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Intracranial Hemorrhage Diagnosis Using Deep Learning: A Survey of Techniques, Frameworks, and Challenges

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ABSTRACT

Intracranial hemorrhage (ICH) is a life-threatening medical emergency that demands rapid and accurate diagnosis to improve survival and clinical outcomes. With advancements in artificial intelligence (AI), particularly deep learning, significant progress has been made in automating ICH detection, segmentation, and classification using medical imaging data, especially computed tomography (CT) scans. This survey presents a detailed analysis of various deep learning architectures, such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), U-Net, and hybrid ensemble methods, applied in ICH research. We review key segmentation and classification models, discuss optimization strategies, explore the role of synthetic data and augmentation, and emphasize the increasing importance of explainable AI in clinical practice. Publicly available datasets and evaluation metrics are also examined to highlight the current landscape. Our work emphasizes studies published mostly in the past five years, addressing gaps in prior surveys such as the limited focus on augmentation strategies and interpretability. The paper concludes by identifying persistent challenges and proposing future directions for research to enhance clinical applicability of AI-based ICH diagnosis systems.

1. Introduction

Artificial intelligence (AI) is a field of computer science dedicated to building systems that can replicate human cognitive abilities such as reasoning, learning, perception, and decision-making [1]. These systems process large volumes of data to recognize patterns and generate responses, often with greater speed and consistency than human counterparts [2, 3]. At the core of AI are advanced techniques like machine learning and deep learning, which enable machines to improve their performance over time by learning from experience. Unlike traditional rule-based programming, AI

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systems adapt to new data and changing conditions, making them useful for complex, data-intensive tasks [4, 5]. In recent years, AI has seen rapid growth across a wide range of domains, including software development [6], manufacturing processes [7], education [8], finance [9], agriculture [10], legal services [11, 12], media literacy [13], and digital libraries [14]. Simultaneously, increasing expectations for better healthcare outcomes have driven the adoption of AI in medical and health-related fields, where it offers new possibilities for addressing long-standing challenges.

AI is increasingly being applied in medicine to address challenges like limited healthcare resources and rising patient needs. In medical imaging, AI assists in tasks such as segmentation, disease detection, and image enhancement, improving diagnostic accuracy and efficiency [1, 15]. In genetic testing, it helps analyze complex genetic data quickly and accurately, enabling better disease prediction and personalized treatments [16-18]. AI also contributes to drug development by speeding up drug discovery and reducing costs [19]. In clinical practice, it supports doctors in diagnosis and treatment planning, with proven success in areas like diabetic retinopathy and skin cancer detection [20, 21]. Beyond diagnostics, AI tools assist patients in understanding symptoms and managing their care [22, 23], while future applications may include robotic surgery [24, 25] and virtual nursing [26]. These advancements highlight the need to incorporate AI and its ethical implications into medical education [27].

Brain diseases represent a wide and critical category of medical conditions that affect the structure and function of the brain, often leading to serious or irreversible damage [28]. Disorders such as stroke, brain tumors, sleep disturbances, multiple sclerosis, epilepsy, Parkinson’s disease, and various forms of dementia are among the most commonly encountered neurological issues [29]. In clinical practice, understanding the type, location, severity, and possible outcomes of these diseases is crucial for effective care [30]. AI has emerged as a powerful tool in this context, with applications that span from preprocessing steps [31-33] to advanced diagnostic modeling [34, 35]. AI techniques are increasingly used to support key tasks such as segmenting lesions, classifying disease subtypes, detecting pathological brain tissue, and predicting patient outcomes. These methods are especially valuable in analyzing large volumes of brain data, which often require precise localization of abnormalities and detailed structural analysis [36, 37].

Intracranial hemorrhage (ICH) is a critical neurological emergency involving bleeding within the brain tissue or surrounding meningeal spaces [38]. It accounts for a significant proportion of stroke cases and is associated with high rates of mortality and long-term disability. Patients who survive an ICH episode often require intensive rehabilitation to address complications such as cognitive impairment, motor dysfunction, and mental health issues [39, 40]. Early and accurate diagnosis is essential to improving outcomes [41], yet in emergency settings, time constraints and the limited availability of experienced radiologists often hinder prompt evaluation. This diagnostic bottleneck is particularly pronounced in low-resource environments, where delays or errors can have life-threatening consequences [42, 43]. To address these challenges, AI has been introduced as a supportive tool in the assessment of ICH. AI models, especially those based on medical imaging, can quickly process brain scans to detect signs of hemorrhage, prioritize urgent cases, and assist clinicians in making faster, more reliable decisions [44]. By alleviating the diagnostic burden on radiologists and improving consistency in emergency care, AI offers a promising avenue for enhancing ICH management and patient survival.

This survey provides a comprehensive and structured overview of the current landscape of deep learning approaches applied to ICH detection, segmentation, and classification using computed tomography (CT) imaging. This work makes the following key contributions:

- Reviewing studies published primarily in the past five years, ensuring coverage of the most up-to-date and clinically relevant advances.
- Tracing the progression of deep learning architectures and their applications in ICH detection, segmentation, and classification.
- Highlighting augmentation strategies, synthetic data generation, and optimization techniques as critical enablers for overcoming data scarcity and improving model performance.
- Emphasizing the increasing role of explainable AI in bridging the gap between high-performing algorithms and real-world clinical adoption.
- Reviewing publicly available datasets and evaluation protocols, offering a structured reference for benchmarking.
- Identifying persistent limitations and propose research pathways to enhance the clinical applicability of AI-based ICH diagnosis systems.

The rest of the paper is organized as follows: Section 2 provides an overview of the clinical variants of ICH. Section 3 introduces deep learning algorithms commonly used in ICH research. Section 4 presents deep learning frameworks developed for ICH detection and analysis. Section 5 reviews publicly available datasets for ICH, while Section 6 outlines the evaluation metrics used to assess model performance. Section 7 discusses the current challenges and future directions in the field, and finally, Section 8 concludes the survey.

2. Classification and Clinical Variants of Intracranial Hemorrhage

ICH is a broad term encompassing various forms of bleeding within the skull, each differing in location, underlying cause, and clinical severity. The classification of ICH is typically based on the anatomical location of bleeding [45], presented in Figure 1.

