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Review On Intracranial Hemorrhage Detection Using Deep Learning

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Abstract: **Intracranial hemorrhage (ICH) is a life-threatening medical emergency that requires rapid and quick assessment and management. Due to its high mortality rate, early detection and classification on non-contrast computed tomography (CT) are essential for ensuring a promising prediction and controlling the occurrence of neurologic deficits. However, there is delay in the primary detection of ICHs due to a lack of prompt access to radiologists who read the scans. Spontaneous notification systems can be designed using the deep-learning artificial intelligence (AI) methods. Recently, many attempts have been made to apply the deep-learning methods for the detection of ICH on CT images. Deep learning models can be used to accelerate the time it takes to identify them. The purpose of this work is to explore the application of machine learning and deep learning in ICH detection and identify the suitability and further road in this research.**

Index Terms - ***Intracranial Hemorrhage. Deep learning, CNN***

I. INTRODUCTION

The brain is a most significant organ in the mortal body which controls the whole functionality of other organs and helps in making decisions. It is the main control center of the central nervous system and is accountable for performing the daily voluntary and involuntary activities in the human body.

To most people, a brain bleed simply means any bleed inside the head. However, a doctor who treats brain bleeds such as neurologists and neurosurgeons, would say that a brain bleed which is also known by the medical term intracranial hemorrhage is a broad term. The doctors identify brain bleeds by their precise location. Intracranial hemorrhage (ICH) bothers various patients who suffer from trauma, stroke, aneurysm, vascular malformations, high blood pressure, illicit drugs and blood clotting complaints. ICH is a type of stroke which accounts for 10-15% of all strokes and carries very high mortality and morbidity. It refers to the abnormal accumulation of blood within the brain tissues and membranes covering the skull.

Varied types of ICH can be identified by their diverse shape, location, and size. Primary diagnosis of ICH, preferably within 24 hours, is important in decreasing patient mortality. They are classified into different types depending on the location of the bleed each carrying different prognosis. Different types of Haemorrhage are: Extra Dural Haemorrhage, Sub Dural Haemorrhage, Sub Arachnoid Haemorrhage, Intracerebral, Intraventricular Haemorrhage).

Doctors' use CT scan or MRI images to identify Intracranial hemorrhage (ICH) (Fig1a and b). CT scans are more widely used than MRIs and are typically less expensive. Diagnosis time involves taking a head computerized tomography (CT) and a radiologist making a diagnosis based on CT interpretation. CT scans consist of a series of X-ray images taken in different angles, combined to form 3D cross-sectional images of the brain. Non contrast CT scan aids in definitive diagnosis of ICH differentiating between Ischemia and Haemorrhage stroke and also assists in identifying the location and size of Haemorrhage, surrounding edema, mass effect and midline shift with high sensitivity and specificity. Non contrast CT is the most rapid and easily available tool for diagnosis. CT scans are gray scale images with low SNR, poor contrast and high incidents of image artifacts. Hence if CT scans are considered, one need to adapt many preprocessing techniques before proceeding to the identification of ICH.

MRI scanned images are also considered to identify brain hemorrhages. The technology used in an MRI allows doctors to examine soft tissues without bones obstructing the view. An MRI uses no radiation and is considered a safer alternative to a CT scan. There have been no documented side effects from radio waves and magnetism to date. Over time, it has become preferable than other imaging technologies due to its harmless characteristics and producing high contract images.

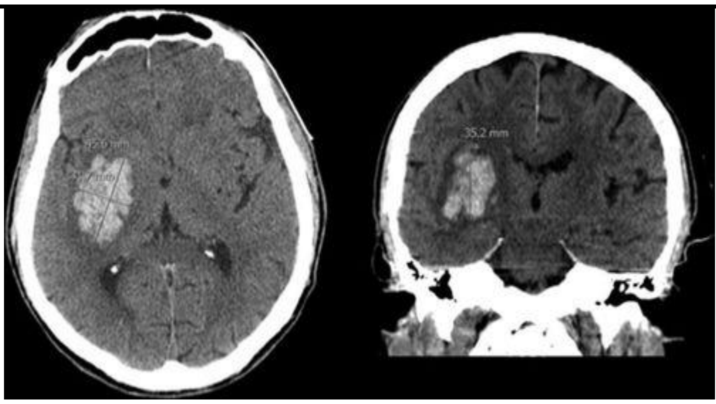
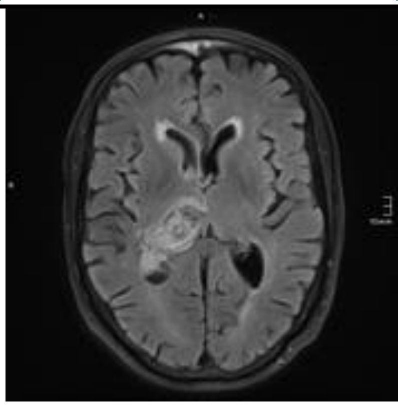


