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Artificial Intelligence in Stroke Diagnosis: A Bibliometric Analysis

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Abstract

Objectives: Stroke is one of the life-threatening conditions that is considered as 5th leading cause of death that requires urgent intervention. The objective of this study was to identify and review the importance of Artificial Intelligence (AI) in the diagnosis of stroke.
Methods: A review that includes AI and stroke-related studies which are conducted in accordance with the PRISMA chart. A variety of search engines were used to collect 121 articles then a master Excel sheet was used to extract the necessary data which underwent many steps of filtration to exclude the unrelated articles before starting the analysis process.
Results: Out of 121 studies published between 2013 to 2022 identified at the beginning of the study, only 39 studies were used in the final analysis. The majority of studies, thirteen (32.5%), were published in 2021 compared to 2014 which represents the least year of publications of such studies with only three (7.5%) studies. More than half of the studies, 22 (56.41%) of studies were retrospective type of studies. Seven (17.5%) of the studies were conducted in China which represents the highest number of studies to be published in a country. Among all studies included, the most common modality of AI used was machine learning 15 (38.5%). Conclusion: The number of AI studies in the past 10 years is increasing year after year and most of these studies are retrospective.

Keywords: Artificial intelligence; Machine learning; Stroke

Abbreviations
Computerized tomography (CT); Computed tomography angiography (CTA); Computed tomography perfusion (CTP); Computed tomography venography (CTV); Magnetic resonance imaging (MRI); Magnetic resonance angiography (MRA); Magnetic resonance perfusion (MRP); Transient ischemic attack (TIA); Artificial intelligence (AI); Diffusion-weighted imaging (DWI)

Introduction

Stroke is a serious life-threatening medical condition and urgent treatment is essential (1). A stroke is a neurological deficit attributed to an acute focal injury of the central nervous system that affects the arteries leading to and within the brain (2,3). There are two types of strokes which are ischemic and hemorrhagic stroke(3). Ischemic stroke occurs when the blood supply is obstructed. On the other hand, hemorrhagic stroke occurs when a blood vessel ruptures (3). A transient ischemic attack caused by a temporary clot is called a mini stroke (3).

In the United States, stroke is considered the 5th leading cause of death and disability (3). More than 795,000 people are being diagnosed with stroke in the United States (4). In the United States, Every 40 seconds there is a case of stroke that is being reported (5). The number of patients diagnosed with a stroke that reported to Khoula Hospital, in Muscat, Oman from November 2017 to April 2018 was 193 patients of which 82.9% of them were ischaemic strokes (6).

Previous studies showed various activity limitations including walking restrictions limitations in self-care activities and limitations in domestic life after discharging stroke patients from the hospitals (7). These patients were unable to return to their previous occupations, had decreased social interactions, and inability to participate in religious activities (7). In 2016, the total cost of care provided to stroke patients in the US was \$103.5 billion while \$68.5 billion was the total cost accounted for indirect from underemployment and premature death (8).

DOI: 10.5123/inj.2024.1.inj5
ISSN:2093-4777 | E-ISSN:2093-6931
Vol. 27 Iss. 3 (2023)

To diagnose the stroke we can use different imaging modalities for example computerized tomography (CT), CT angiography (CTA), CT perfusion (CTP), CT venography (CTV), magnetic resonance imaging (MRI), MR angiography (MRA), MR perfusion (MRP), ultrasonography, nuclear medicine, and angiography(9). Each imaging modality has its pros and cons (9). If the stroke is suspected, the first imaging technique done is Non-contrasted computed tomography to exclude the hemorrhagic stroke (9). MRI is used to evaluate acute ischemic stroke, hemorrhagic brain lesions, and transient ischemic attack (TIA) but it's contraindicated if a patient is having pacemakers, metallic foreign bodies, aneurysm clips, implantable devices, claustrophobia to MRI (9).

The treatment of stroke is considered an emergency treatment that depends on whether the patient is having an ischemic stroke or hemorrhagic stroke (10). If the patient is having an ischemic stroke and arrives at a hospital within 3 hours of the first symptom, thrombolytic medications such as Tissue plasminogen activator (tPA) are usually provided to the patient that helps to improve the chances of recovering from a stroke (11). Endovascular procedures are another treatment option that helps in repairing a weak spot or break in a blood vessel in patients with hemorrhagic stroke (11). On the other hand, if the stroke is caused by a ruptured aneurysm, surgical treatment is usually done by placing a metal clip to stop the blood loss (11).