The most common category is intracerebral hemorrhage, which refers to bleeding directly into the brain tissue. This can be further subdivided into two subtypes: intraparenchymal hemorrhage (IPH) and intraventricular hemorrhage (IVH). IPH typically results from chronic hypertension, trauma, or the hemorrhagic transformation of ischemic stroke, and involves bleeding within the functional brain tissue [46, 47]. IVH, by contrast, affects the ventricular system—the cavities where cerebrospinal fluid is produced and circulated—and may disrupt normal fluid dynamics, leading to dangerous increases in intracranial pressure [48].

Another major subtype is subarachnoid hemorrhage (SAH), which occurs in the space between the pia mater and the arachnoid membrane. The most frequent cause of SAH is the rupture of an intracranial aneurysm, a pathological dilation of a cerebral artery. Although unruptured aneurysms carry a relatively low annual risk of bleeding, their rupture leads to sudden, severe headaches and can result in high rates of disability or death, making early identification and preventive treatment crucial [49, 50].

Subdural hemorrhage (SDH) involves bleeding between the arachnoid membrane and the dura mater, most often caused by head trauma. It may present acutely or develop chronically over days or weeks, particularly in older adults or individuals on anticoagulant therapy. Chronic SDH is associated with slow venous bleeding that gradually compresses the brain, often leading to cognitive or motor decline [51].

Epidural hemorrhage (EDH), by contrast, is bleeding between the dura mater and the inner surface of the skull. It is commonly linked to skull fractures that damage the middle meningeal artery. EDH may lead to rapid neurological deterioration due to the swift accumulation of blood and resultant brain compression. Its hallmark presentation includes a brief lucid interval followed by a sudden loss of consciousness, necessitating immediate surgical intervention [52].

Beyond spontaneous hemorrhages, traumatic intracranial hemorrhage (tICH) is a key consequence of traumatic brain injury (TBI)—a condition arising from external mechanical forces such as falls, motor vehicle accidents, or sports injuries. Although most TBIs are classified as mild, approximately 10% of patients with mild TBI may develop tICH, which can lead to complications such as cerebral vasospasm and may require neurosurgical intervention [53].

These classifications underscore the clinical complexity of ICH and highlight the need for timely, accurate diagnosis. Given the wide range of presentations and high stakes associated with delayed or missed detection, especially in emergency settings, computational tools and AI-based methods are increasingly being explored to support clinical decision-making.

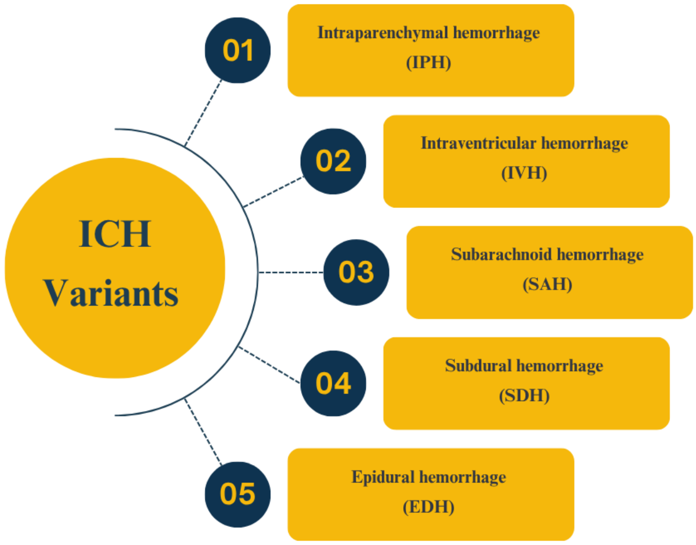

Figure 1: Types of intracranial hemorrhage.

3. Deep learning algorithms used in ICH researches

Recent advancements in deep learning have significantly impacted the field of ICH detection and classification. Deep learning algorithms, with their ability to automatically extract complex features from medical images, have shown superior performance compared to traditional machine learning methods (see Figure 2). Among these, convolutional neural networks (CNNs) and their variants have been the cornerstone due to their exceptional capability in spatial feature extraction from CT scans. Additionally, recurrent neural networks (RNNs) and their advanced forms like long short-term memory (LSTM) and bidirectional long short-term memory (BiLSTM) have been employed to capture sequential or contextual dependencies in imaging data. Furthermore, specialized architectures such as U-Net have been extensively used for precise segmentation of hemorrhagic regions.

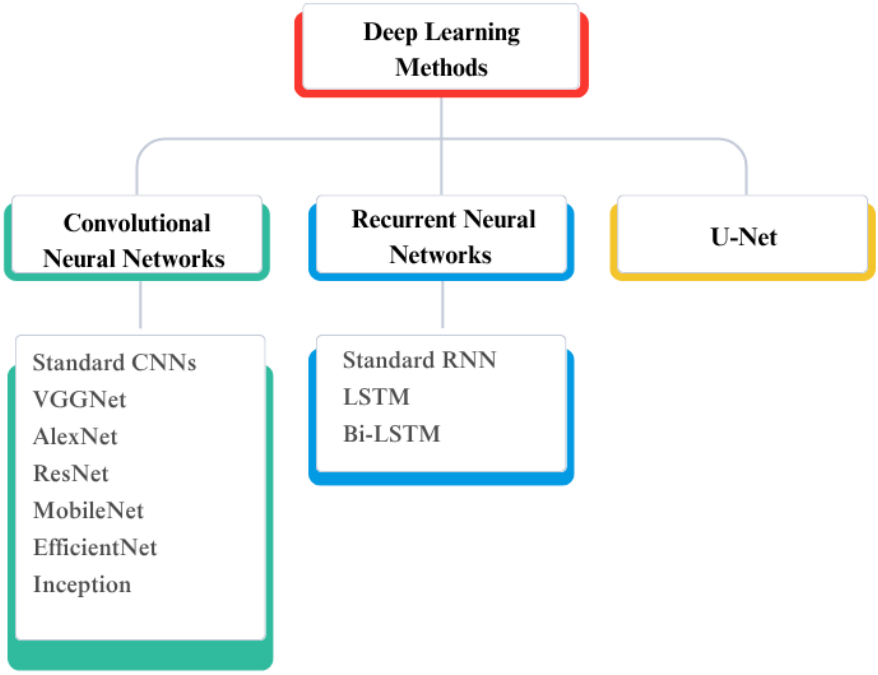

Figure 2: The most common algorithms in ICH.

