UNIVERSA MEDICINA

pISSN: 1907-3062 / eISSN: 2407-2230

Univ Med 2026;45:322-331

DOI: https://doi.org/10.18051/UnivMed.2026.v45.322-331

REVIEW ARTICLE

Transforming intracranial hemorrhage detection with artificial intelligence: advances in neuroimaging

Finidya Septiani[1]*, Vininta Fazharyasti[1,2], Terawan Agus Putranto[1,2], Nataliandra N. Maarifat[1,2], Samuel Tandionugroho[1,2], and Muhammad Irvanie Rama Harahap[1,2]

[1]Department of Radiology, Universitas Pembangunan Nasional Veteran Jakarta, Jakarta, Indonesia

[2]Department of Radiology, Gatot Soebroto Army Hospital, Jakarta, Indonesia

*** Correspondence Author:**

septianifinidya@gmail.com

Date of first submission, March 28, 2026
Date of final revised submission, August 8, 2026
Date of acceptance, August 23, 2026

Cite this article as: Septiani F, Fazharyasti V, Putranto TA, Maarifat NN, Tandionugroho S, Harahap MIR. Transforming intracranial hemorrhage detection with artificial intelligence: advances in neuroimaging. Univ Med 2026;45:322-331

ABSTRACT

Intracranial hemorrhage (ICH) represents a challenging neurological emergency, characterized by bleeding within the cranial vault. Timely intervention in this case is directly linked to reduced mortality and prevention of permanent sequelae. The interpretation of radiological examination for ICH is full of challenges, including anatomical variations, imaging artifacts, and small hemorrhages. Artificial Intelligence (AI), particularly through the application of deep learning (DL) models such as Convolutional Neural Networks (CNNs), has emerged as a transformative adjunctive technology for radiological interpretation. This study reviews the growing field of AI for ICH detection on non-contrast head CT scans. A literature search was conducted in major databases (PubMed, ScienceDirect, SpringerLink, Google Scholar) for English articles from 2016 - 2026 using keywords related to artificial intelligence, deep learning, intracranial hemorrhage, and its variations. The analysis synthesizes performance metrics reported in recent studies, such as sensitivity, specificity, and area under the receiver operating characteristic curve (AUC-ROC). This study explores the potential of AI in quantifying hemorrhage volume, precise localization, classification of hemorrhage subtypes, and integration into clinical workflows for triage and decision support. Challenges and considerations that accompany the clinical translation of AI are also defined, including the need for external validation, the nature of complex algorithms, ethical and legal standings, data security, and integration into existing radiology information systems. The integration of AI into ICH care signifies a paradigm shift from standardized treatment protocols toward dynamic, precision medicine. This review explores the role of AI in augmenting the diagnosis and management of intracranial hemorrhage, emphasizing its role as a powerful tool to enhance the clinical acumen of radiologists.

Keywords: Artificial intelligence, non-contrast computed tomography, deep learning, intracranial hemorrhage

Abbreviations
AI : Artificial Intelligence
AUC: Area Under the Curve
AUC-ROC: Area Under the Receiver Operating Characteristic Curve
CLAIM: Checklist for Artificial Intelligence in Medical Imaging
CNN: Convolutional Neural Network
CT: Computed Tomography

DL: Deep Learning
EDH: Epidural Hematoma
FDA: Food and Drug Administration
ICH: Intracranial Hemorrhage
IPH: Intraparenchymal Hemorrhage
IT: Information Technology
NCCT: Non-Contrast Computed Tomography
ROC: Receiver Operating Characteristic
RSNA: Radiological Society of North America
SAH: Subarachnoid Hemorrhage
SDH: Subdural Hematoma
XAI: Explainable Artificial Intelligence

INTRODUCTION

The human brain, a vital organ with unparalleled complexity, is enclosed within the protection of the cranium. This bony enclosure, while offering important mechanical protection, also creates a rigid compartment. Consequently, any pathological accumulation of blood within intracranial space (also broadly termed intracranial hemorrhage (ICH)) poses an immediate and severe danger to both life and neurological function.[1] The ICH comprises several distinct types, each with its own unique pathophysiological mechanism, anatomical predilection, and clinical implications.[2] These types include intraparenchymal hemorrhage (IPH, where bleeding occurs within the brain tissue itself); subdural hematoma (SDH, involving the collection of blood between the dura and the arachnoid mater); epidural hematoma (EDH, characterized by bleeding between the skull and the dura); and subarachnoid hemorrhage (SAH, where blood extravasates into the subarachnoid space surrounding the brain).[3]

The high rates of mortality and permanent disability associated with ICH underscore the critical need for immediate and accurate diagnosis.[1] Every bit of delay in identifying and managing the hemorrhage can lead to irreversible damage due to increased intracranial pressure, mass effect, cerebral ischemia, and excitotoxicity. However, rapid initiation of appropriate therapeutic interventions, ranging from medical management to even neurosurgical or endovascular procedures, is heavily contingent upon the swift and precise radiological identification of the intracranial hemorrhage and its characteristics.[4,5]

Non-contrast computed tomography (NCCT) of the head has long been established as the primary imaging modality and the gold standard for the initial evaluation of suspected ICH in emergency settings due to widespread availability, rapid image acquisition time, and high sensitivity for acute hemorrhage. However, the interpretation of head CT scans remains a challenge. Radiologists must navigate a complex array of potential pitfalls, including:[6] (i) subtle or small hemorrhages that can be easily overlooked; (ii) anatomical variations; (iii) the presence of imaging artifacts; and (iv) lesions that mimic hemorrhage (such as calcifications or tumors).