The use of artificial intelligence (AI) has been enabled by the use of labelled big data, along with markedly enhanced cloud storage and computing power in all sectors(12). The beginning of AI in medicine has an impact on clinicians, predominantly via rapid, accurate image interpretation that helps improve workflow and reduce medical errors (12). AI is being used to deal with major diseases including cancers, neurological and cardiac conditions (13). AI is important nowadays in neuroradiology by playing pivotal roles in the diagnosis and management of sensitive diseases such as stroke (14). Machine learning has the role of predicting and analyzing the performance of stroke treatment by measuring the outcome of intravenous thrombolysis in ischemic stroke during emergencies to know if a patient with tPA treatment would have an intracranial hemorrhage (13). This study aims to review the role of AI in identifying and diagnosis of stroke.

Methods

2.1 Search Strategy

This is a systematic review that is conducted by Preferred Reporting Items for Systematic Reviews and Meta-analyses (PRISMA) guidelines that involve different studies regarding AI and its ability to detect stroke (Figure 1). Different search engines have been used to conduct the systematic review including PubMed, Microsoft Academy, Scopus, Wiley online library, Cambridge Journal, Lippincott Williams & Wilkins journal, BMJ journal, Cochrane, Web of Science and, clinical trials. A variety of keywords have been used to cover all possible articles related to the systematic review such as "Machine learning", "Artificial intelligence", "AI", "Cerebrovascular", "Endovascular" and "Stroke". Furthermore, a combination of the keywords applied during the period of searching, for instance, "Machine learning and stroke", "AI and Stroke", and "Artificial intelligence and Stroke". The search period was limited to 2 weeks.

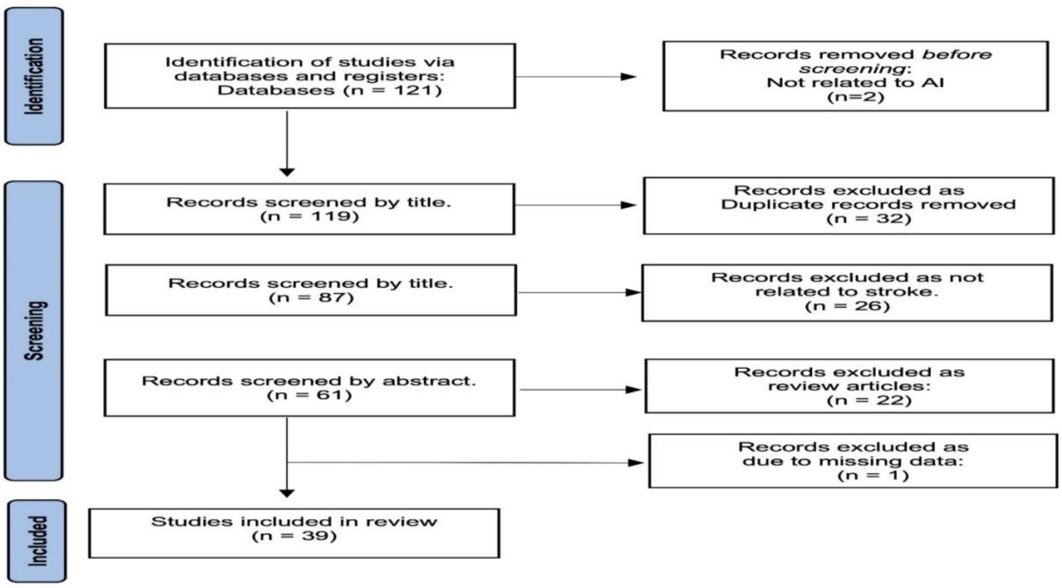

Figure 1: PRISMA chart

DOI: 10.5123/inj.2024.1.inj5
ISSN:2093-4777 | E-ISSN:2093-6931
Vol. 27 Iss. 3 (2023)

2.2 Inclusion criteria

Studies that are published in the English language including adults (age ≥18), both genders and studies conducted to identify or diagnose stroke only were included in this systematic review.

2.3 Exclusion criteria

Studies of the pediatric population (age < 18), review articles, animal-based studies, meta-analysis and studies involving diagnosis other than stroke as part of the cerebrovascular accident were excluded from this study.

2.4 Data extraction and analysis

Titles of the identified articles were used as an initial screening to exclude articles based on the exclusion criteria as mentioned previously. Then, the abstract followed by the full article text was reviewed in depth for further screening and including the best articles related to this systematic review. An Excel master sheet was made to extract the needed data to conduct this study such as article title, first author name, year of publication, country, study design, modality of AI, brief description of the method of AI, validation method, diagnosis identified by AI, number of patients in AI group, standard method, statistics analysis used, results of the analysis, outcome, recommendations made by author and limitation of each study.

