COMPARATIVE STUDY OF ARTIFICIAL INTELLIGENCE DETECTION TECHNOLOGY FROM EXCEPTION ISCHEMIC STROKE REQUIRING MEDICAL HELP IMAGING

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ABSTRACT

Artificial intelligence is revolutionizing the interpretation of medical images, helping healthcare professionals save time on magnetic scans, CT scans and X-rays. Stroke is a global health problem, and ischemic stroke is one of the leading causes of death and disability in humans. Symptoms of an ischemic stroke appear suddenly and worsen within minutes, as most ischemic strokes occur suddenly, progress rapidly, and lead to the death of brain tissue within minutes or hours. This is why early detection of stroke is essential and remains a challenge for neurophysicists. Neurophysicists routinely use a variety of detection techniques to detect, assess and evaluate the ex-tent of premature ischemic changes in acute stroke brain imaging. Although several effective techniques exist, these methods have limitations due to unenhanced CT scans and invasive techniques. This study aims to demonstrate the limitations of certain methods, to determine detection methods by comparing the detection performance of automated and human brains. Stroke was evaluated through a literature review of recent studies.This article highlights comparative studies of different artificial intelligence (AI) techniques using medical imaging and allows the authors to orient themselves within these comparative studies, thus projecting themselves into the challenges facing artificial intelligence.

KEYWORDS

Artificial Intelligence, Medical Imaging, MRI, CT-scan, Ischemic Stroke

1. INTRODUCTION

Computerized detection systems can help identify abnormalities that clinicians might miss, thereby improving the accuracy of disease detection. With the increase in average life expectancy, stroke has become the third leading cause of death globally [1]. There are two types of stroke, hemorrhagic stroke and ischemic stroke, but in this work we will focus on the most common ischemic stroke [2]. An ischemic stroke is caused by obstruction of blood flow to the part of the brain supplied by one or more small arteries. Lacunar stroke is a subtype of ischemic stroke that is relatively difficult to identify because it appears on computed tomography (CT) as small hypodense areas less than 15 mm in diameter. Clinical diagnosis of lacunar stroke is difficult in the first few hours after stroke onset. The advent of new stroke treatment modalities, such as intravenous recombinant tissue plasminogen activator (rtPA) administration and/or endovascular mechanical thrombectomy, provides tools for clinicians to restore brain perfusion and prevent permanent neurological damage [3]. Continued improvement in treatment guidelines and increasingly sophisticated care in specialized units have contributed to minimizing primary treatment complications and improving secondary stroke prevention [4, 5, 6]. However, rapid

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diagnosis and clinical treatment of ischemic stroke remain critical for optimal patient selection. The use of rtPA or mechanical thrombectomy carries significant risks, and careful patient selection (e.g., inclusion of those presenting in an appropriate rtPA window and distinction of those who are ideal candidates for image-defined actuatable penumbra endovascular intervention) is a prerequisite for achieving clinical benefit [7]. Given the complex decisions that need to be made and the need to optimally analyze large volumes of patient data in a limited amount of time, the application of artificial intelligence (AI) is expected to help further accelerate and optimize the clinical management of stroke. AI applications in stroke imaging can also help manage patients when the radiologist is not present (such as at night or in an underserved area) or when the radiologist is not an expert (eg, a non-neuroradiologist). The remainder of this paper will specifically address the management of ischemic stroke, including the different types of medical imaging that exist, the utility of artificial intelligence in the rapid diagnosis and interpretation of stroke. To carry out the rest of this paper we will organize ourselves as follows: in section 2 we present related work on medical imaging techniques. In Section 3, we present a comparative study of different artificial intelligence techniques for detecting ischemic stroke using medical imaging. In section 4 we present the limitations noted in the literature review and highlight future challenges.

