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Optimization of Radiology Diagnostic Services for Patients with Stroke in Multidisciplinary Hospitals

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ABSTRACT

Background: Effective radiology diagnostic services are crucial for the timely and precise diagnosis and treatment of stroke, a medical emergency, in multidisciplinary hospitals. However, the efficiency of these services might be impeded by various logistical and operational challenges present in a multidisciplinary hospital setup. **Objective:** This review endeavours to explore the ways for optimizing stroke management in multi-disciplinary hospitals, delving into its benefits, current challenges, and future prospects. **Methods:** Electronic databases, namely PubMed, Scopus, and Web of Science, were utilized for this review. Studies that focus on the organizational and functional aspects of radiology diagnostic services in multidisciplinary hospitals for stroke patients were analysed. **Results:** This review delves into a variety of strategies that could be harnessed to enhance radiology diagnostic services, thereby better-serving stroke patients in multidisciplinary hospital settings. It sheds light on the current hurdles in the optimization of stroke management, discussing them in detail. This article also explores the application and significance of Process Mapping in streamlining workflow for stroke management in hospitals, providing insights into its benefits, challenges, and future implications. Furthermore, the potential of Artificial Intelligence (AI) and Machine Learning (ML) in refining stroke management processes is also analysed and discussed. **Conclusion:** The quest for optimizing the organization of radiology diagnostic services in multidisciplinary hospitals unveils a multi-pronged pathway. It beckons a harmonious blend of technological innovation, operational finesse, and multidisciplinary camaraderie. stepwise implementation of the identified optimization strategies, coupled with a continual assessment of their impact on patient care and operational efficiency, is recommended.

Keywords: stroke, radiology, diagnostics, multidisciplinary hospitals, review.

1. BACKGROUND

Stroke stands as a formidable public health menace, claiming millions of lives and leaving others with debilitating morbidities every year on a global scale (1). The crucial pivot towards improved patient outcomes hinges significantly on the timeliness and accuracy of stroke diagnosis (2). Radiology diagnostic services, encompassing computed tomography (CT) scans, magnetic resonance imaging (MRI), and angiography, among others, are instrumental in deciphering the enigma of stroke, paving the way for informed treatment planning and intervention (3).

Yet, a troubling spectrum of variability shadows the organizational framework and effectiveness of these pivotal diagnostic services across diverse multidisciplinary healthcare settings (2, 4). This variability potentially mirrors a deeper narrative of inequitable healthcare infrastructure and systemic discrepancies, often manifested in the quality and accessibility of stroke diagnostic services (5, 6).

The tale of stroke's global onslaught continues to be grim, with an astonishing 13.7 million fresh cases and a staggering 5.5 million fatalities recorded annually (3, 7). A closer inspection reveals a geographical tapestry of incidence rates, each thread coloured by disparate risk factors, healthcare infrastructural strengths or weaknesses, and the robustness or frailty of public health policies in place (8-11). These geographical discrepancies not only underscore the uneven battlefield against stroke but also beckon a unified, global response to bridge these chasms (12, 13).

The essence of "time is brain" encapsulates the urgency that defines stroke diagnosis and management (14, 15). With every ticking minute, an estimated loss of 1.9 million neurons potentially veers the patient further from the path of recovery, spotlighting the indomitable role of rapid and precise diagnosis (16, 17). The armamentarium of radiological techniques stands at the forefront of this battle, acting as both the eyes and the sword in understanding the extent of cerebral insult and carving out a tailored plan of therapeutic action (18).

Thus, galvanizing a heightened state of readiness and effectiveness within the radiology diagnostic sectors across hospitals demands an uncompromised priority. Fostering an environment of technological and operational excellence, underpinned by a culture of continuous learning and quality improvement, could usher a transformative era of stroke management. By meticulously chiselling away the barriers that impede the seamless flow of diagnostic processes, and by orchestrating a harmonized dance of multidisciplinary collaborative efforts, the global healthcare community could inch closer towards relegating the menace of stroke into the annals of history. The radiological diagnostics for stroke mainly include CT scans, MRI, and angiography (19). These imaging modalities serve different purposes: while CT scans are generally faster and used for initial screening to rule out haemorrhage, MRI provides a more detailed view of the ischemic area (20-24). Angiography can be utilized to identify large vessel occlusions and other vascular abnormalities, which could be critical for treatment planning.

Despite advances in radiological technology, there exists substantial variability in the availability, quality, and organization of radiological services across multidisciplinary hospitals (21, 25, 26). These inconsistencies can stem from differences in hospital resources, radiologist expertise, and local and national healthcare policies.

While numerous studies have explored the technical aspects and clinical effectiveness of radiological imaging in stroke care, there is a paucity of research focusing explicitly on the organizational and functional aspects of these services (27-30). Furthermore, patient perspectives on the quality of these diagnostic services have been largely overlooked, representing a significant gap in the literature.

The diagnostic pathway for stroke patients is often complex, requiring an effective organizational model to ensure timely diagnosis and initiation of appropriate treatment. An optimized radiology service could also facilitate more efficient use of healthcare resources and improve patient outcomes.

2. OBJECTIVE

The organization and functioning of radiology diagnostic services for stroke care in multidisciplinary hospitals represent a vital yet understudied area. The variability in these services necessitates a comprehensive review to identify best practices and areas for improvement. This review endeavours to explore the ways for optimizing stroke management in multidisciplinary hospitals, delving into its benefits, current challenges, and future prospects.

