Artificial intelligence for MRI stroke detection: a systematic review and meta-analysis

ELECTRONIC SUPPLEMENTARY MATERIAL

Insights Imaging (2024) Bojsen JA, Elhakim MT, Graumann O, et al.

Table S1. Search strings for all databases searched for the systematic review of artificial intelligence for MRI stroke detection.

Ovid MEDLINE(R) ALL 1946 to October 31, 2023

1	Exp Magnetic resonance Imaging/
2	((magnetic resonance or MR or NMR) adj2 (imag* or tomograph* or scan*)).tw.
3	(MRI or MRIs or NMRI).tw.
4	(diffusion weighted imag* or DWI or T2-weighted imag*).tw.
5	1 or 2 or 3 or 4
6	cerebrovascular disorders/ or exp basal ganglia cerebrovascular disease/ or exp brain ischemia/ or exp carotid artery diseases/ or exp cerebrovascular trauma/ or exp intracranial arterial diseases/ or exp intracranial arteriovenous malformations/ or exp "intracranial embolism and thrombosis"/ or exp intracranial hemorrhages/ or stroke/ or exp brain infarction/ or vasospasm, intracranial/
7	(stroke or poststroke or post-stroke or cerebrovasc$ or brain vasc$ or cerebral vasc$ or cva$ or apoplex$ or SAH).tw.
8	((brain$ or cerebr$ or cerebell$ or intracran$ or intracerebral) adj5 (isch?emi$ or infarct$ or thrombo$ or emboli$ or occlus$)).tw.
9	((brain$ or cerebr$ or cerebell$ or intracerebral or intracranial or subarachnoid) adj5 (haemorrhage$ or hemorrhage$ or haematoma$ or hematoma$ or bleed$)).tw.
10	((transi$ adj3 isch?em$ adj3 attack$) or TIA$1).tw.
11	6 or 7 or 8 or 9 or 10
12	exp Artificial Intelligence/
13	((artificial or machine or deep) adj6 (intelligence or learning)).tw.
14	12 or 13
15	5 and 11 and 14

Embase Classic+Embase 1947 to 2023 October 31

1. Exp Magnetic resonance Imaging/
2. ((magnetic resonance or MR or NMR) adj2 (imag* or tomograph* or scan*)).tw.
3. (MRI or MRIs or NMRI).tw.
4. (diffusion weighted imag* or DWI or T2-weighted imag*).tw.
5. 1 or 2 or 3 or 4
6. cerebrovascular disease/ or exp basal ganglion hemorrhage/ or exp brain hematoma/ or exp brain hemorrhage/ or exp brain infarction/ or exp brain ischemia/ or exp carotid artery disease/ or cerebral artery disease/ or exp cerebrovascular accident/ or exp intracranial aneurysm/ or exp occlusive cerebrovascular disease/ or vertebrobasilar insufficiency/ or stroke/ or stroke patient/ or stroke unit/
7. (stroke or poststroke or post-stroke or cerebrovasc$ or brain vasc$ or cerebral vasc$ or cva$ or apoplex$ or SAH).tw.
8. ((brain$ or cerebr$ or cerebell$ or intracran$ or intracerebral) adj5 (isch?emi$ or infarct$ or thrombo$ or emboli$ or occlus$)).tw.
9. ((brain$ or cerebr$ or cerebell$ or intracerebral or intracranial or subarachnoid) adj5 (haemorrhage$ or hemorrhage$ or haematoma$ or hematoma$ or bleed$)).tw.
10. ((transi$ adj3 isch?em$ adj3 attack$) or TIA$1).tw.
11. 6 or 7 or 8 or 9 or 10
12. exp Artificial Intelligence/
13. ((artificial or machine or deep) adj6 (intelligence or learning)).tw.
14. 12 or 13
15. 5 and 11 and 14

Cochrane Central Register of Controlled Trials Issue 10 of 12, October 2023

#1	MeSH descriptor: [Magnetic Resonance Imaging] explode all trees
#2	((magnetic resonance or MR or NMR) NEAR/2 (imag* or tomograph* or scan*)):ti,ab,kw
#3	(MRI or MRIs or NMRI):ti,ab,kw
#4	(diffusion weighted imag* or DWI or T2-weighted imag*):ti,ab,kw
#5	{OR #1-#4}
#6	MeSH descriptor: [Basal Ganglia Cerebrovascular Disease] this term only
#7	MeSH descriptor: [Brain Ischemia] this term only
#8	MeSH descriptor: [Carotid Artery Diseases] this term only
#9	MeSH descriptor: [Cerebrovascular Trauma] this term only
#10	MeSH descriptor: [Intracranial Arterial Diseases] this term only
#11	MeSH descriptor: [Intracranial Arteriovenous Malformations] this term only
#12	MeSH descriptor: [Intracranial Embolism and Thrombosis] this term only
#13	MeSH descriptor: [Intracranial Hemorrhages] this term only
#14	MeSH descriptor: [Stroke] explode all trees
#15	MeSH descriptor: [Brain Infarction] explode all trees
#16	MeSH descriptor: [Vasospasm, Intracranial] explode all trees
#17	MeSH descriptor: [Cerebrovascular Disorders] explode all trees
#18	(stroke or poststroke or "post-stroke" or cerebrovasc* or brain next vasc* or cerebral next vasc* or cva* or apoplex* or SAH):ti,ab,kw
#19	((brain* or cerebr* or cerebell* or intracran* or intracerebral) near/5 (isch*mi* or infarct* or thrombo* or emboli* or occlus*)):ti,ab,kw
#20	((brain* or cerebr* or cerebell* or intracerebral or intracranial or subarachnoid) near/5 (haemorrhage* or hemorrhage* or haematoma* or hematoma* or bleed*))
#21	{OR #6-#20}
#22	MeSH descriptor: [Artificial Intelligence] explode all trees
#23	((artificial:ti,ab OR machine:ti,ab OR deep:ti,ab) NEAR/6 (intelligence:ti,ab OR learning:ti,ab))
#24	{OR #22-#23}
#25	(#5 AND #21 AND #24)