3.1. Convolutional Neural Networks and Variants

3.1.1. Standard CNNs

CNNs are a foundational deep learning architecture specifically designed for analyzing visual data. They operate by progressively learning spatial hierarchies of features from images through a sequence of specialized layers. A typical CNN is composed of three key types of layers:

- **Convolutional Layer**: This is the core building block where the network learns to detect features such as edges, textures, and patterns by applying filters (kernels) over the input image. These filters slide across the image, producing feature maps that highlight regions of interest. Stacking multiple convolutional layers enables the network to capture increasingly abstract and complex features.
- **Pooling Layer**: Following convolution, pooling layers are used to reduce the spatial dimensions of the feature maps. This process, often performed using max-pooling, helps retain the most prominent features while reducing the number of parameters and computational load. Pooling also introduces a level of translation invariance, making the model more robust to small shifts in the input.
- **Fully Connected Layer**: At the final stage, the high-level features extracted by previous layers are flattened and passed to one or more dense layers. These layers perform the actual decision-making tasks, such as classification or regression. The network's final output is typically generated using a Softmax or sigmoid function, depending on the specific application.

The combination of these layers allows CNNs to learn both local and global patterns in image data, making them particularly effective in medical imaging applications such as detecting ICH in CT scans [54, 55].

3.2.2. VGGNet

VGGNet, developed by the Visual Geometry Group at Oxford, is a deep convolutional neural network architecture that gained prominence for its effectiveness in large-scale image recognition tasks. One of its core design principles is the use of multiple stacked convolutional layers with small 3×33 \times 33×3 kernels, rather than larger single filters. This layered approach enables the network to capture more complex and hierarchical visual features, mimicking the effect of a larger receptive field while maintaining computational efficiency.

There are several versions of VGG, including VGG-11, VGG-13, and VGG-16, which differ primarily in the number of convolutional layers. VGG-11 serves as a baseline model with 8 convolutional layers followed by 3 fully connected layers, while VGG-13 and VGG-16 introduce additional convolutional layers in early and deeper stages respectively, allowing for more fine-grained feature extraction. All versions maintain a consistent use of max-pooling layers (typically 2×22 \times 22×2) to progressively reduce spatial dimensions and computational cost [56-58].

3.3.3. AlexNet

AlexNet is a landmark CNN architecture that played a pivotal role in the resurgence of deep learning for computer vision. Introduced in 2012, it significantly outperformed previous models in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC), cutting the classification error rate in half. The architecture deepened the CNN structure by increasing the number of convolutional and fully connected layers compared to earlier models like LeNet. It also introduced several key innovations: the use of ReLU activation for faster convergence, overlapping max pooling, local response normalization, and training across two GPUs to overcome hardware limitations of the time. Large convolutional filters (such as 11×11 and 5×5) were used in the early layers to capture complex spatial patterns. AlexNet's success demonstrated the potential of deep neural networks on large-scale image datasets and laid the foundation for more advanced CNN architectures that followed [59, 60].

3.3.4. ResNet (Residual Networks)

ResNet introduces residual learning to address the degradation and vanishing gradient problems in deep networks. By using skip connections—which directly pass inputs to deeper layers—ResNet allows the model to learn residuals instead of full mappings. This structure enables the training of very deep architectures like ResNet-50 and ResNet-101 without performance loss. These models combine convolutional layers with residual blocks, followed by pooling and fully connected layers. In ICH detection, ResNet's depth and stability make it well-suited for capturing complex patterns in CT images [61, 62].

3.3.5. MobileNet

MobileNet is a CNN architecture tailored for mobile and embedded devices, where computational resources are limited. Its defining innovation is the use of depth-wise separable convolutions, a technique that breaks standard convolutions into two lightweight operations: depth-wise convolution (which applies filters to each channel independently) and point-wise convolution (which combines the outputs). This design drastically reduces the number of parameters and computational load without sacrificing much accuracy. As a result, MobileNet is ideal for real-time image classification tasks on devices with limited memory and processing power. In the context of ICH detection, MobileNet offers an efficient solution when fast, low-resource inference is required [63].

3.3.6. EfficientNet

EfficientNet is a modern CNN architecture designed to achieve high accuracy while maintaining computational efficiency. Its key innovation is the compound scaling method, which uniformly scales the network's depth, width, and input resolution using a single coefficient. This balanced scaling leads to models that are both powerful and lightweight.

EfficientNet employs MBConv blocks (Mobile Inverted Bottleneck Convolutions), which combine channel expansion and compression to optimize performance while minimizing resource usage. The architecture comes in several versions, from B0 to B7, each progressively more complex. Lighter models like B0–B4 offer a strong trade-off between accuracy and speed, making them ideal for tasks such as ICH detection from CT scans, where both precision and efficiency are crucial [64, 65].

3.3.7. Inception

Inception, or GoogLeNet, is a deep CNN architecture introduced by Szegedy et al. [66] that focuses on improving classification accuracy while minimizing computational cost. Its core innovation is the inception module, which performs parallel convolutions using filters of multiple sizes (1×1, 3×3, 5×5) and pooling operations within the same layer. This design enables the network to extract features at multiple spatial scales simultaneously, following a "split, transform, and merge" strategy. Inspired by the Network-in-Network (NIN) idea [67], Inception replaces traditional layers with these branched blocks for richer and more efficient feature representation.

To further reduce computation, the architecture uses 1×1 convolutions as bottlenecks before larger filters, sparse connections to avoid redundant features, and global average pooling instead of fully connected layers. Auxiliary classifiers are also added to help with training and prevent vanishing gradients. It contains only 4 million parameters—significantly fewer than predecessors like AlexNet—demonstrating high efficiency. However, its complex and heterogeneous module structure can make it less flexible, and the use of bottleneck layers may sometimes reduce important information across stages [68].