Results

3.1 Study selection

Titles of the identified articles were used as an initial screening to exclude articles based on the exclusion criteria as mentioned previously. A total of 121 studies were identified, but 119 remained after excluding non-AI related studies as shown in Figure 1. Then, 32 studies were excluded due to duplication to remain with 87 studies only. Due to the variety of conditions included under the umbrella of cerebrovascular accidents, a decision was made to full article text were reviewed in depth for further screening and including the best articles related to this systematic review which excluded 26 studies due to non-stroke related then another 22 were excluded as those were article reviews rather than studies. Finally, 39 studies as shown in Table 1 were included in the systematic review.

Study	Design	Level of Evidence	Sample
Janne Haman (14)	Retrospective Study	3b	222
Anthony Shek (15)	Not mentioned		2327
Li Yang (16)	Cross-sectional survey	4b	450
Charlotte Sabine Weyiand (17)	Retrospective Study	3b	154
Ching-Heng Lin (18)	Prospective study	1b	40293
Lennard Wolff (19)	Prospective study	1b	459
Bence Gunda (20)	Retrospective Study	3b	399
Iris Q.Dgrunwald (21)	Prospective study	1b	98
Romain Bourcier (22)	Retrospective Study	3b	607
Cheemun Lum (23)	Retrospective Study	3b	46
Eun-Jae Lee,a* Yong-Hwan Kim,a* Namkug Kim,b Dong-Wha Kanga (24)	Retrospective Study	3b	116
Su-Kyeong Jang,a,* Jun Young Chang (25)	Prospective study	1b	6731
Wu Qiu (26)	Retrospective Study	3b	284
Raul G.Nogueira (27)	Retrospective Study	3b	23223
Bat-Orgil Bat-Erdene (28)	Meta-analysis	3b	N/A

Marcin Sawicki (29)	Retrospective Study	3b	108
Yutao Guo (30)	Prospective study	1b	3435224
Sang Hoon Chae (31)	Prospective study	1b	23
Yahav-Dovrat (32)	Retrospective Study	3b	1180
Sunil A. Sheth (33)	Prospective study	1b	297
Hidehisa Nishi (34)	Retrospective Study	3b	502
Jia Xu (35)	Expermintal study	1b	10 rabbits
Junfeng Sun (36)	Cohort study	3b	92
Hidehisa Nishi (37)	Retrospective Study	3b	250
Matthew T.Stib(38)	Retrospective Study	3b	540
Dougho Park 1 (39)	Retrospective Study	3b	1066
M.D. Li, (40)	Retrospective Study	3b	20414
Jens K. Boldsen (41)	Retrospective Study	3b	108
Xuehua Wen (42)	Cohort study	3b	123
Johan Wasselius (43)	Prospective study	1b	84
Jeremy Hofmeister (44)	Retrospective Study + Prospective study	1b	156
Yang Wang (45)	Prospective study	1b	1124
Kicky G. van Leeuwen (46)	Cohort study	3b	71840
Xiaodong Zhang (47)	Prospective study	1b	98
Vida Abedi (48)	Retrospective Study	3b	2091
Paul Bentley (49)	Retrospective Study	3b	330
Lai Wei (50)	Retrospective Study	3b	344
Esra Zihni (51)	Retrospective Study	3b	314
Hamed Asadi (52)	Retrospective Study	3b	107
A M Boers (53)	Cohort study	3b	34

Table 1: Continued

First author	Validation methods	No. of patients in AI group	standard method
Janne Hamann (14)	Not mentioned	222	National Institutes of Health Stroke Scale
Anthony Shek (15)	Not mentioned	2327	current clinical curation methods (SSNAP)
Li Yang (54)	Not mentioned	450	classical logistic regression models
Charlotte Sabine Weyiand (17)	Not mentioned	154	CTA-based reference standard
Ching-Heng Lin	Two processes, the clinical-logic validation, non-linear regression method	40293	mRS score
Lennard Wolff (55)	Comparison of computed ASPECTS to observers ASPECTS.	459	reference standard: every CT scan was first rated by two expert readers from a pool of eight readers
Bence Gunda (57)	Not mentioned	399	Non-contrast CT scans (16-slice scanner)

