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Recognizing Intracranial Hemorrhage in CT Images by Deep Learning Models

Haoyu Shi

Penn State College of Engineering, Penn State University, Pennsylvania, United state
hfs5367@psu.edu

Abstract:

Intracranial hemorrhage (ICH) is a life-threatening neurological emergency that requires rapid and accurate diagnosis to improve patient outcomes. While CT imaging is the clinical standard for ICH detection, manual interpretation by radiologists is often time-consuming and prone to variability. In recent years, artificial intelligence (AI) has shown great potential in automating this diagnostic process. This paper presents a comprehensive review of AI-based methods for ICH detection, focusing on three major algorithmic approaches: artificial neural networks (ANNs), convolutional neural networks (CNNs), and vision transformers (ViTs). ANN models provide early insights through manually designed features, while 3D CNNs significantly improve spatial understanding of bleeding areas through end-to-end learning. ViT-based models further advance the field by leveraging global attention mechanisms to capture long-range dependencies between CT slices. This paper highlights key innovations across various categories, discusses the clinical relevance of recent architectures, and identifies challenges currently faced by AI detection, including lack of interpretability, domain generalization capabilities, and patient data privacy issues. Through a modular comparison of representative studies, this research provides valuable insights into the development and deployment of artificial intelligence in neuroimaging tasks. By combining technological advancements with practical considerations, this review aims to provide resources for researchers and clinicians and offer a timely and comprehensive perspective on the ongoing development of AI in medical diagnostics.

Keywords: Intracranial hemorrhage; deep learning; artificial intelligence.

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1. Introduction

Intracranial Hemorrhage (ICH), commonly known as cerebral hemorrhage, is an ICH caused by the rupture of a blood vessel in the brain. This condition can be caused by trauma, hypertension, aneurysm, or other vascular anomalies. ICH is a neurological emergency that has a significant impact on life and requires rapid diagnosis and intervention by a physician. Accurate detection and classification of the type of intracerebral hemorrhage is critical for determining the appropriate treatment.

Previously, detection and evaluation of ICH relied on manual interpretation of Computed Tomography (CT) scans by radiologists [1]. Although experienced physicians can perform this process efficiently, it is time-consuming, prone to human error, and often costly, especially in areas with limited medical specialist resources. In addition, differences in the skill levels of clinicians and diagnostic errors caused by long working hours may lead to inconsistent assessment results, thereby delaying critical treatment. In emergency situations where decisions must be made quickly, these limitations may pose a significant risk to patient treatment. In recent years, artificial intelligence (AI) has become a powerful tool for supporting clinical decision-making in medical imaging by providing faster, more consistent, and lower-cost analysis results [2]. AI-based assistance systems can improve diagnostic efficiency and alleviate doctors' work pressure by quickly screening CT scans to identify potential bleeding, prioritizing urgent cases, and even assisting in distinguishing bleeding types.

AI technologies, particularly deep learning and Convolutional Neural Networks (CNNs) have already demonstrated impressive capabilities in image classification, object detection, and segmentation in fields such as autonomous driving, facial recognition, and natural language processing. These same technologies are now beginning to revolutionize the healthcare sector. For example, Rajpurkar et al. developed the CheXNet model, a 121-layer CNN that achieved the same level of accuracy as radiologists in detecting pneumonia from chest X-rays [3]. Similarly, Google's DeepMind successfully applied artificial intelligence to the segmentation of eye structures in optical coherence tomography (OCT), achieving high precision [4].

Driven by these technologies, researchers are increasingly applying AI models to brain CT scan analysis for ICH detection and classification [5]. These efforts have focused on automated systems for recognizing the presence, type, and location of hemorrhages. Various models have been proposed that utilize advanced deep learning techniques such as 3D CNNs, attention mechanisms, and hybrid architectures that combine imaging data with clinical metadata [6]. For example, Alis et al. (2022) proposed a joint CNN-RNN model with an attention mechanism that captures spatial patterns across slices and preserves contextual information. The attention layer helps focus on key regions, improving both diagnostic accuracy and interpretability in clinical settings [7]. The 3D CNNs extend traditional 2D CNNs by processing volumetric data, allowing the model to learn the spatial patterns of consecutive CT slices rather than processing each slice in isolation. This is because bleeding may span multiple slices and exhibit complex spatial structures. Attention mechanisms draw on natural language processing techniques to assign higher weights to regions with abnormal density or morphology, helping the model focus on the most relevant areas in the scan and thereby improving the interpretability of the image. Hybrid models combine image-based deep learning with structured clinical inputs to achieve context-aware predictions that better reflect a doctor's diagnostic reasoning. The purpose of these models is not only to improve diagnostic accuracy but also to assist in clinical triage, helping to prioritize urgent cases in high-traffic environments and reduce treatment time, which is critical for patient survival and subsequent treatment.

This paper aims to provide a systematic review of recent AI-based ICH analysis methods. It will offer a qualitative summary of key methods, highlighting innovative model designs and clinical applications. The paper discusses methodological strengths and limitations and offers insights into the ongoing challenges and potential future directions for more reliable, transparent, and integrated AI systems in neuroimaging.