3.2. Recurrent Neural Networks and Variants
3.2.1. Standard RNN

RNNs are a foundational class of deep learning models designed specifically to handle sequential data. Unlike traditional feedforward networks that process inputs independently, RNNs maintain an internal memory that enables them to capture information from previous steps in a sequence. This makes them particularly suited for tasks where the order and context of data points matter. The recurrent connections in RNNs allow the model to retain and use past information, essentially giving it a form of temporal awareness. Despite their conceptual power, early RNNs faced significant challenges in practical applications, most notably the vanishing gradient problem. This issue occurs during training, where gradients either diminish or explode as they are backpropagated through long sequences, making it difficult for the network to learn dependencies over extended time intervals.

As a result, standard RNNs struggled with tasks that required understanding relationships across distant elements in a sequence [69, 70].

3.2.2. Long Short-Term Memory (LSTM)

The introduction of LSTM [71] networks marked a major advancement in overcoming RNN limitations. LSTM architecture incorporates a specialized memory cell and a series of gates that regulate the flow of information into, through, and out of the cell. These gates control what information should be kept, updated, or forgotten, allowing the network to maintain important features across long sequences. This enables LSTMs to effectively learn and preserve long-term dependencies, making them a popular choice for various sequence modeling tasks, such as medical time-series analysis, language modeling, and video analysis.

3.2.3. Bidirectional LSTM (BiLSTM)

Building upon the success of LSTM, BiLSTM models further enhance sequence understanding by processing input data in both forward and backward directions. While traditional RNNs and LSTMs only consider past information, BiLSTM networks also integrate future context, offering a more comprehensive view of the entire sequence. This dual perspective is particularly beneficial for tasks where both preceding and succeeding data points influence prediction, such as in medical diagnosis or natural language processing. By maintaining separate memory paths for each direction, BiLSTM models can better capture complex dependencies in sequential data [72].

3.3. U-Net-Based Models

U-Net is a widely used deep learning architecture tailored for image segmentation tasks, especially in medical imaging. Its distinctive U-shaped design consists of two main parts: an encoder (contracting path) and a decoder (expanding path). The encoder progressively extracts hierarchical features from the input image by applying repeated convolution and pooling operations, effectively capturing context at multiple scales. Conversely, the decoder reconstructs the spatial resolution through upsampling and convolution, ultimately producing a segmentation mask with the same dimensions as the original image.

A key feature of U-Net is the skip connections that link corresponding layers in the encoder and decoder. These connections enable the network to fuse shallow, fine-grained features from early layers with deeper, more abstract features, improving localization accuracy and segmentation quality. Despite its strengths, U-Net can encounter difficulties distinguishing between similar structures such as skull and lesion pixels and bridging the semantic gap between low-level and high-level features. Nevertheless, its fully convolutional, end-to-end framework has made U-Net a standard choice for complex image segmentation problems in medical applications [73-75].

4. Deep Learning Frameworks for ICH

The application of deep learning in ICH research has evolved into a structured ecosystem of frameworks that span segmentation, classification, and prognosis modeling. These frameworks leverage diverse architectural paradigms—ranging from encoder-decoder networks like U-Net for precise lesion localization to convolutional and recurrent neural networks for robust subtype classification. Optimization techniques, ensemble learning, and data augmentation further enhance diagnostic performance. Figure 3 provides a conceptual overview of these interrelated components, illustrating how deep learning pipelines are tailored to address specific ICH detection and analysis tasks. This section reviews key frameworks that underpin the current state-of-the-art in ICH-focused deep learning research.

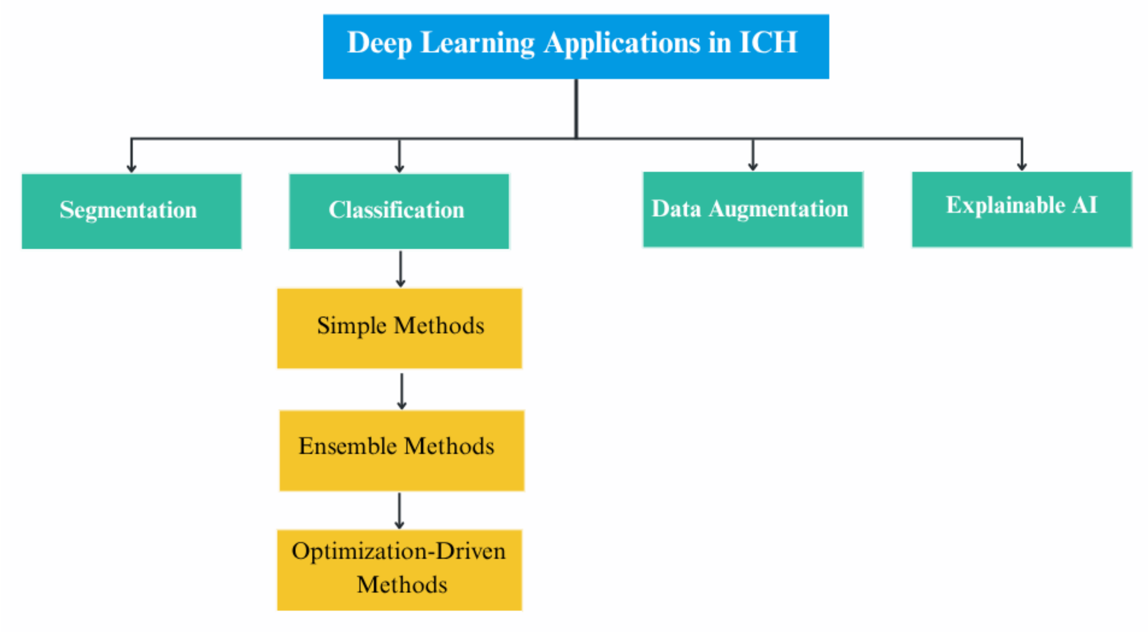

Figure 3: Deep learning for ICH.

4.1 Segmentation Models

Segmentation models for ICH focus on precisely delineating hemorrhagic regions. These approaches predominantly build upon encoder-decoder architectures such as U-Net and its variants, often enhanced with attention mechanisms, adversarial training, and hybrid feature extraction methods. Additionally, traditional and unsupervised segmentation techniques are also explored to complement deep learning frameworks.