DOI: 10.5123/inj.2024.1.inj5
ISSN:2093-4777 | E-ISSN:2093-6931
Vol. 27 Iss. 3 (2023)

			DICOM images from non-contrast CT , CT angiography
Iris Q.Dgrunwald (21)	Comparision of software's resutls with a refrence standard opinion derived from 3 expert neuroradiologists.	98	NR scoring
Romain Bourcier (22)	Not mentioned	607	EVTs: Combined CA + SR strategy
Cheemun Lum, MD, FRCP (23)	Not mentioned	46	NECT : nonenhanced computed tomography.
Eun-Jae Lee,a* Yong-Hwan Kim,a* Namkug Kim,b Dong-Wha Kanga (24)	Supervised machine learning include the support vector machine, decision tree, linear re- gression, logistic regression, naive Bayes, and random forest methods.	116	Several prognostic scoring systems, Age, and National Institute of Health Stroke Scale (SEDAN) scores
Su-Kyeong Jang,a,* Jun Young Chang (17)	Receiver Operating Characteristics (ROC) curve analysis	6731	Not mentioned
Wu Qiu (26)	Not mentioned	284	CTP - Computed Tomography Cerebral Perfusion Analysis
Raul G.Nogueira (27)	Comparing the satellite macroenvironment application assessment with the ground view from the CSCs microenvironement	23223	Not mentioned
Bat-Orgil Bat-Erdene (28)	Not mentioned	Not mentioned	Not mentioned
Marcin Sawicki (29)	Experienced neuroradiologist's reading as the reference	108	Unenhanced CT scans
Yutao Guo (30)	Not mentioned	3435224	Traditional logistic regression model
Sang Hoon Chae (31)	Compared the accuracy between models based on each sensor data using the following formula: Accuracy = (TP + TN) / (TP + TN + FP + FN)	23	self-directed practice
Yahav-Dovrat (32)	Not mentioned	1180	a single neuroradiologist read CTA scans per examination.
Sunil A. Sheth (33)	Not mentioned	297	Advanced neuroimaging interpretation
Hidehisa Nishi (34)	Not mentioned	502	Pre-treatment scoring methods (the Pittsburgh Response to Endovascular Therapy score, the Stroke Prognostication Using Age and National Institutes of Health

			Stroke Scale index, the Totaled Health Risks in Vascular Events score, the Houston Intra-Arterial Therapy score, and the Houston Intra-Arterial Therapy 2 score)
Jia Xu (35)	Not mentioned	10 rabbits	e mobile CT
Junfeng Sun (36)	Not mentioned	92	Manual segmentation and automatic segmentation
Hidehisa Nishi (34)	Not mentioned	250	Pre-treatment neuroimaging data - Prognostic information
Matthew T.Stib (38)	Not mentioned	540	CT angiography with 3-minute examination after CT
Dougho Park 1 (39)	Not mentioned	1066	Acute Stroke Registry and Analysis of Lausanne (ASTRAL) score and ischemic stroke predictive risk score (ISCORE)
M.D. Li (17)	Not mentioned	20414	Radiology report of head CT and brain MR imaging
Jens K. Boldsen (41)	Not mentioned	108	With Magnetic Resonance Imaging (MRI), diffusion-weighted imaging
Xuehua Wen (42)	Not mentioned	123	magnetic resonance imaging (MRI) , and diffusion-weighted imaging (DWI)
Johan Wasselius (43)	Not mentioned	84	Not mentioned
Jeremy Hofmeister (44)	Not mentioned	156	brain imaging
Yang Wang (45)	Not mentioned	1124	Computed tomography (CT)
Kicky G. van Leeuwen (46)	Not mentioned	71840	CTA with or without CT perfusion (CTP), the images are evaluated by a radiologist and/or neurologist
Xiaodong Zhang (46)	Not mentioned	98	Both DWI and ADC and a neuroradiologist was invited for discussion to make the drawing as accurate as possible.
Vida Abedi (48)	Not mentioned	2091	Not mentioned
Paul Bentley (49)	Radiologist derived-scores or manual SVM, SEDAN scores, HAT scores	330	Not mentioned
Lai Wei (50)	5-fold cross-validation was also performed	344	Manual labelling segmentation
Esra Zihni (51)	Traditional methods	314	Not mentioned

DOI: 10.5123/inj.2024.1.inj5
ISSN:2093-4777 | E-ISSN:2093-6931
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	including logistic regression		
Hamed Asadi (52)	Logistic regression models allow for the identification and validation of predictive variables.	107	Not mentioned
A M Boers (53)	Compared with manual delineation assessment by two blinded observers	34	Not mentioned

Table 1: Overview of studies included in the systemic review.