Moreover, the diagnostic performance can be influenced by the radiologist's level of experience, fatigue, and the inherent subjectivity of human perception.[2,6] These factors collectively contribute to a significant rate of diagnostic errors in ICH detection, with potentially catastrophic consequences for patient outcomes.[7]

The advent of artificial intelligence (AI) and the subfield of deep learning (DL) has ushered in a new era of possibilities in medical image analysis.[5,6] In its broadest sense, it refers to the capability of machines to mimic intelligent human behavior. Moreover, deep learning is a subset of AI inspired by the structure and function of the human brain which employs artificial neural networks with multiple layers to learn hierarchical representations of data from large datasets.[8] Convolutional neural networks (CNNs) have emerged as a particularly powerful class of DL architectures for image-based tasks, demonstrating remarkable success in various domains, including medical imaging.[9] Convolutional neural networks are designed to automatically learn spatial features from input images, making them exceptionally well-suited for identifying complex patterns such as those associated with ICH on CT scans.[10]

The application of AI algorithms can be trained to rapidly analyze NCCT images, flag potential hemorrhages, quantify their volume, classify their type, and even prioritize urgent cases for further radiologist review. This capability has the potential to significantly reducing turnaround times for critical findings while also minimizing the risk of human oversight.[1,2,6] This literature review aims to provide a critical synthesis of the current state of AI for the detection of intracranial hemorrhage on non-contrast head CT scans, its challenges and future directions on how AI can serve as an adjunctive tool especially in radiology.

METHODS

This narrative review synthesized current evidence on the use of artificial intelligence and deep learning architecture in the detection of intracranial hemorrhage using non-contrast brain CT-scan. To ensure broad coverage of the relevant literature, a structured search was conducted of major biomedical and engineering databases, including PubMed, ScienceDirect, SpringerLink, and Google Scholar. The keywords used to perform the literature search from the date of inception up to March 15th, 2026, were "artificial intelligence", "deep learning", "intracranial hemorrhage", "computed tomography", and their variations. The search focused on studies addressing AI-related methodologies and technologies relevant to ICH, such as machine learning, deep learning, neuroimaging analysis, prognostic modelling, surgical navigation, and brain–computer interface. Initially, 3,399 articles were found to match the inclusion criteria, but eventually, only 55 articles were selected for analysis and synthesis. A total of 1,310 articles were removed due to duplication, 870 articles were not performed on humans and 460 articles were either abstract only, case report, and editorial study. Record screening found 317 irrelevant studies and 210 basic experimental trials. A total of 22 articles were removed due to lack of access and 155 articles were removed due to lack of useful data or different imaging techniques (Figure 1).

