cowling, 2021[56]	Mortality		✓	✓																	✓	
Forssten, 2021[57]	Mortality		✓	✓			✓	✓	✓	✓	✓		✓	✓	✓		✓		✓	✓		
Li, 2021[59]	Mortality		✓			✓					✓					✓	✓					
Cary Jr, 2021[60]	Mortality		✓	✓	✓			✓		✓				✓	✓	✓	✓					✓
Xing, 2022[63]	Mortality		✓												✓			✓		✓		
Oosterhoff, 2022[65]	Mortality		✓	✓									✓	✓	✓			✓				
Lei, 2022[66]	Mortality		✓	✓									✓		✓			✓				
Kitcharanant, 2022[67]	Mortality		✓	✓				✓					✓	✓	✓		✓					
Harris, 2022[64]	Mortality, Major Complications		✓	✓							✓		✓		✓		✓			✓		
Karnuta, 2019[51]	LOS		✓	✓	✓			✓														
Sund, 2009[48]	LOS			✓		✓				✓		✓	✓	✓	✓				✓	✓		
Zhong, 2021[62]	LOS							✓														
Ottenbacher, 2004[47]	Living setting		✓	✓	✓	✓															✓	✓
Shtar, 2021[61]	mFIM	✓	✓	✓														✓	✓			✓
Oosterhoff, 2021[58]	Post-op Delirium		✓	✓															✓			✓

eTable 5 – Comparison of Area Under the Curve values between machine learning models and traditional statistical (multivariable logistic or linear regression) prediction models.
ML = Machine learning; AUC = Area Under the Curve

Study	ML Model 1 year mortality AUC	Control 1 year mortality AUC
Lin, 2010[49]	0.949	0.784
Shi, 2013[50]	0.901	0.745
Cowling, 2021[51]	0.804	0.798
Forssten, 2021[52]	0.72	0.74
Cary Jr, 2021[60]	0.758	0.756
Xing, 2022[63]	0.813	0.797
Kitcharanant, 2022[67]	0.95	0.91
Average	**0.84**	**0.79**
P-value	**P = 0.09**	