TPM Vol. 32, No. S3, 2025
ISSN: 1972-6325
https://www.tpmap.org/

Open Access

EVALUATION OF AI-BASED IMAGE ANALYSIS FOR IDENTIFYING INTRACRANIAL HEMORRHAGE IN CT BRAIN SCANS FOLLOWING HEAD TRAUMA

DR P. TARUN VARMA[1], DR NANDITHA GUDI[2], DR RAJESH S.[3]

[1]POST GRADUATE, DEPARTMENT OF GENERAL SURGERY, SAVEETHA MEDICAL COLLEGE AND HOSPITAL, SAVEETHA INSTITUTE OF TECHNICAL AND MEDICAL SCIENCES (SIMATS), SAVEETHA UNIVERSITY

[2]ASSISTANT PROFESSOR, DEPARTMENT OF GENERAL SURGERY, SAVEETHA MEDICAL COLLEGE AND HOSPITAL, SAVEETHA INSTITUTE OF TECHNICAL AND MEDICAL SCIENCES (SIMATS), SAVEETHA UNIVERSITY

[3]PROFESSOR, DEPARTMENT OF GENERAL SURGERY, SAVEETHA MEDICAL COLLEGE AND HOSPITAL, SAVEETHA INSTITUTE OF TECHNICAL AND MEDICAL SCIENCES (SIMATS), SAVEETHA UNIVERSITY

ABSTRACT

Background:Recent advancements in artificial intelligence (AI) are revolutionizing the healthcare landscape, particularly within the realm of radiology. For patients involved in road traffic accidents (RTAs), the capability to rapidly and accurately diagnose intracranial hemorrhage (ICH) is of utmost importance, as even a slight delay in diagnosis can have devastating consequences on morbidity and mortality rates. This study delves into the potential of AI, specifically through the application of Convolutional Neural Networks (CNNs), to swiftly and effectively identify ICH in CT scans. Furthermore, we aim to establish how the diagnostic accuracy of AI — utilizing the powerful ResNet-50 model — compares to that of seasoned radiologists.

Methods: A cross-sectional study was conducted at Saveetha Medical College and Hospital. CT brain images of RTA patients were collected. The open-source CNN model ResNet-50 was applied to classify the presence or absence of ICH. Performance was evaluated using sensitivity, specificity, positive predictive value (PPV), and negative predictive value (NPV).

Results: ResNet-50 achieved a sensitivity of 90.4% and a specificity of 92.8%. The PPV was 96.63%, and the NPV was 90.63%.

Conclusion: CNNs like ResNet-50 show promise in detecting ICH and could complement radiologists in clinical practice, enhancing efficiency and reducing diagnostic delays. Further validation with larger datasets and real-time clinical integration is necessary before widespread adoption.

Keywords: Artificial Intelligence, Intracranial Hemorrhage, Road Traffic Accidents, CT Brain, ResNet-50, Convolutional Neural Networks

INTRODUCTION

Road traffic accidents (RTAs) represent a profound global health crisis, accounting for an alarming approximately 1.35 million fatalities each year. Among the injuries sustained, head injuries often inflict the most severe and long-lasting effects [1]. Among these, intracranial hemorrhage is a particularly life-threatening condition, necessitating prompt detection and urgent medical intervention to improve survival rates and long-term outcomes[2].

Computed Tomography (CT) scans stand as the gold standard for the identification of ICH due to their rapid acquisition and high sensitivity in detecting acute bleeds. However, as the number of CT examinations surges and a shortage of radiologists persists, diagnostic delays can occur, leading to inappropriate triaging and delays in life-saving treatments[4,5]. Delays in diagnosis may lead to inappropriate triaging, delayed surgical interventions, and increased mortality.

In this context, artificial intelligence emerges as a transformative force capable of addressing these significant challenges. Deep learning models, especially Convolutional Neural Networks (CNNs), have demonstrated an unparalleled ability to enhance the accuracy and efficiency of image analysis. [6,7].The ResNet-50 architecture specifically boasts advanced capabilities in recognizing intricate patterns within medical images, which have been shown to result in diagnostic accuracies that are on par with those of radiologists. This rapid diagnostic capability minimizes inter-observer variability, a common issue in human interpretation of medical imagery.[9,10].