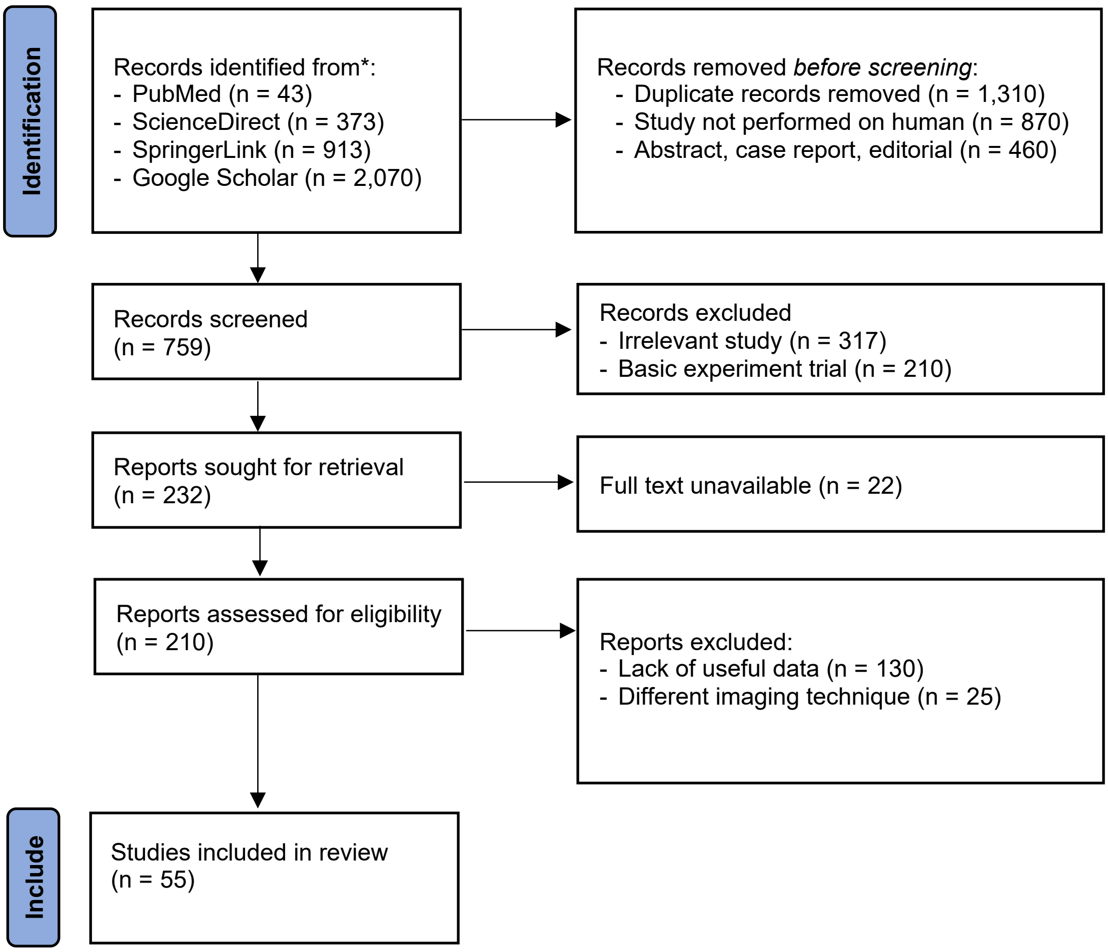

Figure 1. Study identification flowchart

The "armamentarium" of artificial intelligence for detecting ICH

The quest to harness the power of Artificial Intelligence for the detection of intracranial hemorrhage (ICH) has led to the exploration and development of a diverse array of computational methodologies. Among these, DL, and particularly CNNs, have emerged as the predominant and most successful approaches.[11] These sophisticated algorithms are designed to automatically learn intricate patterns and features directly from medical images, such as non-contrast head CT scans, enabling them to identify subtle signs of hemorrhage that might be challenging for the human eye, especially under suboptimal conditions.[11,12] Understanding the nuances of these methodologies behind AI usage for ICH detection is crucial for appreciating their capabilities, limitations, and potential impact on clinical practice. The most frequently cited and utilized architecture is the CNN. The CNNs are a class of deep learning models specifically designed to process data that has a grid-like topology, such as an image, consisting of convolutional layers as the core building blocks.[13] They employ a set of learnable filters that convolve across the width and height of the input image, computing the dot product between the filter and local regions of the image. This operation allows the network to detect various local features, such as edges, corners, and textures, therefore detecting hyperdense regions suggestive of blood in ICH cases.[13,14]

Multiple filters are typically used in each convolutional layer to learn a diverse set of features. As the image progresses through successive convolutional layers, the network learns to recognize increasingly complex and abstract features. Pooling layers, often interspersed between convolutional layers, serve to reduce the spatial dimensions (width and height) of the feature maps, decreasing the computational complexity of the network and making the learned representations more robust to small variations. Meanwhile, fully connected layers, typically found at the end of the CNN architecture, take the high-level features learned by the preceding convolutional and pooling layers and use them to perform classification or regression tasks. In the case of ICH detection, the fully connected layers would output a probability indicating the presence or absence of hemorrhage, and potentially classify its type or location.[15,16]

Prior studies mention several specific CNN variants that have been applied to ICH detection, each with its own innovation in the field. The U-Net architecture, originally developed for biomedical image segmentation, has been widely adopted for ICH detection and segmentation tasks due to its encoder-decoder structure that enables precise localization.[17] Meanwhile, residual networks (ResNet) have addressed the vanishing gradient problem in deep networks, enabling the training of substantially deeper architectures that have achieved state-of-the-art performance in ICH classification.[18] Dense convolutional networks (DenseNet) have improved feature propagation and reuse, demonstrating strong performance in multi-class ICH subtype classification.[19]

Transfer learning has also emerged as a valuable technique in ICH detection, where pre-trained models on large natural image datasets are fine-tuned for medical imaging tasks. A previous study has demonstrated that transfer learning can achieve high accuracy in classifying ICH subtypes, with overall accuracy reaching 89.64% and 82.5% respectively, even with limited medical imaging data.[20] This approach leverages the hierarchical feature learning already captured in pre-trained networks, reducing the data requirements for training effective ICH detection models.[21] Three-dimensional (3D) CNNs have been developed to capture the volumetric context of CT scans, processing entire CT volumes rather than individual slices. These architectures can leverage the spatial relationships between adjacent slices, potentially improving detection accuracy for hemorrhages that span multiple slices.[22] Hybrid models combining 2D and 3D approaches have also shown promise in balancing computational efficiency with volumetric context understanding.[23] The selection of a specific AI architecture often involves trade-offs between performance, computational complexity, interpretability, and the specific requirements of the clinical task (as in simple detection vs. detailed segmentation and classification). The ongoing research and development in this field continue to refine these architectures and explore novel hybrid approaches to further enhance the accuracy and robustness of AI for ICH detection.[24]

Performance evaluation and clinical integration of AI for ICH detection

The transition of AI models from experimental frameworks to instruments of tangible clinical worth depends critically on thorough performance assessment and their incorporation into established medical workflows. In the domain of ICH identification, the efficacy of AI algorithms is customarily gauged through conventional metrics derived from the confusion matrix, which contrasts the algorithm's accuracy against a reference standard, typically defined by the consensus of experienced radiologists interpreting the images. These quantitative measures furnish insights into an AI model's diagnostic precision, dependability, and prospective influence on patient management.[25,26]

