Search strategies

Database: PubMed, MEDLINE, Web of Science, CINAHL Plus Full Text

Limit: English language, an article published between January 2018 – December 2022

Population: Adults with ischemic stroke (≥ 18 years old)

Intervention: Neural Networks

The search terms: (Ischemic Stroke* OR Ischaemic Stroke* OR CryptogenicIschemic Stroke* OR Cryptogenic Stroke* OR Cryptogenic Embolism Stroke* OR Wake up Stroke* OR AcuteIschemic Stroke* OR Embolic Stroke* OR Cardioembolic Stroke* OR Cardio-embolic Stroke* OR Thrombotic Stroke* OR Acute Thrombotic Stroke* OR Lacunar Stroke* OR Lacunar Syndrome* OR Lacunar Infarction* OR Lacunar Infarct*) AND (Computer Neural Network* OR Computer Neural Networks OR Perceptron* OR Neural Network Model* OR Connectionist Model* OR Neural Network Model* OR Neural Network* OR Computational Neural Network* OR Deep Learning OR Hierarchical Learning) AND (Diagnos* OR Diagnos* and Examination* OR Postmortem Diagnos* OR Antemortem Diagnos*)

Supplementary Table 1. *Search strategies*

Database (Search time)	Search	Search String
PubMed and MEDLINE	1	("ischemic stroke*"[Title/Abstract] OR "ischaemic stroke*"[Title/Abstract] OR "stroke*"[Title/Abstract] OR "cryptogenic stroke*"[Title/Abstract] OR "cryptogenic embolism stroke*"[Title/Abstract] OR "wake up stroke*"[Title/Abstract] OR "acuteischemic stroke*"[Title/Abstract] OR "embolic stroke*"[Title/Abstract] OR "cardioembolic stroke*"[Title/Abstract] OR "cardio embolic stroke*"[Title/Abstract] OR "thrombotic stroke*"[Title/Abstract] OR "acute thrombotic stroke*"[Title/Abstract] OR "lacunar stroke*"[Title/Abstract] OR "lacunar syndrome*"[Title/Abstract] OR "lacunar infarction*"[Title/Abstract] OR "lacunar infarct*"[Title/Abstract])

Database (Search time)	Search	Search String
	2	("computer neural network*"[Title/Abstract] OR "computer neural networks"[Title/Abstract] OR "perceptron*"[Title/Abstract] OR "neural network model*"[Title/Abstract] OR "connectionist model*"[Title/Abstract] OR "neural network*"[Title/Abstract] OR "computational neural network*"[Title/Abstract] OR "deep learning"[Title/Abstract] OR "hierarchical learning"[Title/Abstract])
	3	(("diagnos*"[Title/Abstract] OR "diagnos*"[Title/Abstract]) AND "examination*"[Title/Abstract]) OR "postmortem diagnos*"[Title/Abstract] OR "antemortem diagnos*"[Title/Abstract]
	4	1 AND 2 AND 3
Web of Science	1	(Ischemic Stroke* OR Ischaemic Stroke* OR CryptogenicIschemic Stroke* OR Cryptogenic Stroke* OR Cryptogenic Embolism Stroke* OR Wake up Stroke* OR AcuteIschemic Stroke* OR Embolic Stroke* OR Cardioembolic Stroke* OR Cardio-embolic Stroke* OR Thrombotic Stroke* OR Acute Thrombotic Stroke* OR Lacunar Stroke* OR Lacunar Syndrome* OR Lacunar Infarction* OR Lacunar Infarct*)
	2	(Computer Neural Network* OR Computer Neural Networks OR Perceptron* OR Neural Network Model* OR Connectionist Model* OR Neural Network Model* OR Neural Network* OR Computational Neural Network* OR Deep Learning OR Hierarchical Learning)
	3	(Diagnos* OR Diagnos* and Examination* OR Postmortem Diagnos* OR Antemortem Diagnos*)
	4	1 AND 2 AND 3
CINAHL Plus Full Text	1	TX(Ischemic Stroke* OR Ischaemic Stroke* OR CryptogenicIschemic Stroke* OR Cryptogenic Stroke* OR Cryptogenic Embolism Stroke* OR Wake up Stroke* OR AcuteIschemic Stroke* OR Embolic Stroke* OR Cardioembolic Stroke* OR Cardio-embolic Stroke* OR Thrombotic Stroke* OR Acute Thrombotic Stroke* OR Lacunar Stroke* OR Lacunar Syndrome* OR Lacunar Infarction* OR Lacunar Infarct*)
	2	TX(Computer Neural Network* OR Computer Neural Networks OR Perceptron* OR Neural Network Model* OR Connectionist Model* OR Neural Network Model* OR Neural Network* OR Computational Neural Network* OR Deep Learning OR Hierarchical Learning)

