Literature Review for Automatic Detection and Classification of Intracranial Brain Hemorrhage Using Computed Tomography Scans

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Literature Review for Automatic Detection and Classification of Intracranial Brain Hemorrhage Using Computed Tomography Scans

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Abstract. Intracranial Brain Hemorrhage is a serious threat to health and life, it requires immediate and efficient medical treatments. It comprises five broad categories, namely epidural hemorrhage, subdural hemorrhage, subarachnoid hemorrhage, intraventricular hemorrhage, and intraparenchymal hemorrhage. We can distinguish between these subtypes on the basis of the character of bleeding and its location in the brain region. Developments in the field of Artificial Intelligence and Machine Learning particularly Computer Vision over years help the research community to propose studies, which can be used to fight various medical diseases and emergencies. Computed Tomography scans of the brain play a significant role and are popularly used for the evaluation of intracranial hemorrhage. Location of hemorrhage on unenhanced Computed Tomography scans of the brain and differences in X-ray attenuation helps in detecting different subtypes of Intracranial Brain Hemorrhage. In this article, we have provided an extensive literature review for the problem of detection and classification of Intracranial Brain Hemorrhage in past 15 years. We have explored the objectives and applications of the existing studies, the methods adopted for diagnosis in them, and different pre-processing techniques that were applied to image data. We concluded our study by stating some major research challenges on the basis of previously done work in the field, their possible solutions which can be followed in future works and limitations of this study. This paper aims to help and facilitate radiologists, medical experts, and other researchers in understanding the way how machine learning can be potentially used in the diagnosis of Hemorrhage.

Keywords: Intracranial Brain Hemorrhage, Literature Review, Diagnosis, Machine Learning, Deep Learning, Head CT scans, Convolutional Neural Networks, Feature Extraction, Medical Images Pre-Processing.

1 Introduction

In this study, we have investigated the problem of detection of Intracranial Brain Hemorrhage and the classification of its various subtypes. Intracranial Hemorrhage (ICH) is a life-threatening emergency that corresponds to acute bleeding within the skull (cranium) [1]. It is a severe type of stroke that occurs when the brain is deprived of oxygen and blood supply. The most common reasons for the occurrence of Intracranial Hemorrhage are arteriovenous malformations, hypertension (High blood pressure), and head trauma. Other possible causes include vascular abnormalities, venous infarction, bleeding disorders or treatment with anticoagulant therapy, atherosclerosis (buildup of fatty deposits in the arteries), and smoking or heavy alcohol use. The symptoms of Intracranial Hemorrhage depend on the affected part of the brain. Generally, symptoms of bleeding within the brain include difficulty in breathing, severe headache, loss of vision, loss of balance, light sensitivity, dizziness, and sudden weakness. Intracranial hemorrhage constitutes a major threat and can be fatal. Rapid bleeding into intracranial compartments can even cause sudden death. According to recent medical surveys, Brain Hemorrhage has become one of the main causes of death and many disabilities. As per the various studies done in India, the diffusion of stroke ranges from 334 to 424/100,000 in urban areas and 84 to 262/100,000 in rural areas [2].

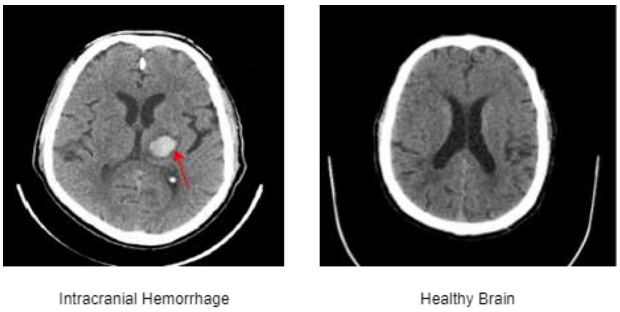

Fig. 1. Sample images of CT scan with Intracranial Hemorrhage (marked with red arrow) and Healthy Brain.

Intracranial Brain Hemorrhage comprises five types, named as, epidural hemorrhage, subdural hemorrhage, subarachnoid hemorrhage, intraventricular hemorrhage, and intraparenchymal hemorrhage [1].