There are several performance indicators to quantify AI detection prowess. These include sensitivity, denoting its capacity to accurately recognize true instances of ICH; specificity, reflecting its ability to correctly identify studies devoid of hemorrhage; overall accuracy, representing the aggregate proportion of correct classifications; and the area under the receiver operating characteristic curve (AUC-ROC). [27,28] The AUC-ROC metric condenses the model's discriminative ability across all conceivable classification thresholds into a singular value; an AUC of 1.0 signifies flawless classification, whereas a value of 0.5 indicates performance equivalent to flipping a coin. For instance, a recent study demonstrated that AI algorithms achieve 89-90% sensitivity and 93-95% specificity for detecting brain hemorrhage on CT scans, matching or exceeding human radiologist performance.[29] Similarly, another systematic review reported pooled sensitivity of 92.3% and specificity of 94.8% across multiple ICH detection studies.[30]

This demonstration of high accuracy suggests that AI models can attain diagnostic proficiency on par with that of human specialists in identifying ICH on non-contrast CT examinations. Such elevated performance accentuates the models' potential as a formidable screening instrument, particularly for discerning subtle or readily overlooked hemorrhagic lesions. Nevertheless, a cautious interpretation of these metrics is imperative, taking into account variables such as the composition and magnitude of the datasets utilized for model training and evaluation, the prevalence of ICH within these datasets, and the precise criteria employed to define the reference standard.[31,32] Moreover, in a screening context, maximizing sensitivity is often prioritized to curtail false negatives (missed hemorrhages), even if this entails a marginal compromise in specificity (resulting in more false positives), as false positives can be subsequently filtered through expert human review.[33]

The practical utility of AI transcends mere detection; its effective assimilation into the clinical workflow is a decisive factor governing its real-world applicability. A prevalent strategy involves leveraging AI for worklist triage and prioritization.[34] The AI algorithms can process incoming CT scans with minimal latency and designate studies exhibiting a high likelihood of ICH, elevating their priority within the radiologist's interpretation queue. This form of "active reprioritization" seeks to diminish the time-to-diagnosis for critical cases, ensuring that patients with potentially life-threatening conditions receive expedited attention. Prior research has demonstrated that AI-based triage can reduce median wait times for positive cases in emergency settings.[35]

An alternative integration presents AI-derived findings as a form of "second opinion" or decision support. This can materialize as a discreet notification on the display upon accessing a potentially positive case, or through the superimposition of AI-generated segmentation masks or heatmaps onto the CT images to accentuate areas of concern.[36] The objective is not to replace the radiologist's diagnostic acumen but to augment it, offering another perspective that can bolster diagnostic confidence and mitigate the probability of oversight. For example, a previous study by Kang et al.[37] revealed that assistance from a deep learning system significantly enhanced the diagnostic precision of non-expert interpreters when evaluating brain CT scans, an effect particularly pronounced when faced with significant diagnostic uncertainty. This indicates that AI tools may hold particular value for clinicians with less specialized training or in clinical environments where access to expert neuroradiological opinion is constrained. (Figure 2)

Several commercial AI tools have received regulatory approval for clinical use in ICH detection. FDA-cleared platforms such as Aidoc, Viz.AI, and RapidAI have been deployed in clinical settings, demonstrating real-world effectiveness in reducing diagnostic delays and improving workflow efficiency.[38,39] A study evaluating the real-world performance of the Viz.AI algorithm demonstrated high accuracy for ICH volume quantification on non-contrast head

CT imaging, supporting its utility in clinical decision-making.[40] However, achieving successful clinical integration necessitates meticulous attention to user interface design, seamless interoperability with existing hospital IT infrastructures, and a thorough understanding of the impact on radiologist behavior and workflow dynamics. The aspiration is to cultivate a symbiotic interaction because AI amplifies the radiologist's capabilities without imposing additional burdens or disruptions.

Navigating the challenges and charting the future of AI in ICH detection

Despite the satisfactory performance metrics reported for AI models in ICH detection, the progression from a validated research algorithm to a dependable, broadly accepted clinical instrument is imposed by substantial challenges. Among the most important is the need for rigorous and comprehensive external validation. A significant proportion of AI models are initially developed and validated using datasets that are relatively homogeneous and often sourced from a single institution. In contrast, the clinical environment is characterized by extensive heterogeneity encompassing diverse patient demographics, variations in CT scanner manufacturers and models, differences in imaging protocols (slice thickness, reconstruction algorithms, radiation dose), and fluctuations in manifestation of pathologies.[41,42]

Consequently, an AI model demonstrating exceptional performance on one specific dataset may exhibit a considerable decline in its effectiveness when applied to data originating from a different institution or acquired with different scanner hardware. This underscores the necessity of evaluating AI models on extensive, multi-institutional, and diverse datasets that accurately mirror the complexities of real-world clinical practice prior to any large-scale deployment.[43,44] External validation studies have revealed that some AI tools demonstrate lower performance in real-world settings compared to published literature, with one study reporting a sensitivity of 75.6% and a specificity of 92.1% in clinical deployment. [45] Furthermore, continuous surveillance of AI performance following clinical implementation is essential to identify any potential drift or deterioration in accuracy over time.[46]