Database (Search time)	Search	Search String
	3	TX(Diagnos* OR Diagnos* and Examination* OR Postmortem Diagnos* OR Antemortem Diagnos*)
	4	1 AND 2 AND 3

Supplementary Table 2. *Summary Table*

- Reference - Year - Country	- Sample size (total) - Target population - Age (year) - Gender - Methodological quality (MQ)*	Objective	Neural Network approach/algorithm	The main feature(s)	Main/optimal results	Implementation for Clinical Practice
(Oman et al., 2019) - 2019 - Finland	- 60 - Acute ischemic stroke (AIS) - Age (Median, Min-Max): Group A = 73, 47-82, Group B = 68, 26-91 - Gender: Male = 29, Female = 31 - MQ = 90 %	To investigate the feasibility of ischemic stroke detection from computed tomography angiography source images (CTA-SI) using three-dimensional convolutional neural networks.	Three-dimensional convolutional neural networks (3D-CNNs)	- CTA-SI - Non-contrast computed tomography (NCCT) - Computed tomography perfusion (CTP)	Stroke detection was improved when cerebral hemispheric comparison, CTA-SI, and NCCT were included in the CNN analysis (sensitivity = 0.93, specificity = 0.82, an area under the curve (AUC) = 0.93).	The research findings show the potential of CNNs for a rapid, precise, and fully automated method to assist healthcare providers (e.g., radiologists and clinicians) in the detection/diagnosis of AIS.
(Nishio et al., 2020) - 2020 - Japan	- 238 - AIS - Age: Not applicable - Gender: Not applicable - MQ = 90 %	To develop and evaluate an automatic AIS detection system involving a two-stage deep learning model.	Two-stage deep convolutional neural networks (Two-stage DCNNs)	Computed tomography (CT) images refer to head magnetic resonance imaging (MRI) images in which an MRI examination was performed within 24 hours following the CT scan.	A board-certified radiologist with software (DCNNs) has improved AIS detection (sensitivity = 41.3 %, precision = 62 %, false positive per one case = 0.388).	The results of the current study demonstrate that the detection system involving a two-stage deep learning model could significantly improve the sensitivity of radiologists in the detection of AIS. However, future studies with more diverse sample sizes and feasibility studies are

- Reference - Year - Country	- Sample size (total) - Target population - Age (year) - Gender - Methodological quality (MQ)*	Objective	Neural Network approach/algorithm	The main feature(s)	Main/optimal results	Implementation for Clinical Practice
						recommended before use in the clinical field.
(Sheng et al., 2022) - 2022 - China	- 210 - Ischemic Penumbra (IP) in Early Acute Cerebral Infarction (ACI) - Age (Mean, SD): 60.17 ± 7.98 - Gender: Male = 145, Female = 65 - MQ = 90 %	To investigate the effect of the local higher-order singular value decomposition denoising algorithm (GL-HOSVD) in diffusion-weighted imaging (DWI) image and evaluate the effect in examining IP of early ACI patients.	The local higher-order singular value decomposition denoising algorithm (GL-HOSVD)	DWI image	The DWI based on the GL-HOSVD denoising algorithm shows optimal specificity, accuracy, and consistency (81.25 %, 87.62 %, and 0.52, respectively) in terms of IP detection.	The results showed that the GL-HOSVD algorithm had a high sensitivity, specificity, accuracy, and consistency in IP detection are worthy of clinical application and promotion. Moreover, this study reflects that the deep learning algorithm has a good development prospect in the field of imaging, and its clinical auxiliary effect can be expected in the future.
(Wang et al., 2021) - 2021 - China	- 345 - AIS - Age (Mean, SD): 67 ± 2 - Gender: Male = 188, Female = 157	To identify AIS from widely available non-contrast computed tomography (NCCT) and CT angiography	3D-CNNs	- NCCT - CTA - CTA + (8-second delay after CTA)	The diagnostic decisions according to the Endovascular Therapy Following Imaging Evaluation for Ischemic Stroke 3 (DEFUSE3) showed high accuracy when using NCCT, CTA,	This study's results show the high potential of using deep learning to assist clinicians in detecting acute stroke lesions with widely available NCCT and CTA images.