- Epidural Hemorrhage: It is a type of hemorrhage in which the blood accumulates between the thick outer membrane, that is, the dura mater and the skull. The main cause of such hemorrhage is when a skull fracture or injury tears the underlying blood vessel.
- Subdural Hemorrhage: It is a type of hemorrhage in which the blood accumulates within the skull but outside the tissue of the brain. It causes when any brain injury bursts the outer blood vessels on the skull head. It sometimes does not show symptoms and needs no treatment.
- Subarachnoid Hemorrhage: It is a type of hemorrhage in which the blood accumulates in the space surrounding the brain. It is mainly caused when any blood vessel presents on the surface of the brain's outer tissue bursts. It is a severe type of stroke and needs immediate treatment.

- Intraventricular Hemorrhage: It is a type of hemorrhage in which the blood accumulates into the brain's ventricular system. It mainly occurs due to a lack of oxygen in the brain or traumatic birth. It also has a high mortality rate, especially among newborn babies.
- Intraparenchymal Hemorrhage: It is a type of hemorrhage in which the blood accumulates within the brain parenchyma region, that is, the tissue region of the brain. It mainly occurs due to sudden trauma, tumors, rupture of inner brain arteries or veins, or birth disorders.

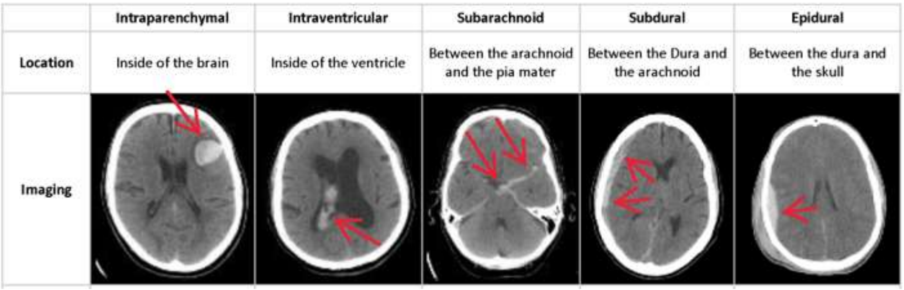

Fig. 2. Types of hemorrhages: (From Left to Right) Intraparenchymal, Intraventricular, Subarachnoid, Subdural, Epidural. Source [21].

It is well known that India is facing a shortage of both trained medical staff and medical facilities. As per statistics presented in Jayakrishnan Thayyil et al. [3], India comprises approx. 17% of the total world population but contributes to about 20% of the total world disease burden. About 70% of the total population of the country resides in rural areas but approx. 74% of the total trained medical staff lives in urban areas, leaving behind 26% for the majority of the population. As per a survey conducted in March 2018, a shortfall in health facilities at different levels is about: 18% at the Sub-Centre level, 22% at the PHC level, and 30% at the CHC level [4]. Thus, there is a lot of burden on the existing medical staff. The professional medical staff works day and night for the wellbeing of society. Examples of this have been seen in the past two years during the COVID-19 pandemic. The advancements in science and technology, particularly in the field of artificial intelligence should be implemented and used in such a way that it helps and supports our medical workforce. AI-assisted tools and chatbots, AI-powered robots, and various computer-aided diagnostic systems should be promoted more and more. Real-time automatic diagnosis of severe health issues like Intracranial Brain Hemorrhage will definitely prove a milestone in medical history. It will save the lives of thousands of patients per year who lost their lives due to late treatment and improper diagnosis of Hemorrhage.

The rest of this paper is organized as follows: Section 2 describes the existing methods of diagnosis of ICH and comparison between CT scan images and MRI images for diagnosis purpose, Section 3 describes how machine learning and deep learning techniques can assist in the detection of ICH and also presents the summary of some previously done works, the comparison table and analysis based on the obtained table. Section 4 describes some limitations of this study, presents the future research work for related to the field and lastly, concludes our paper.