Earlier work by Wang et al. [76] applied a basic U-Net for ICH segmentation, leveraging its encoder-decoder structure as a foundational technique. Li et al. [77] proposed a U-Net variant augmented with adversarial training to segment hemorrhagic lesions in 3D CT images. Their method improved segmentation accuracy and robustness; however, it remained limited by the requirement for large labeled datasets to optimize classification performance. Similarly, Hssayeni et al. [78] applied a U-Net model to 3D CT data, validating segmentation performance with Jaccard and Dice coefficients through five-fold cross-validation, confirming high accuracy.

Yuan et al. [79] enhanced the U-Net architecture with residual octave convolution (ResOctConv) modules and a mixed attention mechanism (MAM) to address the semantic gap in segmenting irregular hemorrhage lesions. Tested on CT scans from 40 patients, the improved model outperformed both the standard U-Net and region growing algorithms. Hassan et al. [80] developed a U-Net-based model employing MobileNet and Xception backbones through transfer learning. Trained on the RSNA dataset, their model achieved detection accuracies of 98% for IPH and IVH, and 97% for subdural hemorrhage (SDH). Ahmed and Prakasam [81] introduced IHSNet, a framework integrating MUNet-based segmentation with classification of ICH subtypes. The model attained a segmentation accuracy of 98.53% and classification accuracy of 98.71%. Dice coefficients reported for hemorrhage types were 0.77 (IVH), 0.84 (EDH), 0.64 (IPH), 0.80 (SDH), and 0.92 (SAH), demonstrating strong performance across subtypes.

Beyond supervised methods, Kumar et al. [82] introduced an unsupervised framework utilizing entropy-based techniques for ICH segmentation. The pipeline combines fuzzy c-means (FCM) clustering, skull removal, thresholding, and edge-based active contour models, refined by a level set method initialized with entropy-based thresholding. Tested on CT images from 35 patients, their method surpassed traditional FCM and fuzzy active contour approaches.

Anupama et al. [83] proposed a multi-stage pipeline involving Gabor filtering for image enhancement, followed by grab-cut segmentation integrated with deep learning. Subsequent classification of hemorrhage subtypes using a CNN.

Focusing on acute cerebral hemorrhage, Xu et al. [84] presented CHSNet, which incorporates an encoder-decoder architecture enhanced by Residual Recurrent Convolutional Layers (Res-RCL), Atrous Spatial Pyramid Pooling, and Attention Gates. Trained on 5,998 CT slices from 203 stroke patients, CHSNet achieved Dice scores of 0.918 and Intersection over Union (IoU) of 0.853 on simpler cases, and 0.716 and 0.604 on more complex cases. The model supports 3D visualization and localization of lesions, offering significant clinical utility for stroke diagnosis and treatment planning.

In a novel approach, Wang et al. [85] developed GroupCapsNet, a grouped capsule network aimed at efficient ICH segmentation. By grouping input capsules and modifying the squashing function, GroupCapsNet reduces computational overhead while maintaining segmentation accuracy. Evaluated on 210 CT slices, it delivered competitive results, facilitating neurosurgical treatment planning.

4.2. Classification and diagnosis
4.2.1 Simple Deep Learning-Based Classification

These approaches leverage standalone deep learning architectures—primarily CNNs, RNNs, and artificial neural networks (ANNs)—without extensive use of feature engineering or ensemble methods. The focus lies in direct learning from raw or pre-processed CT scan data to classify ICH types.

Early work by Kuo et al. [86] employed a Deep Convolutional Neural Network (D-CNN) for ICH detection, emphasizing the importance of large-scale annotated datasets for effective model training. Although the model achieved promising results, its dependence on high computational resources and long training times raised concerns about practical deployment in clinical settings.

Gautam and Raman [87] introduced a 13-layer CNN architecture for stroke type classification, incorporating pre-processing techniques such as normalization and contrast enhancement to improve image quality. While their model demonstrated improved classification performance, it similarly relied heavily on abundant training data, a recurring limitation across CNN-based solutions.

Further extending CNN capabilities, Gençtürk et al. [88] proposed a two-stage deep learning framework that first localizes hemorrhagic regions using Mask Scoring R-CNN and then classifies hemorrhages with EfficientNet-B2. Their method achieved notable accuracy on both public and private datasets—over 91% in patient-based evaluations and up to 97.33% in random partitioning—highlighting the advantage of spatial localization prior to classification.

To improve classification robustness and scalability, Soni [55] conducted a comparative study evaluating various pre-trained CNN architectures—including VGGNet, AlexNet, EfficientNetB2, ResNet, MobileNet, and InceptionNet—on the RSNA ICH dataset. The models were enhanced via transfer learning and hyperparameter tuning. Among these, VGGNet implemented within TensorFlow emerged as a particularly effective solution for fast and scalable CT scan classification, underscoring the value of leveraging pre-trained architectures in medical imaging tasks.

Beyond CNNs, Alis et al. [89] explored temporal modeling by adopting RNNs for hemorrhage detection in non-contrast head CT images. While details on implementation and performance were limited, the shift toward RNNs indicates an interest in capturing sequential patterns in imaging data. In another distinct direction, Lee et al. [90] developed an ANN focused on reducing diagnostic latency. While achieving reasonably accurate results, the model struggled with variance and bias, particularly when trained on imbalanced datasets, reflecting a common issue in clinical deep learning applications.

Integrating imaging with clinical data, Wang et al. [91] introduced a 90-day prognosis prediction model for ICH patients using CT scans captured within six hours of symptom onset. Features extracted from hematoma and edema regions using ResNet50 were combined with structured clinical data. Among 1,098 patients, the merged Clinical–Deep Learning model achieved the highest AUC (0.94), significantly outperforming models based solely on clinical or imaging features. This study demonstrates the potential of hybrid input strategies even within end-to-end deep learning pipelines.