- Reference - Year - Country	- Sample size (total) - Target population - Age (year) - Gender - Methodological quality (MQ)*	Objective	Neural Network approach/algorithm	The main feature(s)	Main/optimal results	Implementation for Clinical Practice
	- MQ = 100 %	(CTA) using deep learning.			and CTA+ (0.90±0.04).	
(Stib & Vasquez, 2020) - 2020 - USA	- 540 - AIS - Age (Mean, SD): Training cohort = 70.8 ± 12.9, Validation cohort = 74.4 ± 13.2, Test cohort = 69.4 ± 14.5 - Gender: Male = 387, Female = 153 - MQ = 90 %	To develop a convolutional neural network to detect large vessel occlusion (LVO) at multiphase CTA.	Deep Convolutional Neural Networks (DCNNs)	CTA	CNNs trained to detect LVOs at multiphase CTA achieved an AUC of 0.89 and a sensitivity of 100%.	CNNs could detect the presence of LVO, and its diagnostic performance was enhanced by using delayed phases at multiphase CTA examinations. This research is an essential step in incorporating deep learning to triage LVOs in the emergency setting and can potentially shorten the time to LVO detection with ultimate improvements in patient outcomes.

- Reference - Year - Country	- Sample size (total) - Target population - Age (year) - Gender - Methodological quality (MQ)*	Objective	Neural Network approach/algorithm	The main feature(s)	Main/optimal results	Implementation for Clinical Practice
(Shinohara et al., 2020) - 2020 - Japan	- 22 - AIS - Age (Mean, SD): 75 ± 14 - Gender: Male = 13, Female = 9 - MQ = 90 %	To develop an interactive deep learning-assisted identification of the hyperdense middle cerebral artery sign (HMCAS) on NCCT among patients with AIS.	DCNNs	NCCT	The diagnostic performance of DCNN for HMCAS show sensitivity = 82.9%, specificity = 89.7%, accuracy = 86.5%, AUC = 0.947.	DCNNs appear potentially beneficial for identifying HMCAS on NCCT in patients with AIS. However, further studies, including larger sample sizes with various populations, are recommended before testing for feasibility in the clinical setting.
(Yang et al., 2022) - 2022 - China	- 88 - AIS - Age (Range): 33–79 - Gender: Male = 54, Female = 34 - MQ = 90 %	To discuss the application values of deep learning algorithm-based computed tomography perfusion (CTP) imaging combined with head and neck computed tomography angiography (CTA) in diagnosing early AIS.	A new deconvolution network model based on deep learning (AD-CNNnet)	- CTP - CTA	The results showed that the peak signal-to-noise ratio (PSNR) and feature similarity (FSIM) of the AD-CNNnet method were significantly higher than those of traditional methods, while the normalized mean square error (NMSE) was significantly lower than that of traditional algorithms ($P < 0.05$). The sensitivity of the AD-CNNnet method	The results of this study provide a reference for the combined application of artificial intelligence technology (AD-CNNnet) and clinical imaging. Before implementation in the clinical setting, more patient sample data will be collected in the later study to further explore the application value of CTP combined with CTA based on deep learning algorithm in the

- Reference - Year - Country	- Sample size (total) - Target population - Age (year) - Gender - Methodological quality (MQ)*	Objective	Neural Network approach/algorithm	The main feature(s)	Main/optimal results	Implementation for Clinical Practice
					was 93.66%, and the specificity was 96.18%.	prognosis of patients with AIS.
(Lu et al., 2022) - 2022 - China	- 986 - AIS - Age (Median, IQR): 55, 47-65 - Gender: Male = 664, Female = 322 - MQ = 90 %	To develop a deep-learning model to identify AIS in NCCT and evaluate its diagnostic performance and capacity for assisting radiologists in decision-making.	Two-stage DCNNs	NCCT	The AUC of the deep learning model were 83.61% (sensitivity = 68.99%, specificity = 98.22%, and accuracy = 89.87%)	The developed model can help screen early AIS and save more time. The healthcare team, especially, radiologists and clinicians assisted with the model can provide more effective guidance in making patients' treatment plans in the clinic.
(Zhang et al., 2021) - 2021 - China	- 300 - IS - Age (Mean, SD): 66.53 ± 12.13 - Gender#: Male ~ 159, Female ~ 141 - MQ = 90 %	To apply deep learning in ischemic stroke lesion detection using MRI Images	DCNNs (Faster R-CNN + YOLOV3 + SSD)	MRI images	Three categories of deep learning object detection networks including Faster R-CNN, YOLOV3, and SSD are applied to implement automatic lesion detection with the best precision of 89.77%.	This study result shows that DCNNs can improve the intelligence level of computer-aided diagnosis of stroke and promote the development of the theory and practice of artificial intelligence in the medical field. In the future, more data on IS should be collected to increase the generalizability of result.

*Based on the Checklist for Diagnostic Test Accuracy Studies of the Joanna Briggs Institute Critical Appraisal tools. Percentage of “Yes” = The number of "yes"/ (the number of "unclear"+ the number of "no”) × 100 (See table 3 in main document).
#In this study, the author only reported that the proportion of males and females of the patients is about 9/8. Therefore, Male ~ 159 and Female ~ 141 are approximate numbers.