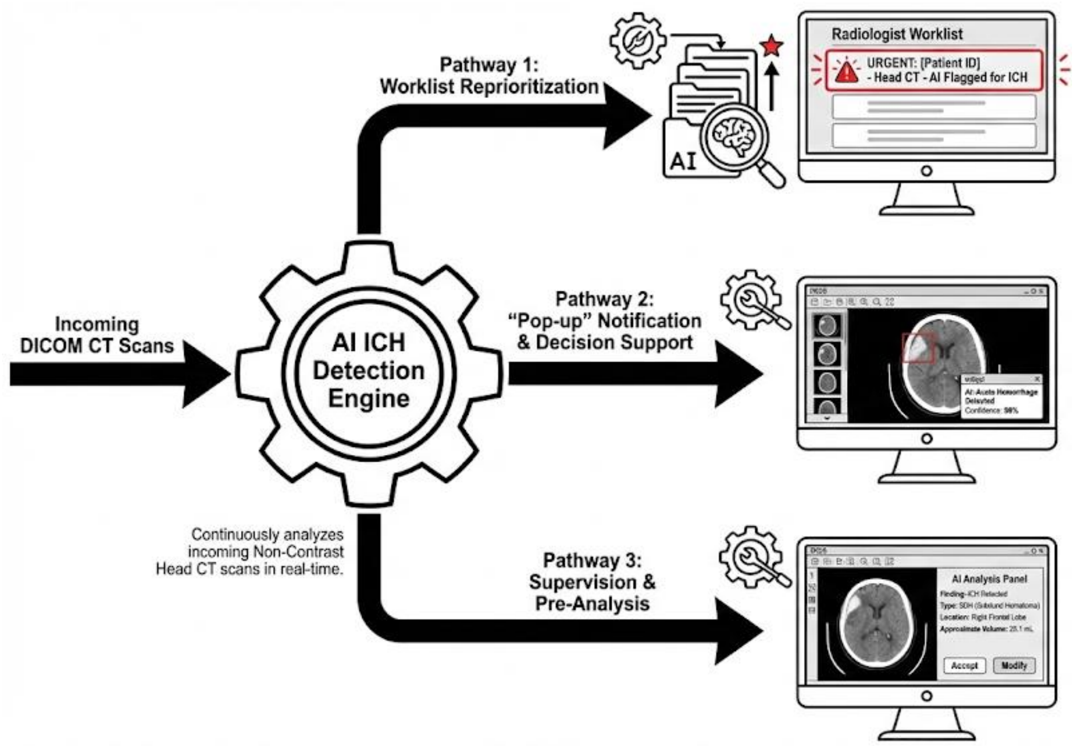

Figure 2. Integration Flow of AI to ICH analysis from Brain CT-scan
(original artwork by the authors)

Another formidable challenge relates to the frequently cited "black box" nature inherent to many deep learning architectures. Although these algorithms can attain remarkable predictive accuracy, the underlying logic driving their decision-making processes often remains incomprehensible to human observers. This deficit in explainability or interpretability can impede trust and acceptance among clinical practitioners, who require an understanding of why an AI system proffers a specific recommendation, especially in high-stakes diagnostic scenarios such as ICH.[47,48] Should the system produce inconsistent results, comprehending its decision-making pathway is vital for ascertaining the root cause and implementing preventive measures for the future. The emergence of explainable AI (XAI) approaches, including attention mechanisms and gradient-based visualization techniques, has begun to address this limitation by highlighting which image regions contribute most to model predictions.[49]

Other significant challenges for the use of AI in healthcare are ethical and legal challenges. The ethical and legal landscape surrounding the deployment of AI in healthcare is equally intricate and multifaceted. Critical issues include patient data privacy and security, the potential for algorithmic bias where AI models might exhibit differential performance across demographic subgroups if trained on non-representative data, and the account of responsibility in instances of diagnostic errors.[50] Previous research has identified sociodemographic biases in commercial AI models for ICH detection, with lower performance observed in certain patient populations, highlighting the urgent need for diverse training datasets and systematic bias assessment before clinical deployment.[51] These concerns necessitate careful establishment of clear regulatory frameworks and guidelines to oversee the development, validation, and clinical application of AI systems.

Looking forward, the role of AI in ICH detection is anticipated to evolve beyond simplistic binary classification. There is a burgeoning emphasis on developing AI models that are proficient in more detailed analytical tasks, such as precise localization and segmentation of hemorrhagic lesions, volumetric quantification of hematoma size, and classification of ICH subtypes.[52,53] Additionally, AI-based prognosis prediction models are being developed to predict functional outcomes and mortality in ICH patients, integrating clinical variables with imaging features to support clinical decision-making.[54] The study by Matsumoto et al.,[55] which investigated the application of transfer learning for ICH detection in postmortem CT imaging, exemplifies the potential for AI utilization in specialized fields such as forensic medicine. Sustained collaboration among radiologists, computer scientists, biomedical engineers, and ethicists will be indispensable for fostering innovation and ensuring that AI technologies are developed and implemented in a manner that maximizes patient benefit while minimizing potential risks.

Despite its comprehensive scope, this review is subject to several limitations that should be acknowledged, such as various deep learning architectures employed in the studies, which may produce different outcomes. Moreover, different inclusion criteria of the subjects in the studies may also influence the results. The different integration approaches in the studies should also be highlighted as it shows distinct consequences.