3. MATERIAL AND METHODS

Information Sources and Search Strategy

Electronic databases, namely PubMed, Scopus, and Web of Science, were utilized for this review. Additional studies were identified through hand-searching the reference lists of included papers and related reviews. The search strategy involved a combination of keywords and Medical Subject Headings (MeSH) terms such as "Stroke," "Radiology," "Diagnostics," "Multidisciplinary Hospitals," "Organizational Models," "Effectiveness," and "Patient Satisfaction."

Data Collection Process

Two independent reviewers screened titles and abstracts for eligibility. Full-text articles were then assessed for inclusion against the eligibility criteria. Disagreements were resolved through discussion or third-party adjudication.

Quality Assessment

The quality of each included study was assessed using the Quality Assessment Tool for Observational Cohort and Cross-Sectional Studies, developed by the National Institutes of Health. The evaluation was conducted by two independent reviewers, with any disagreements resolved through discussion or third-party adjudication.

Inclusion Criteria: Studies published in peer-reviewed journals from January 2010 to October 2023.

Studies that focus on the organizational and functional aspects of radiology diagnostic services in multidisciplinary hospitals for stroke patients. Studies that evaluate effectiveness and/or patient satisfaction related to radiology services for stroke. Studies published in English.

Exclusion Criteria: Non-peer-reviewed articles, conference papers, and opinion pieces. Studies focused exclusively on technical aspects of radiology without discussing organizational or functional elements.

Studies not related to stroke- Risk of Bias Assessment

Risk of bias was assessed using the Cochrane Collaboration's tool for randomized trials for intervention studies and the ROBINS-I tool for non-randomized studies. The results of the risk of bias assessment were utilized in the data synthesis and interpretation.

Current challenges

The journey of efficacious stroke management commences with early recognition of its symptoms. The more promptly a stroke is identified, the quicker medical intervention can be deployed. Public awareness campaigns that educate on the early signs of a stroke, such as sudden numbness, confusion, vision problems, and severe headaches, play a pivotal role in reducing the delay in seeking medical attention.

The initial hurdle to efficient stroke treatment is the precise and prompt identification of stroke symptoms as they manifest (7, 30, 31). Given that the majority of patients first encounter these symptoms within community settings rather than medical facilities, this aspect potentially accounts for significant delays in some instances (32-36). Addressing such a problem squarely falls under the purview of public health initiatives aiming at amplifying the general public's awareness regarding strokes (7). Upon a patient's arrival at the hospital, swift progression through diagnostic procedures, encompassing initial tests, radiological studies, and intervention planning is crucial (32, 37). Adequate infrastructural support, particularly in medical imaging services, is essential in this case. It underscores the need for a well-orchestrated plan to enhance stroke care, aiming at optimizing operational workflows, bolstering care responsiveness, and fostering robust communication and teamwork across all domains (7).

In fact, cultivating an environment conducive for ongoing training and education within and outside the medical community could also be pivotal. This could encompass community outreach programs, regular training sessions for medical personnel, and leveraging digital platforms to spread awareness. Incorporating technological advancements like telemedicine and AI-driven diagnostic tools could further bolster the efficacy and timeliness of stroke treatment (38-40).

Moreover, creating feedback loops between community, emergency medical services, and hospital teams can ensure continuous improvement in stroke recognition and treatment processes. Evaluating and adjusting protocols based on real-world data and outcomes will contribute to a more adaptive and efficient stroke care ecosystem. Through a concerted effort from both public health sectors and medical institutions, alongside leveraging technological innovations, the path towards minimizing delays and optimizing stroke treatment can be significantly smoothed out, ultimately contributing to better patient outcomes and enhanced community health.

Up to date, there is a range of strategies and protocols have been developed to markedly reduce delay times in emergency services response and the coordinated handling of patient admissions to hospitals (7). A pivotal factor lies in the capability to execute multiple tasks, particularly when the patient is otherwise engaged to the hospital. Such comprehensive tasks pre-notification, swift triage protocols, expeditious execution of laboratory and medical imaging assessments, prompt feedback mechanisms, and the mobilization of a dedicated interdisciplinary team (7). Such a team, consisting of professionals from emergency medicine, neurology, and medical imaging departments, is tasked with hastening both diagnosis and subsequent treatment processes [7]. The breadth of research aimed at optimizing medical imaging services in the milieu of acute stroke treatment is substantial, albeit primarily honed on process-specific and patient-centric factors.

Moreover, recent studies have delved into examining the ripple effects of operational variables, such as emergency department crowding, on acute stroke care management [41-43]. The influx of patients, particularly during peak hours or unforeseen calamities, may tether the already strained resources further, potentially affecting the timely delivery of critical stroke care services. This underscores the exigency for devising robust contingency plans and scalable operational frameworks that can adeptly handle surges in patient inflow while maintaining the efficacy and timeliness of stroke care delivery.

Additionally, there's a burgeoning emphasis on the integration of cutting-edge technology within the emergency care spectrum. Technologies such as Artificial Intelligence (AI), Machine Learning (ML), and Telemedicine are being heralded as game-changers in facilitating quicker diagnoses, ensuring seamless communication among interdisciplinary teams, and enabling remote monitoring and consultations (44-46). The infusion of these technologies could play a quintessential role in further trimming the delay times, thereby substantially improving the prognosis and recovery trajectories for stroke patients.