2. RELATED WORK ON MEDICAL IMAGING TECHNIQUES USED IN STROKE

There are different medical imaging techniques namely Computer Tomography (CT), Magnetic Resonance Imaging (MRI), Mismatch Concept, Ultrasound studies, Echocardiography (TTE / TOE). The AI techniques that we will discuss in the rest of this paper uses imaging techniques namely CT and MRI. For this reason, we will focus the literature review on these two techniques. Immediate CT reliably distinguishes between hemorrhagic and ischemic strokes and detects signs of ischemia as early as 3 hours after stroke onset. Patients who have had stroke symptoms for 3 hours may be candidates for tPA treatment on arrival at the emergency department. However, tPA cannot be administered to patients with intracerebral hemorrhage (ICH). The only reliable way to distinguish ischemic stroke from hemorrhagic stroke is brain imaging. Non-contrast computed tomography (NCCT) is the standard imaging modality for the detection of acute ICH [8]. NCCT is faster, more extensive, and less expensive than MRI. However, NCCT may not identify changes caused by hyperacute ischemic stroke, and brainstem strokes may be particularly difficult to visualize on scans. Furthermore, NCCT did not provide any information on the extent and severity of hypoperfusion. Due to deficiencies in NCCT, new methods of imaging stroke with CT scans are being explored. These methods include computed tomography angiography (CTA) and perfusion computed tomography (PCT) [9]. CTA aids in treatment selection, especially when large vessel occlusion suggests that intra-arterial thrombolysis or mechanical thrombectomy should be considered. These CT techniques are not always available in acute situations. They can provide information on vascular patency or occlusion (occlusion location and occlusion segment length), but also collateral capacity and the presence of severe cortical hypoperfusion, although estimates of the magnitude of hypoperfusion may be inaccurate [10].Alternatively, PCT may help detect areas of hypoperfusion in the brain before morphological changes are observed on NCCT scans, and thus aid in lesion localization. In a study by Murphy and colleagues [11], MDT parameters were used to differentiate between infarcted and penumbral tissue in a small sample of patients. In this study, we believe that CTA/PCT imaging significantly improves the overall accuracy of stroke assessment compared with CT and provides valuable information on infarct/penumbra extent, collateral circulation, and other pathophysiological aspects, as suggested by the authors in [9]. These promising CT techniques should help future physicians to identify appropriate therapeutic interventions for patients with acute ischemic stroke. MRI is particularly important in acute stroke patients with abnormal symptoms. Although MRI is more expensive and less used, it may be a better early detection method for treating stroke patients. One of the limitations of MRI is that the examination takes longer than necessary, which can delay treatment and may not be suitable for unstable patients. Besides high cost and limited availability, MRI is not recommended for patients with pacemakers or metal devices. Although one study showed that MRI can be performed in patients with a 1.5 T pacemaker [12]. A study comparing NCCT and MRI in patients with suspected acute stroke showed that MRI can detect acute stroke, acute ischemic stroke, and chronic bleeding. Because MRI can detect acute and chronic hemorrhage as well as acute ischemic stroke, some physicians believe that MRI should be the imaging technique of choice for diagnosing patients with suspected stroke because it is similar to NCCT in detecting acute intracranial hemorrhage. Overall, the sensitivity of MRI for the diagnosis of any acute stroke was 83% and CT was 26% [13]. Because MRI can detect acute and chronic bleeding as well as acute ischemic stroke, some physicians believe that MRI should be the imaging modality of choice for diagnosing patients with suspected stroke [13, 14]. The use of MRI may have significant advantages over the use of CT in identifying patients suitable for tPA in early acute stroke. MRI may also be a better method than CT to determine which stroke patients may benefit from tPA administered after a 3- hour window [15]. Techniques used for assessment include diffusion-weighted imaging, perfusion-weighted MRI, and magnetic resonance angiography (MRA). Diffusion-weighted images provide information on early cerebral ischemia and disease progression. Perfusion-weighted imaging uses a contrast agent to identify hypoperfused brains. Perfusion-weighted imaging lesions were visible immediately after occlusion and disappeared shortly after occlusion. The difference between perfusion weighted and diffusion-weighted imaging can detect tissues at risk of infarction; these tissues are the targets of tPA [16]. Currently, CT is the most commonly used initial imaging modality for the evaluation of patients with sudden neurological deficits. A limitation of TCD is that the assessment of the posterior cerebral arteries may not be as reliable as anterior examinations [17].