Fig (1a) CT scans of Brain



Fig(1b) MRI of Brain

There is shortage of Radiologists who interpret findings of the CT scan and in India it is estimated that there are around 10,000 radiologists for a population of over a billion. In this scenario, it is very much necessary to develop machines which can automatically identify ICH for further treatments.

II. **DETECTION TECHNIQUES:** Algorithms used in identifying intracranial hemorrhages can be largely divided into ML and DL algorithms. Both methodologies follow same workflow of data preprocessing trailed by model training and prediction. Additional accuracies have led DL preferred over traditional ML in these applications.

ML algorithms commonly used are clustering algorithms such as fuzzy clustering and classification algorithms such as decision trees, support vector machines (SVMs), logistic regression classifiers. But, these algorithms are optimized to perform well on small, well defined tasks. Good expert domain knowledge and extensive data preprocessing are mandatory for such algorithms. To guide the learning of the ML model, specific samples with clear pathology is required. Due to these factors, the performance of ML-based ICH identification systems lags their clinical usefulness.

Research in image analysis has shifted towards DL these days. The development of parallel processing, computing, access to increasing amounts of data and theoretical advances in DL have enlarged the possibility of DL uses. DL is built on an artificial neural network structure, moved by the human brain. DL algorithms can extract more information than ML algorithms, while eliminating the need for wide data preprocessing and feature-handcrafting. Deep learning systems can identify meaningful patterns and features within large datasets. Convolutional Neural Network (CNN) can be used in the classification of normal and hemorrhage brain. Deep learning techniques take Machine Learning to a new level where machines can learn to carry out tasks, with the help of neural networks. There are different types of deep learning models that are both accurate and effectively tackle problems that are too complex for the human brain. They come with their own functionalities and practical approach. Once these models are recognized and put in the correct circumstances, they can lead to good solutions. Commonly used DL algorithms are Convolutional neural networks, Recurrent Neural networks, Generative Adversarial networks, self-organizing maps, Deep reinforcement learning networks etc. Among these, CNN is commonly used in ICH identification.

CNN is an advanced and high-potential type of the classic artificial neural network. It is built to handle higher complexity, preprocessing, and data compilation. CNNs are feed-forward neural networks which contain consecutive connected layers, where subsequent layers process higher-level abstractions. It takes reference from the order of planning of neurons present in the visual cortex of an animal brain. The CNNs can be considered as one of the most efficient and flexible models for specializing in image as well as non-image data. This will help in deriving relevant image data in the form of smaller units. The CNNs are suitable for jobs, such as image recognition, image analysis, image segmentation, video analysis, and natural language processing.

Another DL model, the recurrent neural network (RNN), performs similar abstractions, but is specialized to analyze sequential input data such as text and language. Both these models train via supervised learning, an approach which uses datasets annotated with ground truth reference labels.

In CNN, there are different types. Most commonly used ones are ResNet, AlexNet, VGG, Inception etc.

Alexnet is constructed using 5 or more convolution layers. For the three massive linear layers, it uses max-pooling layers, ReLu activation functions, and dropout. The network can be used to classify images into 1000 different categories.

ResNet is a deep learning model which was introduced by Shaoqing Ren, etal. ResNet is one of the most widely used and effective deep learning models to date. ResNet is built using the concept of "skip-connections" and uses a lot of batch-normalization to let it train hundreds of layers successfully without sacrificing speed over time

VGG is a convolutional neural network design which is based on denser networks. Small 3 x 3 filters are used in the network. The network is known for its simplicity, with simple pooling layers and a fully linked layer as additional components.

Inception CNNs are based on batch normalization and different versions of it do exist. These are used for lowering the computational cost of deep networks without sacrificing generalization.