IEEE Xplore 2004-2023 October 31

(((magnetic resonance OR MR OR NMR OR diffusion weighted OR T2-weighted) NEAR/2 (imag* OR scan*) OR (MRI OR MRIs OR NMRI OR DWI)) AND ((stroke OR cerebrovascular) OR((brain OR cerebral OR intracranial) NEAR/5 ((ischemic OR infarct OR thrombo* OR emboli* OR occlus*) OR (hemorrhage OR hematoma OR bleed*)))) AND ((artificial OR machine OR deep) NEAR/6 (intelligence OR learning)))

Table S2. Modified QUADAS-2 for use in the systematic review of artificial intelligence for MRI stroke detection. Parts removed from the original QUADAS-2 are marked with crossed text and parts added are marked with bold text.

Domain 1: Patient selection	
Question 1: Was a consecutive or random sample of patients enrolled?	Yes/no/unclear
Question 2: Was a case-control design avoided?	Yes/no/unclear
Question 3: Did the study avoid inappropriate exclusions?	Yes/no/unclear
Could the selection of patients have introduced bias?	RISK: Low/high/unclear
Domain 2: Index test(s)	
~~Question 1: Were the index test results interpreted without knowledge of the results of the reference standards?~~	~~Yes/no/unclear~~
Question 1: Is the test set separated from the training set?	**Yes/no/unclear**
Question 2: Is the test set externally collected from the training set?	**Yes/no/unclear**
Question 3: If a threshold was used, was it pre-specified?	Yes/no/unclear
Could the conduct of interpretation of the index test have introduced bias?	RISK: Low/high/unclear
Domain 3: Reference standard	
Question 1: Is the reference standard likely to correctly classify the target condition?	Yes/no/unclear
Question 2: Were the reference standard results interpreted without knowledge of the results from the index test?	Yes/no/unclear
Could the reference standard, its conduct, or its interpretation have introduced bias?	RISK: Low/high/unclear
Domain 4: Flow and timing	
Question 1: Was there an appropriate interval between the index test(s) and the reference standard?	Yes/no/unclear
Question 2: Did all patients receive a reference standard **AND** did all patients receive the same reference standard?	Yes/no/unclear ~~Yes/no/unclear~~
Question 3: Were all patients included in the analysis?	Yes/no/unclear
Could the patients flow have introduced bias?	RISK: Low/high/unclear

Table S3. Full text reports excluded with reasons for exclusion in the systematic review of artificial intelligence for MRI stroke detection.

Excluded due to wrong participants:

1. Behera TK, Khan MA, Bakshi S. Brain MR Image Classification Using Superpixel-Based Deep Transfer Learning. IEEE Journal of Biomedical and Health Informatics. 2022((Behera, Bakshi) Department of Computer Science and Engineering, National Institute of Technology Rourkela, Odisha, India(Khan) Computer Science Department, HITEC University, Taxila, Pakistan):1-11. https://dx.doi.org/10.1109/JBHI.2022.3216270
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5. Hussein R, Zhao MY, Shin D, et al., editors. Multi-task Deep Learning for Cerebrovascular Disease Classification and MRI-to-PET Translation2022.
6. Muhammad A, Guojun W. Segmentation of Calcification and Brain Hemorrhage with Midline Detection. 2017 IEEE International Symposium on Parallel and Distributed Processing with Applications and 2017 IEEE International Conference on Ubiquitous Computing and Communications (ISPA/IUCC). 2017:1082-90. 10.1109/ISPA/IUCC.2017.00164
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8. Sathish R, Rajan R, Vupputuri A, Ghosh N, Sheet D. Adversarially Trained Convolutional Neural Networks for Semantic Segmentation of Ischaemic Stroke Lesion using Multisequence Magnetic Resonance Imaging. Annual International Conference of the IEEE Engineering in Medicine and Biology Society IEEE Engineering in Medicine and Biology Society Annual International Conference. 2019;2019(101763872):1010-3. https://dx.doi.org/10.1109/EMBC.2019.8857527
9. Talo M, Yildirim O, Baloglu UB, Aydin G, Acharya UR. Convolutional neural networks for multi-class brain disease detection using MRI images. Computerized medical imaging and graphics : the official journal of the Computerized Medical Imaging Society. 2019;78(cmi, 8806104):101673. https://dx.doi.org/10.1016/j.compmedimag.2019.101673
10. Zhang Y, Hu Q, Guo Z, Xu J, Xiong K. Multi-Class Brain Images Classification Based on Reality-Preserving Fractional Fourier Transform and Adaboost. 2018 IEEE 3rd International Conference on Image, Vision and Computing (ICIVC). 2018:444-7. 10.1109/ICIVC.2018.8492732
11. Assam M, Kanwal H, Farooq U, Shah SK, Mehmood A, Choi GS. An Efficient Classification of MRI Brain Images. IEEE Access. 2021;9:33313-22. 10.1109/ACCESS.2021.3061487
12. Talo M, Baloglu UB, Yildirim O, Rajendra Acharya U. Application of deep transfer learning for automated brain abnormality classification using MR images. Cognitive Systems Research. 2019;54((Talo, Baloglu, Yildirim) Department of Computer Engineering, Munzur University, Tunceli, Turkey(Rajendra Acharya) Department of Electronics and Computer Engineering, Ngee Ann Polytechnic, Singapore(Rajendra Acharya) Department of Biomedical Engineering):176-88. http://dx.doi.org/10.1016/j.cogsys.2018.12.007
13. A V, A S, Metun M, P R, editors. Supervised Machine Learning System Based Segmentation and Classification of Strokes Using Deep Learning Techniques2022.
14. Patil A, Govindaraj S, editors. An AI Enabled Framework for MRI-based Data Analytics for Efficient Brain Stroke Detection2023.
15. Yadav PK, Patel S, Das S, Singh S, Sharma A, editors. MRI Based Automatic Brain Stroke Detection Using CNN Models Improved with Model Scaling2023.

