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Automated Detection of Intracranial Hemorrhage from Head CT Scans Applying Deep Learning Techniques in Traumatic Brain Injuries: A Comparative Review

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Abstract

Traumatic brain injury (TBI) is not only an acute condition but also a chronic disease with long-term consequences. Intracranial hematomas are considered the primary consequences that occur in TBI and may have devastating effects that may lead to mass effect on the brain and eventually cause secondary brain injury. Emergent detection of hematoma in computed tomography (CT) scans and assessment of three major determinants, namely, location, volume, and size, is crucial for prognosis and decision-making, and artificial intelligence (AI) using deep learning techniques, such as convolutional neural networks (CNN) has received extended attention after demonstrations that it could perform at least as well as humans in imaging classification tasks. This article conducts a comparative review of medical and technological literature to update and establish evidence as to how technology can be utilized rightly for increasing the efficiency of the clinical workflow in emergency cases. A systematic and comprehensive literature search was conducted in the electronic database of PubMed and Google Scholar from 2013 to 2023 to identify studies related to the automated detection of intracranial hemorrhage (ICH). Inclusion and exclusion criteria were set to filter out the most relevant articles. We identified 15 studies on the development and validation of computer-assisted screening and analysis algorithms that used head CT scans. Our review shows that AI algorithms can prioritize radiology worklists to reduce time to screen for ICH in the head scans sufficiently and may also identify subtle ICH overlooked by radiologists, and that automated ICH detection tool holds promise for introduction into routine clinical practice.

Keywords
- intracranial hemorrhage
- traumatic brain injury
- deep learning
- AI/ML
- convolutional neural network
- screening/detection tool
- automated intracranial hemorrhage

Introduction

Traumatic brain injury (TBI) has devastating effects on patients and their families.[1] This subtle but prevalent phenomenon impacts millions of lives annually and results in mortal consequences. As per the Indian Head Injury Foundation (IHIF), brain injury rates in India are the highest in the world, with one in six TBI patients

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succumbing to their injuries. Most of these deaths occur within 2 hours of the injury.[2] Some of these deaths may be prevented by timely and appropriate therapy.[3]

The Glasgow Coma Scale (GCS) is used to classify the severity of TBI as mild, moderate, and severe according to their level and severity.[4] At the time of presentation, patients with moderate or severe TBI have a depressed GCS.[5] The clinical outcomes of TBI depend on multiple factors and vary across the institution or health care system, region, and age group.[5] TBI is now recognized as not only an acute condition but also a chronic disease with long-lasting effects, which include a higher probability of developing neurodegenerative disorders later in life.

Intracranial hemorrhage (ICH) is classified as a primary injury that occurs during impact but expands with time. A comprehensive review conducted by the Brain Trauma Foundation revealed that all types of ICH are linked to an unfavorable prognosis, resulting in increased in-hospital mortality and disability even after 6 months of the injury.[6] The study further established that a hematoma larger than 50 mL in severe head injuries significantly contributes to higher mortality rates.[7] ICH can be classified according to the location into epidural hemorrhage (EDH), subdural hemorrhage (SDH), intraparenchymal hemorrhage (IPH), and subarachnoid hemorrhage (SAH). Few studies involving TBI patients have found that ICH can develop or enlarge in the 48 hours after injury.[6]

Several methods have been developed to detect ICHs or to measure hemorrhage volume using standard image processing approaches.[8] Some other studies only considered large ICH, which is unchallenging to detect.[9]

The emergency team in many trauma centers is responsible for the initial assessment and resuscitation of TBI cases. Medical imaging plays an essential role in identifying intracranial injury in patients with TBI and serves several objectives, including the detection of injuries that require immediate surgical or procedural intervention, identification of injuries that may benefit from early medical therapy or close neurological monitoring, and determination of patient prognosis. The preferred method for diagnosing and characterizing TBI is noncontrast head computed tomography (CT) due to its speed, widespread availability, and ability to provide adequate contrast between blood and brain tissues.[10] The identification of ICH on the head CT scans and the evaluation of their location, volume, and size are essential for prognosis and making informed decisions.[2]

With booming research initiatives, automated systems have expanded to include various image analysis techniques, providing clinicians with the ability to identify diseases, plan treatments, assess risks, and determine prognosis. Radiologists can use these systems' interpretations as supplementary tools in making final decisions. Automated detection tools that incorporate machine learning (ML) and deep learning (DL) techniques can efficiently learn and predict abnormalities present in large datasets. Typically, automated detection systems utilize a combination of image processing techniques, including preprocessing, segmentation, feature extraction, feature selection, and classification.[2]

Numerous ML and DL techniques have been employed for detecting and segmenting brain structures to enable volumetric analysis (such as NEUROShield),[11] as well as screening ICH and other related pathologies.[12–15] Advanced image processing techniques have been devised to detect ICH, potentially enhancing the speed and precision of ICH detection, thereby improving the patients' prognosis.