Artificial intelligence research in ICH spans a spectrum from exploratory retrospective model-development studies—which remain the most prevalent—to externally validated predictive models, and, in rare instances, prospective clinical evaluations or real-world implementations. However, successful generalization requires careful validation against domain-specific data heterogeneity, imaging protocols, and outcome definitions. Prospective multicenter studies evaluating the portability of ICH-trained models to other hemorrhagic or space-occupying lesions—and vice versa—will be essential to establish robust, cross-disease AI platforms. Such efforts align with the broader vision of a learning healthcare system, where AI continuously refines its performance.

CONCLUSION

The integration of artificial intelligence (AI) into the field of neuroimaging for the detection of intracranial hemorrhage represents a paradigm shift with profound implications for patient care. The ability of AI to rapidly analyze imaging and provide objective second opinions can significantly enhance diagnostic efficiency, reduce turnaround times, and mitigate the risk of human error, particularly in high-pressure, high-volume emergency settings. However, the challenges of ensuring generalization through external validation across diverse and heterogeneous real-world datasets remain paramount.

Conflict of Interest

None disclosed.

Acknowledgements

The authors would like to thank the Staff of the Radiology Department at Gatot Soebroto Central Army Hospital for the support regarding the completion of the study.

Funding

The study was fully financed by the authors

Authors' Contributions

FS, VF, TAP, NNM, ST, MIRH contributed to the initial design of the study. FS, VF, TAP, were involved in the data acquisition, FS, VF, TAP, NNM were involved in ~~the~~ data analysis, FS, VF, TAP, MIRH were involved in the interpretation of data included in the study. FS, VF, TAP drafted the manuscript, while VF, TAP, MIRH revised the manuscript. All authors approved the final version of the manuscript.

Data Availability Statement

There are no data associated with this article

Declaration of AI Usage in Scientific Writing

The authors declare that there was no use of generative AI in the research and writing process, and the responsibility for the final manuscript lies entirely with the authors

REFERENCES

1. 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;392:2388-96. doi: 10.1016/S0140-6736(18)31645-3.
2. Flanders AE, Prevedello LM, Shih G, et al. . Construction of a machine learning dataset through collaboration: the RSNA 2019 brain CT hemorrhage challenge. Radiol Artif Intell 2020;2:e190215. https://doi.org/10.1148/ryai.2020190211. Erratum: Radiol Artif Intell 2020;2. DOI:10.1148/ryai.2020209002.
3. Arbabshirani MR, Fornwalt BK, Mongelluzzo GJ, et al. Advanced machine learning in action: identification of intracranial hemorrhage on computed tomography scans of the head with clinical workflow integration. NPJ Digital Med 2018;287:927-34. https://doi.org/10.1038/s41746-017-0015-z.
4. Grewal M, Srivastava MM, Kumar P, Varadarajan S. Radiologist-level accuracy detection of intracranial hemorrhage on computed tomography. arXiv 2018; arXiv:1710.04934. https://doi.org/10.48550/arXiv.1710.04934.
5. Kuo W, Häne C, Mukherjee P, Malik J, Yuh EL. Expert-level detection of acute intracranial hemorrhage on head computed tomography using deep learning. Proc Natl Acad Sci USA 2019;116:22737-45. https://doi.org/10.1073/pnas.190802111.
6. Kang DW, Kim M, Park GH, et al. Deep learning-assisted detection of intracranial hemorrhage: validation and impact on reader performance. Neuroradiology 2025;67:1511-9. doi: 10.1007/s00234-025-03560-x
7. Silva-Filho JE, de Aguiar AWO, Silva CM, de Albuquerque DF, Gurgel-Filho ED. Artificial intelligence in diagnostic imaging: collaborative asset or looming replacement? Oral Radiol 2026;42:473-6. doi: 10.1007/s11282-025-00871-w.
8. LeCun Y, Bengio Y, Hinton G. Deep learning. Nature 2015;52:436-44. doi: 10.1038/nature14539.
9. Litjens G, Kooi T, Bejnordi BE, Setio AAA, et al. A survey on deep learning in medical image analysis. Med Image Anal 2017;42:60-88. doi: 10.1016/j.media.2017.07.005.
10. Hosny A, Parmar C, Quackenbush J, Schwartz LH, Aerts HJWL. Artificial intelligence in radiology. Nat Rev Cancer 2018;18:500-10. doi: 10.1038/s41568-018-0016-5.
11. Ye H, Gao F, Yin Y, et al. Precise diagnosis of intracranial hemorrhage and subtypes using a three-dimensional joint convolutional and recurrent neural network. Eur Radiol 2019;29: 6191-201. doi: 10.1007/s00330-019-06163-2.
12. Cortés-Ferre L, Gutiérrez-Naranjo MA, Egea-Guerrero JJ, Pérez-Sánchez S, Balcerzyk M. Deep learning applied to intracranial hemorrhage detection. J Imaging 2023;7;9:37. https://doi.org/10.3390/jimaging9020037.
13. Shin HC, Roth HR, Gao M. Deep convolutional neural networks for computer-aided detection: CNN architectures, dataset characteristics and transfer learning. IEEE Trans Med Imaging 2016; 35:1285-98. doi: 10.1109/TMI.2016.2528162.
14. Tajbakhsh N, Shin JY, Gurudu SR, et al. Convolutional neural networks for medical image analysis: full training or fine tuning? IEEE Trans Med Imaging 2016;35:1299-312. doi: 10.1109/TMI.2016.2535302.