4.2.2 Ensemble Deep Models

Ensemble deep learning approaches aim to enhance classification accuracy and generalizability by integrating multiple architectures or combining deep models with traditional classifiers. A foundational effort in this area was presented by Ye et al. [92], who developed a joint CNN-RNN framework to detect ICH and classify its five subtypes. Their retrospective study involved 2,836 subjects and 76,621 non-contrast head CT slices, with radiologist-verified annotations serving as ground truth. The model trained on both subject-level and slice-level labels, achieving excellent performance (AUC $\geq$ 0.98 for binary classification and AUC > 0.8 across all subtypes), while processing a full CT scan in under 30 seconds. Notably, the algorithm outperformed junior radiologists, demonstrating the clinical viability of deep ensemble methods.

Building on similar architecture, Liu et al. [93] proposed an enhanced CNN–RNN framework to address shortcomings of traditional CNNs in ICH subtype classification—namely, poor feature discrimination, class imbalance, and the neglect of subtype interdependencies. Their model introduced a fine-grained CNN module for more nuanced feature extraction and a novel loss function to explicitly model subtype correlations.

In a related line of work, Burduja et al. [94] combined a Bi-LSTM network with the ResNeXt-10 architecture for hemorrhage subtype classification. By aligning temporal sequence modeling (via Bi-LSTM) with powerful spatial feature extraction (via ResNeXt-10), the model showed strong performance when benchmarked against expert radiologist assessments. However, the approach incurred high computational costs, reflecting a trade-off between accuracy and scalability in real-world applications.

A different fusion strategy was explored by Ozaltin et al. [95], who introduced OzNet, a hybrid deep learning pipeline for brain hemorrhage classification. Their method integrated a custom CNN with Neighborhood Component Analysis (NCA) for feature selection and combined the deep features with various classical classifiers. The OzNet-NCA-ANN configuration achieved perfect classification accuracy (100%), emphasizing the potential of combining deep learning with lightweight machine learning models in medical diagnostics.

Similarly targeting the integration of diverse model architectures, Barin et al. [96] proposed a hybrid model that combines EfficientNet-B3 and Inception-ResNet-V2 to classify five ICH subtypes from cranial CT scans. This dual-architecture approach outperformed each individual model, reaching 98.5% accuracy, and showcased the benefits of model complementarity in deep ensemble settings.

Further architectural innovation was introduced by Akram et al. [97] through a dual-branch model based on Xception for ICH subtype classification. Their framework captured both spatial and instantaneous features, which were subsequently merged into 3D spatial context vectors before being passed through a decision tree for final classification. Evaluated on the RSNA 2019 dataset, the model achieved remarkable subtype-specific accuracies—99.49% for intraventricular and subarachnoid hemorrhages, 99.10% for intraparenchymal, and 98.09% for subdural—outperforming many existing CAD-based approaches.

4.2.3 Optimization-Driven Architectures

Optimization-driven architectures leverage metaheuristic algorithms and advanced feature selection techniques to enhance the segmentation, feature extraction, and classification processes in ICH diagnosis. These methods focus on improving model performance by effectively navigating large solution spaces and optimizing critical parameters in preprocessing and classification stages.

Sengupta et al. [98] introduced a hybrid deep learning framework that begins with region-of-interest segmentation via Otsu's thresholding, followed by feature extraction using Tamura descriptors and Gradient Local Ternary Patterns (GLTP). To refine feature selection, the authors employed a modified genetic algorithm augmented with infinite feature selection. The optimized feature set was then classified using a Bi-LSTM network. This comprehensive approach achieved remarkable results, with 99.80% accuracy, 99.40% sensitivity, and 99.48% specificity, surpassing several traditional classifiers including Naïve Bayes, Random Forest, SVM, and vanilla RNN/LSTM models.

Building upon swarm intelligence paradigms, Alfaer et al. [99] proposed AICH-FDLSI, an automated ICH diagnostic framework integrating deep learning with nature-inspired optimization. The method's pipeline involves median filtering for noise reduction, followed by image segmentation through seagull optimization combined with Otsu multilevel thresholding. Feature extraction merges Capsule Networks (CapsNet) and EfficientNet, with hyperparameters finely tuned using the deer hunting optimization algorithm. Classification is performed using a fuzzy support vector machine (FSVM). Evaluation on a benchmark ICH dataset revealed that AICH-FDLSI significantly outperformed existing methods, highlighting the strength of combining swarm intelligence with deep architectures and fuzzy classifiers.

Similarly, Vrbančič et al. [100] presented a transfer learning approach enhanced by Grey Wolf Optimization (GWO) to detect hemorrhagic regions. This metaheuristic algorithm guided model fine-tuning and feature selection, resulting in superior performance over classical techniques. However, the computational complexity of GWO posed challenges for efficient exploration of the solution space, suggesting potential trade-offs between optimization precision and practical runtime.

In another notable contribution, Mansour and Aljehane [101] developed a hybrid segmentation-classification pipeline that integrates Kapur's thresholding with Elephant Herd Optimization (EHO) for precise CT region segmentation. Extracted features were subsequently fed into an Inception V4 network, with classification achieved via a multi-layer perceptron. This combination demonstrated strong efficacy across multiple test scenarios, illustrating the benefit of hybridizing threshold-based segmentation with nature-inspired optimization for feature selection and classification.

4.3. Data Augmentation and Synthetic Data Generation

Data augmentation methods aim to enrich training datasets with artificially generated or transformed images to improve generalization and robustness. Zhang et al. [102] introduced a novel two-stage pipeline to generate synthetic hemorrhagic lesions on non-hemorrhagic CT scans. Their framework consists of an Artificial Mask Generator (AMG) and a Lesion Synthesis Network (LSN), which together create realistic synthetic training examples. This augmentation approach significantly improved the detection accuracy of small hemorrhages, demonstrating the value of synthetic data in challenging cases.

Wang et al. [103] proposed SWDL-Net, a semi-supervised deep learning architecture designed to achieve accurate ICH segmentation even with minimal labeled data. SWDL-Net integrates Laplacian pyramid techniques for enhanced edge representation and deep convolutional upsampling for detailed feature refinement. Utilizing a difference learning mechanism to combine these components, the model effectively delineates lesion boundaries. Evaluations on 271 patient cases and the public Brain Hemorrhage Segmentation Dataset (BHSD) revealed that SWDL-Net outperforms comparable methods, maintaining high segmentation accuracy with as little as 2–5% labeled training data.