This review article will compare the techniques and methods used by different studies to automatically detect and analyze ICH from head CT scans of TBI cases.

Materials and Methods

Search Strategy

We have done a comparative review by conducting a comprehensive and systematic literature search in the database of PubMed and Google Scholar to recognize studies related to the automated detection of ICH. The search period was from 2013 to 2023 (11 years).

A set of Medical Subject Headings (MeSH) terms, keywords, and specific terms were utilized to describe the automated detection of ICH in TBI cases. The keywords used, either individually or in combination, included the following: "deep learning" OR "machine learning" AND "head CT" AND "hemorrhage," "automated intracranial hemorrhage," "TBI," "CT images," "automatic detection and classification," and "CNN." Articles were reviewed initially by titles and abstracts, and then by reading the full content of the remaining articles. The references of the included studies were also scrutinized to identify more prospective studies. The studies were not evaluated and excluded based on their quality and risk of bias. Please refer to ►**Table 1** for a detailed explanation of the inclusion and exclusion criteria.

The literature was divided into two categories, category 1 consisting of small datasets ($<$ 100 scans) and category 2 consisting of large datasets ($>$ 900 scans). Both categories were analyzed separately.

Results

Of the 15 studies that matched the inclusion criteria, the study design varied from detection of hemorrhage to segmentation of hemorrhage, and detection and classification of ICH. There were seven articles in category 1 (►**Table 2**) with a dataset size ranging from 27 to 82 CT scans, where different DL techniques were employed, including AI-based DL, Recurrent Attention DenseNet (RADnet), U-Net, dynamic graph convolutional neural network (DG-CNN), Inception v4, etc.

The sensitivity of the models ranged from 89.6 to 97.8%, and the specificity ranged from 50.4 to 97.78%. The overall accuracy ranged from 81.82 to 95.06%.

There were eight articles in category 2 (►**Table 3**), with the dataset size ranging from 904 to 536,266 CT scans, and different DL techniques were employed, including deep convolutional neural network (DCNN), 3D CNN, U-Net, ResNet18, Inception v3, Inception ResNet-v2, ROI-based convolutional neural network (CNN) framework, AlexNet-SVM model, 3D joint CNN–recurrent neural network

Table 1 Inclusion/exclusion criteria

Sl no.	Categories	Inclusion	Exclusion
1	Type of dataset	• Noncontrast head CT scans	• MRI scans. Contrast-based CT scans, EEG
2	Pathology and study outcomes	• Studies related to ICH and its types • Automated analysis of ICH in humans due to TBI • CT imaging for automated detection and assessment of ICH	• Animal subjects • Treatment planning or diagnostic tools • Hemorrhage other than ICH • ICH caused by any other condition (e.g., stroke)
3	Methodology and study design	• Automated detection using CNN, 3D CNN, and deep learning-based architectures for automated analysis of ICH	• Biochemical or pathological research, and statistical analysis • Computer vision techniques
4	Type of journals referred	• Peer-reviewed journals, systematic reviews, and webpages related to deep learning techniques	• Scientific abstracts, conference proceedings, letters to the editor, and articles without full text
5	Time period	• 2013–2023	• Before 2013
6	Language	• English	• Other than English

Abbreviations: CNN, convolutional neural networks; CT, computed tomography; EEG, electroencephalogram; ICH, intracranial hemorrhage; MRI, magnetic resonance imaging; TBI, traumatic brain injury.

(CNN-RNN), and cascade DL constructed using 2 CNN and dual fully convolutional network (FCN).