Excluded due to wrong intervention:

1. Ahmed KS, Shariar KS, Naim NH, Alam MGR, editors. Intracranial Hemorrhage Detection using CNN-LSTM Fusion Model2022.
2. Alshammari A, Atiyah N, Alaboodi H, Alshammari R. Identification of stroke using deepnet machine learning algorithm. International Journal of Medical Engineering and Informatics. 2023;15(5):416-29. https://dx.doi.org/10.1504/IJMEI.2023.133083
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4. Koh TS, Wu XY, Cheong LH, Lim CCT. Assessment of perfusion by dynamic contrast-enhanced imaging using a deconvolution approach based on regression and singular value decomposition. IEEE transactions on medical imaging. 2004;23(12):1532-42. 10.1109/TMI.2004.837355
5. Kothala LP, Guntur SR, editors. An efficient False Negative Reduction System for the Identification of Intracranial Hemorrhage2022.
6. Mazurek MH, Parasuram NR, Peng TJ, et al. Detection of Intracerebral Hemorrhage Using Low-Field, Portable Magnetic Resonance Imaging in Patients With Stroke. Stroke. 2023;54(11):2832-41. https://dx.doi.org/10.1161/STROKEAHA.123.043146
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8. Roder M, Rosa GH, Papa JP, Guimar DC, x00E, es P, editors. Enhancing Shallow Neural Networks Through Fourier-based Information Fusion for Stroke Classification2021.
9. Okashi OMA, Mohammed FM, Aljaaf AJ. An Ensemble Learning Approach for Automatic Brain Hemorrhage Detection from MRIs. 2019 12th International Conference on Developments in eSystems Engineering (DeSE). 2019:929-32. 10.1109/DeSE.2019.00172
10. Cirio JJ, Ciardi C, Buezas M, et al. Implementation of artificial intelligence in hyperacute arterial reperfusion treatment in a comprehensive stroke center. Neurologia Argentina. 2021((Cirio, Ciardi, Buezas, Caballero, Lopez, Lopez, Chasco, Lammertyn) Unidad de Stroke, Clinica La Sagrada Familia-Instituto Medico ENERI, Buenos Aires, Argentina(Diluca) Servicio de Diagnostico por Imagenes, Clinica La Sagrada Familia-Instituto Medico ENER). http://dx.doi.org/10.1016/j.neuarg.2021.07.003

Excluded due to wrong comparator:

1. Aboudi F, Drissi C, Kraiem T, editors. Efficient U-Net CNN with Data Augmentation for MRI Ischemic Stroke Brain Segmentation2022.
2. Amin J, Sharif M, Raza M, Anjum MA, Bukhari SAC. Convolutional neural network with batch normalization for glioma and stroke lesion detection using MRI. Cognitive Systems Research. 2020;59((Amin) Department of Computer Science, University of Wah, Pakistan(Amin, Sharif, Raza) Department of Computer Science, COMSATS University Islamabad, Wah Campus, Pakistan(Anjum) College of EME, NUST, Pakistan(Bukhari) Division of Computer Science, Mathemat):304-11. http://dx.doi.org/10.1016/j.cogsys.2019.10.002
3. Artzi M, Aizenstein O, Jonas-Kimchi T, Myers V, Hallevi H, Ben Bashat D. FLAIR lesion segmentation: application in patients with brain tumors and acute ischemic stroke. European journal of radiology. 2013;82(9):1512-8. https://dx.doi.org/10.1016/j.ejrad.2013.05.029
4. Babu R, Pushpalatha N, editors. An Effective Application of Deep Learning in the Early Diagnosis of Stroke2023.
5. Bao Q, Mi S, Gang B, Yang W, Chen J, Liao Q. MDAN: Mirror Difference Aware Network for Brain Stroke Lesion Segmentation. IEEE journal of biomedical and health informatics. 2022;26(4):1628-39. https://dx.doi.org/10.1109/JBHI.2021.3113460
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15. Do L-N, Baek BH, Kim SK, Yang H-J, Park I, Yoon W. Automatic Assessment of ASPECTS Using Diffusion-Weighted Imaging in Acute Ischemic Stroke Using Recurrent Residual Convolutional Neural Network. Diagnostics (Basel, Switzerland). 2020;10(10). https://dx.doi.org/10.3390/diagnostics10100803
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18. Han L, Liu L, Hao Y, Zhang L. Diagnosis and Treatment Effect of Convolutional Neural Network-Based Magnetic Resonance Image Features on Severe Stroke and Mental State. Contrast media & molecular imaging. 2021;2021(101286760):8947789. https://dx.doi.org/10.1155/2021/8947789

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Excluded due to wrong study design:

1. Mounika S, R. S R, editors. Comprehensive Study on RS_FMRI and EEG Using Deep Learning Approach for Brain Stroke2023.

Table S4. Setting and artificial intelligence characteristics of included studies in the systematic review of artificial intelligence for MRI stroke detection.