2 Methods for Diagnosis of Brain Hemorrhage

Intracranial Brain Hemorrhage is a severe type of stroke that can affect the functioning of brain cells and thus can lead to critical symptoms and can eventually lead to the death of a patient. Fast and effective treatment is generally required in case of an ICH emergency. In some cases, major surgeries can also be done to save the life of a patient. Diagnosis of ICH is done by either CT scan or Magnetic Resonance Imaging (MRI) [5, 7]. Neurologists and Radiologists require images of inner regions of the brain, in order to locate and confirm the presence of hemorrhage. Further, they perform the volumetric analysis of ICH on the basis of the spread of blood over brain tissues. This is an important step of treatment because performing this provides information about location, position, volume, and subtype of hemorrhage. Generally, a CT scan is done first, and then if further clear and detailed images are required then MRI is done. Due to the better image quality of MRI sometimes, it is being assumed that MRI should be preferred over CT scan for diagnosis, but this is not always true. CT scans have many advantages over MRI. Imaging in case of CT scan is fast, generally takes 10-15 minutes while MRI might take 35-45 minutes and in case of an emergency, the patient might not have that much time and need instant treatment. Moreover, a CT scan can also be performed if the patient is taking a drip but MRI cannot be done in that case. CT scan machines are easily available as compared to MRI machines and performing CT scans is also less costly. MRI scan cannot be performed in case if a patient is having any metallic or electrical implant in the body. Also, in MRI the body of the patient is completely passed into the machine thus it might lead to a state of unconsciousness. Sometimes, patients might not fit into the MRI scanning machine due to their weight. Generally, it is recommended to the patient to stay still in the MRI machine but sometimes it might not be feasible for the patient due to old age or pain. MRI also has some advantages over CT scan like the dose of harmful X-rays is high in case of CT scan while MRI works on the magnetic and electrical power. Frequent CT scans can increase the risk of cancer to the patient. The quality of images and information provided by MRI scans are much better as compared to CT scan images.

Thus, it can be seen that both types of diagnostic imaging processes have their own pros and cons. It has been observed that the image quality of a CT scan is sufficient enough to provide details and information about brain hemorrhage so that doctors can start initial treatment. Head CT scan images can even show the acute hemorrhage or abnormality present in brain tissues. That's why doctors prefer CT scans over MRI for the accurate diagnosis of Brain Hemorrhage. If frequent imaging reports are required or radiologists need further details of inner brain tissues then MRI is done. Due to these reasons, we have chosen Computed Tomography (CT) scan for the diagnosis of Intracranial Brain Hemorrhage as our work.

3 Machine Learning for Diagnosis of Brain Hemorrhage

Intracranial Brain Hemorrhage is a very serious health problem that requires immediate and intensive medical treatment. The delay in proper treatment might lead to the death of the patient. The diagnosis of ICH using CT scans is a very complex process and generally requires a very experienced radiologist. Sometimes it is not possible to have an experienced radiologist available all the time. Which leads to a lack of treatment. Moreover, the volumetric analysis of ICH using CT scan images is a very complex and error-prone process. In the case of complex ICH, it becomes very difficult to estimate the volume of the Hemorrhage. Thus, a rapid and accurate alternative method of diagnosis is necessary for the treatment process achieving success over ICH. The advancements in the field of machine learning and deep learning, particularly computer vision, attracts the research community to propose computer-aided, rapid, and accurate mechanisms for the automatic diagnosis of various diseases. As the diagnosis of hemorrhage depends on the images obtained from CT scan or MRI, a self-learning algorithm can be trained to obtain a model that can learn the patterns from the normal and abnormal images. On the basis of these learnt patterns the model can detect the traces of disease present in medical images. In recent years, a lot of work has been done in the field of diagnosis using machine learning [9-18, 24-25]. Some of these are, detection of pneumonia and COVID-19 using X-ray images of chest, classification of brain tumor into benign and malignant, detection of breast cancer, treatment of dead cells related skin infections, detection of degenerative diseases like Parkinson and Alzheimer, in Diabetic Retinopathy, assisting doctors for prescribing medicines and ICU calls, detection of stage of Diabetes and many more.

The detection and classification of ICH using machine learning techniques generally follows the pipeline presented in Figure 3. The first stage of the pipeline is Data collection or Data acquisition, in this stage the medical images along with proper metadata of patients are collected from different hospitals or radiology centers. These images are later used for training and testing of models. The following step is the Data preparation step, which includes various data pre-processing techniques applied on the medical images to make them ready for the input to model. This is an important step as in this step noise and extra, unwanted information are removed from images and various data augmentation techniques are applied. Next stage is Dataset partition, this stage includes dividing the dataset into training, validation and test sets. Following is the Training stage, this is the most important stage in the pipeline as it includes feature extraction, feature selection and classification on the basis of features obtained. The performance of the model is highly dependent on the methods that are being adopted for feature extraction and classification in this stage. Lastly, the trained model is being tested on the test dataset images and performance and generalizability of the model is evaluated on the basis of various parameters like accuracy, recall, precision, F1-score, AUC, sensitivity, specificity etc.