3.2 Study characteristics

Table 2 summarizes all the included studies which were published between 2013 and 2022. Figure 2 shows the number of studies published in each year which was as follows: three (7.5%) studies were published in 2014. Four (10.0%) studies were published in 2013, 2016, 2017 and, 2018 respectively which represent the minimum number of studies to be published per year. Followed by two (5.0%) studies in 2019. In addition, eleven (27.5%) studies were published in 2020. Furthermore, thirteen (32.5%) studies which is the highest number of studies involved in this systematic review were published in 2021 compared to six (15.0%) studies published in 2022. All these studies were conducted in Atlanta, Australia, Canada, China, Denmark, Germany, France, Germany, Island, Japan, Korea, Netherlands, occupied Palestine, Poland, South Korea, Switzerland, Taiwan, United Kingdom, and the USA.

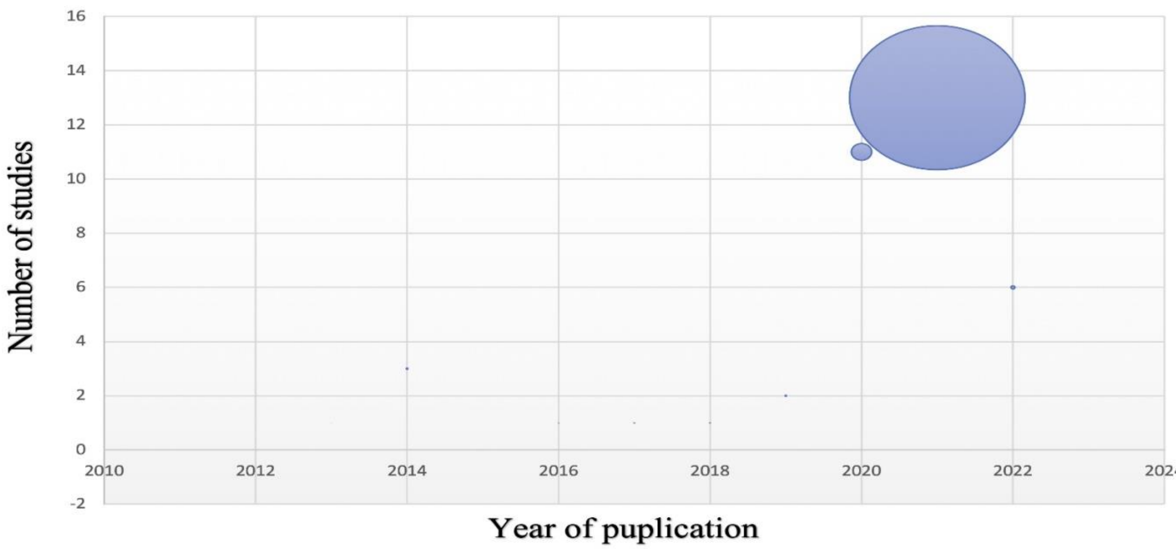

Figure 2: Year of publications

First author	Year of publication	Study design	Modality of AI
Janne Hamann (14)	2020	Retrospective Study	Machine learning
Anthony Shek (15)	2021	Not mentioned	Machine learning - enabled method (MedCAT)
Li Yang (54)	2020	Cross-sectional survey	Machine learning - support vector machine and Bayesian network
Charlotte Sabine Weyiand (17)	2022	Retrospective Study	Deep learning algorithm