	Year and First author	Ref	Setting				Artificial intelligence				
			Comparator	Time frame	Reference standard	Sample origin	FDA/CE approval	Classifier type	Neural Network	Architecture name	Sequences used
Overall low risk of bias	2023 Krag C	(32)	non-ischaemic strokes	4w	neuroradiologist	Denmark	CE approved	CNN	yes	not reported	FLAIR, DWI, SWI/T2*GRE
	2023 Lee, K	(33)	normal	24h	2 radiologists in consensus	Taiwan	none	CNN	yes	modified LeNet	DWI
	2023 Yang, X	(34)	non-strokes	not reported	2 neuroradiologists in consensus	China	none	CNN	yes	MSMT-DL	FLAIR, T1, T2
	2023 Wu, Y	(35)	non-strokes	72h	3 neuroradiologists in consensus	not reported	none	CNN	yes	VGG-16 ResNet-50 CBAM-VGG	DWI
	2022 Bridge, C	(36)	non-strokes with no diffusion restriction	acute ischaemic stroke unspecified	radiologists and neurologists	set 1-3: Massachussetts USA set 4: Brazil	none	CNN	yes	UNet	ADC,DWI B1000
	2022 Tasci, B	(37)	set 1: normal diffusion set 2: white matter hyperintensities, atrophy, normal	acute ischaemic stroke unspecified	1 physician	Turkey	none	CNN	yes	ResNet, DenseNet	set 1: ADC, DWI set 2: T2
	2022 Qiu, J	(38)	intracranial stenosis	not reported	2 radiologists in consensus	China	none	CNN	yes	YOLOv5	TOF-MRA
	2021 Liu, C	(39)	transitory ischaemic attack (MRI non-visible stroke)	set 1: early subacute ischaemic stroke unspecified set 2: two scan time frames: 3h and 24h	1 neuroradiologist	set 1: Maryland USA set 2: STIR database	none	CNN	yes	DAGMNet	ADC, DWI

Table S4 continued.

			Setting				Artificial intelligence				
	Year and First author	Ref	Comparator	Time frame	Reference standard	Sample origin	FDA/CE approval	Classifier type	Neural Network	Architecture name	Sequences used
Overall low risk of bias continued	2021 Nael, K	(40)	Normal, abnormals, mass effect, acute infarction (if detection type is acute haemorrhage) or acute haemorrhage (if detection type is acute infarction)	acute ischaemic stroke unspecified; acute haemorrhagic stroke and extra-axial haemorrhage unspecifed	single radiologist re-evaluation of radiology report (for external test set)	not reported	none	CNN	yes	custom	ADC, FLAIR, Trace (Optional: T1, T2, T2*)
	2020 Duan, Y	(41)	lacunes, white matter hyperintensities, microbleeds	not reported	3 expert radiologists	China	none	CNN	yes	UNet	DWI b1000, FLAIR, T1, T2*
	2020 Dørum, E	(42)	normal	14d	radiology report	Norway	none	Shrinkage LDA	no	-	FLAIR, T1, T2* for fMRI
	2020 Federau, C	(43)	normal	24h	three neuro-radiologists in consensus	Switzerland	none	CNN	yes	UNet	DWI b1000
	2020 Herzog, L	(44)	transitory ischaemic attack (MRI non-visible stroke)	not reported	neurologist with aid from radiology report	Switzerland	none	CNN	yes	custom	DWI
	2019 Bizzo, B	(45)	normal, other unknown non-stroke findings (e.g. neoplasia)	acute ischaemic stroke unspecified	radiologist using radiology report	Massachussetts USA	none	CNN	yes	Ynet	ADC, DWI
	2007 Uchiyama, Y	(46)	non-stroke	not reported	two independent neuro-radiologists	Japan	none	MLP	yes	-	T1, T2

Table S4 continued.

	Year and First author	Setting: Ref	Setting: Comparator	Setting: Time frame	Setting: Reference standard	Setting: Sample origin	Artificial intelligence: FDA/CE approval	Artificial intelligence: Classifier type	Artificial intelligence: Neural Network	Artificial intelligence: Architecture name	Artificial intelligence: Sequences used
Overall high risk of bias	2023 Yaman, S	(47)	normal, atrophy, WMI	not reported	specialist radiologist	Turkey	none	CNN	yes	AlexNet GoogleNet DenseNet VGG MobileNet ResNet SqueezeNet	T2
	2022 Arnold, T	(48)	high grade glioma, low grade glioma, multiple sclerosis	subacute ischaemic stroke unspecified	3 neuro-radiologists	ISLES 2015, BRATS 2019, MICCAI 2008, MS-SEG-2016, OASIS3 databases	none	CNN	yes	DenseNet	Axial FLAIR
	2022 Eshmawi, A	(49)	normal	subacute ischaemic stroke unspecified haemorrhagic stroke not reported	not reported	AANLIB	none	CNN	yes	MobileNet CapsuleNet EfficientNet	T2
	2022 Guo, Y	(50)	non-strokes	24h	RAPID	China	none	LDA	no	-	DSC-PWI
	2022 Li, J	(51)	normal	7d	1 radiologist & 1 neurologist	China	none	SVM	no	-	FMRI (slow-4 and slow-5)
	2021 Cetinoglu, Y	(52)	non-ischaemic stroke patients	acute ischaemic stroke unspecified	2 neuro-radiologists	Turkey	none	CNN	yes	MobileNet	dwi
	2021 Cui, L	(53)	non-acute ischaemic stroke patients	24h	clinicians	China	none	CNN	yes	MedicalNet, DeepSym	ADC, DWI, PWI, T1
	2021 Hossain, S	(54)	non-stroke	not reported	not reported	Kaggle.com Radiopedia.org medscape.com	none	LRC	no	-	not reported