Hussain et al. [104] developed a hybrid attention-based ResNet model aimed at improving ICH detection and classification. Their approach enhances feature extraction while reducing feature redundancy using principal component analysis (PCA). To address class imbalance inherent in hemorrhage subtypes, they employed a deep convolutional generative adversarial network (DCGAN) for synthetic data generation. Tested on the RSNA 2019 dataset, the model achieved high accuracies: 99.2% for epidural hemorrhage, 97.1% for intraparenchymal hemorrhage, 96.7% for both intraventricular and subdural hemorrhages, and 96.1% for subarachnoid hemorrhage, with a highest F1-score of 96.1% for epidural hemorrhage classification.

4.4. Explainable AI

The growing integration of AI in clinical diagnosis necessitates models that are not only accurate but also interpretable and transparent to ensure clinical trust and adoption. Recent works in ICH detection and classification have emphasized explainability alongside performance. Mahmood et al. [105] introduced a fuzzy deep learning approach built upon ResNet50 to improve the classification of ICH subtypes in CT scans. By integrating fuzzy logic into the deep learning framework, their method enhances interpretability and achieves high classification accuracy across multiple hemorrhage types, including subdural, epidural, intraventricular, intraparenchymal, and subarachnoid hemorrhages. This hybrid approach bridges the gap between model complexity and clinical comprehensibility.

Yang et al. [106] developed a transfer learning-based 3D U-Net model to differentiate intracerebral hemorrhage caused by cerebral venous sinus thrombosis (CVST-ICH) from spontaneous ICH (sICH) using non-contrast CT scans. Since misdiagnosis can result in inappropriate treatment, their model addresses an important clinical challenge. Training on 102 CVST-ICH and 306 age-matched sICH patients with external validation on 38 CVST-ICH and 119 sICH cases, the model attained an internal AUC of 0.94, sensitivity of 0.96, and specificity of 0.80, and external AUC of 0.85, sensitivity of 0.87, and specificity of 0.82. Interpretability analyses revealed that the model focuses on hemorrhage edge features, which correlates with clinical assessment criteria. The model also improved diagnostic accuracy among nine physicians reviewing the CT images, underscoring its potential clinical utility pending further validation.

Qiu et al. [107] proposed a machine learning-based risk assessment model to predict lower extremity deep vein thrombosis (DVT) in patients hospitalized with spontaneous ICH. Using Boruta and LASSO for feature selection, six key predictors were identified. Five machine learning algorithms were evaluated, with the Light Gradient Boosting Machine (LGBM) model achieving superior accuracy based on ROC analysis. Calibration was assessed using calibration curves and Brier scores, and clinical utility was validated through Decision Curve Analysis (DCA). Model interpretability was enhanced using SHapley Additive exPlanations (SHAP) values, facilitating understanding of individual risk factors and supporting clinical decision-making.

Umapathy et al. [108] proposed an ensemble deep learning framework combining SE-ResNeXT and LSTM networks for early detection and subtype classification of ICH. Utilizing the RSNA brain CT hemorrhage challenge and CQ500 datasets, the model employed windowing-based preprocessing and automatic feature extraction. Classification encompassed five hemorrhage subtypes: epidural, intraventricular, subarachnoid, intraparenchymal, and subdural. To enhance interpretability, Gradient-weighted Class Activation Mapping (Grad-CAM) was used to localize regions of interest within CT images. The model achieved an overall classification accuracy of 99.79% and an F1-score of 0.97. Subtype accuracies ranged from 98% to 99.89%.

5. Datasets for ICH Detection and Segmentation

The advancement of machine learning techniques for the detection, classification, and segmentation of ICH relies on high-quality datasets with diverse imaging conditions and expert annotations. This section presents a comprehensive overview of publicly available and curated private datasets commonly used for ICH-related research. These datasets vary in size, modality, labeling granularity (classification vs. segmentation), and the types of hemorrhages covered. Table 1 presents a comparative summary of the most widely used datasets for ICH.

- RSNA ICH Detection Dataset [109]: Released during the 2019 RSNA Machine Learning Challenge, this dataset was created in collaboration with the Radiological Society of North America and the American Society of Neuroradiology. It includes a large collection of DICOM-formatted non-contrast head CT scans labeled at the slice level for six hemorrhage types: EDH, SDH, SAH, IPH, IVH, and a general "any ICH" class. With hundreds of thousands of labeled slices, this dataset has become the benchmark for training and evaluating classification models in ICH detection. It is freely accessible for non-commercial research purposes.
- CQ500 Dataset [110]: The CQ500 dataset, developed by the Centre for Advanced Research in Imaging, Neurosciences and Genomics (CARING), India, includes approximately 200,000 CT slices from 491 head CT studies. It covers a broad spectrum of brain abnormalities, including hemorrhage, skull fractures, and midline shift. The scans were acquired using a range of CT devices from GE and Philips. Although most images lack pixel-level annotations required for segmentation, CQ500 provides rich diversity for training classification models. Some studies have augmented its utility by manually labeling subsets for segmentation tasks, particularly subdural hematoma (SDH), significantly enhancing its value for algorithm development.

- PhysioNet ICH Dataset (Al-Hilla Teaching Hospital) [78]: This dataset, available through PhysioNet, consists of CT scans from 82 patients with traumatic brain injury, collected in Iraq. It includes 229 CT studies, with 173 showing EDH and 56 with subdural hemorrhage (SDH). Out of the total, 36 patients had some form of ICH. A total of 318 slices with visible hemorrhage were used for training and evaluation. The dataset is imbalanced in terms of hemorrhage subtypes and lacks full 3D segmentation masks, making it more suitable for classification tasks rather than pixel-wise segmentation.
- INSTANCE 2022 (INtracranial Hemorrhage SegmenTAtion ChallengE): This dataset was developed for the MICCAI Brain Lesion and Hemorrhage Segmentation Challenges (2022/2023). It includes non-contrast CT scans along with expert-generated segmentation masks of various hemorrhage subtypes. The dataset provides voxel-level annotations and is specifically tailored for benchmarking semantic segmentation algorithms. Access may require registration and approval for academic use. It is one of the few publicly available datasets offering ground truth masks for multiple ICH types. The dataset consists of 100 samples for training, 30 for validation, and 70 for testing.