Furthermore, fostering a culture of collaborative learning and continuous improvement among the different stakeholders can significantly contribute to refining the existing protocols and identifying latent bottlenecks within the emergency care continuum. Regular training sessions, workshops, and collaborative research endeavours can be instrumental in staying abreast of evolving best practices and integrating them within the operational frameworks, thereby ensuring that the stroke patients receive timely and optimal care.

The race against time

The long waiting times in medical imaging services pose a considerable barrier to the effective and timely diagnostics of the stroke. Each minute lost in waiting for imaging services like CT or MRI translates to a further deterioration in the patient's neurological status. The longer the wait, the greater the extent of irreversible neuronal damage, often expressed through the adage "time is brain" in stroke management. This deterioration consequently leads to a worsened prognosis and decreased quality of life post-stroke (19, 47, 48). Delayed imaging and subsequent treatment not only compromise patient outcomes but also inflate healthcare costs. The longer hospital stays, increased need for rehabilitation services, and potential for repeated imaging due to initially delayed services cumulatively

References	Methods	Study subjects	Study aims	Outcomes
[58]	Five diverse XAI methods, such as Shapley Additive Values (SHAP), ELI5, QLattice, Local Interpretable Model-agnostic Explanations (LIME) and Anchor, have been used to decipher the model predictions.	5110 patients with strokes ranged in age from roughly 40 to 80 years old, while those without strokes ranged in age from 0 to 80	To predict stroke in patients using heterogeneous classifiers and explainable artificial intelligence	Maximum accuracy of 96% was obtained by the stacked model. Five XAI approaches were applied for the predictions of the model. They were Anchor, QLattice, Eli5, SHAP, and LIME. Age, bmi, average glucose level, hypertension, and heart disease were found to be the most crucial variables for the prediction of stroke. The proposed algorithm was compared with other related research, and the effectiveness of establishing classifier dependability.
[64]	Head and neck CT angiography (CTA) scans performed during stroke codes and run through an AI software engine (Viz LVO).	1822 head and neck CT angiography (CTA) scans	To determine the accuracy of AI software in a real-world, three-tiered multihospital stroke network.	Accuracy metrics were analysed for two different groups: ICA-T and M1 ±M2. For the ICA-T/M1 versus the ICA-T/M1/M2 group, sensitivity was 93.8% vs 74.6%, specificity was 91.1% vs 91.1%, negative predictive value was 99.7% vs 97.6%, accuracy was 91.2% vs 89.8%, and area under the curve was 0.95 vs 0.86, respectively. Detection rates for ICA-T, M1, and M2 occlusions were 100%, 93%, and 49%, respectively. As expected, the algorithm offered better detection rates for proximal occlusions than for mid/distal M2 occlusions.
[63]	The proposed model of mutation model using a distance map was integrated into the generative adversarial network (GAN) to generate a synthetic dataset. The Euclidean distance was used to compute the average distance of each pixel with its neighbour in the right and bottom directions. Furthermore, semi-supervised GAN was enhanced and transformed into supervised GAN.	Images of ischemic stroke lesions: of 94 and 62 cases for training and test sets.	A new synthetic dataset to handle the limited number of images in the ISLES-2018 dataset for semantic segmentation using a model-based mutation and distance map has been generated, presented, and evaluated.	The results showed that the mutation model enhances the dice coefficient of the proposed GAN model by 2.54%. Furthermore, it slightly enhances the recall of the proposed GAN model compared to other GAN models.
[65]	The architecture of the proposed intelligent hospital for the connected health modules consisted of a wearable sensors module that sends signal streams for signal processing modules and mobile AI health for stroke prediction	The EMG Lower Limb dataset includes different 24 patients. The mHealth dataset includes 10 different subjects. EMG Physical Action dataset contains 4 subjects	To test a new mobile AI smart hospital platform architecture for stroke prediction and emergencies. In addition, this research is focused on developing and testing different modules of integrated AI software based on XAI architecture.	The proposed techniques achieved high accuracy as stacked CNN reaches almost 98% for stroke diagnosis. The GMDH neural network proved to be a good technique for monitoring the EMG signal of the same patient case with an average accuracy of 98.60% to an average of 96.68% of the signal prediction. Moreover, extending the GMDH model and a hybrid LSTM with dense layers deep learning model has improved significantly the prediction results that reach an average of 99%.
[66]	The rescanned images were reconstructed with a hybrid iterative reconstruction (IR) algorithm (reference group), images of the first scan were reconstructed with both the hybrid IR (motion group) and the MC algorithm (MC group). Image quality was compared in terms of standard deviation (SD), signal-to-noise ratio (SNR), contrast-to-noise ratio (CNR), the mean squared error (MSE), peak signal-to-noise ratio (PSNR), structural similarity index (SSIM), and mutual information (MI), as well as subjective scores.	Total of 53 cases, where motion artefacts were found in the first scan so that an immediate rescan was taken, were retrospectively enrolled.	To evaluate the clinical performance of an artificial intelligence (AI)-based motion correction (MC) reconstruction algorithm for cerebral CT.	Compared with the motion group, the SNR and CNR of the MC group were significantly increased. The MSE, PSNR, SSIM, and MI with respect to the reference group were improved by 44.1%, 15.8%, 7.4%, and 18.3%, respectively (all $p < 0.001$). Subjective image quality indicators were scored higher for the MC than the motion group ($p < 0.05$). Improved lesion detectability and higher AUC (0.817 vs 0.614) in the ASPECTS assessment were found for the MC to the motion group. The AI-based MC reconstruction algorithm has been clinically validated for reducing motion artefacts and improving diagnostic performance of cerebral CT.