Table S4 continued.

	Year and First author	Ref	Setting: Comparator	Setting: Time frame	Setting: Reference standard	Setting: Sample origin	Artificial intelligence: FDA/CE approval	Artificial intelligence: Classifier type	Artificial intelligence: Neural Network	Artificial intelligence: Architecture name	Artificial intelligence: Sequences used
Overall high risk of bias continued	2023 Yaman, S	(55)	normal, glioma	not reported	not reported	ISLES2015, BRATS2015 databases	none	CNN	yes	VGG	FLAIR
	2020 Liu, S	(56)	normal	acute ischaemic stroke unspecified	clinical specialists	China	none	KNN	yes	-	not reported
	2020a Nayak, D	(57)	normal, degenerative, infectious, tumor	not reported	not reported	med.harvard.edu/ AANLIB/	none	RVFL-AE	yes	custom	T2
	2020b Nayak, D	(58)	normal, degenerative, infectious, tumor	not reported	not reported	med.harvard.edu/ AANLIB/	none	K-ELM	yes	custom	T2
	2020 Nazari-Farsani, S	(59)	normal	acute ischaemic stroke unspecified	1 neuroradiologist	Finland	none	SVM	no	-	ADC, DWI, T1
	2019 Gaidhani, B	(60)	normal	not reported	not reported	ATLAS database	none	CNN	yes	LeNet	T1
	2019 Nayak, D	(61)	normal, degenerative, infectious, tumor	not reported	not reported	med.harvard.edu/ AANLIB/	none	Kernel RVFL	yes		T2
	2019 Ortiz-Ramon, R	(62)	age cohort with no acute strokes	2w	not reported	United Kingdom	none	SVM	no	-	FLAIR, T1, T2
	2019 Phan, A	(63)	epidural haematoma, subdural haematoma, subarachnoid haemorrhage	not reported	unspecified number ofspecialists and doctors	Vietnam	none	CNN	yes	custom	not reported
	2013 Saritha, M	(64)	normal, degenerative, infectious, tumor	not reported	not reported	med.harvard.edu/ AANLIB/	none	PNN	yes	custom	T2

CNN: Convolutional neural network, LDA: Linear discriminant analysis, MLP: Multilayer perceptron, SVM: Support vector machine, LRC: Logistic regression classifier, KNN: K-nearest neighbor, RVFL: Random vector functional link, AE: Autoencoder, PNN: Probabilistic neural network, ADC: Apparent diffusion coefficient, DWI: Diffusion weighted images, FLAIR: Fluid attenuated inversion recovery, fMRI: Functional magnetic resonance imaging

Table S5. In-depth risk of bias of included studies in the systematic review of artificial intelligence for MRI stroke detection.

	Year and first author	Patient selection domain	Index test domain	Reference standard domain	Flow and timing domain
Overall low risk of bias	2023 Krag, C	yes	yes	yes	yes
		yes	yes	yes	yes
		yes	yes		yes
	2023 Lee, K	yes	yes	yes	yes
		yes	no	yes	yes
		yes	no		yes
	2023 Yang, X	yes	yes	yes	yes
		yes	no	yes	yes
		yes	yes		yes
	2023 Wu, Y	yes	yes	yes	yes
		yes	no	yes	yes
		yes	unclear		yes
	2022 Bridge, C	yes	yes	yes	yes
		yes	yes[1]	yes	yes
		no	yes		yes
	2022 Tasci, B	unclear	yes[2]	unclear[3]	yes
		unclear	yes[2]	yes	yes
		yes	unclear		yes
	2022 Qiu, J	yes	yes	yes	yes
		yes	no	yes	yes
		yes	yes		yes
	2021 Liu[4]	yes[3]	yes[3]	yes[3]	yes
		yes[3]	yes[3]	yes	yes
		unclear	yes		yes
	2021 Nael, K	unclear	yes	yes	yes
		unclear	yes	yes	yes
		yes	no		yes
	2020 Duan, Y	unclear	yes	yes	yes
		yes	no	yes	yes
		yes	no		yes
	2020 Dørum, E	yes	no	yes	yes
		no	no	yes	yes
		yes	no		yes
	2020 Federau, C	unclear	yes	yes	yes
		no	no	yes	yes
		yes	no		yes
	2020 Herzog, L	unclear	unclear	yes	yes
		yes	no	yes	yes
		yes	no		yes
	2019 Bizzo, B	yes	unclear	yes	yes
		yes	unclear	yes	yes
		yes	no		yes
	2007 Uchiyama, Y	yes	yes	yes	yes
		yes	no	yes	yes
		yes	yes		yes

Table S5 continued.