3. Related Work on Stroke Detection Methods using AI

Rapid detection of ischemic infarction is important to classify patients as potential candidates for thrombolysis due to the narrow window of therapeutic effect. Several studies have used ML algorithms to identify ischemic infarction on CT or MRI. Tang et al. [18] developed a computerized automatic detection (CAD) protocol using a circular adaptive region of interest (CAROI) approach on non-contrast head CT to detect subtle changes in attenuation in ischemic stroke patients. They found that CAD improved stroke detection for ER and radiology residents (AUC (area under the curve) for ER from 0.879 to 0.942 and AUC for radiology residents from 0.965 to 0.990), but did not significantly improve detection for experienced radiologists who already had high stroke detection. Another study showed that ANN (artificial neural network) was able to detect acute stroke (confirmed by clinical, CT and MRI imaging data) within 4.5 hours of onset with an average sensitivity of 80%, distinguishable from stroke mimics, with a specificity of 86.2%. [19].

3.1. Core Infarct Volume Segmentation

The diagnosis of LVO (large vessel occlusion) is critical in identifying candidates who may benefit from mechanical thrombectomy. In NCCT, the SVM (support vector machine) algorithm identified MCA dot characters in acute stroke patients with high sensitivity (97.5%) [25]. A neural network combining various demographic, imaging, and clinical variables to predict OVL outperformed most other preclinical prediction scales with an accuracy of 0.820 [26]. CNN-based commercial software Viz-AI algorithm v3.04 detected proximal LVO with 86% accuracy, 90.1% sensitivity, 82.5 specificity, 86.3% AUC (95% CI, 0.83-0.90; $P \leq 0.001$) and intraclass correlation coefficient (ICC) was 84.1% (95% CI, 0.81 to 0.86; $P \leq 0.001$) and Viz-AI algorithm v4. 1.2 Achieving the ability to identify Large Vessel Occlusion (LVO) with a notable degree of precision, boasting a sensitivity of 82% and specificity of 94% [27]. Up to this point, there hasn't been any research to confirm whether artificial intelligence techniques can effectively distinguish other potentially treatable conditions, like M2 blockages, intracranial Internal Carotid Artery (ICA) obstructions, and posterior circulation occlusions. CNN Dice scores were 0.7 for white matter hyper intensities and 0.4 for stroke. uResNet demonstrated slight superiority over CNN DeepMedic in the detection of white matter hyperintensities, white matter hyperintensities, and strokes compared to human expertise. The R-values obtained were 0.951 and 0.791 for white matter hyperintensities and strokes, respectively, using uResNet, while they were 0.942 and 0.688 using DeepMedic [21].The first study to apply a deep learning (DL) approach to CTA (computed tomography angiography) images for the detection of acute ischemic middle cerebral artery stroke used a 3D CNN (DeepMedic). This achieved a sensitivity of 0.93, a specificity of 0.82, an AUC of 0.93 and a Dice score of 0.61. Another study showed that a CNN could rapidly distinguish acute strokes from false positives within just 4.5 minutes of symptom onset, with an average sensitivity of 80.0% and specificity of 86.2% [22]. However, this CNN had limitations, including a tendency to overestimate the volume of small infarcts and underestimate that of large infarcts compared with manual segmentation performed by expert radiologists, as well as difficulties in differentiating old from new strokes. The largest group study using Computed Tomography (CTP) to diagnose central infarcts based on an Artificial Neural Network (ANN) succeeded in accurately determining central infarct volume. The results show an area under the curve (AUC) of 0.85, a sensitivity of 0.9 and a specificity of 0.62. Significantly, these results did not differ significantly from a model incorporating clinical data, which achieved an AUC of 0.87, sensitivity of 0.91 and specificity of 0.65 [23]. Although the study minimized the time between baseline DWI acquisition by CTP and MRI imaging, any delay between CTP and MRI imaging may have limited the accurate determination of central infarction because of core expansion or inversion. A model incorporating a U-net CNN classifier and RF architecture was able to accurately segment acute ischemic strokes on NCCT images, demonstrating strong agreement with DWI manually segmented central volumes (correlation coefficient $r=0.76$, $P<0.001$) as well as with DWI manually segmented ASPECTS scores (correlation coefficient $r=-0.65$, $P<0.001$). In addition, agreement approached significance when dichotomizing infarcts using a volume threshold of 70 mL (McNemar test, $P=0.11$). Volume discrepancies were attributed to undetectable early ischemic findings, partial volume averaging, and CT stroke mimics.