The sensitivity and specificity of the models were reported in a few of the studies and ranged from 71.5 to 97.91% and from 83.5 to 98.76%, respectively. However, some studies did not report these metrics. Dawud et al only reported the third parameter, "accuracy," which was 93.48%.[16] The DL model with the highest sensitivity was of Cho et al,[17] followed that of by Irene et al.[12]

Both their works are based on CNN models; however, the dataset sizes have major differences. But it can be inferred that the technique used majorly affects the outcome of the model. The balance between sensitivity and specificity was best achieved by Cho et al.[17]

To summarize, variations in sensitivity, specificity, and accuracy of the models were observed across studies, with dataset size and the DL technique used being important factors contributing to these differences. Nonetheless, these findings provide a promising avenue for future research in this area.

Discussion

Diagnosing TBI is not a single telltale as there is no distinctive feature that characterizes the pathology. Instead, radiologists must identify a combination of partial anomalies to diagnose this complex injury. Detection, image processing, and diagnosis are termed medical image analysis. In recent years, ML- and DL-based systems have been developed for medical image analysis.[18] Medical image analysis is an active field of research for ML because the data are relatively structured and labeled. Techniques such as deep neural networks, CNN, and RNN are suitable for medical image analysis solutions.[19]

These techniques apply to multiple functions such as image registration, physiological modeling based on images, segmentation of images, and others. The DL techniques can recognize patterns in visual inputs and assign class labels to inputs.

Popular DL architectures for image processing include CNNs and unique CNN frameworks such as AlexNet, VGG, Inception, and ResNet.[20]

The CNN has acquired rapid attention in image processing due to its self-organization and self-learning features. CNN is an artificial neural network that extracts image features with increasing complexity by using convolution and pooling filters on the input, which are implemented as neural network layers. The convolutional layers extract features from the input images using fixed-sized filters, and the pooling layers spatially reduce and accumulate these features using maximum or average pooling techniques. The features are then passed through the fully connected layers and the activation function to classify the inputs based on a reduced set of feature vectors.[16,21]

CNN-based architectures have some limitations. First, they require many training images to generate convolution filters (kernels). Second, implementing and training the model requires significant computational resources. Finally, the final model lacks transparency as it does not provide insight into which image descriptors, structures, or characteristics were used by the final discriminant classifier.

CNN has overall promising results when it comes to image processing and image classification given that it is trained by using huge and superior quality data. The quality of data is purpose specific. For ICH detection, the dataset should be of head CT scans taken under a certain protocol, without artifacts, and of specific slice thickness.

Currently, the conventional technique is to manually select the necessary CT scan slices, identify hemorrhage, and measure its volume. Although this method may provide accurate results, it is a laborious and time-consuming task, particularly in large clinical settings, and may introduce errors.[2] More importantly, radiologists may

Table 2 Category 1 studies (dataset less than 100 scans)

Sl no.	Name of the author	Article title	Year of publication	Deep learning technique used	CT dataset	Purpose or findings	Result		
							Sensitivity	Specificity	Accuracy
1	Prevedello et al	Automated critical test findings identification and online notification system using artificial intelligence in imaging	2017	AI-based deep learning approach	76	Detection of hemorrhage, mass effect/ hydrocephalus	90	85	NA
2	Grewal et al	RADnet: radiologist level accuracy using deep learning for hemorrhage detection in CT scans	2018	Recurrent Attention DenseNet (RADnet)	77	Detection of ICH	0.8864	NA	81.82
3	Hssayeni et al	Intracranial hemorrhage segmentation using a deep convolutional model.	2020	U-Net	82	Detection and segmentation of hemorrhage	97.28	50.4	NA
4	Irene et al	Segmentation and approximation of blood volume in intracranial hemorrhage patients based on computed tomography scan images using deep learning method	2020	DG-CNN	27	Localization and segmentation of hemorrhage	97.8	95.6	NA
5	Anupama et al	Synergic deep learning model–based automated detection and classification of brain intracranial hemorrhage images in wearable networks	2020	GrabCut-based segmentation and synergic deep learning	82	Detection and classification of ICH	94.01	97.78	87.5
6	Watanabe et al	Improvement of the diagnostic accuracy for intracranial hemorrhage using deep learning–based computer assisted detection	2021	U-Net	40	Detection of ICH	89.6	81.2	87.5
7	Mansour et al	An optimal segmentation with deep learning based inception network model for intracranial hemorrhage diagnosis.	2021	Inception v4, multilayer perceptron	82	Detection and classification of ICH	93.56	97.56	95.06