Overall high risk of bias	2023 Yaman, S	no no unclear	no no no	unclear yes	yes yes yes
	2022 Arnold	no no unclear	yes no no	yes unclear	yes yes no
	2022 Eshmawi, A	no no unclear	no no no	unclear unclear	yes unclear yes
	2022 Guo, Y	no yes yes	no no no	unclear yes	yes yes yes
	2022 Li	no no yes	no no unclear	yes yes	yes yes yes
	2021 Cetinoglu	no no yes	yes no unclear	yes yes	yes yes yes
	2021 Cui[5]	unclear yes unclear	no no unclear	yes yes	yes yes yes
	2021 Hossain, S	no no unclear	yes unclear no	unclear unclear	yes no unclear
	2021 Kadry, s	no no unclear	yes no no	unclear unclear	yes unclear yes
	2020 Liu, S	unclear no unclear	no no no	unclear unclear	yes yes yes
	2020a Nayak, D	no no unclear	yes unclear no	unclear unclear	yes unclear yes
	2020b Nayak, D	no no unclear	unclear unclear no	unclear unclear	yes unclear yes
	2020 NazariFarsani, S	no no yes	yes no no	yes yes	yes yes yes
	2019 Gaidhani, B	unclear no unclear	yes no no	unclear no	yes unclear unclear
	2019 Nayak, D	no no unclear	unclear unclear no	unclear unclear	yes yes yes
	2019 Ortiz-Ramon, R	no no unclear	unclear no no	unclear unclear	yes unclear yes
	2019 Phan, A	unclear no unclear	yes no no	yes yes	yes yes yes
	2013 Saritha, M	no no unclear	yes no no	unclear unclear	yes yes yes

[1]for stroke code and international datasets
[2]only dataset 2
[3]no info dataset 2, dataset 1: yes
[4]STIR dataset is a mix of datasets. Insufficient reporting of ground truth labellers, but the STIR steering committee consists of numerous researchers from wellestablished universities.
[5]Ambiguous separation of training and validation. Bias evaluation is of all patients.

Table S6. MI-CLAIM reported items for included studies in the systematic review of artificial intelligence for MRI stroke detection.

	Year and first author	Ref	Study design (Part 1)	Data and optimization (Parts 2, 3)	Model Performance (part 4)	Model Examination (part 5)	Reproducibility (Part 6)	Overall % completed
Studies with an overall low risk of bias	2023 Krag, C	(32)	5/5	4/4	2/3	3/4	No code sharing	82
	2023 Lee, K	(33)	5/5	4/4	1/3	4/4	no code sharing	82
	2023 Yang, X	(34)	5/5	3/4	2/3	4/4	full sharing of code	88
	2023 Wu, Y	(35)	5/5	4/4	1/3	4/5	no code sharing	78
	2022 Bridge, C	(36)	5/5	4/4	3/3	4/5	no code sharing	89
	2022 Tasci, B	(37)	5/5	4/4	2/3	3/5	no code sharing	78
	2022 Qiu, J	(38)	5/5	4/4	2/3	4/4	no code sharing	88
	2021 Liu, C	(39)	5/5	4/4	3/3	4/4	full sharing of code	100
	2021 Nael, K	(40)	5/5	4/4	2/3	4/4	full sharing of code	94
	2020 Duan, Y	(41)	5/5	3/4	2/3	3/4	no code sharing	76
	2020 Dørum, E	(42)	5/5	4/4	3/3	5/5	no code sharing	94
	2020 Federau, C	(43)	5/5	4/4	3/3	4/4	no code sharing	94
	2020 Herzog, L	(44)	5/5	4/4	3/3	4/4	full sharing of code	100
	2019 Bizzo, B	(45)	5/5	3/4	0/3	0/5	no code sharing	44
	2007 Uchiyama, Y	(46)	5/5	3/4	2/3	2/4	no code sharing	71
	Category %		100	93	69	79	29	84
Studies with an overall high risk of bias	2023 Yaman, S	(47)	5/5	3/4	1/3	2/5	no code sharing	61
	2022 Arnold, T	(48)	5/5	4/4	1/3	4/5	no code sharing	78
	2022 Eshmawi, A	(49)	1/5	3/4	1/3	2/5	no code sharing	39
	2022 Guo, Y	(50)	5/5	3/4	1/3	1/5	no code sharing	56
	2022 Li, J	(51)	5/5	2/4	3/3	4/4	full sharing of code	88
	2021 Cetinoglu, Y	(52)	5/5	3/4	3/3	4/4	no code sharing	88
	2021 Cui, L	(53)	5/5	3/4	2/3	4/4	no code sharing	82
	2021 Hossain, S	(54)	3/5	2/4	2/3	1/5	no code sharing	44
	2021 Kadry, s	(55)	4/5	4/4	2/3	2/5	no code sharing	67
	2020 Liu, S	(56)	4/5	3/4	2/3	0/5	no code sharing	50
	2020a Nayak, D	(57)	2/5	3/4	1/3	4/4	no code sharing	59
	2020b Nayak, D	(58)	2/5	2/4	1/3	4/4	no code sharing	53
	2020 Nazari-Farsani, S	(59)	5/5	4/4	3/3	4/4	no code sharing	94
	2019 Gaidhani, B	(60)	3/5	4/4	2/3	2/5	no code sharing	61
	2019 Nayak, D	(61)	2/5	3/4	2/3	2/5	no code sharing	50
	2019 Ortiz-Ramon, R	(62)	4/5	4/4	3/3	4/4	no code sharing	88
	2019 Phan, A	(63)	3/5	3/4	0/3	1/5	no code sharing	39
	2013 Saritha, M	(64)	2/5	3/4	1/3	1/5	no code sharing	39
	Category %		72	78	57	55	6	63
	Total %		**85**	**85**	**63**	**66**	**15**	**72**

Table S7. Notes supplementing the results reported in Table 4.