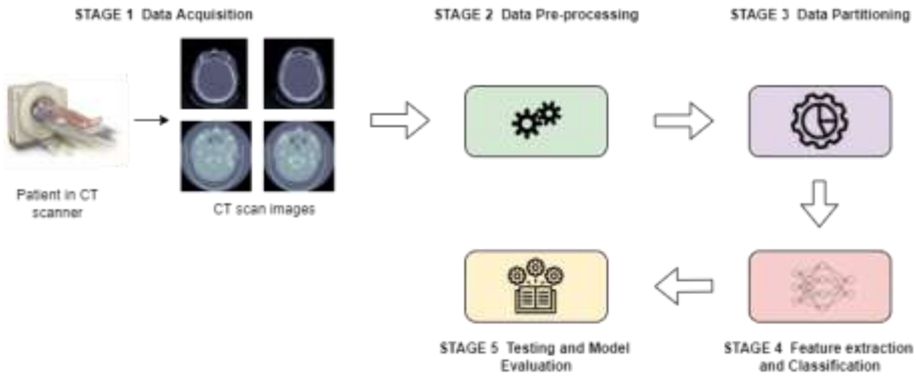

Fig. 3. The block diagram represents the general pipeline for the diagnosis of Brain Hemorrhage.

Depending on the Stage 4, Feature extraction and Classification, the approaches for building pipeline can be divided into three types:

- Machine Learning Algorithms for both feature extraction and classification.
- Deep Learning Models for feature extraction and Machine Learning Algorithms for classification.
- Deep Learning Models for both feature extraction and classification.

3.1 Machine Learning Algorithms for Both Feature Extraction and Classification

In this approach, after applying suitable data pre-processing methods to input images, the useful features are extracted using different standard methods and then traditional machine learning based classifiers like SVM, Random Forest, KNN etc. are trained on the obtained features.

Shuchi Saini et al. [5], presented the comparison between various ICH segmentation algorithms. Majorly, three techniques have been used for the segmentation of ICH, named as, Thresholding technique, Region Growing technique, and Clustering techniques. The authors have implemented and compared the proposed multilevel segmentation approach (MLSA), watershed method, and EM method on the basis of time taken to process single image and average PCC values. The MLSA technique has performed better than other methods.

Bahare Shahangian et al. [6], implemented a pipeline for the segmentation of the hematoma region for its area evaluation and classification into subtypes. This pipeline includes pre-processing techniques, skull removal method, brain ventricles removal technique, morphological filtering processes, segmentation of ICH region, feature extraction, quantifiable feature selection using genetic algorithm, and lastly, classification of ICH into subtype. The skull and brain ventricles were removed by applying a check on the intensity values of the CT scan. Then a median filter was applied to remove noise and the largest area object had been selected from the binary image to get only the brain region. ICH segmentation was performed by applying a threshold to pixel intensities. For the classification purpose, a KNN algorithm and a multilayer perceptron (MLP) model with tan sigmoid activated output layer were trained. MLP model outperformed KNN.

Ruizhe Liu et al. [7], dealt differently with the nasal cavity and encephalic region CT scans. From Figure 4 we can observe that both types of CT scans have different textures, thus, the method working efficiently with brain regions might not work well with the nasal cavity. Both are separated on the basis of texture analysis using Wavelet transform. Skull removal and gray matter removal methods were applied to the encephalic region to get segmented hemorrhages. Then 12 different features corresponding to intensity distribution and texture descriptions were extracted. Entropy calculation was employed to select good features and a Support Vector Machine (SVM) classifier was trained to distinguish abnormal slices (slice consisting of ICH) from normal slices.

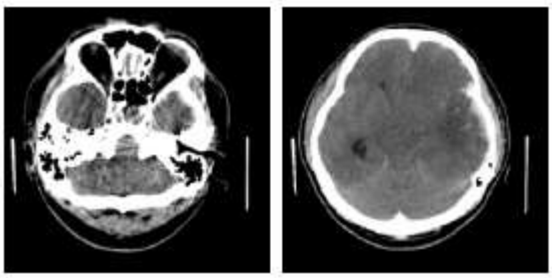

Fig. 4. Nasal Cavity (left side image) and Encephalic Region (right side image). Source [7].

