Stroke Prehospital Decision Support Systems Based on Artificial Intelligence: Grey Literature Scoping Review

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Abstract: Stroke is a leading cause of mortality and disability worldwide. Therefore, there is a growing interest in prehospital point-of-care stroke clinical decision support systems (CDSSs), which with improved precision can identify stroke and decrease the time to optimal treatment, thereby improving clinical outcomes. Artificial intelligence (AI) may be a route to improve CDSSs for clinical benefit. Deploying AI in the area of prehospital stroke care is still in its infancy. There are several existing systematic and scoping reviews summarizing the progress of AI methods for stroke assessment. None of these reviews include grey literature, which could be a valuable source of information, especially when analysing future research and development directions. This paper aims to use grey literature to investigate stroke assessment CDSSs based on AI. The study adheres to PRISMA guidelines and presents seven records showcasing promising technologies. These records included three clinical trials, two smartphone applications, one master thesis and one PhD dissertation, which identify electroencephalogram (EEG), video analysis and voice and facial recognition as potential data sources for early stroke identification. The integration of these technologies may offer the prospect of faster and more accurate CDSSs in the future.

1 INTRODUCTION

Stroke is a leading cause of death and disability worldwide (Chennareddy et al., 2022). It is caused by either a bleeding, called haemorrhagic stroke, or a clot in one or more of the brain's blood vessels, called ischemic stroke which accounts for approximately 85% of cases (Meyran et al., 2020). For ischemic stroke, two types of treatment are deployed: thrombolysis (clot-dissolving drugs) or thrombectomy (mechanically removing the clot) (Lumley et al., 2020; Shlobin et al., 2022). The latter is an advanced treatment that requires a specialist at a comprehensive stroke centre (CSC) and is suited for thrombectomy candidates, i.e., patients with large vessel occlusion (LVO) with still viable brain tissue that can be restored (Chennareddy et al., 2022; Nicholls et al., 2022). Brain cells die as time passes without treatment; hence, quick treatment is a critical factor (Shlobin et al., 2022).

Most stroke patients are initially handled by a prehospital team in an ambulance according to

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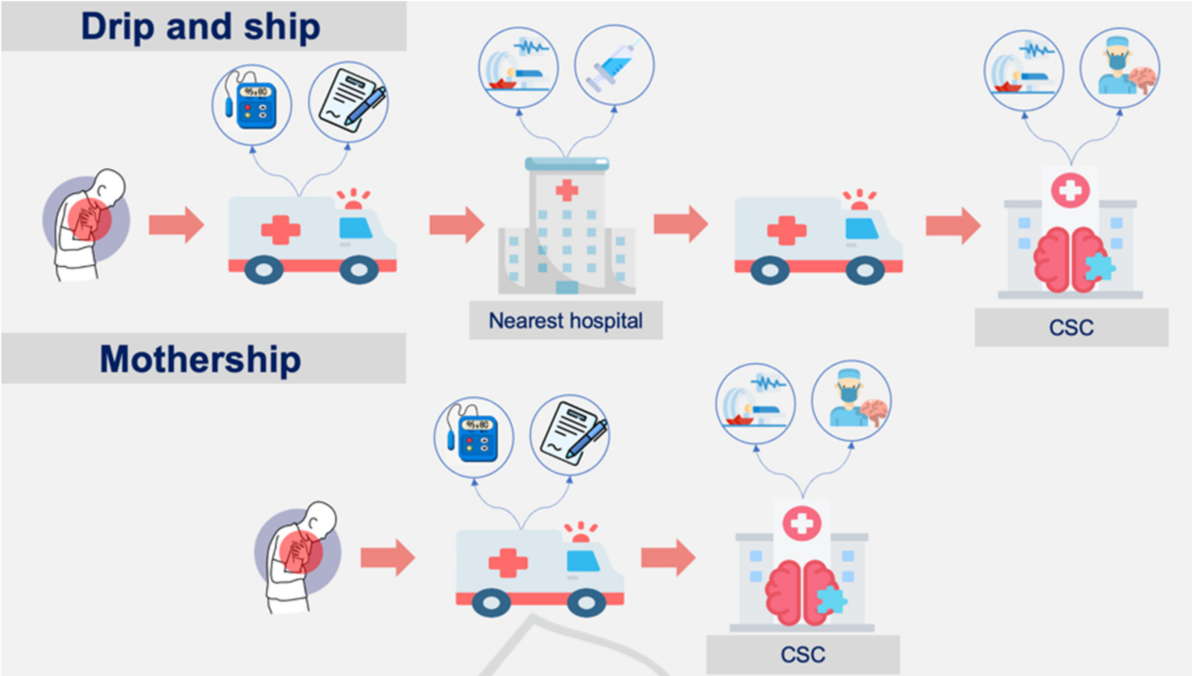