15. He K, Zhang X, Ren S, Sun J. Deep residual learning for image recognition. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Las Vegas, 27-30 June 2016.p.770-8. doi: 10.1109/CVPR.2016.90.
16. Ronneberger O, Fischer P, Brox T. U-net: convolutional networks for biomedical image segmentation. In: International Conference on Medical Image Computing and Computer-Assisted Intervention. Cham (Switzerland): Springer;2015.p.234-41. https://doi.org/10.48550/arXiv.1505.04597.
17. Wang HC, Wang SC, Xiao F, et al. Development of a clinically applicable deep learning system based on sparse training data to accurately detect acute intracranial hemorrhage from non-enhanced head computed tomography. Neurol Med Chir (Tokyo) 2025;65:103-12. doi: 10.2176/jns-nmc.2024-0163.
18. Huang G, Liu Z, Van Der Maaten L, Weinberger KQ. Densely connected convolutional networks. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition 2017:4700-8. https://doi.org/10.48550/arXiv.1608.06993.
19. Zhou Q, Zhu W, Li F, Yuan M, Zheng L, Liu X. Transfer learning of the ResNet-18 and DenseNet-121 model used to diagnose intracranial hemorrhage in CT scanning. Curr Pharm Des 2022;28:287-95. doi: 10.2174/1381612827666211213143357.
20. Soni J. Toward the detection of intracranial hemorrhage: a transfer learning approach. Art Int Surg 2025;5:221-38. http://dx.doi.org/10.20517/ais.2024.46.
21. Raghu M, Zhang C, Kleinberg J, Bengio S. Transfusion: understanding transfer learning for medical imaging. In: Advances in Neural Information Processing Systems. 33rd Conference on Neural Information Processing Systems (NeurIPS 2019), Vancouver, Canada. https://doi.org/10.48550/arXiv.1902.07208.
22. Chang PD, Kuoy E, Grinband J, et al. Hybrid 3D/2D convolutional neural network for hemorrhage evaluation on head CT. Am J Neuroradiol 2018;39:1609-16. doi: 10.3174/ajnr.A5742.
23. Burduja M, Ionescu RT, Verga N. Accurate and efficient intracranial hemorrhage detection and subtype classification in 3D CT scans with convolutional and long short-term memory neural networks. Sensors (Basel) 2020;20:5611. doi: 10.3390/s20195611.
24. Agarwal S, Wood D, Grzeda M, et al. Systematic review of artificial intelligence for abnormality detection in high-volume neuroimaging and subgroup meta-analysis for intracranial hemorrhage detection. Clin Neuroradiol 2023;33:943-56. doi: 10.1007/s00062-023-01291-1.
25. Zhao M, Li W, Hu Y, et al. Deep-learning tool for early identification of non-traumatic intracranial hemorrhage etiology and application in clinical diagnostics based on computed tomography (CT) scans. Peer J 2025;13:e18850. doi: 10.7717/peerj.18850.
26. Xia X, Zhang X, Cui J, et al. Difference of mean Hounsfield units (dHU) between follow-up and initial noncontrast CT scan predicts 90-day poor outcome in spontaneous supratentorial acute intracerebral hemorrhage with deep convolutional neural networks. Neuroimage Clin 2023;38:103378. doi: 10.1016/j.nicl.2023.103378.
27. Saito T, Rehmsmeier M. The precision-recall plot is more informative than the ROC plot when evaluating binary classifiers on imbalanced datasets. PLoS One 2015;10:e0118432. doi: 10.1371/journal.pone.0118432.
28. Karamian A, Seifi A. Diagnostic accuracy of deep learning for intracranial hemorrhage detection in non-contrast brain CT scans: a systematic review and meta-analysis. J Clin Med 2025;14:2377. doi: 10.3390/jcm14072377.
29. Alhasan MS, Azzam AY, Alhasan AS, et al. Diagnostic performance and clinical applications of artificial intelligence for intracranial bleeding detection: a meta-analysis. Brain Spine 2025;5:105866. doi: 10.1016/j.bas.2025.105866.
30. Maghami M, Sattari SA, Tahmasbi M, Panahi P, Mozafari J, Shirbandi K. Diagnostic test accuracy of machine learning algorithms for the detection intracranial hemorrhage: a systematic review and meta-analysis study. Biomed Eng Online 2023;22:114. doi: 10.1186/s12938-023-01172-1.
31. Oakden-Rayner L, Dunnmon J, Carneiro G, Re C. Hidden stratification causes clinically meaningful failures in machine learning for medical imaging. In: Machine learning for medical imaging. Proc ACM Conf Health Inference Learn (2020) ;2020:151-9. doi: 10.1145/3368555.3384468.
32. Zech JR, Badgeley MA, Liu M. Variable generalization performance of a deep learning model to detect pneumonia in chest radiographs: a cross-sectional study. PLoS Med 2018;15:e1002683. doi: 10.1371/journal.pmed.1002683.
33. Xu Y, Huang C. Artificial intelligence for traumatic brain injury imaging: a translational review from algorithm development to clinical implementation. Front Neurol 2026; 17:1798780. doi: 10.3389/fneur.2026.1798780.
34. Prevedello LM, Erdal BS, Ryu JL, et al. Automated critical test findings identification and online notification system using artificial intelligence in imaging. Radiology 2017;285:923-31. doi: 10.1148/radiol.2017162664.