2. Methods

2.1 Artificial Neural Networks (ANNs)

2.1.1 Feature-based feedforward ANN

Artificial neural networks have been applied in the early stages of automated intracranial hemorrhage (ICH) detection, primarily relying on handcrafted feature extraction. For instance, Graziano et al. developed a multi-layer feedforward ANN that classified CT scans using statistical, morphological, and pixel-level features extracted from segmented images [8]. The system utilized a manually designed feature set extracted from segmented CT images, including statistical, morphological, and pixel-based descriptors. These features were fed into a multi-layer feedforward ANN for classification. Their method was evaluated on a dataset of 200 head CT scans. The simplicity and interpretability of architecture make it suitable for low-resource settings; however, the reliance on manually engineered features limits its scalability and robustness compared to modern deep learning approaches.

2.1.2 Histogram-based ANN with backpropagation

While Graziano et al. focused on using a structured set of statistical and morphological features, subsequent studies explored variations in preprocessing and network configuration to improve classification performance. For example, Hermawan et al. implemented an ANN model incorporating histogram-based feature extraction and backpropagation training strategies [9]. The workflow involved preprocessing techniques such as grayscale normalization and histogram equalization, followed by segmentation and feature extraction using histogram-based and morphological parameters. These features were input into a feedforward backpropagation neural network trained on a dataset of 100 images. However, similar to other early ANN-based approaches, its performance is constrained by the manual design of features and limited adaptability to complex image patterns.

2.2 Convolutional Neural Networks (CNNs)

2.2.1 2D CNN with clinical integration

The limitations of ANN methods led to a paradigm shift toward CNNs, which offer superior performance by learning features directly from raw CT images without manual engineering. For instance, Chilamkurthy et al. developed one of the earliest large-scale deep learning models for intracranial hemorrhage detection using a 2D CNN architecture [10]. Their model was trained on over 300,000 non-contrast head CT scans, using slice-level annotations for five hemorrhage subtypes. The network included a ResNet-50 backbone for feature extraction and a fully connected classification head. Notably, the model also incorporated a triage module to prioritize critical cases in real-time, representing a significant step toward clinical deployment. This work demonstrated the scalability and clinical value of CNN-based ICH detection.

2.2.2 3D CNN for volumetric analysis

Arbabshirani et al. proposed a 3D CNN architecture to automatically detect intracranial hemorrhage from volumetric CT scans [11]. Unlike 2D slice-based models, their approach processes entire CT volumes to capture spatial continuity across slices. The model was trained on 10,159 annotated CT studies from multiple clinical sites, achieving high performance across diverse scanner types and acquisition protocols. Key contributions include the use of 3D spatial context and end-to-end training, which improved detection of subtle hemorrhages often missed by 2D methods. This work established the clinical utility of 3D CNNs in large-scale, real-world ICH screening.

2.2.3 CNN-RNN hybrid with attention

Alis et al. introduced a hybrid deep learning model combining convolutional and recurrent neural networks (CNN-RNN) with an attention mechanism to detect ICH in non-contrast head CT scans [12]. The model used InceptionResNetV2 as the CNN backbone for slice-level feature extraction and a bi-directional gated recurrent unit (Bi-GRU) to capture inter-slice dependencies. An attention layer was integrated to enhance the model's focus on diagnostically relevant slices.

2.3 Vision Transformers (ViTs)

Despite the success of CNN-based models in capturing local spatial features and achieving high diagnostic accuracy, their inherent limitation lies in the restricted receptive field and difficulty in modeling long-range dependencies. To address this, researchers have recently begun exploring Vision Transformer (ViT) architectures, which leverage self-attention mechanisms to capture global contextual information across CT slices more effectively.

2.3.1 Scopeformer: CNN-ViT hybrid model

Barhoumi and Rasool proposed a hybrid n-CNN-ViT architecture named Scopeformer for intracranial hemorrhage classification [13]. Their method integrates multiple pretrained Xception CNNs as feature extractors, each initialized with different datasets including ImageNet and GAN-augmented CT images. These CNN-generated feature maps are concatenated and passed to a 12-layer Vision Transformer, enabling global attention across enriched multi-scale representations. The model's modularity and feature fusion strategy can address ViT's limitations on small datasets and low-level detail representation.

2.3.2 DeepViT-ICH: lightweight transformer

Roy et al. introduced DeepViT-ICH, a vision transformer model specifically designed for classifying intracranial hemorrhage using non-contrast CT images [14]. The architecture incorporates depth-wise attention to reduce the computational complexity of standard ViT models while maintaining high accuracy. CT slices are preprocessed and embedded into patch tokens, which are then passed through a series of transformer blocks with layer-wise token aggregation. Its primary innovation lies in using a lightweight transformer design.