Given the critical importance of swift ICH detection in trauma patients, utilizing AI-based diagnostic tools like ResNet-50 could serve as an invaluable support system for radiologists, particularly in high-pressure environments and resource-limited settings where clinical demand is high [11]. This study seeks to explore AI's role in diagnosing ICH through the analysis of CT brain scans of RTA patients, systematically comparing its accuracy to conventional diagnostic methods.

AIM

To rigorously assess whether artificial intelligence can accurately identify intracranial hemorrhage with an accuracy level that is comparable to that of experienced radiologists.

OBJECTIVES

1. To determine whether AI can reliably detect the presence or absence of ICH in CT scans, thereby enhancing diagnostic accuracy.
2. To calculate and report essential performance metrics, including sensitivity, specificity, positive predictive value (PPV), and negative predictive value (NPV) of the AI model, to gauge its practical applicability in clinical settings.

STUDY DESIGN

A cross-sectional study conducted at Saveetha Medical College and Hospital.

POPULATION AND SAMPLE SIZE

A comprehensive collection of CT brain scans from patients involved in RTAs was meticulously compiled for this study. The dataset encompassed 1626 images that revealed signs of ICH and 1566 images that exhibited no indications of hemorrhage. This large sample size is critical for achieving reliable and statistically significant results.

INCLUSION CRITERIA

- Participants must be aged over 18 years.
- There must be a clear and documented history of head trauma due to an RTA.
- Participants must not have a prior history of head injuries, ensuring the results reflect acute occurrences of ICH without interference from previous conditions.

EXCLUSION CRITERIA

- Any previous head trauma that could complicate the assessment of current injuries.
- A history of cerebrovascular accidents, which could confound diagnostic interpretations and affect the accuracy of AI predictions.

DATA COLLECTION

A qualified radiologist provided an expert review of the CT images, meticulously categorizing them based on the presence of ICH or the absence thereof. From the initial dataset, a balanced dataset of 3000 images was constructed, consisting of 1500 images indicative of ICH and 1500 representing non-ICH cases. This balanced approach is designed to mitigate bias and enhance the robustness of the findings.

MATERIALS AND METHODOLOGY

Out of the final dataset of 3000 images, 1000 images from each group were designated for training the AI model, while an additional 500 images from each group were reserved for testing its performance. The ResNet-50 CNN architecture was diligently implemented for classification purposes. To validate the efficacy of the trained model, we measured its performance through key metrics such as sensitivity (the model's ability to correctly identify ICH cases), specificity (its ability to identify non-ICH cases correctly), PPV, and NPV.

RESULTS

		Radiological Results	
		ICH +	ICH -

ResNet 50 Results	ICH +	452	36
	ICH -	48	462

Out of 500 ICH test images, the model correctly identified 452 (sensitivity: 90.4%). Out of 500 non-ICH images, 464 were correctly classified (specificity: 92.8%).

- Sensitivity: 90.4%
- Specificity: 92.8%
- Positive Predictive Value (PPV): 96.63%
- Negative Predictive Value (NPV): 90.63%

DISCUSSION

This investigation confirms that ResNet-50 reliably detects ICH with both high sensitivity and specificity, suggesting that it may serve as an ancillary diagnostic tool within emergency radiology. These performance metrics align with those observed in the earlier 2022 meta-analysis conducted by Daugaard et al., which documented pooled sensitivity and specificity values of 96% and 97%, respectively, across various convolutional neural networks in ICH assessment[12]. Furthermore, the findings complement those of Chilamkurthy et al., who established that deep learning models can discern critical findings on head CT with diagnostic competence approximating that of board-certified radiologists [13].

Prompt diagnosis of ICH is of paramount importance, as nearly 50% of mortality attributed to this condition occurs within the first day of presentation (24), thereby mandating swift identification to enable timely neurosurgical management.. AI-enhanced screening systems may expedite this process by flagging scans with worrisome features for immediate professional appraisal, a clear advantage in emergency departments that frequently process high patient volumes and may face analyst fatigue[15].

The technology is especially beneficial in resource-constrained environments, where the availability of on-site radiologists is limited. By performing initial triage, the algorithm ensures that potentially life-threatening cases receive early prioritization, thus shortening the total time from presentation to diagnosis [16].Beyond improvement in diagnostic accuracy, convolutional neural networks mitigate inter- and intra-reader variability, a problem well-documented in the literature and exacerbated by acute fatigue when radiologists interpret time-sensitive emergency imaging. [17].