[76]	ResNet-18, a deep residual convolutional neural network and the gradient-weighted class activation mapping (Grad-CAM) technique was employed to visually explore and understand the network's decisions.	CT images from Kaggle's Head CT-Hemorrhage database were considered, which contains 100 images of normal brains (without pathology) and 100 images of brains with hemorrhage.	To differentiate computer tomography (CT) images of healthy brains and ICH using a ResNet-18, a deep residual convolutional neural network. In addition, the gradient-weighted class activation mapping (Grad-CAM) technique was employed to visually explore and understand the network's decisions.	The proposed detector based on a deep residual convolutional neural network, the ResNet-18, without the need for a preprocessing step, automatically extracts the characteristics of colour CT images, and detects ICH with an average accuracy of 95.93%, specificity of 96.20%, sensitivity of 95.65%, and precision of 96.40%, and an average computation time of 165.90 s during training (160 images) and 1.17 s during the test (40 CT images), on a Core i3 Windows-based Laptop without GPU (graphics processing unit) as a co-processor.
[77]	Expert ASPECTS readings on NCCT were used as ground truths. A deep learning-based automatic detection (DLAD) algorithm was developed for automated ASPECTS scoring based on 168 training patient images using a convolutional neural network (CNN) architecture. An additional 90 testing patient images were used to evaluate the performance of the DLAD algorithm, which was then compared with ASPECTS readings on NCCT as performed by physicians.	A total of 258 patient images with suspected acute ischemic stroke (AIS)	To automate The Alberta Stroke Program Early CT Score (ASPECTS) that is a standardized scoring tool used to evaluate the severity of acute ischemic stroke (AIS)	The sensitivity, specificity, and accuracy of DLAD for the prediction of ASPECTS were 65%, 82%, and 80%, respectively. These results demonstrate that the DLAD algorithm was not inferior to radiologist-read ASPECTS on NCCT. With the assistance of DLAD, the individual sensitivity of the ER physician, neurologist, and radiologist improved. The proposed DLAD algorithm exhibits a reasonable ability for ASPECTS scoring on NCCT images in patients presenting with AIS symptoms. The DLAD algorithm could be a valuable tool to improve and accelerate the decision-making process of front-line physicians
[62]	Fundus images at 548, 605, and 810 nm wavelengths were collected. Three classical deep neural network (DNN) models (Inception V3, ResNet50, SE50) were trained. Sociodemographic and selected routine clinical data were obtained.	A total of 150 atrial fibrillation (AF) participants without suffering from Ischemic stroke (IS) within 1 year after discharge and 100 IS participants with persistent arrhythmia symptoms or a history of AF diagnosis	To predict ischemic stroke risk from atrial fibrillation based on multi-spectral fundus images using deep learning	The accuracy of all deep neural network (DNNs) with the single-spectral or multi-spectral combination images at the three wavelengths as input reached above 78%. The IS detection performance of DNNs with 605 nm spectral images as input was relatively more stable than with the other wavelengths. The multi-spectral combination models acquired a higher area under the curve (AUC) scores than the single-spectral models.

Table 1. Research studies on the use of Artificial Intelligence (AI) and Machine Learning (ML) for diagnostics and treatment of ischemic strokes.

contribute to a financial strain on both the healthcare system and patients (17).

Moreover, the challenge extends beyond just managing the inflow of requests. It encompasses ensuring that medical imaging services are adeptly integrated within the larger emergency care continuum. Hence, improving the interdepartmental communication and coordination becomes paramount. An optimally functioning system would facilitate seamless transition of patients from one stage of care to the next, ensuring that the necessary imaging services are promptly conducted and the results swiftly communicated to the relevant healthcare providers for timely intervention.

Additionally, investing in training and capacity-building for staff within medical imaging services is crucial. This includes fostering a culture of continuous learning and adaptation to new technologies and protocols. By doing so, the efficiency and effectiveness of workflow management can be substantially improved. Furthermore, exploring partnerships with external imaging centres or adopting tele-radiology services can also augment the capacity and responsiveness of medical imaging services (49-51). This approach can ensure that the high demand is met promptly, especially during peak times, and that the quality of care remains uncompromised.

Lastly, a patient-centric approach should underpin all improvement initiatives. Engaging with patients to understand their experiences and efficient feedback for process enhancement can contribute significantly to reducing waiting times and improving the overall quality of emergency care. Through a holistic approach, encompassing technological advancements, operational refinements, and patient engagement, the quest for enhanced efficiency in medical imaging services in the face of breastfeeding demand can be significantly advanced.