Common methodology used in detection is summarized below:

CT/MRI data of brain => Image windowing => Normalization=>ROI extraction => Skull removal => CNN algorithms => Classification algorithms

Accuracy in detecting Brain Hemorrhage when learning algorithms are used is calculated as

accuracy= (N[p]× sensitivity +N[n]× specificity) / total number of cases where *N[p]* and *N[n]* denote the numbers of positive cases and negative cases in the validation set, respectively. Sensitivity and specificity are given by

Sensitivity=$\frac{True\ Positives}{True\ positives+False\ negetives}$

Specificity=$\frac{True\ negetives}{True\ negetives+False\ positives}$

F1 score index is also used to measure accuracy of detection which is given by

F1 score (Dice index): F1 = $\frac{2.True\ Positive}{2.true\ Positive+False\ positive+False\ negetive}X100$

In last one decade, Brain Hemorrhage Detection and Classification Systems based on CNN algorithms have gained importance among the researchers community. Next section reviews the recent works published in this area.

III. LITERATURE REVIEW:

An approach to detect intracranial hemorrhage types in computed tomography images of the head is proposed in paper [1]. The model trained for each hemorrhage subtype is based on a double-branch convolutional neural network of ResNet-50 architecture. It extracts features from two chromatic representations of the input data: a concatenation of the image normalized in different intensity windows and a stack of three consecutive slices creating a 3D spatial context. The obtained results justify the use of a combination of double-source features with the random forest classifier. The system outperforms state-of-the-art methods in terms of F1 score. The highest detection accuracy was obtained in intraventricular (96.7%) and intraparenchymal hemorrhages (93.3%).

Non-contrast head CT scan which is the current standard for initial imaging of patients with head trauma or stroke symptoms is dealt in Paper [2]. The authors have aimed to develop and validate a set of deep learning algorithms for automated detection of the following key findings from these scans: intracranial hemorrhage and its types (ie, intraparenchymal, intraventricular, subdural, extradural, and subarachnoid); calvarial fractures; midline shift; and mass effect. Results show that deep learning algorithms can accurately identify head CT scan abnormalities requiring urgent attention, opening up the possibility to use these algorithms to automate the process.

The study done by Xiaohong W Gao and others [3] explores the significance and impact on the application of the burgeoning deep learning techniques to the task of classification of CT brain images, in particular utilizing convolutional neural network (CNN), aiming at providing supplementary information for the early diagnosis of Alzheimer's disease. The two major contributions of the paper constitute a new 3-D approach while applying deep learning technique to extract signature information rooted in both 2D slices and 3D blocks of CT images and an elaborated hand-crated approach of 3D KAZE.

Authors in paper [4] have employed the AlexNet, Vgg-16, ResNet-18, ResNet-34, and ResNet-50 pre-trained models to automatically classify MR images in to normal, cerebrovascular, neoplastic, degenerative, and inflammatory diseases classes. They have obtained the best classification accuracy of 95.23% ± 0.6 with the ResNet-50 model among the *five* pre-trained models. They claim that their model is ready to be tested with huge MRI images of brain abnormalities which will help the clinicians to validate their findings after manual reading of the MRI images.

Issue of misdiagnosed hemorrhages in the brain, especially when the symptoms are acute like headaches or loss of consciousness is addressed in paper[5]. Using Machine learning algorithms authors have created a model that can detect such types of acute brain hemorrhages and further classify them into subtypes. Knowing where exactly the hemorrhage is located can be very helpful in directly operating that area of the brain which can result in quick responses. In addition to detection and classification, a different model is created to conduct segmentation on these CT scan images to identify the affected area.

Neural network approach is used in paper[6] to find and classify the condition based upon the CT scan. The model architecture implemented is based on a time distributed convolutional network. They observed accuracy above 92% from such architecture, provided enough data and have further extended with federated learning. This is helpful in pooling learned parameters without violating the inherent privacy of the data involved.

A tool to help radiologists in the detection of intracranial hemorrhage (ICH) and its five (05) subtypes in computed tomography (CT) images is designed in paper[7]. Five deep learning models are tested: ResNet50, VGG16, Xception, InceptionV3 and InceptionResNetV2. Before training these models, preprocessing operations are performed like normalization and windowing. Authors claim that VGG-16 architecture provides the best performances. The model achieves an accuracy of 96%.

In paper [8], authors assess the feasibility of using the algorithm for the detection of intracranial haemorrhage (ICH) and the classification of its subtypes, without employing the convolutional neural network (CNN). As per their novel method, for the classification of the ICH to subtypes, the accuracy rate for subarachnoid haemorrhage (SAH) was considerably excellent at 91.7%. They claim that their approach can greatly reduce the ICH diagnosis time in an actual emergency situation with a fairly good diagnostic performance.

A deep convolutional neural network is used by authors of paper[9] to simultaneously learn features and classification, eliminating the multiple hand-tuned steps. They claim that performance is improved by computing the mean output for rotations of the input image and applying post processing to significantly improve specificity.