3.2. Large Vessel Occlusion

The diagnosis of LVO (large vessel occlusion) is critical in identifying candidates who may benefit from mechanical thrombectomy. In NCCT, the SVM (support vector machine) algorithm identified MCA dot characters in acute stroke patients with high sensitivity (97.5%) [25]. A neural network combining various demographic, imaging, and clinical variables to predict OVL outperformed most other preclinical prediction scales with an accuracy of 0.820 [26]. CNN-based commercial software Viz-AI algorithm v3.04 detected proximal LVO with 86% accuracy, 90.1% sensitivity, 82.5 specificity, 86.3% AUC (95% CI, 0.83-0.90; $P \leq 0.001$) and intraclass correlation coefficient (ICC) was 84.1% (95% CI, 0.81 to 0.86; $P \leq 0.001$) and Viz-AI algorithm v4. 1.2 It offers the ability to detect LVOs with a high sensitivity of 82% and specificity of 94%, as reported in reference [27]. To date, no studies have assessed whether AI techniques can also be accurate in identifying other potentially treatable lesions, including M2, intracranial CAI and posterior circulation occlusion.

3.3. Aspects Grading

ASPECTS is a widely used clinical grading system to assess the extent of early ischemic stroke in NCCT and has been used in randomized clinical trials to select candidates for thrombectomy [28, 29, 30]. However, classification can be difficult, and interobserver agreement varies. A commercial software platform with automated ASPECTS scoring (e-ASPECTS, Brainomix) performed as well as neuroradiologists when scoring ASPECTS on NCCT in acute stroke patients [31]. However, e-ASPECTS did not perform as well as neuroradiologists when scoring ASPECTS in acute stroke patients with an abnormal-looking CT at baseline (e.g., leukoencephalopathy, old infarcts, or other parenchymal defects), demonstrating a correlation coefficient of 0.59 versus 0.71 -0.80 for those in the know [32]. A study found that an automatic ASPECTS detection algorithm on NCCT using texture feature extraction to train an HF classifier produced ASPECTS scores that closely matched DWI ASPECTS scores produced by experts (ICC = 0.76 and κ = 0.6 when used for all 10 ASPECTS regions). Another commercial software platform with automated ASPECTS scoring (Rapid ASPECTS version 4.9; iSchemaView) showed better agreement with DWI-tracked ASPECTS grades (κ = 0.9) compared with moderate agreement for neuroradiologists (k 0.56-0.57), and the software performed well in the immediate time interval of 1 hour after stroke onset (κ = 0.78) and better at 4 hours after stroke onset (κ = 0.92) [33]. The platform showed better agreement bet ween ASPECTS score and infarct volume in patients with large hemisphere infarction compared to clinically experienced readers [34].