2.3.3 TransMed: multimodal ViT framework

Huang et al. proposed TransMed, a transformer-based framework for multi-modal medical image classification, demonstrating its adaptability to tasks such as ICH detection [15]. The model combines modality-specific CNN encoders with a vision transformer that fuses features

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across modalities through self-attention. Though originally designed for combining CT and MRI, the architecture effectively captures global dependencies in intra-modality applications as well. Key innovations include hierarchical tokenization and cross-attention for multi-source fusion. The approach highlights the potential of ViTs to integrate diverse clinical inputs, offering a scalable strategy for complex diagnostic tasks involving hemorrhage subtypes.

3. Discussion

3.1 Challenges

Although artificial intelligence has demonstrated outstanding performance in ICH detection, several key challenges remain that limit its widespread application in clinical settings. One key issue is the lack of interpretability in many deep learning models. Most CNN- and Transformer-based architectures operate like "black boxes," unable to provide clear reasoning processes or visual explanations for clinical interpretation when generating predictive results. While tools like Grad-CAM or attention maps can offer some degree of heatmap visualization, the regions related to radiological features—such as hematoma borders, surrounding edema, or tissue displacement—often remain unclear. As Richardson et al. pointed out, both patients and clinicians express significant concerns about the invisibility of AI decision-making, especially when algorithms contradict clinical intuition yet lack transparent explanations [16]. This algorithmic gap erodes patient trust and poses major obstacles to regulatory approval for high-risk diagnostic applications.

Another issue is the limited generalizability of current AI models across different populations and healthcare settings. Many models are trained on data collected from specific demographic groups or fixed national populations, often limited to a single institution. These models often perform poorly when deployed to external datasets, as these datasets typically exhibit differences in data collection parameters, patient anatomical structures, and disease prevalence rates. For example, differences in bone density between ethnic groups or age-related changes in brain atrophy can significantly affect CT image contrast and the visibility of bleeding. When models are not tested on representative populations, AI systems may become overly adapted to specific environments, thereby reducing their safety and effectiveness when performing AI detection on patients in other countries.

The third issue concerns data privacy and the ethical implications of using patient neuroimaging data in large-scale model training. Deep learning models typically require thousands of annotated CT scan images, which necessitates the establishment of centralized data warehouses to aggregate sensitive patient data. However, traditional de-identification procedures often fail to adequately safeguard data security, and patient-specific images may still inadvertently disclose health information. Patients are often unaware that their medical images are being used for model training, and most AI developers lack mechanisms for dynamic consent, data withdrawal, or localized privacy controls. Additionally, the growing reliance on cloud-based data inference and third-party computing platforms has heightened concerns about data regulation and international information transmission. Integrating such privacy protection tech-nologies is crucial for ensuring patient autonomy, legal compliance, and long-term trust in AI systems.

Finally, even with high diagnostic accuracy, AI models must overcome practical barriers to clinical integration. Many systems were not designed with real-world hospital infrastructure in mind, resulting in limited interoperability with Picture Archiving and Communication Systems (PACS), triage workflows, and reporting protocols. Richardson et al. noted that the practicality of AI depends not only on performance metrics but also on its ability to enhance clinical decision-making in a transparent and collaborative manner, rather than relying solely on the judgment of clinicians [16]. Current AI tools often lack user interfaces that support interactive feedback or real-time monitoring by clinicians. Additionally, the introduction of AI must avoid introducing cognitive load, time burden, or legal ambiguity into the diagnostic process.

3.2 Future Prospects

Looking ahead, there are several directions that hold promises for addressing the current limitations of ICH detection. To enhance the interpretability of AI, future models may integrate domain-specific knowledge and rule-based expert systems to help align AI outputs with clinical reasoning. Visualization tools like Grad-CAM could be further refined to provide neuroscientists with clearer, anatomically accurate explanations, thereby improving credibility and usability. Similarly, to address the issue of limited generalization capabilities, current AI development efforts should explore some advanced adaptive technologies such as domain adaptation and domain generalization algorithms. These methods enable models to adapt to different imaging protocols and patient populations, ensuring more robust performance across diverse clinical settings. Finally, to protect patient privacy, maintaining data decentralization can reduce the risk of data breaches and enhance compliance with privacy regulations. To transition artificial intelligence from research prototypes to routine radiology care, future efforts must adopt a socio-technical perspective, requiring the collaborative involvement of physicians, ethicists, and patients at every stage of system development, deployment, and evaluation. These strategies collectively pave the way for safer, more reliable, and clinically relevant medical artificial intelligence imaging tools.

4. Conclusion

In summary, artificial intelligence shows great market potential in the detection and classification of intracranial hemorrhage using CT imaging technology. From early artificial neural networks to advanced CNNs and transformer-based architectures, AI models have achieved gradual improvements in accuracy, efficiency, and clinical applicability. However, this technology still faces several key challenges, including limited interpretability, poor generalization across different populations, and unresolved privacy issues. Addressing these challenges requires interdisciplinary collaboration, with a focus on explainable AI, robust domain adaptation, and privacy-preserving training techniques such as federated learning. Future AI development should also prioritize clinical integration and user-centered design to ensure that AI tools not only perform well technically, but also enhance trust, transparency, and usability in actual medical settings. Through continuous innovation and professional deployment, AI is likely to become an indispensable and powerful assistant in the fields of neuroimaging and emergency diagnosis in the future.

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