A unique challenge in Computed tomography (CT) is to identify tiny subtle abnormalities in a large 3D volume with near-perfect sensitivity. Authors in paper [10] used a single-stage, end-to-end, fully convolutional neural network to achieve accuracy levels comparable to that of highly trained radiologists, including both identification and localization of abnormalities that are missed by radiologists. They demonstrated an end-to-end network that performs joint classification and segmentation with examination-level classification comparable to experts, in addition to robust localization of abnormalities, including some that are missed by radiologists, both of which are critically important elements for this application

Comparison of the work considered by different authors above gives a clear picture of the status of intracranial hemorrhage detection using deep learning algorithms and the direction of research in this field.

Table 3.1: Comparison of research on of intracranial hemorrhage

Reference	Technology used	Data Set considered	Findings	Accuracy	Limitations
[1]	CCN-ResNet-50	CT scans	Intraventricular and intraparenchymal hemorrhages	93-97%	Failed to give best classification accuracy with respect to Epidural Hemorrhage type.
[2]	Deep learning algorithms	CT scans	Five types of haemorrhage, midline shift, mass effect, and calvarial fracture.	Lower performance <90%	False negative scans are overlooked.
[3]	2D and 3D CNN combined	CT scans	Early diagnosis of Alzheimer's disease	80-93%	Neuro-pathologic changes in the temporal lobe, and other problems are not considered
[4]	AlexNet, Vgg-16, ResNet-18, ResNet-34, and ResNet-50	MRI images	Classification of MR images in to normal, neoplastic, cerebrovascular, degenerative, and inflammatory diseases classes.	Up to 95%	Costly and time consuming
[5]	Efficient Net architecture & UNet	CT scans	Detection and segmentation of brain images	Good accuracy	Problems in dealing balance in data efficiently and also in processing data
[6]	Time distributed convolutional network	CT scans	The system could detect acute intracranial hemorrhage and its subtypes.	Accuracy above 92%	Expensive communication and limited storage
[7]	Five deep learning models are tested: ResNet50, VGG16, Xception, InceptionV3 and InceptionResNetV2.	CT Scans	Models for Intracranial Hemorrhage Recognition	VGG model achieves an accuracy of 96%.	Epidural hemorrhage is excluded
[8]	Novel deep learning algorithm	CT Scans	Detection and classification of intracranial haemorrhage	Overall accuracy rate was 69.6%, highest at 91.7%.	Sample size variation causing distortion in images
[9]	Deep convolutional neural network	CT Scans	Detecting intracranial Hemorrhage	81-98% accuracy	The subarachnoid hemorrhages were relatively difficult to detect.
[10]	Fully convolutional neural network (FCN) called PatchFCN.	CT Scans	Expert -level detection of acute intracranial hemorrhage	High accuracy, >90%	Leave space to attain better accuracy

In these studies, 2D CNN and 3D CNN algorithms are considered to detect ICH. Few of the papers considered different DL algorithms and have compared the performance. Sensitivity was most widely used to report algorithm performance, followed by specificity. Common procedure followed is to consider 2D/3D tomography slices, with slice-level ground truth (GT) labels. An output prediction is formed for each slice. The final prediction for the patient is attained by combining predictions for all slices in the study. Most of the papers considers CT scans while a very few papers considered MR images for detection of ICH.

Main limitation in DL applications is dataset size, especially when medical images are considered. These images must be obtained with approval, de identified, and ground truth-labeled with radiologist expertise. Without a suitably large dataset, CNNs can over fit on training data, causing an overestimated performance on training data and poor generalization to new data. This is an important issue for complex architectures such as 3D CNNs. By simplifying the model, the model's affinity to over fit can be reduced. Thus, deep, complex architectures are not necessarily the best.

Challenges to rapid deployment of machine-generated decisions relate to perceived lack of trust in machine-generated decisions, as well as workflow integration and cost considerations. An important issue afflicting DL models is their lack of interpretability. Due to the complex methods of feature extraction, it can be impossible to explain DL models' predictions.

IV. CONCLUSIONS:

In this paper, we have explored intracranial brain hemorrhage and its types, way of identifying blood leakage inside the brain through CT scans and MRIs, usage of deep learning methods to detect & classify ICH in human brain. Many researchers are working in this direction and trying to bring more accuracy in detecting ICH using different CNN and novel deep learning algorithms. Along with accuracy, researchers have to concentrate on workflow integration and cost considerations too.

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