3.4. Other Factors in Treatment Choice

Various factors, including the onset of collateral circulation, penumbra, and stroke, are important in evaluating potentially viable tissue and determining eligibility for treatment. An automated commercial software program (e-CTA; Brainomix) that combines depth and traditional ML(machine learning) techniques to determine CTA collateral status improved the consensus score among experienced neuroradiologists by 0.58 compared to visual inspection alone The ICC of (0.46–0.67) to 0.77 (0.66– 0.85; P=0.003) [35]. Pseudo-continuous arterial spin labelling technique performed well for penumbra prediction using the DL model (AUC=0.958) [36]. The algorithm outperformed traditional ML algorithms and was able to predict eligibility for endovascular therapy according to the criteria of the DEFUSE 3 study (Endovascular Therapy after Imaging for Ischemic Stroke). Another study evaluating various traditional ML models for predicting stroke onset showed that including DL features in the model improved AUC (i.e. DWI-FLAIR mismatch) compared to ground truth, including logistic regression and DL features. The optimal AUC was 0.765 for MR imaging and MR perfusion (MRP) images [37]. Lee et al. [38] used DWI-FLAIR misfit to predict stroke onset time <4.5 hours and found that traditional ML models were more sensitive than stroke neurologists (sensitivity for stroke neurologists = 48.5%, sensitivity for logistic regression was 75.8%, P = 0.020, SVM was 72.7%, P=0.033, RF (random forest) was 75.8%, P=0.013).

3.5. Forecast

Various ML algorithms have been used to predict imaging and clinical outcomes after ischemic stroke. Earlier classical ML studies found that generalized linear models combining DWI and perfusion-weighted MR imaging images were superior to DWI (p=0.02) or PWI (p=0.04) in predicting tissue outcomes in terms of voxels [39]. A CNN-patch sampling based on the Tmax function on MRP outperformed the single voxel-based regression model in predicting final infarct volume with an average accuracy of 85.3 ± 9.1% compared with 78.3 ± 5.5% [40]. Another CNN outperformed other ML methods in predicting final infarct volume including MRI, MRP, and FLAIR data with an AUC of 0.88 ± 0.12 [41]. Fate and showed significantly different final infarct volume (P=0.048) [42]. CNN based on MRP source images was able to predict final infarct volume mit predicted AUC of 0.871 ± 0.024 [43]. A multicenter study showed that the final infarct volume predicted by the attention driven U-Net DL algorithm with DWI and MRP as input was independent of reperfusion status, with a median AUC of 0.92 (IQR, 0.87-0.96) and significant overlap Able to predict baseline plausibility of FLAIR sequences obtained 3-7 days after baseline presentation (dice score, 0.53; IQR, 0.31-0.68)[44]. The e-ASPECTS software was able to predict adverse clinical outcome after thrombectomy (Spearman correlation = -0.15; p = 0.027) and was an independent predictor of adverse outcome in multivariate analysis (OR, 0.79; 95% CI, 0.63-0.99) also showed high consensus with 3 ASPECTS expert readers (ICC = 0.72, 0.74 and 0.76) [45]. Traditional ML techniques combining clinical data and core-penumbra mismatch ratio derived from MR imaging and MRP to determine post thrombolysis clinical outcomes performed with an AUC of 0.863 (95% CI, 0.774–0.951) for short-term (day 7) outcomes and 0.778 (95% CI, 0.668–0.888) for long-term (day 90) outcomes[46]. Decision tree-based algorithms, including Extreme Gradient Boosting and Gradient Boosting Machine, were able to use AUCs of 0.746 (Extreme Gradient Boosting) and 0.748 (Gradient Boosting Machine). Performance was improved when 24-hour NIHSS and recanalization results were included [47]. Machine learning techniques, such as regularized logistic regression, linear Support Vector Machines (SVM), and Random Forest (RF), demonstrated superior performance when compared to current pre-treatment scoring approaches in forecasting positive clinical outcomes (defined as an mRS score of ≤ 2 at the 90-day mark) for patients with the specified medical conditions. The AUC of the ML model for LVO undergoing thrombectomy was 0.85-0.86, while the preprocessing score was 0.71-0.77 [48]. Accuracy of a combined CNN and ANN approach combining clinical and NCCT data in predicting functional thrombolytic outcomes at 24-hour NIHSS The accuracy was 0.71 for a 90-day mRS of 0-1, an improvement of ≥4 and an accuracy of 0.74. Finally, conventional ML techniques and neural networks were used to predict pre-treatment hemorrhagic transformation in acute ischemic stroke from MRP source images and DWI, with the highest AUC of 0.837 ± 2.6% using nuclear spectral regression ML techniques [49]. A limitation of this study is variable recanalization between participants, which may confound the results.