In cases where an acute stroke is suspected, it's

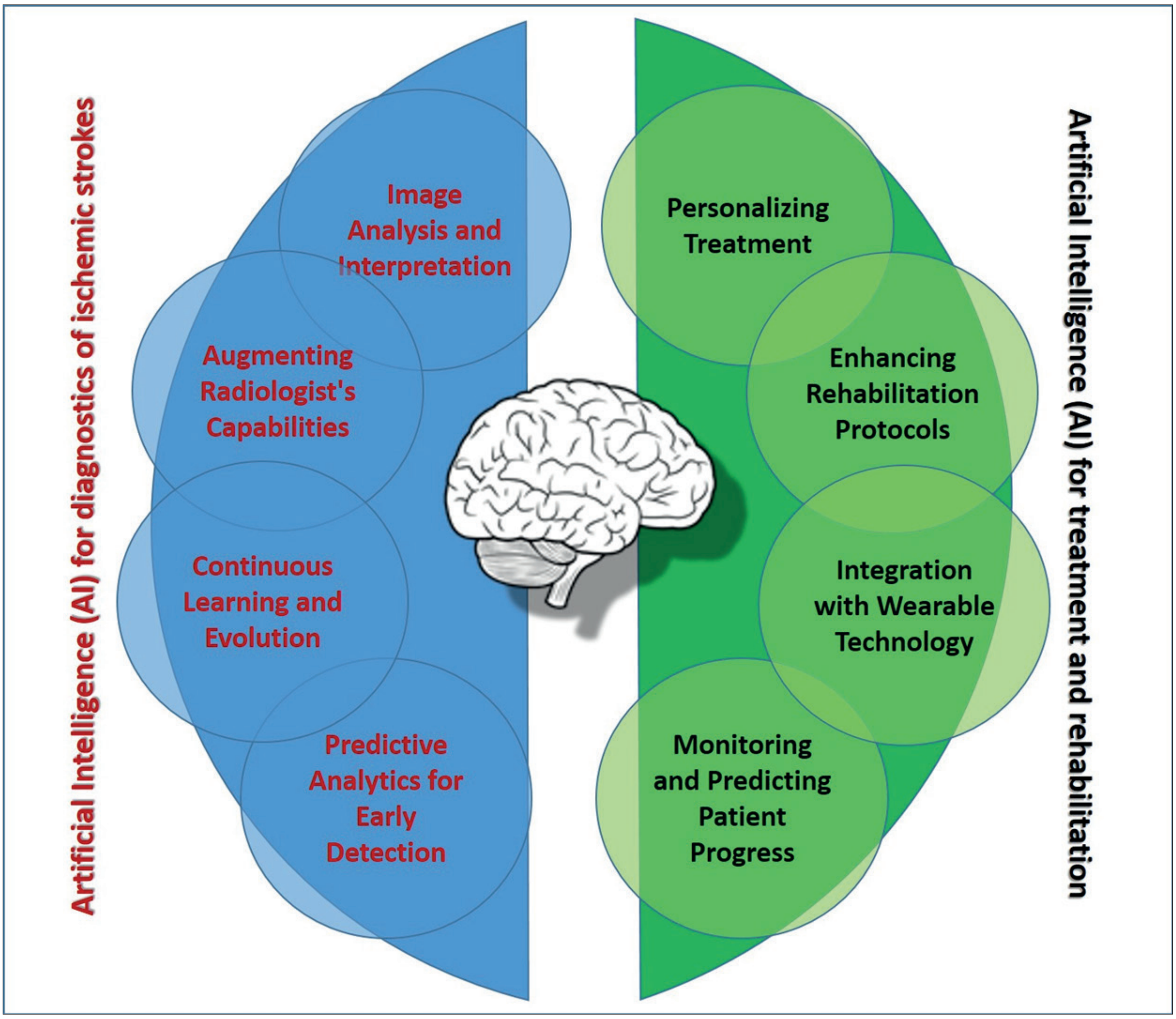

Figure 1. The scheme of fields of application of AI for stroke management.

imperative that computed tomography studies be meticulously analysed by a neuro-radiologist. However, a common challenge arises from the often scant availability of neuro-radiologists within many hospital settings. To circumvent this hurdle, Tele-radiology systems have been adopted, enabling neuro-radiologists to remotely access and analyse imaging studies stored in PACS (Picture Archiving And Communication System)[52, 53]. This remote access fosters a conducive environment for timely, expert analysis regardless of the neuro-radiologist's physical location. Whether the analysis is conducted in-person or remotely, the generated reports by neuro-radiologists are securely stored within the RIS (Radiology-Information-System).

The adoption of Tele-radiology not only bridges the geographical and resource gaps but also accelerates the diagnostic process, which is quintessential in acute stroke scenarios where every minute counts (54-56). This streamlined and tech-empowered approach significantly augments the hospital's capacity to deliver prompt and precise care, thus improving the prognosis and recovery trajectory for stroke patients. Moreover, the amalgamation of HER (Health Electronic Record), RIS, and PACS forms is a synergized digital framework, fostering seamless inter-departmental communication and coordination, which are crucial for effective emergency response and comprehensive stroke care.

Help of Artificial Intelligence (AI) and Machine Learning (ML)

The advent of sophisticated software tools, leveraging Artificial Intelligence (AI) and Machine Learning (ML), has opened avenues for real-time data analytics and predictive modelling. By harnessing these technologies, medical imaging services can forecast demand surges, optimize resource allocation, and enhance scheduling efficiency, thereby significantly reducing waiting times. Moreover, real-time tracking of workflow processes can provide invaluable insights for identifying bottlenecks and implementing targeted improvements.