Figure 1: Drip-and-ship and mothership strategies.

predefined procedures including medical history, patient assessment, glucose and vital signs monitoring. In addition, various clinical stroke scales are used to predict the likelihood of stroke and its severity. These scales are symptom-based tests that assess the patient's stroke symptoms such as speech, facial expression and arm and leg movements (Nicholls et al., 2022). In hospital settings, the most commonly used scale is called the National Institutes of Health Stroke Scale (NIHSS); it is a validated scale with a sensitivity of 86% and a specificity of 60% for LVO (Nicholls et al., 2022). In prehospital settings, the observation for NIHSS is too complicated to carry out for the ambulance teams, therefore simpler, mostly unvalidated scales, e.g., Los Angeles Motor Scale, are frequently used. The accuracy of prehospital stroke diagnosis, when relying solely on stroke scales, remains low, with a 64% sensitivity (Chennareddy et al., 2022), suggesting the need for considering additional diagnostic methods or factors in enhancing diagnostic accuracy.

It is crucial to streamline prehospital stroke management (Fassbender et al., 2020). Currently, stroke is typically confirmed at hospitals after brain imaging is performed, such as computed tomography (CT) and magnetic resonance imaging (MRI) (Magnusson et al., 2022). According to international stroke management guidelines, such as those recommended by the American Stroke Association, patients with suspected stroke are typically transported to the nearest hospital. If the nearest hospital is not a CSC and LVO is confirmed, the patient should be transferred to a CSC where thrombectomy can be performed (Nicholls et al., 2022). This strategy is called drip-and-ship (Figure 1). Patients with a high probability of LVO may be transported directly to the CSC, which is called the mothership strategy (Fassbender et al., 2020; Nicholls et al., 2022). Identification of more LVO patients in the prehospital setting is crucial to reducing prehospital delays and improving patient outcomes (Nicholls et al., 2022).

The research group Care@Distance–Remote and Prehospital Digital Health at Chalmers University of Technology is focused on developing AI-based prehospital clinical decision support systems (CDSSs) for acute diseases, such as stroke. Our aim is to enhance the performance in the identification of LVO and provide support to reduce treatment delays. This is in line with the American Heart Association Guidelines (2019), which called for further research to identify effective prehospital procedures for triaging patients to the appropriate centers, including hospital bypass algorithms (Nicholls et al., 2022). Artificial intelligence (AI) and machine learning (ML) deployed in CDSS can play an important role in improving stroke assessment (Murray et al., 2020; Shlobin et al., 2022). AI encompasses computer tasks challenging for humans, including CDSSs, which could be defined to fall within the AI realm although employing basic algorithms influenced by clinical experience. The focus of this study is however specifically on advanced ML algorithms, characterized by their complex model architectures and data-driven techniques, as we investigate their potential for enhancing early stroke characterization.