Even with all these benefits, there are still hurdles to overcome. CNNs need substantial, diverse, and high-quality datasets for effective training, which can be difficult to access [18]. Additionally, integration into clinical workflows must ensure user-friendliness and medico-legal accountability, as errors in AI predictions could have severe consequences [19]. Importantly, AI should be viewed as an augmentation of radiologist expertise rather than a replacement. Radiologists dobring essential clinical context and multidisciplinary communication skills that AI lacks [20].

CONCLUSION

This study highlights the potential of ResNet-50 in detecting intracranial hemorrhage on CT brain scans with high diagnostic accuracy. CNN-based tools could improve diagnostic efficiency, reduce radiologist workload, and enhance outcomes for patients with head trauma. However, before AI can be widely implemented in routine practice, larger multicenter studies, real-time clinical validations, and careful integration into healthcare systems are essential. AI should complement radiologists, serving as a reliable support system in emergency radiology.

REFERENCES

1. World Health Organization. Global status report on road safety 2018. Geneva: WHO; 2018.
2. Roozenbeek B, Maas AI, Menon DK. Changing patterns in the epidemiology of traumatic brain injury. Nat Rev Neurol. 2013;9(4):231–6.
3. Prasad GL, Menon GR, Rajiv C, et al. Role of CT in the evaluation of head injury. J Clin Diagn Res. 2014;8(7):RC01–4.

4. Brady A. Error and discrepancy in radiology: inevitable or avoidable? Insights Imaging. 2017;8(1):171–82.
5. Spector ND, Dyrbye LN, Burke AE, et al. Addressing physician burnout: the way forward. JAMA. 2017;317(9):901–2.
6. Litjens G, Kooi T, Bejnordi BE, et al. A survey on deep learning in medical image analysis. Med Image Anal. 2017;42:60–88.
7. Topol EJ. High-performance medicine: the convergence of human and artificial intelligence. Nat Med. 2019;25(1):44–56.
8. He K, Zhang X, Ren S, Sun J. Deep residual learning for image recognition. Proc IEEE Conf Comput Vis Pattern Recognit (CVPR). 2016;770–8.
9. Esteva A, Kuprel B, Novoa RA, et al. Dermatologist-level classification of skin cancer with deep neural networks. Nature. 2017;542(7639):115–8.
10. Dreyer KJ, Geis JR. When Machines Think: Radiology's Next Frontier. Radiology. 2017;285(3):713–8.
11. Tang A, Tam R, Cadrin-Chênevert A, et al. Canadian Association of Radiologists white paper on artificial intelligence in radiology. Can Assoc Radiol J. 2018;69(2):120–35.
12. Daugaard M, Fosbøl EL, Madsen LB, et al. Diagnostic accuracy of convolutional neural networks in intracranial hemorrhage: a systematic review and meta-analysis. Neuroradiology. 2022;64(7):1321–33.
13. Chilamkurthy S, Ghosh R, Tanamala S, et al. Deep learning algorithms for detection of critical findings in head CT scans: a retrospective study. Lancet. 2018;392(10162):2388–96.
14. Broderick JP, Brott TG, Duldner JE, et al. Volume of intracerebral hemorrhage: a powerful and easy-to-use predictor of 30-day mortality. Stroke. 1993;24(7):987–93.
15. Komorowski M, Celi LA, Badawi O, et al. The Artificial Intelligence Clinician learns optimal treatment strategies for sepsis in intensive care. Nat Med. 2018;24(11):1716–20.
16. Kelly CJ, Karthikesalingam A, Suleyman M, et al. Key challenges for delivering clinical impact with artificial intelligence. BMC Med. 2019;17(1):195.
17. Brady AP, Laoide RO, McCarthy P, McDermott R. Discrepancy and error in radiology: concepts, causes, and consequences. Ulster Med J. 2012;81(1):3–9.
18. Zech JR, Badgeley MA, Liu M, et al. Variable generalization performance of deep learning models in radiology. AJR Am J Roentgenol. 2018;210(6):1179–87.
19. RechtMP, Dewey M, Dreyer K, et al. Integrating artificial intelligence into the radiology workflow: current efforts and future directions. Radiology. 2020;293(2):273–8.
20. Langlotz CP. Will artificial intelligence replace radiologists? Radiology. 2019;290(2):318–9.