Supplementary Table 3. *The methodological quality of the included studies*

Appraisal questions/Reference	(Oman et al., 2019)	(Nishio et al., 2020)	(Sheng et al., 2022)	(Wang et al., 2021)	(Stib & Vasquez, 2020)	(Shinohara et al., 2020)	(Yang et al., 2022)	(Lu et al., 2022)	(Zhang et al., 2021)
I Patient selection									
1. Was a consecutive or random sample of patients enrolled?	+	+	+	+	+	+	+	+	+
2. Was a case-control design avoided?	-	-	-	+	-	-	?	-	?
3. Did the study avoid inappropriate exclusions?	+	+	+	+	+	+	+	+	+
II Index test									
4. Were the index test results interpreted without knowledge of the results of the reference standard?	+	+	+	+	+	+	+	+	+
5. If a threshold was used, was it pre-specified?	+	+	+	+	+	+	+	+	+
6. Is the reference standard likely to classify the target condition correctly?	+	+	+	+	+	+	+	+	+
7. Were the reference standard results interpreted without knowledge of the results of the index test?	+	+	+	+	+	+	+	+	+
8. Was there an appropriate interval between the index test and reference standard?	+	+	+	+	+	+	+	+	+
9. Did all patients receive the same reference standard?	+	+	+	+	+	+	+	+	+
10. Were all patients included in the analysis?	+	+	+	+	+	+	+	+	+
Percentage of yes* (%)	90 %	90 %	90 %	100 %	90 %	90 %	90 %	90 %	90 %

"+": yes; "-": no; "?": unclear; "\": not applicable

*The number of "yes" / (the number of "unclear" + the number of "no”) ×100

Reference

Lu, J., Zhou, Y. R., Lv, W. Z., Zhu, H. Q., Tian, T., Yan, S., . . . Zhu, W. Z. (2022). Identification of early invisible acute ischemic stroke in non-contrast computed tomography using two-stage deep-learning model. *Theranostics*, *12*(12), 5564-5573. https://doi.org/10.7150/thno.74125

Nishio, M., Koyasu, S., Noguchi, S., Kiguchi, T., Nakatsu, K., Akasaka, T., . . . Itoh, K. (2020). Automatic detection of acute ischemic stroke using non-contrast computed tomography and two-stage deep learning model. *Computer Methods and Programs in Biomedicine*, *196*, Article 105711. https://doi.org/10.1016/j.cmpb.2020.105711

Oman, O., Makela, T., Salli, E., Savolainen, S., & Kangasniemi, M. (2019). 3D convolutional neural networks applied to CT angiography in the detection of acute ischemic stroke. *European Radiology Experimental*, *3*(1), Article 8. https://doi.org/10.1186/s41747-019-0085-6

Sheng, H., Wang, X. L., Jiang, M. P., & Zhang, Z. S. (2022). Deep Learning-Based Diffusion-Weighted Magnetic Resonance Imaging in the Diagnosis of Ischemic Penumbra in Early Cerebral Infarction. *Contrast Media Mol Imaging*, *2022*, Article 6270700. https://doi.org/10.1155/2022/6270700

Shinohara, Y., Takahashi, N., Lee, Y., Ohmura, T., & Kinoshita, T. (2020). Development of a deep learning model to identify hyperdense MCA sign in patients with acute ischemic stroke. *Jpn J Radiol*, *38*(2), 112-117. https://doi.org/10.1007/s11604-019-00894-4

Stib, M. T., & Vasquez, J. (2020). Detecting Large Vessel Occlusion at Multiphase CT Angiography by Using a Deep Convolutional Neural Network. *297*(3), 640-649. https://doi.org/10.1159/000486689

10.1148/radiol.2020200334

Wang, C. Y., Shi, Z., Yang, M., Huang, L. X., Fang, W. X., Jiang, L., . . . Wang, H. (2021). Deep learning-based identification of acute ischemic core and deficit from non-contrast CT and CTA. *Journal of Cerebral Blood Flow and Metabolism*, *41*(11), 3028-3038, Article 0271678x211023660. https://doi.org/10.1177/0271678x211023660

Yang, Y., Yang, J. J., Feng, J., & Wang, Y. (2022). Early Diagnosis of Acute Ischemic Stroke by Brain Computed Tomography Perfusion Imaging Combined with Head and Neck Computed Tomography Angiography on Deep Learning Algorithm. *Contrast Media Mol Imaging*, *2022*, Article 5373585. https://doi.org/10.1155/2022/5373585

Zhang, S. J., Xu, S. H., Tan, L. W., Wang, H. Y., & Meng, J. L. (2021). Stroke Lesion Detection and Analysis in MRI Images Based on Deep Learning. *Journal of Healthcare Engineering*, *2021*, Article 5524769. https://doi.org/10.1155/2021/5524769