Mahmoud Al-Ayyoub et al. [8], proposed a pipeline that includes skull removal, segmentation of ICH, morphological methods, extraction of the region of interest, feature extraction, and classification. For the segmentation purpose, Otsu's method was applied followed by the opening transformation technique. Region of Interest is obtained by applying the region growing algorithm on the output obtained after segmentation. Finally, features based on the size, shape, and position of Hemorrhage ROI were extracted. The SVM, Multinomial Logistics Regression (MLR), Multilayer Perceptron model, Decision Tree, and Bayesian Network classifiers were trained independently on features. The MLR classifier outperforms others.

3.2 Deep Learning Models for Feature Extraction and Machine Learning Algorithms for Classification

In this approach, after applying suitable data pre-processing methods to input images, the pre-trained Convolutional Neural Networks are imported and are trained end-to-end in order to extract features from images. The traditional machine learning algorithms applied on the top of these CNN models are then trained for performing classification using the obtained features.

Hojjat Salehinejad et al. [9], stacked three windows of CT scan images to get 3-channel input for 2D-CNN models. They have used pre-trained SE-ResNeXt-50 and SE-ResNeXt-101 models as the backbone for extracting features from images and have applied traditional machine learning algorithms like LightGBM, CatBoost, and XGboost for classification. To utilize the interdependency among slices of a CT scan they applied a sliding window module. For testing the generalizability of the models, they tested them on a private external validation dataset. This is an important step, especially in the case of medical images. Testing the models on a dataset consisting of temporally and geographically different images indicates the generalization power of models.

Agata Sage et al. [10], have applied regions of interest, that is, brain region cropping and skull removal methods before giving images input to the ResNet-50 model. They performed brain region cropping by determining the largest binary object from the CT scan image after applying Otsu Algorithm. The skull removal method was applied by reducing the values of pixels having the highest intensities to zero. Two branch architecture was used to train the classification model. In the first branch, three different windows were stacked and in the second branch, three consecutive subdural windows were stacked to get a 3-channel image. SVM and Random Forest were applied on top of the ResNet-50 network for predicting the class.

3.3 Deep Learning Models for Both Feature Extraction and Classification

In this approach, after applying suitable data pre-processing methods to input images, the pre-trained Convolutional Neural Networks are imported and then transfer learning protocol is followed to train these models for performing classification. The features obtained from the pre-output layer of these models can also be used to train Bi-LSTM network layers in order to utilize the spatial interdependence among slices of CT scan.

Jiajie He et al. [11], developed a classification model using pre-trained CNN models like SE-ResNeXt50 and EfficientNet-B3 as the backbone. They have used weighted multi-label logarithmic loss for the training of models. For improving the performance, they employed K-fold cross-validation (K = 10 in their case) and pseudo-label technique. Using the pseudo-label technique, 52260 new images were added into the training dataset which was originally present as unlabeled data in the RSNA dataset [21].

Emily Anaya et al. [12], proposed a multi-label classification model for classifying ICH into its subtypes. The features were extracted using pre-trained MobileNet and ResNet-50 networks. On the basis of experimental results, the authors concluded that it is most difficult to detect epidural hemorrhage using a CT scan. This is probably due to the presence of an epidural hematoma near the skull region of the head.

Juan Sebastian Castro et al. [13], proposed a binary classification model for detecting hemorrhage in CT scans. The brain region from CT scans was extracted from the background and then a single window (WW= 80; WL=50) was applied to get the brain parenchyma region. They have used pre-trained VGG-16 and a customized

CNN model as the backbone for the classification model. The training was performed using two protocols, one is slices randomized and another is subject randomized.

Tomasz Lewicki et al. [14], presented a multi-label classification model for the detection and classification of ICH into its subtypes. Due to heavy negative bias and high-class imbalance among positive classes in the RSNA dataset [21], class weights were applied to loss function and recall/precision tuning was performed. A batch of 3-channel CT scan images produced by stacking three different windows was fed as input to the ResNet-50 model for training purposes.