35. Gu Z, Dogra S, Siriruchatanon M, Kneifati-Hayek J, Kang SK. Radiology workflow assistance with artificial intelligence: establishing the link to outcomes. J Am Coll Radiol 2026;23:389-8. doi: 10.1016/j.jacr.2025.10.018.
36. Lee H, Yune S, Mansouri M, Kim M, et al. An explainable deep-learning algorithm for the detection of acute intracranial haemorrhage from small datasets. Nat Biomed Eng 2019;3:173-82. doi: 10.1038/s41551-018-0324-9.
37. Kang DW, Kim M, Park GH. Deep learning-assisted detection of intracranial hemorrhage: validation and impact on reader performance. Neuroradiology 2025;67:1511-9. doi: 10.1007/s00234-025-03560-x.
38. Kau T, Ziurlys M, Taschwer M, Kloss-Brandstätter A, Grabner G, Deutschmann H. FDA-approved deep learning software application versus radiologists with different levels of expertise: detection of intracranial hemorrhage in a retrospective single-center study. Neuroradiology 2022;64:981-90. doi: 10.1007/s00234-021-02874-w.
39. Abed S, Hergan K, Pfaff J, Dörrenberg J, Brandstetter L, Gradl J. Artificial intelligence for detecting traumatic intracranial haemorrhage with CT: a workflow-oriented implementation. Neuroradiol J 2026;39:119-25. doi: 10.1177/19714009251346477.
40. Odland I, Liu KJ, Wu D, et al. Real-world evaluation of the accuracy of the Viz.AI automated intracranial hemorrhage volume calculation tool. J Neurointerv Surg 2025;18:234-40. doi: 10.1136/jnis-2024-022564.
41. Neves G, Warman PI, Warman A, et al. External validation of an artificial intelligence device for intracranial hemorrhage detection. World Neurosurg 2023;173:e800-e7. doi: 10.1016/j.wneu.2023.03.019.
42. Salehinejad H, Kitamura J, Ditkofsky N. A real-world demonstration of machine learning generalizability in the detection of intracranial hemorrhage on head computerized tomography. Sci Rep 2021;11:17051 doi: 10.1038/s41598-021-95533-2.
43. Yacoub JH, Bourne MD, Krishnan P. The virtual radiology reading room: initial perceptions of referring providers and radiologists. J Digit Imaging 2023:36;787–93. doi: 10.1007/s10278-022-00745-1.
44. Del Gaizo AJ, Osborne TF, Shahoumian T, Sherrier R. Deep learning to detect intracranial hemorrhage in a national teleradiology program and the impact on interpretation time. Radiol Artif Intell 2024;6:e240067. doi: 10.1148/ryai.240067.
45. Antulov R, Kusk MW, Højrup Knudsen G, Eisner Lynggaard S, Lysdahlgaard S, Antonov V. Real-world integration of an automated tool for intracranial hemorrhage detection in an unselected cohort of emergency department patients—an external validation study. Diagnostics 2026;16:282. doi: 10.3390/diagnostics16020282.
46. Mongan J, Moy L, Kahn CE Jr. Checklist for artificial intelligence in medical imaging (CLAIM): a guide for authors and reviewers. Radiol Artif Intell 2020;2:e200029. doi: 10.1148/ryai.2020200029.
47. Lipton ZC. The mythos of model interpretability. arXiv 2017; arXiv:1606.03490. https://doi.org/10.48550/arXiv.1606.03490.
48. Rudin C. Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead. Nat Mach Intell 2019;1:206-15; doi: 10.1038/s42256-019-0048-x.
49. Caterson J, Lewin A, Williamson E. The application of explainable artificial intelligence (XAI) in electronic health record research: a scoping review. Digit Health 2024;10:20552076241272657. doi: 10.1177/20552076241272657.
50. Gerke S, Minssen T, Cohen G. Ethical and legal challenges of artificial intelligence-driven healthcare. Artificial Intelligence in Healthcare 2020:295–336. doi: 10.1016/B978-0-12-818438-7.00012-5.
51. Trang A, Putman K, Savani D, et al. Sociodemographic biases in a commercial AI model for intracranial hemorrhage detection. Emerg Radiol 2024;31:713-23. doi: 10.1007/s10140-024-02270-w.
52. Arab A, Chinda B, Medvedev G, et al. A fast and fully-automated deep-learning approach for accurate hemorrhage segmentation and volume quantification in non-contrast whole-head CT. Sci Rep 2020;10:19389. doi: 10.1038/s41598-020-76459-7.
53. Ahmed SN, Prakasam P. Intracranial hemorrhage segmentation and classification framework in computer tomography images using deep learning techniques. Sci Rep 2025;15:17151. doi: 10.1038/s41598-025-01317-3.
54. Chen Y, Rivier CA, Mora SA, et al. Deep learning survival model predicts outcome after intracerebral hemorrhage from initial CT scan. Eur Stroke J 2025;10:225-35. doi: 10.1177/23969873241260154.
55. Matsumoto R, Matsuo H, Sugimoto M, et al. Deep learning-based detection of intracranial hemorrhages in postmortem computed tomography: comparative study of 15 transfer-learned models. Appl Sci 2025;15:10513. https://doi.org/10.3390/app151910513.