	Year and first author	Ref	Notes
Overall low risk of bias	2023 Krag, C	(32)	Reported for total included patients. Also reported for non-enriched cohort (89;86;90; nr)
	2023 Lee, K	(33)	Calculated using confusion matrix. ACI and PCI strokes were split.
	2023 Yang, X	(34)	MSMT-DL reported (best). Models using other sequences were also reported.
	2023 Wu, Y	(35)	Calculated averages from each reported area using VGG with CBAM for the four small areas.
	2022 Bridge, C	(36)	Results for non-training stroke code test set (largest of externally collected). Also reported primary set (nr; 98; 98; 0,998) international (nr; 100; 98; 0.998) and training hospital set (nr; 89; 95; 0.964)
	2022 Tasci, B	(37)	Results for Dataset 2 and Iterative Majority voting (External and best). Multiple other results are reported.
	2022 Qiu, J	(38)	Calculated using confusion matrix. Occlusion of intracranial artery counts as stroke vs stenosis of any grade.
	2021 Liu, C	(39)	All results for DAGMnet-CH3 (proposed AI). Multiple other AI tested. Results for STIR-2 dataset (sensitivity) and "Testing - not visible" dataset (specificity). Also reported STIR-1 sensitivity (90%) and Test sensitivity (99%)
	2021 Nael, K	(40)	External testing dataset reported. Also reported for internal testing dataset (88; 92; 88; 0.95) and (81*; 89*; 81*; 0.90*)
	2020 Duan, Y	(41)	
	2020 Dørum, E	(42)	LOAD2 used (best). Also reported REST (nr; 47; 56;nr) and LOAD1 (nr; 50; 47; nr)
	2020 Federau, C	(43)	CS40DB used (best). Also reported CDB (nr; 85; 48;nr), S2DB (nr; 77; 68;nr), CS2DB (nr; 80; 76; nr)
	2020 Herzog, L	(44)	FC-NN 3Ch-MC is used (best). Also reported 1D-CNN 3Ch-MC (95; nr; nr; 0.86)
	2019 Bizzo, B	(45)	
	2007 Uchiyama, Y	(46)	Modular classifier is used (best). Also reported single classifier (35; 97; 29; nr).

Table S7 continued.

Overall high risk of bias	2023 Yaman, S	(47)	
	2022 Arnold, T	(48)	F1-score of 76% reported instead. Results for 64mT (Best AUC). Also reported 3T (F1:77; nr; nr; 0.94)
	2022 Eshmawi, A	(49)	Ischemia calculated using confusion matrix. Hemorrhage were contained in the reported total results. Epoc-2000 used (best)
	2022 Guo, Y	(50)	Reported for DA in DRF group_D, where Lasso + PCA_Lasso ties with Lasso + Tsne_Lasso
	2022 Li, J	(51)	Results for combined Slow-4+Slow-5 (Best AUC, accuracy and specificity). Also reported ipsilesional Slow-4 (73; 68; 76; 0.80) (Best sensitivity) and multiple other with lower parameters.
	2021 Cetinoglu, Y	(52)	Results for MobileNetV2 (best). Also reported EfficientNetB0 (93; 93; 93; nr)
	2021 Cui, L	(53)	Results for DeepSym-3D-CNN (best). Also reported for ADC images only (73; 71; 76; 0.701) and DWI+ADC images only (81; 85; 77; 0.843)
	2021 Hossain, S	(54)	
	2021 Kadry, S	(55)	SVM-Cubic VGG16 reported (best). No stroke specific data available for VGG19 or ResNet50. Also reported SoftMax VGG16 (97,5;100;96,67; nr) and SVM-RBF VGG16 (98,25; 100; 97,67; nr)
	2020 Liu, S	(56)	KNN used (best). Also reported BPNN (89,09; nr; nr), PLSR (88,18; nr; nr; nr), EB (86,36; nr; nr; nr)
	2020a Nayak, D	(57)	MD-2 is used (largest dataset). Figure 5 actual and predicted labels have been swapped (denominator must be reference standard). Also reported for MD-1 (100;100;100; nr)
	2020b Nayak, D	(58)	MD-2 FCEntF-I is used (largest dataset with best specificity). Also reported MD-2 FCEntF-II (97; 93; 98; nr), MD-1 FCEntF-I (99; 93; 100; nr) and MD-1 FCEntF-II (97; 87; 100; nr)
	2020 Nazari-Farsani, S	(59)	
	2019 Gaidhani, B	(60)	Discrepancy between reported and calculated accuracy measurement. Also discrepancy for test population size (122 in table vs 126 reported)
	2019 Nayak, D	(61)	MD-2 is used (largest dataset). Also reported MD-1 (97; 93; 98; nr)
	2019 Ortiz-Ramon, R	(62)	Figure readout: TP=54%, TN=70%, FP= 38%, FN=21%. Multiple classifiers are intermixed. For AUROC Multiple parameters are tested. The best is found in table 6 with parameters: SVM, LBP T2W - SS, MIC
	2019 Phan, A	(63)	
	2013 Saritha, M	(64)	