AI and ML have significantly augmented medical imaging analysis such as CT scans and MRIs, which are pivotal in stroke diagnosis (57, 58). Algorithms can now identify cerebral haemorrhages, infarcts, and other relevant anomalies swiftly and precisely, speeding up the diagnostic process (40). The review and summary of recent research studies on the use of Artificial Intelligence (AI) and Machine Learning (ML)

Ref.	Study aims	Methodology	Results
[78]	To reduce 'door to CT' time and to reduce 'door to needle' time (DNT) to the national target of less than 30min. A third aim was to increase the number of patients undergoing Endovascular thrombectomy (EVT).	A stroke quality improvement (QI) team consisting of the hospital stroke consultant lead, a stroke clinical nurse specialist, a stroke care registrar, clinical nurse specialist and a radiology specialist registrar was formed. A retrospective analysis patient's charts and radiology records from the previous year in 2017 and extrapolated the median door to CT time was 38min and the median DNT was 105min in these patients. An inclusive interdepartmental meeting was held with representation from members of staff involved in every step of the patient journey including; paramedics, switch telephone staff, ED registration clerical staff, laboratory staff, ED doctors and nurses, porters, radiographers, radiologists, general medical doctors and care of the elderly/stroke physicians. A large process map was created on a whiteboard by mapping out the existing steps to CT access and thrombolysis in a sample patient who had a stroke attending our hospital.	The reduction of door to CT time and to reduction of 'door to needle time' to the national target of less than 30 min.
[79]	To explore reasons for non-adherence to thromboprophylaxis guidelines in atrial fibrillation from the perspectives of general practitioners (GPs) and to map these reasons to the Capability, Opportunity, Motivation-Behaviour (COM-B) model to identify potential opportunities to support practice change	An exploratory qualitative descriptive study among GPs practising in Western Australia (a semi-structured interview)	Nine of the 10 GPs initially consented participated in the semi-structured interview. Two themes emerged from analysis of the interview transcripts: (1) GPs' decision-making process and (2) Patient refusal to take anticoagulants. The Motivation-Behaviour (COM-B) model mapping identified behavioural factors that could impact adherence: capability (GPs' knowledge and understanding of AF guideline recommendations), opportunity (access to a cardiologist, and patients' refusal to take OACs), and motivation (using formal bleeding risk assessment tools).
[80]	Optimization of diagnostics and treatment of stroke patients using mapping process of the stroke treatment at the Institute of Psychiatry and Neurology in Warsaw	The value stream mapping for the process of stroke patients treatments in the Institute of Psychiatry and Neurology was developed on the basis of the guidelines of the initial draft of the national VSM standards in health care (three flow streams: patients, resources and information)	The stroke treatment process described by the VSM method enables to indicate space, reserves and potential improvements. Once implemented, corrected and consistently followed in hospital practice, the process provides an opportunity to improve patients' prognoses in a considerable way also through the early, comprehensive and individually-adjusted rehabilitation, e.g. by an early mobilisation of patients after a stroke.
[81]	To improve the quality of ischemic stroke services by reducing the waiting time in the process of carrying out the head CT scan.	The flow of service processes for ischemic stroke patients in the emergency department and all related units were observed directly to calculate the time used in each stage of the process, from triage to the head CT scan. The number of processes observed was 22 patients. The number of samples observed for 2 weeks of simulation was 11 patients. Data were analyzed through several stages using the principle of the lean method, which is done by making a groove from each stage of the process of the head CT scan for ischemic stroke patients in the Emergency Department (ED). The analysis includes time spent at each stage, identification of value and waste, formulation of the Value Stream Map/VSM (the current state in the hospital), determining the root of the problem with the 5 whys method, proposed improvements for waste elimination, as well as making VSM simulations.	In the current value stream map, 87.8% of the head CT scan process in emergency departments/IGD is non-value add/waste. Only 6.9% of the time was spent on value-added and 5.26% on non-value-added but still necessary. After the improvement with the lean method, in the simulated Value Stream Map, it was found that there was a decrease in the lead time of the head CT scan process of ischemic stroke patients in the ED from 175.41 minutes to only 30.09 minutes, an increase in value percentage added activities and decreased non-value-added activities.

Table 2. Processes Mapping for Workflow hospital management: examples of the studies.

for diagnostics and treatment of ischemic strokes is provided on the Table 1.

Moreover, AI and ML facilitate the rapid identification of strokes by analysing medical images significantly faster than human radiologists, which is critical for initiating timely interventions. AI algorithms, trained with extensive datasets, often demonstrate superior precision in identifying subtle anomalies in imaging data that might elude human observation. Leveraging historical and real-time data, ML algorithms can predict the onset of stroke, enabling preventive measures. Radiomics enables the extraction of a vast array of features from radiological images, further augmenting diagnostic accuracy (59, 60).