Table 3 Category 2 studies (dataset of more than 900 scans)

Sl no.	Name of the author	Article title	Year of publication	Deep learning technique used	CT dataset	Purpose or findings	Result		
							Sensitivity	Specificity	Accuracy
1	Arbabshirani et al	Advanced machine learning in action: Identification of intracranial hemorrhage on computed tomography scans of the head with clinical work flow integration	2017	DCNN	46,583	Detection of ICH	71.5	83.5	NA
2	Titano et al	Automated deep-neural-network surveillance of cranial images for acute neurologic events	2018	3D CNN	37,236	Detection of ICH	NA	NA	NA
3	Chilamkurthy et al	Deep learning algorithms for detection of critical findings in head CT scans: a retrospective study	2018	Combination of DL algorithms: U-Net, ResNet18, random forest classifier	21,095 in Qure25k and 491 in CQ500	Detection of ICH, classification and segmentation. (5 classes)	92	70	NA
4	Lee et al	An explainable deep-learning algorithm for the detection of acute intracranial hemorrhage from small datasets	2018	VGG16, ResNet-59, Inception v3 and Inception ResNet-v2	904	Detection and classification of ICH. (5 classes)	78.3	92.9	NA
5	Chang et al	Hybrid 3D/2D convolutional neural network for hemorrhage evaluation on head CT	2018	ROI-based CNN framework	5,36,266	Detection and Quantification of Hemorrhage	95	97	NA
6	Dawud et al	Application of deep learning in neuroradiology: brain hemorrhage classification using transfer learning	2019	AlexNet-SVM model	12,635	Detection and classification of ICH. (4 classes)	95	90	93.5
7	Ye et al	Precise diagnosis of intracranial hemorrhage and subtypes using a three-dimensional joint convolutional and recurrent neural network	2019	3D Joint CNN-RNN	76,621	Detection and classification of ICH	80	93.2	NA
8	Cho et al	Improving Sensitivity on identification and delineation of intracranial hemorrhage lesion using cascaded deep learning models	2019	Cascade deep learning constructed using 2 CNN and dual FCN	1,35,974	Detection, classification, and segmentation of ICH	97.9	98.8	NA

not be available during the night when maximum cases of TBI are present. Because of these reasons, various automated tools are being developed to assist radiologists in providing image interpretation for diagnosing the patient's condition quickly and effectively.

Recently the convolutional-based approach is getting attention and a few notable studies have used this technique for neuroradiology purposes. Zaki et al used traditional computer vision techniques such as morphological processing to detect fractures, and Yamada et al to retrieve scans with fractures. Both these studies failed to measure the accuracies on a clinical dataset. Automated midline shift detection has also been explored using non-DL methods. Gao et al used CNNs to classify head CT scans to help diagnose Alzheimer's disease.[2]

More specific studies have made a notable impact by working exclusively on ICH in TBI cases. Such research work has been categorized as those who worked on small datasets (< 100) and those who collected large datasets (> 900). The results section consists of the table and its details. This part will discuss the techniques they used and the impact they made.

This review of the literature was focused on the techniques used to understand the scope of DL in image analysis. Few of the studies have assessed the performance of a variety of DL techniques by working on a limited dataset(s).

Prevedello et al assessed the performance of a DL algorithm on a dataset of 76 scan images to detect hemorrhage, mass effect, hydrocephalus, and suspected acute infarct. The investigators grouped the condition into two categories, with hemorrhage, mass effect, and hydrocephalus in one category and acute infarct in another. They reported a sensitivity of 90% in the case of the hemorrhage, mass effect, and hydrocephalus.[9] Grewal et al proposed a RADnet, which incorporates slice-level context and classification for improved hemorrhage detection in CT scans. The authors conducted a comparison between their computer-aided diagnosis (CAD) system and human experts, and found that the system achieved an accuracy of 81.82%. However, the types of ICH considered were not mentioned in their report.[22] Watanabe et al created a computer-assisted system by working on U-Net to detect hemorrhage.[23] Anupama et al utilized a combination of GrabCut-based segmentation and DL techniques to detect hemorrhage and classify its subtypes. They used a dataset of 82 CT scans.[14] On the other hand, Mansour and Aljehane developed an Inception V4 network for automated feature extraction and multilayer perceptron for ICH classification.[24]