DOI: 10.5123/inj.2024.1.inj5
ISSN:2093-4777 | E-ISSN:2093-6931
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Ching-Heng Lin (55)	2020	Prospective study	Machine learning - ML modle
Lennard Wolff (56)	2020	Prospective study	Frontier ASPECTS software, Early CT score (ASPECTS) software
Bence Gunda (57)	2022	Retrospective Study	e-stroke Suite (CE marked software), e-ASPECTS , e-CT analysis
Iris Q.Dgrunwald (21)	2019	Prospective study	e-CTA module (Tan score)
Romain Bourcier (22)	2020	Retrospective Study	Not mentioned
Cheemun Lum (23)	2014	Retrospective Study	ASPECTS
Eun-Jae Lee,a* Yong-Hwan Kim,a* Namkug Kim,b Dong-Wha Kanga (24)	2017	Retrospective Study	The support vector machine (SVM), the artificial neural network (ANN), Recurrent neural network (RNN), Convolutional neural network (CNN), e-ASPECTS software
Su-Kyeong Jang,a,* Jun Young Chang (17)	2020	Prospective study	Deep learning (DL), support vector machine (SVM), random forest (RF), XGboost (XGB)
Wu Qiu (26)	2021	Retrospective Study	mCTA model
Raul G.Nogueira (27)	2021	Retrospective Study	The Viz Neuroimaging Platform
Bat-Orgil Bat-Erdene (28)	2021	Meta-analysis	Not mentioned
Marcin Sawicki (29)	2021	Retrospective Study	Not mentioned
Yutao Guo (30)	2021	Prospective study	AI ML-based algorithms
Sang Hoon Chae (31)	2020	Prospective study	A smartwatch and Machine Learning Model
Yahav-Dovrat (32)	2021	Retrospective Study	Viz LVO Algorithm
Sunil A. Sheth (33)	2919	Prospective study	Machine learning
Hidehisa Nishi (34)	2022	Retrospective Study	Machine learning
Jia Xu (35)	2022	Experimental study	multichannel microwave
Junfeng Sun (36)	2022	Cohort study	Not mentioned
Hidehisa Nishi (34)	2020	Retrospective Study	Deep learning machine
Matthew T.Stib (38)	2020	Retrospective Study	Deep Convolutional Neural Network
Dougho Park 1 (39)	2021	Retrospective Study	Machine learning
M.D. Li (17)	2021	Retrospective Study	Natural language processing of radiology reports.
Jens K. Boldsen (41)	2018	Retrospective Study	ATLAS
Xuehua Wen (42)	2021	Cohort study	Radiomics analysis

Johan Wasselius (43)	2021	Prospective study	Classical machine learning models, state-of-the art deep learning models
Jeremy Hofmeister (44)	2020	Retrospective Study + Prospective study	Not mentioned
Yang Wang (45)	2022	Prospective study	intelligent CT-Cranial Automatic Planbox Imaging Towards AmeLiorating neuroscience (CAPITAL)
Kicky G. van Leeuwen (46)	2021	Cohort study	Not mentioned
Xiaodong Zhang (47)	2016	Prospective study	Machine learning: dictionary learning method
Vida Abedi (48)	2021	Retrospective Study	Machine Learning
Paul Bentley (49)	2014	Retrospective Study	Machine Learning
Lai Wei (50)	2021	Retrospective Study	Machine learning
Esra Zihni (51)	2020	Retrospective Study	Machine learning framework
Hamed Asadi (52)	2014	Retrospective Study	Machine learning
A M Boers(53)	2013	Cohort study	Machine learning

Table 2: Summary of included studies

Out of 39 studies, seven studies (17.5%) were done in China which represents the highest number of studies to be published in a country among all studies involved in this systematic review as shown in Figure 3. Followed by the United Kingdom with five (12.5%) studies and three (7.5%) studies in Germany. All the remaining countries participated in one (2.5%) study. Figure 4 shows more than half of the studies were retrospective studies 22 studies (56.41%), followed by 10 (25.64%) prospective studies, 5 (12.82%) Cohort studies, one (2.5%) cross-sectional study and one (2.56%) experimental study. In these studies, the minimum sample size of patients was 10 (0.0003%) and the maximum sample size among the included studies was 3435224 (95.1%). The most common modality of AI used among all 39 studies was Machine learning 15 (38.5%) as represented in Figure 5. The second two modalities of AI used were ASPECTS software and support vector machine (SVM) 3 (7.7%). mCTA model and Viz LVO Algorithm 2 (5.1%) were the third most common modalities of AI used among the 39 articles, followed by the remaining modalities 1 (2.6%) including AI ML-based algorithms, ATLAS, Deep Convolutional Neural Network, Deep learning algorithm, intelligent CT-Cranial Automatic Planbox Imaging T, Multichannel microwave, Natural language processing of radiology reports and Radiomics analysis.