Convolutional Neural Networks have shown immense promise in image recognition tasks, including identifying strokes from CT scans and MRIs. Deep learning frameworks delve into multiple layers of analysis, providing insightful diagnostics essential for stroke management. Yousaf et al. proposed a model based on convolutional neural networks to concurrently detect and categorize two brain disorders, namely tumours and Ischemic strokes (61). A unique dataset was constructed by amalgamating two open-source datasets: BRATS 2015 and ISLES 2015. Such a method aids in preserving fine-grained low-level information and differentiating overlapping features throughout the encoding phase, alongside the UNET's skip connections. The dataset is apportioned into training and validation subsets at a ratio of 80:20, ensuring a balanced representation of images in each training batch to mitigate the class imbalance issue. The proposed model has demonstrated an average accuracy of 99.56%, a specificity of 99.99%, a precision of 99.59%, and an F1-score of 99.57%.

Timely diagnosis and management of stroke is a critical determinant of patient outcomes, often demarcating the thin line between recovery and permanent disability or death. AI and ML have emerged as ground-breaking tools capable of revolutionizing stroke diagnostics through real-time monitoring systems (62). This essay aims to explore the potentials and intricacies involved in integrating AI and ML into real-time monitoring systems for stroke diagnostics, discussing the technological frameworks, implementation challenges, and the prospective trajectory of this amalgamation (63).

AI and ML could significantly augment the speed and accuracy of imaging analysis, enabling real-time diagnosis of stroke from imaging modalities like CT scans and MRIs (39, 64). Predictive analytics facilitated by ML algorithms can foresee potential stroke occurrences based on real-time monitoring of critical physiological parameters (65, 66). AI-powered anomaly detection systems can identify subtle, yet critical deviations in patient data, triggering immediate alerts for medical intervention (67).

Deep learning frameworks, particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), hold promise in real-time image and sequence analysis crucial for stroke diagnostics (68, 69). Natural Language Processing (NLP) can enhance real-time monitoring by interpreting clinical notes and electronic health records to provide a holistic view of patient diagnosed with the stroke (70, 71). In addition, cloud-based AI solutions can enable real-time data processing and analytics, ensuring prompt diagnostic insights and decision support. The scheme of fields of application of AI for stroke management is depicted in the Figure 1.

Despite the evident advantages, there are some issues related to AI and ML technologies to be resolved yet. It includes ensuring data privacy and security in real-time monitoring systems, necessitating robust cybersecurity measures. Algorithmic bias stemming from skewed training data can result in inequitable healthcare outcomes, demanding meticulous validation and continuous algorithm refinement. Moreover, rigorous clinical validation and coherent regulatory frameworks are vital and needed for ensuring the reliability and safety of AI/ML-powered real-time monitoring systems.

Processes Mapping for Optimizing Workflow

In the dynamically complex environment of healthcare, the concept of workflow stands as a linchpin in ensuring efficient service delivery, patient satisfaction, and overall healthcare efficacy. As healthcare systems globally grapple with burgeoning demands amidst resource constraints, the quest for optimized workflows becomes a cardinal pursuit. Process Mapping, a potent tool borrowed from the realms of industrial engineering and quality management, offers a viable pathway toward understanding, analysing, and improving healthcare workflows (72). Such a tool can be harnessed for the optimisation of workflow in the multi-disciplinary hospitals for stroke management. It provides a sandbox environment where different workflow configurations can be tested and refined, thereby ensuring optimized process frameworks.

Given that stroke imaging evaluations may encompass Head Computed Tomography (Head CT) and Angio Computed Tomography (Angio CT) studies, it was imperative for the healthcare managers to map out the processes and information systems employed in facilitating these critical diagnostic evaluations [7, 38]. The objective is to draw a coherent map that details the journey from the point of imaging request to the completion and analysis of the imaging studies (36).

The mapping process commenced with the identification of the initiation point, which is typically the request for imaging studies by a healthcare provider. Following the request, the sequential steps including patient preparation, actual imaging, image analysis, report generation, and the dissemination of the imaging report to the relevant healthcare personnel were meticulously mapped. Each stage was dissected to understand the underlying tasks, decision nodes, and potential bottlenecks.

In stroke management, Process Mapping spans across emergency response, diagnosis, treatment, and post-stroke care, showcasing the procedural landscape in a healthcare facility (73). Moreover, the information systems such as Radiology Information System (RIS), Picture Archiving and Communication System (PACS), and Electronic Health Records (EHR) that support the seamless execution of Head CT and Angio CT studies can be analysed [7]. Understanding the interoperability of these systems and their integration within the overall workflow was pivotal in ensuring a well-coordinated and efficient process.

Such an approach ensures the efficiency and time-sensitivity for stroke management (74). Efficient workflows are synonymous with reduced time delays, which is pivotal in stroke management where every minute counts towards better patient outcomes. Moreover, a streamlined and optimized workflow contributes to precise and prompt diagnosis, timely intervention, and improved coordination among multidisciplinary teams, thereby elevating the quality of care provided to stroke patients. By facilitating a data-driven understanding of the process dynamics, Process Mapping supports evidence-based interventions to enhance stroke care workflows.

However, there are a few challenges remained unsolved. It encompasses the resistance to changes from healthcare professionals towards modifying established practices, which may be perceived as disruptive. Another issues are the inherent complexity of stroke care processes and patient variability that pose significant challenges to effective Process Mapping and subsequent workflow optimization. In this regard, advanced technologies like AI and Machine Learning can significantly augment Process Mapping by providing real-time analytics and predictive insights for workflow optimization [75]. The examples of the studies on the Processes Mapping for optimization of the workflow hospital management are provided in the Table 2.