There are a few studies that have focused more on the classification and segmentation of hemorrhagic lesions by using DL techniques and head CT scans. However, such techniques require additional time for data acquisition, preprocessing, and algorithm development. But they have been reviewed for the understanding of the techniques. Hssayeni et al developed a fully automated U-Net model for the detection and segmentation of hemorrhage lesions from 82 CT scans and calculated the Dice coefficient as 0.31.[25] Irene et al proposed a DG-CNN for ICH segmentation and achieved a sensitivity of 97.8%.[12]

Some studies collected large numbers of data for training the DL models. The techniques they used have trivial differences but almost equivalent performance. In the study by Titano et al, they devised a 3D CNN model based on ResNet-50 to detect crucial findings on CT scans. However, they recorded results without comparing them to the gold standard.[26] The study by Dawud et al focused on ICH detection and a four-class classification. They showed that a pretrained, finely tuned AlexNet-SVM model can improve the segmentation accuracy of DL models.[16] Kuo et al proposed a patch-based, fully convolutional network (PatchFCN) for ICH segmentation and classification with high accuracy.[27] Chilamkurthy et al conducted a retrospective study to automatically detect critical findings in head CT scans from CQ500 and Qure2k using a combination of DL algorithms. They retrospectively collected a large dataset from 20 centers in India over 6 years, but excluded patients under the age of 7 years, limiting the training to a specific age range. Their approach utilized a U-Net-based architecture to localize hemorrhagic regions, and a modified ResNet18 for five-class categorization.[28] Arbabshirani et al also employed a DL model to detect ICH in head CT scans and evaluated its potential as a radiology workflow optimization tool.[29]

In a separate study, Lee et al proposed an ensemble model consisting of VGG16, ResNet-50, Inception-v3, and Inception-ResNet-v2 for the localization and classification of five types of hemorrhages, utilizing attention maps for reliable localization and prediction basis for model interpretation. The performance of the model has more specificity but lesser sensitivity.[30] It is worth noting that high sensitivity is a critical characteristic of an automated approach for emergency diagnostic tools.

Ye et al reported an integrated approach with a CNN and an RNN as a part of it, for the detection of five classes of hemorrhage.[31] Cho et al created a method that combines a cascaded CNN to identify areas of hemorrhage and a dual FCN to classify and segment ICH.[17] Technique used by Chang et al is distinctive as they utilized a hybrid 3D/2D mask region of interest (ROI) based CNN framework that can efficiently detect, classify, and segment hematoma simultaneously.[32]

Based on these observations, we can assume that DL algorithms have the capacity to automatically analyze head CT scans, prioritize radiology worklists, and reduce time to diagnosis of ICH. This review offers suggestions for the direction of technological developments in the automated detection of ICH and other pathologies in TBI cases. Such automated technical developments will likely be helpful for teaching and research purposes. They can be a source of training for medical students as well as resident doctors. They can be of great advantage for searching through large sets of CT scans.[11]

Limitations and Future Prospectives

The above-explained studies, which are based on automated detection, have important implications for the widespread adoption of artificial intelligence in detecting ICH in clinical practice.

The review has certain limitations that should be considered. One limitation is that the search process relied on specific keywords and their synonyms, and therefore, few relevant studies may have been missed. Additionally, the review only focused on studies related to the detection and assessment of ICH and did not cover other types of primary and secondary injuries that may occur as a result of TBI.

This review has covered works related to ICH detection, classification, and scarcely hemorrhage region segmentation. Expanding the literature will improve the outcomes of the study. Apart from hemorrhage, we did come across literature related to other critical findings as well and we aim to review literature related to other pathologies in the future.

Conclusion

This review article represents the first comprehensively compiled literature focused on the use of DL techniques for automatically detecting and analyzing ICH in cases of TBI using CT scans. Our review shows that currently an artificial intelligence algorithm can prioritize radiology worklists to reduce time to screen for ICH in the head scans and may also identify subtle ICH overlooked by radiologists. This demonstrates the positive impact of DL techniques in the optimization of radiology workflow. The overall results of this CNN approach suggest that the automated ICH detection tool holds promise for introduction into routine clinical practice.

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Conflict of Interest
None declared.

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