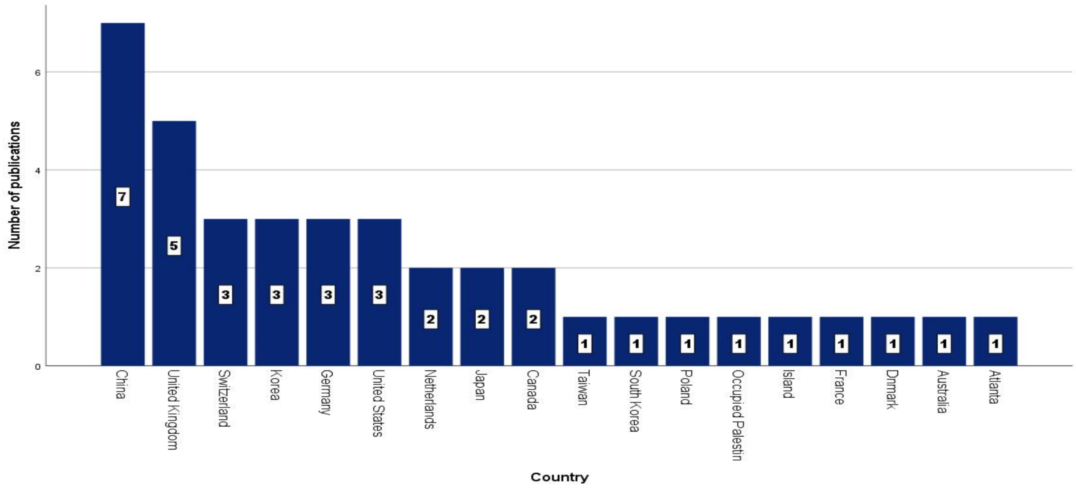

Figure 3: Number of publications per country

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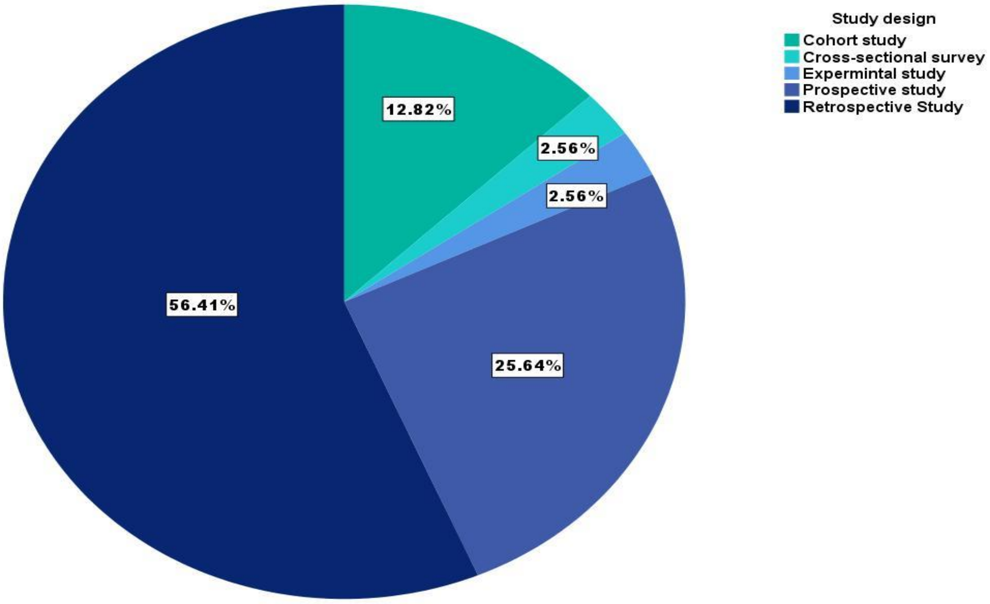