4. LIMITATIONS AND FUTURE WORK

Medical image processing improves patient care. CT scan modelling allows for better diagnosis and simulation provides the best opportunity to practice surgical procedures before performing them. In fact, implementing diagnostic software within the first few hours of a brain obstruction can help detect early signs of ischemia. Here, we find that artificial intelligence provides high-precision and accurate technological solutions for stroke diagnosis, severity and functional outcome prediction. First, the challenge of medical data silos. AI algorithms require large amounts of data, and the accuracy of their results depends largely on the training set on which they were trained. AI algorithms will work well if the training set contains data that reflects the heterogeneity and unpredictability of routine clinical situations. However, in the absence of such training data, it can fail inexplicably. Unfortunately, most of the deep learning algorithms that are deployed have been trained and validated with limited data when comparing the size of medical datasets to those of social networks, Internet applications, automated driving, and other activities for which Health Insurance Portability and privacy concerns are not as stringent as in the health domain. The performance of the trained network can be influenced by the size and quality of the data, which can lead to inadequate generalization. Such public efforts provide datasets and diversification for learning, testing, and validating deep learning algorithms for greater generalization. Further efforts should be made to integrate these datasets to include complex and diverse pathological scans, including organ and tissue scans. It should be noted that the comparative studies presented in this paper are the first steps of the author's research in this area and are intended to bring concrete results in our future work where we intend to propose AI models that can be used in the early detection of stroke, particularly ischemic stroke.

5. CONCLUSION

Early detection and treatment of acute cerebrovascular disease is essential to reduce morbidity and mortality. Current applications of artificial intelligence in this area offer enormous opportunities to improve treatment selection and clinical outcomes by assisting in all stages of diagnosis and treatment, including detection, triage, and outcome prediction. Future research on AI technologies is needed for wider use in different real-world settings. In the future, we plan to propose a method to classify ischemic stroke data, perform feature extraction, and finally synthesize real CT scan data from MRI data, under the constraints of preserving diagnostic criteria.

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AUTHORS

My name is **Sada Anne**, a dedicated academic and researcher who is currently pursuing her doctoral studies while being a part-time lecturer at Alioune Diop University in Bambey. With a deep passion for advancing knowledge in the field of artificial intelligence (AI) methods and their applications in healthcare, especially in the context of stroke research, Sada Anne has established himself as a promising figure in the academic community. My academic career began at Alioune Diop University in Bambey, where I did my undergraduate studies. Throughout my academic career, I have demonstrated keen intelligence and a remarkable ability to solve complex problems in the field of artificial intelligence. Currently, I am immersed in the rigors of doctoral research, where I deepen the field of artificial intelligence and my potential for transformation in the health field. My interest in stroke research illustrates my commitment to addressing critical health care challenges using cutting-edge technologies and data-driven methodologies. In addition to my academic activities, Sada Anne shares his knowledge and passion as a part-time teacher, encouraging the next generation of AI enthusiasts and researchers. My commitment to education and mentoring underscores My belief in the importance of knowledge dissemination and collaborative learning. As an academic and researcher, I am ready to make significant contributions to the fields of artificial intelligence and healthcare. My willingness to push the boundaries of knowledge and sincere desire to improve health care outcomes through innovative artificial intelligence methods are an inspiration. In the ever-changing landscape of artificial intelligence and healthcare, Sada Anne is a promising figure, ready to shape the future of these fields through her unwavering dedication and expertise.