Table 1
Summary of publicly available datasets used for ICH research.

Dataset	Size	ICH Types	Task Type	Available at
RSNA	~750,000 slices	EDH, SDH, SAH, IPH, IVH, Any ICH	Classification	[111]
CQ500	491 samples (~200k slices)	EDH, SDH, SAH, IPH, IVH + other findings	Classification	[112]
PhysioNet	2,434 slices (26 patients)	EDH, SDH, IVH, IPH, SAH	Classification	[113]
INSTANCE	200 samples	Multiple hemorrhage types	Segmentation	[114]

6. Evaluation metrics

To evaluate the performance of models in tasks such as classification and medical image segmentation (e.g., ICH detection), a variety of quantitative metrics are used. These metrics provide insights into different aspects of model performance, such as accuracy, robustness, overlap quality, and error types. Most of the evaluation metrics are derived from the confusion matrix, a fundamental concept that summarizes the number of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN).

- True Positives: Correctly identified hemorrhagic pixels or regions.
- True Negatives: Correctly identified non-hemorrhagic (healthy) pixels or regions.
- False Positives: Pixels or regions incorrectly identified as hemorrhagic (type I error).
- False Negatives: Hemorrhagic pixels or regions missed by the model (type II error).

Table 2 presents a collection of widely used evaluation metrics in the literature, along with their formulas and descriptions. These metrics assess both classification performance (e.g., accuracy, precision, recall) and segmentation quality (e.g., Dice coefficient, Jaccard index, Hausdorff distance), offering a comprehensive framework for model assessment.

Table 2
Common Evaluation Metrics in ICH

Metric Name	Description	Formula
Accuracy	Proportion of correct predictions among all samples.	$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$
Precision	Proportion of predicted positives that are actual positives.	$Precission = \frac{TP}{TP + FP}$
Sensitivity (Recall)	Proportion of actual positives that are correctly identified.	$Sensitivity = \frac{TP}{TP + FN}$
Specificity	Proportion of actual negatives that are correctly identified.	$Specificity = \frac{TN}{TN + FP}$
F1-Score	Harmonic mean of precision and recall, balances false positives and false negatives.	$F1\_score = \frac{2 * Precission * Sensitivity}{Precission + Sensitivity}$
MCC (Matthews Corr.)	The MCC is a correlation coefficient between the observed and predicted classifications, considering all four confusion matrix categories, and is regarded as a balanced measure even if classes are of very different sizes. MCC values range from -1 (total disagreement) to +1 (perfect prediction), with 0 indicating random performance.	$MCC = \frac{TP.TN - FP.FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}$
Dice Coefficient	Measures spatial overlap between predicted and true segmentation; ranges from 0 (no overlap) to 1 (overlap).	$Dice = \frac{2TP}{2TP + FP + FN}$
Jaccard Index	Similar to Dice, the Jaccard index measures the similarity between predicted and ground truth regions, but it is slightly more stringent. The Jaccard index ranges from 0 to 1, where 1 indicates perfect agreement.	$\text{Jaccard} = \frac{TP}{TP + FP + FN}$

HD95 (95% Hausdorff)	Computed using 95th percentile surface distance	Measures worst-case boundary mismatch while reducing sensitivity to outliers.
ASD (Avg. Surface Dist.)	Average Euclidean distance between predicted and ground truth boundaries	Evaluates average boundary error in segmentation results.

7. Challenges and future direction

Despite the promising performance of deep learning models in ICH diagnosis, several challenges hinder their full integration into clinical workflows.

- One of the major limitations in ICH research is the scarcity of well-annotated datasets, particularly for rare subtypes like EDH. This imbalance can hinder model training and lead to biased performance.
- Deep learning models often struggle to generalize across institutions due to variations in imaging protocols, scanner hardware, and patient demographics.
- Many deep models require significant computational resources, making them impractical for real-time use in emergency departments or low-resource settings.
- Most current ICH models rely exclusively on imaging data, overlooking rich contextual information available in patient history, clinical notes, and laboratory results.
- The path to clinical deployment is often obstructed by concerns over patient safety, algorithmic bias, liability, and regulatory compliance.

Machine learning techniques have been leveraged in a variety of complex scenarios across different fields [115-118]. In the clinical setting, to address existing challenges and enhance the utility of deep learning for ICH diagnosis, several future directions can be pursued:

- **Data Scarcity and Class Imbalance:** Collaborative initiatives should focus on curating and sharing large, diverse, and balanced datasets with detailed annotations, including voxel-level segmentations, to enhance model training and evaluation.
- **Poor Generalization Across Clinical Settings:** Domain adaptation and transfer learning techniques should be employed to create models that are robust to domain shifts and can maintain accuracy across diverse clinical environments.
- **Computational Demands and Real-Time Deployment:** Development of lightweight and energy-efficient architectures, such as quantized models [119] and decentralized multi-agent learning [120], is essential for enabling real-time inference on portable devices and edge hardware.
- **Limited Use of Multimodal Data:** Future models should integrate multimodal data, combining structured and unstructured clinical information with imaging, to improve diagnostic accuracy and patient-specific predictions.
- **Regulatory and Ethical Barriers:** Researchers should collaborate with ethicists, clinicians, and regulatory bodies to establish transparent validation protocols, promote fairness, and develop ethical frameworks for responsible AI deployment in healthcare.

8. Conclusion

ICH is a complex, high-risk condition that benefits substantially from rapid and accurate diagnosis. Deep learning has emerged as a transformative technology, offering powerful tools for the detection, classification, and segmentation of ICH from CT images. This survey has examined the broad spectrum of AI techniques applied to ICH, from basic CNNs to sophisticated ensemble and optimization-driven models. It also highlighted the importance of explainability, clinical relevance, and high-quality datasets. Although significant strides have been made, ongoing research must address challenges such as data limitations, lack of generalization, and the need for interpretability. By advancing in these areas, AI can become a reliable and integral part of ICH diagnosis and treatment planning, ultimately enhancing patient outcomes and relieving burden on healthcare systems.

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