Several recent scoping and systematic reviews have summarized the progress of AI methods for stroke assessment; however, none included grey records (Chennareddy et al., 2022; Lumley et al., 2020; Murray et al., 2020; Nicholls et al., 2022; Ruksakulpiwat et al., 2021; Shlobin et al., 2022). Grey literature can be a rich source of information about solutions in premature stages, and the Institute of Medicine Standards for Systematic Review (Berg et al., 2011) and the Cochrane Handbook for Systematic Reviews of Interventions (Higgins et al., 2023) recommend incorporating grey literature in systematic reviews. Our group is currently working on a scoping review that is centered on the peer-reviewed literature (Jalo et al., 2023). This study therefore aims to complement our review and existing reviews by specifically focusing on publicly available grey literature that includes, among others, academic papers (theses and dissertations), non-peer-reviewed conference proceedings, research and committee reports, government reports, clinical trials and ongoing studies to identify promising AI-based CDSSs for prehospital stroke assessment.

2 METHODS

Arksey and O'Malley (Arksey et al., 2005) describe a scoping review as a form of literature review designed to map the relevant literature within a specific research domain. This scoping review was carried out in accordance with Arksey and O'Malley (Arksey et al., 2005), a five-stage methodology including (1) identifying the research question(s), (2) identifying relevant studies, (3) selecting studies, (4) charting the data and (5) collating, summarizing and reporting the results. The optional consultation stage was not conducted in this scoping review because it is challenging to evaluate new AI-based CDSSs due to the intricate algorithms and methods involved.

The methodology started with identifying the research question, and this review aims to answer the following question: what are the promising AI-based CDSSs for stroke assessment in prehospital settings? To answer the identified research question, relevant studies were identified by searching 12 databases, focusing only on recent grey literature such as non-peer-reviewed conference proceedings, theses, dissertations and reports during the past 10 years. The searched databases (ClinicalTrial, ProQuest, Arxiv, EBSCOhost, Networked Digital Library of Theses and Dissertations (NDLTD), University of Wollongong (UOW) library, Bielefeld Academic Search Engine (BASE), World Health Organization (WHO), Canada's drug and health technology agency (CADTH), FiNDit, Open Access Theses and Dissertations (OATD), University of South California (USC) Library and Science daily) were selected based on grey literature recommendations published by James Cook University's library (James Cook University). Google Scholar was not included in this study because a study found that most of the not retrieved records in Google Scholar were grey literature (Yasin et al., 2020).

Search terms included stroke, haemorrhagic stroke, ischemic stroke, artificial intelligence, machine learning and decision support systems, which were systematically combined using Boolean operators (AND, OR) to capture relevant studies. Search strings were defined and adopted for each database.

The third stage was to select studies based on identified eligibility criteria (Table 1). Article screening was done in two steps: (1) title and abstract screening, and (2) full text screening.

Table 1: Eligibility criteria.

Inclusion criteria	Exclusion criteria
Non-peer reviewed records	Peer-reviewed journal and peer-reviewed conference articles
The record reports a method for stroke assessment	No focus on stroke Stroke related to animal studies
The record presents an AI-based tool for stroke assessment in the prehospital setting	No AI-based method is reported, or the method cannot be used in the prehospital setting, e.g., the use of brain imaging is required
Written in English Published between 2012 and 2022	Not written in English Older records or non-retrievable

The included records were then summarized, charted and reported. An Excel sheet was used to extract the following data from each included study: key information, aims, population and study subject characteristics, methodology, main findings and limitations of the study. By applying a consistent approach to each included study, common characteristics and descriptive summary were provided.

3 RESULTS

A total of 1593 grey literature records were identified during Stage 2 (Figure 2). Initial title and abstract screening and duplicate removal resulted in 126 records passed for full-text screening. Among these, 119 did not meet the inclusion criteria, including studies published in peer-reviewed journals, not retrieved data and records irrelevant to the research questions. Seven relevant records were included and are summarized in Table 2. No records were found between 2012 and 2018.

An ongoing clinical trial in the Netherlands tests the accuracy of AI-STROKE algorithms: one or more novel AI-based electroencephalography (EEG) algorithms to detect LVO in ambulances (Coutinho, 2022). EEG is performed using dry electrode EEG caps, and investigators expect it to be done in less than five minutes in ambulances (Coutinho, 2022). The presence or absence of a clot will be confirmed using CT scans at the emergency department (ED) (Coutinho, 2022). The accuracy of the new algorithms will be tested by comparing the area under the receiver operating characteristic curve (AUC), sensitivity, specificity, positive predictive value (PPV) and negative predictive value (NPV) to existing EEG algorithms (Coutinho, 2022).