The journey through the healthcare maze in stroke management is laden with numerous operational intricacies. Process Mapping emerges as a beacon in navigating this maze towards achieving optimized workflows and enhanced patient care. By embracing this methodical approach, coupled with technological advancements and a culture of continuous improvement, hospitals can significantly elevate the standard of stroke care, aligning with the critical dictum of "Time is Brain".

4. DISCUSSION

The insidious onslaught of stroke presents an ongoing medical exigency, affecting millions globally with its spectre of mortality and morbidity. The edifice of effective stroke management pivots on the axle of prompt and accurate diagnosis, underlining the indispensable role of radiology diagnostic services. Within the ecosystem of multidisciplinary hospitals, the orchestration of these diagnostic services often unveils a tapestry of organizational intricacies and potential lacunae. This essay delves into the avenues for ameliorating the organization of radiology diagnostic services for stroke patients in multidisciplinary hospitals, exploring technological, operational, and collaborative dimensions, with an eye towards optimizing patient outcomes and enhancing systemic efficiency.

The harbinger of precision diagnosis in stroke care rests upon advanced imaging technologies like Magnetic Resonance Imaging (MRI), Computed Tomography (CT) scans, and angiography (20, 30, 37). The continuous evolution and adoption of state-of-the-art imaging modalities promise a higher resolution of diagnostic acumen, expediting the delineation of treatment blueprints.

Tele-radiology offers a vista of remote diagnostic collaboration, ensuring that geographical boundaries do not impede the flow of expert insights. Concurrently, the dawn of Artificial Intelligence (AI) in radiology heralds a new epoch of diagnostic precision and speed, where machine learning algorithms augment the capabilities of radiologists in image interpretation.

The fabric of seamless communication between imaging platforms, Electronic Health Records (EHR), and other hospital information systems underpins an efficient diagnostic journey. Enhancing interoperability can significantly truncate time lags and foster real-time collaborative decision-making.

Structuring well-defined, lean workflows within radiology departments can abrogate systemic bottlenecks, ensuring a swift transition of patients from imaging to intervention phases.

It has been thought that the embedding a culture of quality assurance and continuous improvement ensures that the radiology services are perpetually aligned with evolving best practices and regulatory compliances. The robust performance metrics and benchmarking against national and global standards can provide tangible markers for organizational improvements and optimization of stroke management.

There is a need in the integrated care pathways where radiology services are in synergistic tandem with emergency, neurology, and other critical departments can significantly impact the speed and quality of stroke care. Moreover, nurturing an environment of continuous professional development and interdisciplinary training ensures that the collaborative ethos is rooted in competence and up-to-date knowledge.

Instilling a patient-centred philosophy within radiology services ensures that the diagnostic journey aligns with the holistic well-being and comfort of stroke patients, thereby enhancing overall satisfaction and outcomes.

5. CONCLUSION

The quest for optimizing the organization of radiology diagnostic services in multidisciplinary hospitals unveils a multi-pronged pathway. It beckons a harmonious blend of technological innovation, operational finesse, and multidisciplinary camaraderie. As the global healthcare paradigm shifts towards value-based, patient-centric models, the impetus to refine the scaffold of radiology services for stroke care burgeons.

With each stride towards organizational excellence, the collective endeavour can significantly contribute to mitigating the scourge of stroke, propelling healthcare systems closer to the zenith of quality patient care and systemic efficacy. A stepwise implementation of the identified optimization strategies, coupled with a continual assessment of their impact on patient care and operational efficiency, is recommended. Further, fostering a culture of innovation and learning can catalyse the evolution of radiology diagnostic services to meet the emergent demands of stroke care in multidisciplinary hospital environments.

The future directions of research that could optimize the organization of radiology diagnostic services for better stroke management might encompass a range of solutions. For instance, the integration of Advanced AI and Machine Learning: future research can focus on creating AI-driven tools to assist radiologists in swiftly and accurately detecting signs of stroke. Additionally, ML algorithms can predict stroke types and outcomes based on imaging data, providing invaluable guidance to clinical teams. Apart from AI, with the evolution of digital communication, tele-radiology has emerged as a solution to make specialist services available in remote or underserved areas. Future research should delve into optimizing workflows, ensuring image quality during transmission, and regulatory and security concerns associated with remote diagnostics using Telemedicine. The research should focus on techniques and technologies that accelerate the imaging process, reduce the time between image capture and interpretation, and ensure timely delivery of results to clinical teams without compromising diagnostic accuracy. In fact, strokes can be ischemic or haemorrhagic, and distinguishing between them quickly is crucial. Research into integrated multimodal imaging solutions that combine MRI, CT, and other imaging modalities can offer a comprehensive view of brain health, improving diagnostic precision. Apart from technology, the human element in radiology remains irreplaceable. Ongoing research into optimal training methods, incorporating the latest technological advancements, and integrating multidisciplinary approaches will be vital. This would ensure that radiologists are well-equipped to make the most of the tools at their disposal. Research aimed at making advanced radiology services more affordable without compromising quality will be invaluable too. This would ensure that the best diagnostic tools are not limited to just the most advanced or affluent healthcare systems.

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