Figure 4: Percentage of study designs used in the articles

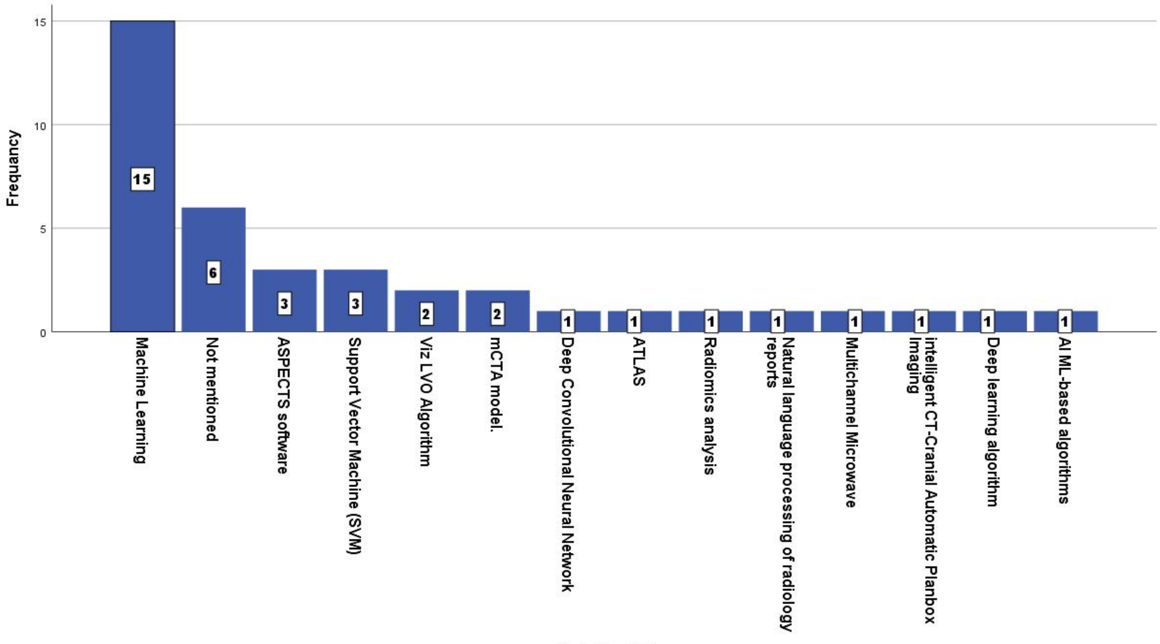

Figure 5: Prevalence of the modality of AI used in the study

Discussion

AI has potential in the field of neuroimaging by aiding in the rapid identification of acute stroke changes seen on imaging. The 39 studies included in our study implemented different software and ML algorithms, and each had its methods for collecting and reporting data using different statistical parameters and outcomes. Therefore, limited comparisons can be made across these diverse studies. The majority of studies reported on the utilization of AI and machine learning in the diagnosis of ischemic stroke specifically, and only 3 studies looked at hemorrhagic stroke. Moreover, the modality of neuroimaging used included non-contrast CT, CTA, and MRI. The preferred modality used in most of the studies was non-contrast CT, attributed to its ability to differentiate between ischemic and hemorrhagic stroke, thereby guiding management. Although MRI is not commonly utilized in an acute setting for stroke diagnosis, diffusion-weighted (DWI) MRI has better sensitivity and specificity in comparison to CT for early detection of ischemic stroke (9). However, it is not routinely used in clinical practice due to issues with availability in healthcare facilities and the time-consuming nature of MRI

DOI: 10.5123/inj.2024.1.inj5
ISSN:2093-4777 | E-ISSN:2093-6931
Vol. 27 Iss. 3 (2023)

scans (9). As such, only 2 studies reported on AI and ML algorithms that relied on MRI and DWI for stroke identification.

Despite conducting a comprehensive review of the available literature that explores artificial intelligence as a valuable tool to guide the timely detection and clinical diagnosis of stroke, several limitations were encountered. Firstly, there were great disparities in the sample sizes reported in the 39 studies, ranging from 10 to 3435224 patients, which affected the confidence intervals and precision of the studies. Hence several of the studies with smaller sample sizes recommended implementing AI in neuroimaging of stroke on a national scale to include more patients and improve study precision. Secondly, the studies included were heterogeneous in nature, with study designs ranging from retrospective (52.5%), prospective (25%), cohort (12.5%), to cross-sectional (2.5%). Moreover, the employment of AI in stroke diagnosis is a novel approach, with the majority of reported studies being review articles. Therefore, as more advancements are made in the field of AI and ML, more rigorous and systematic studies need to be conducted to determine whether these algorithms can accurately detect acute stroke in radiological imaging.

Conclusion

The AI related to stroke studies is becoming more frequent and the number is increasing year after another. For the past 10 years, China has been the leading country in terms of the publication of such a study. A future study is required to improve the field of AI in terms of diagnosis and identification of stroke.

Declaration

Acknowledgments: Not applicable

Funding: All authors have declared that no financial support was received from any organization for the submitted work.

Financial relationships: All authors have declared that they have no financial relationships that might have an interest in the submitted work.

Other relationships: All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

Availability of data and materials: The data generated in the present study may be requested from the corresponding author: Dr. Tariq Al-Saadi as it has been conducted from different institutions.

Authors' contribution: M.A had made a contribution to designing the study and interoperated the date of the study. A.A, A.A, H.A and R.A drafted the article. T.A revised and approved the version to be published.

Ethical approval and consent: Not applicable.

Patient consent for publication: Not applicable.

Competing interests: all authors have seen and agree on the content of the manuscript and there are no conflicts of interest.

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ISSN:2093-4777 | E-ISSN:2093-6931
DOI: 10.5123/inj.2024.1.inj5
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