Another ongoing clinical trial is a prospective observational study in Sweden, which evaluates measurements from EEG, heart rate variability (HRV) and near-infrared spectroscopy (NIRS) separately and combined to provide a specific detection of cerebral ischemia (Block et al., 2020; Block, 2022). The investigators hypothesize that changes in those measurements can indicate cerebral ischemia and reperfusion after being processed by ML classification models. The study aims to find specific patterns in EEG, HRV and NIRS to signify cerebral ischemia and build a monitoring warning system for the diagnosis of upcoming cerebral ischemia (Block et al., 2020; Block, 2022).

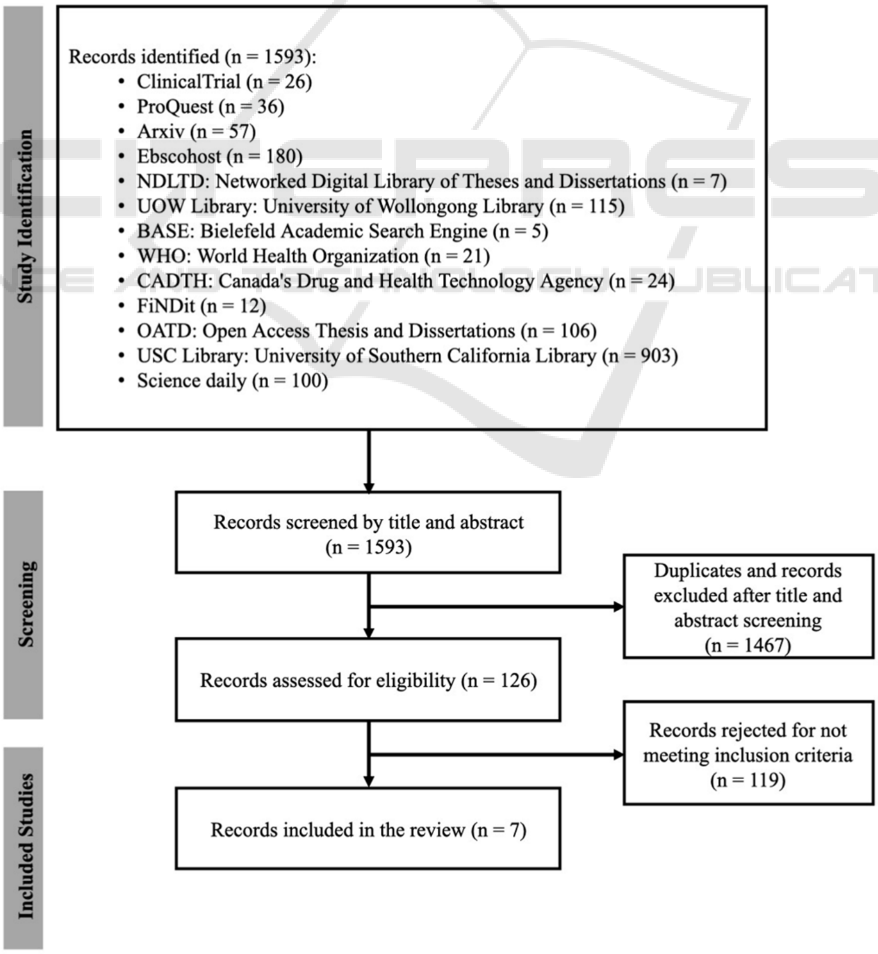

Figure 2: Modified PRISMA flowchart to summarize retrieved records (Page et al., 2021).

An ongoing clinical trial in Norway (Haukeland University Hospital, 2022) works on an AI-based prototype for acute stroke detection in emergency medical calls. The study aims to use audio from emergency calls and available data in hospital records to implement an AI-based detection system and test its performance against the current system by comparing sensitivity and specificity.