Ajay Patel et al. [15], used a private dataset to train the combination of CNN and Bi-LSTM networks for predicting the probabilities corresponding to each class. Initially, features of the CT scan images were extracted using CNN and then the output spatial vectors of consecutive slices were together given as input to Bi-LSTM layers. The Bi-LSTM network was applied to utilize the interdependency among slices of a CT scan. Rotation and Random Shifting augmenting techniques were also applied. The authors also specified the importance of pre-training of CNN models before applying end-to-end training for fine-tuning.

Nhan Nagyun et al. [16], trained a CNN and Bi-LSTM combinational network on the RSNA dataset and used the CQ500 dataset [26] for external validation. They have applied various types of augmenting techniques to improve the generalizability of models. To deal with the class imbalance problem in the RSNA dataset they have applied weighted binary cross-entropy loss for training. They have used ResNet-50 and SE-ResNeXT-50 models as the feature extractors.

Mihail Burduja et al. [17], proposed a slice-based classification model using the ResNeXt-101 network for feature extraction and Bi-LSTM layers on top. The ResNeXt-101 network outputs a 2048-seized feature vector for each image. Then, PCA was applied to reduce the dimensions of this feature vector to a 120-sized vector. This reduced feature vector was given as input to recurrent neural networks. The outputs of RNN were concatenated to the prediction probabilities obtained as outputs from ResNeXt-101. These concatenated feature vectors were used to train the final output softmax activated layer. They have also compared performances of ResNeXt-101 and EfficientNet-B4 and concluded that ResNeXt-101 gives better results. The authors also presented the importance of using spatial dependency of slices of a CT scan. By utilizing this characteristic, the numbers of false positives and false negatives can be reduced. The GRAD-CAM saliency maps were also presented for the approx. visualization of the ICH region.

Hoon Ko et al. [18], proposed a multi-label classification model for the detection of ICH and classification into its subtypes. The model consisted of a combination of pre-trained Xception network and Bi-LSTM layers. The sigmoid activated layer was applied as the output classifying layer. The major positive point of this work is that several image augmenting techniques were applied especially on the Epidural Hemorrhage subclass to deal with the class imbalance issue in the RSNA dataset [21].

Vincy Davis et al. [19], presented a model for the diagnosis and classification of ICH. The model includes conversion of CT scan image into the grayscale image then resizing and edge detection was applied. After that several morphological techniques like opening and closing transformations and boundary smoothing methods were applied. Segmentation of ICH was performed using Watershed Algorithm. The paper also presents the importance of the Watershed algorithm in extracting hematoma regions. An ANN model was trained using features extracted from Gray Level Co-occurrence Matrix (GLCM) method.

Arjun Majumdar et al. [20], proposed a CNN model inspired by U-Net for the segmentation of the ICH region in the CT scan image. The model was trained on the ground truth labeled images. The segmented hematoma was classified into its subtypes. They have applied several data augmentation techniques for achieving better-generalized outcomes. The paper also discussed about possible reasons for achieving better results for intraparenchymal and epidural subtypes and not-so-good results for subarachnoid subtypes.

Table 1, comparing the reviewed papers on the basis of some common parameters primarily related to the implementation of work. The parameters included are application of the paper, dataset used in the paper, windowing policies adopted for the CT scans to convert them into 3-channel images, pre-processing techniques applied before feature extraction and training of models, saliency or heat maps presenting the presence of ICH in CT scan and some major pitfalls of the paper which we came across.

Table 1. Table presents the comparison of reviewed papers on the basis of common parameters.

Author [Year]	**Application of Paper**	**Dataset**	**Window Policy**	**Pre-processing**	**Saliency Map Visualization**	**Major Pitfalls**
Ruizhe Liu et al. [2008]	Splitting of CT scan images into nasal cavity and encephalic region. Classification of ICH into its subtypes.	Private Dataset	-	Skull removal; Gray Matter removal; Wavelet Transforms.	-	1. Dataset not made publicly available. 2. Applicable only on encephalic region images. 3. Poor feature extraction and selection methods.
Shuchi Saini et al. [2013]	Segmentation of ICH region and Detection of abnormal slices of CT scan	Private Dataset	-	-	-	1. No pre-processing techniques applied. 2. No presentation of classifier algorithm was given. 3. Proposed segmentation method is also unclear.
Bahare Shahangian et al. [2013]	Segmentation of ICH region and Classification of ICH into subtypes.	Private Dataset	-	Skull removal; Brain Ventricles removal; Median Filter; Soft tissue Edema removal;	-	1. Dataset is not made publicly available. Small dataset. 2. No window policy applied. 3. Only three subtypes (Epidural,