Table S8a. STATA data from the metadta analysis on artificial intelligence for MRI stroke detection.

```
metadta tp fp fn tn, studyid(id)

********************************** Fitted model ***************************************
    tp ~ binomial(se, tp + fn)
    tn ~ binomial(sp, tn + fp)
    logit(se) = mu_lse + id_lse
    logit(sp) = mu_lsp + id_lsp
    id_lse, id_lsp ~ biv.normal(0, sigma)
    Number of observations = 9
    Number of studies = 9

***************************************************************************************

***************************************************************************************

Between-study heterogeneity statistics
                           covar            rho
                            0.33             0.28
                           Tau.sq           I^2(%)
Generalized                 1.31            54.11
Sensitivity                 1.03            77.60
Specificity                 1.38            30.30

LR Test: RE vs FE model
         Chi2       degrees of
       statistic      freedom        p-val
        253.29          3           0.0000
***************************************************************************************
            Study specific test accuracy: Absolute Measures
***************************************************************************************
```

Study	Sensitivity Estimate	Sensitivity [95% Conf.	Interval]	Specificity Estimate	Specificity [95% Conf.	Interval]
2023 Krag, C	0.89	0.85	0.91	0.90	0.87	0.92
2023 Lee, K	0.73	0.67	0.79	0.91	0.87	0.93
2022 Bridge, C	0.96	0.91	0.99	0.87	0.79	0.92
2022 Tasci, B	0.99	0.95	1.00	0.99	0.98	1.00
2021 Liu, C	0.98	0.94	1.00	0.76	0.72	0.80
2021 Nael, K	0.90	0.86	0.93	0.97	0.95	0.98
2020 Duan, Y	0.76	0.56	0.90	1.00	0.03	1.00
2020 Federau, C	0.91	0.78	0.97	0.75	0.58	0.88
2019 Bizzo, B	0.96	0.85	0.99	0.97	0.95	0.99
Overall	0.93	0.86	0.96	0.93	0.84	0.97

Table S8b. STATA data from the metandi analysis on AI stroke detection in MRI.

```
metandi tp fp fn tn, detail

Refining starting values:

Iteration 0:  Log likelihood = -68.472586
Iteration 1:  Log likelihood = -67.509919
Iteration 2:  Log likelihood = -67.105527
Iteration 3:  Log likelihood = -67.083225

Performing gradient-based optimization:

Iteration 0:  Log likelihood = -67.083225
Iteration 1:  Log likelihood = -67.082997
Iteration 2:  Log likelihood = -67.082997

Mixed-effects logistic regression               Number of obs     =         18
Binomial variable: _metandi_n
Group variable: _metandi_i                      Number of groups  =          9

                                                Obs per group:
                                                              min =          2
                                                              avg =        2.0
                                                              max =          2

Integration points =   5                        Wald chi2(2)      =      66.07
Log likelihood = -67.082997                     Prob > chi2       =     0.0000

------------------------------------------------------------------------------
_metandi_t~e | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
 _metandi_d1 |   2.539721   .3752169     6.77   0.000     1.804309    3.275132
 _metandi_d0 |   2.530999   .4274954     5.92   0.000     1.693124    3.368875
------------------------------------------------------------------------------

------------------------------------------------------------------------------
  Random-effects parameters  |   Estimate   Std. err.     [95% conf. interval]
-----------------------------+------------------------------------------------
_metandi_i: Unstructured     |
                sd(_metan~1) |   1.012188   .3074672      .5580795    1.835804
                sd(_metan~0) |   1.173772   .3301926      .6762903    2.037203
     corr(_metan~1,_metan~0) |   .2763606   .4033303     -.5169318    .8142855
------------------------------------------------------------------------------
LR test vs. logistic model: chi2(3) = 253.28            Prob > chi2 = 0.0000

Note: LR test is conservative and provided only for reference.
```

Table S8b continued.

```
Meta-analysis of diagnostic accuracy

Log likelihood   = -67.082997                 Number of studies =       9
------------------------------------------------------------------------------
             |      Coef.  Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
Bivariate    |
  E(logitSe) |   2.539721   .3752169                      1.804309    3.275132
  E(logitSp) |   2.530999   .4274954                      1.693124    3.368875
Var(logitSe) |   1.024525   .6224293                      .3114527    3.370177
Var(logitSp) |   1.377741   .7751417                      .4573686    4.150198
Corr(logits) |   .2763606   .4033303                     -.5169318    .8142855
-------------+----------------------------------------------------------------
HSROC        |
      Lambda |   5.085277   .6276956                      3.855016    6.315538
       Theta |   .1922981   .5372345                     -.8606622    1.245258
        beta |   .1481082   .4013269     0.37   0.712    -.638478     .9346944
     s2alpha |   3.032832   1.829501                       .929772    9.892825
     s2theta |   .4298701   .2533246                      .1354316     1.36444
-------------+----------------------------------------------------------------
Summary pt.  |
          Se |   .9268799   .0254298                      .8586727    .9635658
          Sp |   .9262866   .0291893                      .8446345    .9667175
         DOR |    159.289   100.2884                      46.37341    547.1453
         LR+ |   12.57411   5.068631                      5.706336    27.70748
         LR- |   .0789389   .0281229                      .0392682    .1586872
       1/LR- |   12.66802   4.513131                      6.301706    25.46591
------------------------------------------------------------------------------
Covariance between estimates of E(logitSe) & E(logitSp)   .0364283
```