Facial palsy is a common symptom in stroke patients; facial recognition is thus an important technique to be used in the detection of stroke. A master thesis from TU Delft presented a system that automatically detects facial paralysis based on deep learning algorithms (Sourlos, 2020). The algorithm first detects a patient's face from an image, then metrics are defined based on landmarks localized on the face, to classify the input image (Sourlos, 2020). In total, 203 images were analysed (60 of healthy subjects, 40 of central palsy patients and 103 of peripheral palsy patients), and an accuracy of 99.5% was achieved for the healthy group and 90.9% for patients with facial palsy (Sourlos, 2020).

Another promising technology is a mobile application called Fatal Recognition that uses facial recognition to detect early signs of stroke (Chan, 2019). Every time patients unlock their screen, an algorithm detects signs of face-drooping, sends alerts to contact emergency services and shows emergency services contact details (Chan, 2019).

Table 2: Summary of the data extracted for novel CDSSs included in the scoping review.

Record	Study design	Year	Location	Goal	Methodology
Algorithm Development Through AI for the Triage of Stroke Patients in the Ambulance with EEG (AI-STROKE) (Coutinho, 2022).	Clinical trial	2022	Netherlands	LVO detection in ambulances	AI-based EEG algorithms with the use of dry electrode caps
Detection of Cerebral Ischemia with Artificial Intelligence (Block, 2022)	Clinical trial	2022	Sweden	Detection of cerebral ischemia	ML models based on EEG, HRV and NIRS
Artificial Intelligence Support in Stroke Calls (AISIS) (Haukeland University Hospital, 2022)	Clinical trial	2022	Norway	Acute stroke detection in emergency medical calls	AI-based detection system using audio calls and health records
Facial Imaging and Diagnosis System for Neurological Disorders (Sourlos, 2020)	Master thesis	2020	Netherlands	Automatic detection of facial paralysis	Deep learning-based system
Fatal Recognition (Chan, 2019)	Mobile application	2019	Hong Kong	Detection of early signs of facial drooping in stroke	AI-based facial drooping detection
AI-Stroke (AI-Stroke, 2022)	Mobile application	2022	France	Indication of stroke and characterization the stroke type	Video analysis and ML to perform NIHSS scale
Human-Centred Machine Learning for Healthcare: Examples in Neurology and Pulmonology (Ramesh, 2020)	PhD dissertation	2020	USA	Hemiparesis detection in stroke patients	Video analysis and ML

A company called AI-Stroke developed a smartphone application to perform the NIHSS test, and it guides the person close to the patient on how to perform the test while recording a video of the patient (AI-Stroke, 2022). The AI algorithm calculates the NIHSS score, indicates the probability of having a stroke and characterizes the stroke type. They aim to create a dataset with videos from stroke patients and healthy volunteers to be used in training the AI model. An ethical application has been approved in France, and the first patient was recently added to the dataset Franc (AI-Stroke, 2022).

Video analysis based on ML was used to detect hemiparesis in stroke patients in a sitting position as a part of a PhD dissertation at the University of California San Diego (Ramesh, 2020). Hemiparesis is usually identified by the NIHSS test by asking the patient to move the arm or leg (Ramesh, 2020). The system was tested by eight stroke specialists, and a video-based assessment was done as part of the NIHSS test at rest in the sitting position. The accuracy of the system was 68% and 61% when moving and at rest, respectively (Ramesh, 2020).

4 DISCUSSIONS

Integration of innovative technology in prehospital clinical assessment may lead to early stroke detection, classification of stroke subtypes and fewer false-positive stroke diagnosis. AI-based prehospital CDSSs for stroke play a crucial role in the context of embedded decision support systems. These innovative technologies leverage the power of AI to assist ambulance teams in making quick and accurate decisions during the critical prehospital phase of stroke care. By analysing various patient data, these systems can quickly identify potential stroke cases, prioritize them based on severity and provide real-time recommendations for appropriate interventions and transportation protocols, thereby allowing for faster treatment and improved clinical outcomes.

The seven included records have highlighted several methods for early stroke detection in the prehospital environment, including EEG brain imaging techniques and automated symptom-based tools. Two clinical studies have used EEG, which has a long-established sensitivity for early stroke detection and has the potential to be used in prehospital settings (Block et al., 2020; Erani et al., 2020). EEG is a physiological monitoring technique that is used to record the brain's electrical activity and can immediately detect changes in brain function (Block et al., 2020; Erani et al., 2020). One of its limitations is the long time spent in applying gel, but this could be overcome by using rapidly applied dry electrodes (Erani et al., 2020). A recent study indicated that EEG signals contain further diagnostic information compared to the current clinical assessment (Erani et al., 2020). The AUC for acute stroke diagnosis was 87.8 and 86.4 for LVO patients when EEG was incorporated into the clinical routine of stroke diagnosis (Erani et al., 2020).

Speech, facial palsy and impaired movement are early stroke symptoms and are currently evaluated by symptom-based clinical stroke scales. Many of the stroke cases remain undetected in the prehospital settings (Fassbender et al., 2020). For example, a study compared the accuracy of 13 clinical stroke scales for detecting thrombectomy candidates and showed that 20% of thrombectomy candidates remained undetected by the use of clinical stroke scales (Fassbender et al., 2020). The recent technologies focusing on early detection of these symptoms thus have the potential to provide more informative CDSS to improve prehospital stroke detection, allowing for faster treatment and improved clinical outcomes.

After applying the eligibility criteria, seven papers were included in this study due to its narrow focus, highlighting the need for further research in the critical field of prehospital stroke assessment. This aligns with a recent scoping review (Nicholls et al., 2022) that aimed to identify LVO detection techniques across various settings and included just nine studies on AI-based methods. Out of these studies, only three focused on AI-based prehospital triaging tools. These tools included a smartphone application designed to aid emergency medical services professionals in patient assessment and destination triage (Nogueira et al., 2017), a prediction model that incorporated various predictors (Chen et al., 2018) and a three-step triage tool aimed at reducing prehospital assessment time (Zhao et al., 2018). Notably, none of the studies presented AI-based solutions involving EEG, video analysis, or voice recognition for early stroke identification. This study has thus presented early-stage research and innovative concepts.

The main strength of this review is that it provides information about the innovative technologies usually not covered in reviews, with the potential to improve stroke detection in prehospital settings. Notably, this study pioneers the examination of a research area that has not been well-explored, as evidenced by the absence of records from 2012 to 2018. The results may thus serve as a basis for developing an AI-based CDSS for early assessment of stroke. Limitations include that this study has been conducted by only one reviewer, and many of the presented results are ongoing clinical trials or yet-to-be-performed studies. Those studies have different study design, population and diagnostic accuracy metrics which makes it difficult to perform technology comparisons. Grey literature also captures information related to emerging research areas that are not yet published in peer-reviewed literature, which makes a direct comparison with published literature not feasible. However, it serves as a valuable source of information by providing preliminary research findings and insights into emerging technologies. Future work may include searching Google Scholar to see if more promising techniques would be captured and widen the scope of the review to include promising detection technologies in hospitals. Future work also includes searching the peer-reviewed literature to identify AI-based CDSSs designed for assessing stroke in the prehospital environment (Jalo et al., 2023).

5 CONCLUSIONS

This review has explored grey literature and advancements in AI-based stroke assessment methods in prehospital settings. It was found that in future stroke assessments CDSS, EEG, audio recognition, facial recognition and video records may be used as data sources for decision-making. We conclude that the reviewed technologies are promising prehospital tools that have the potential to aid in the early assessment of stroke, but they are yet to be tested and validated. There are, however, not many studies in this research area. More studies are warranted due to the large clinical need. Improvements in CDSSs would impact stroke detection and patient triage, increasing the chance for earlier initial treatment and the potential for fewer secondary transfers of patients.

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