						Intracerebral and Subdural Hematoma) are classified. 4. The method proposed for segmentation is based on pixel intensity division. This method is not so promising and might not work better in case of complex CT scans.
Mahmoud Al-Ayyoub et al. [2013]	Segmentation of ICH region and Classification of ICH into its subtypes.	Private Dataset	-	Skull removal; Segmentation using Otsu's method; Opening operation; Region Growing.	-	1. Dataset not made publicly available. 2. Poor feature extraction and selection methods. 3. Only three subtypes (Epidural, Intraparenchymal and Subdural Hematoma) are classified.
Vincy Davis et al. [2017]	Segmentation of ICH region and Classification of ICH into subtypes.	Private Dataset	-	Edge Detection; Opening and Closing operations; Median Filter; Watershed Algorithm (Segmentation)	-	1. Small dataset (just 35 images). 2. No window policy. 3. Only two subtypes (Intracerebral and Subdural Hematoma) are classified. 4. Poor feature extraction and selection methods.
Arjun Majumdar et al. [2018]	Segmentation of ICH region and Classification of ICH into its subtypes.	Private Dataset	-	Data Augmentation	-	1. No proper pre-processing applied. 2. Small private dataset (just 134 CT scans).
Emily Anaya et al. [2019]	Detection and Classification of ICH into subtypes	RSNA	-	-	-	1. No window policy. 2. No pre-processing done. 3. Small dataset (only 5000 images from RSNA were used).
Juan Sebastian Castro et al. [2019]	Detection of ICH in CT scan	CQ500	Brain window (WW= 80; WL=50)	Background Removal; Anisotropic filter	-	1. Small Dataset 2. Only detection of ICH, No classification into subtypes.
Ajay Patel et al. [2019]	Detection of ICH in CT scan using spatial Interdependency among slices of	Private Dataset	-	Data Augmentation	-	1. Not made dataset publicly available. 2. No pre-processing and visualization techniques applied.

	CT scan.					
Jiajie He et al. [2020]	Detection and Classification of ICH into subtypes	RSNA	-	Data Augmentation	-	1. No window policy applied. 2. No pre-processing done.
Tomasz Lewicki et al. [2020]	Detection and Classification of ICH into subtypes	RSNA	Brain window (WW=80; WL=40); Subdural window (WW=200; WL=80); Bone window (WW=2800; WL=600)	-	-	1. No pre-processing done. 2. No visualization of ICH presented 3. Only one classifier is trained
Agata Sage et al. [2020]	Detection and Classification of ICH into subtypes	RSNA	Brain window (WW=80; WL=40); Subdural window (WW=200; WL=100); Bone window (WW=2800; WL=600)	Brain region Cropping; Skull Removal	-	1. Not used spatial interdependency among slices. 2. No saliency map visualization. 3. Only subset of RSNA was used.
Nhan Nagyun et al. [2020]	Detection and Classification of ICH into subtypes using Spatial Interdependency among slices of CT scan.	RSNA; CQ500 (external validation)	Brain window (WW=80; WL=40); Subdural window (WW=215; WL=75); Bone window (WW=2800; WL=600)	Data Augmentation	-	1. No pre-processing and visualization techniques applied.
Mihail Burduja et al. [2020]	Detection and Classification of ICH into subtypes using Spatial Interdependency among slices of CT scan.	RSNA	Brain window (WW=80; WL=40); Subdural window (WW=200; WL=80); Soft Tissue window (WW=380; WL=40)	Data Augmentation	GRAD-CAM heat maps presented	1. No pre-processing techniques applied.
Hoon Ko et al. [2020]	Detection and Classification of ICH in CT scan using Spatial Interde-	RSNA	Brain window (WW=80; WL=40); Subdural	Data Augmentation; Data Balancing	-	1. No pre-processing and visualization techniques applied. 2. Number of labels are shown as number

	pendency among slices of CT scans.		window (WW=200; WL=80); Bone window (WW=1800; WL=400)			of images in dataset which is not correct.
Hojjat Salehinejad et al. [2021]	Detection and Classification of ICH into subtypes using Spatial Interdependency among slices of CT scan.	RSNA; Private dataset (external validation)	Brain window (WW=80; WL=40); Subdural window (WW=200; WL=80); Soft Tissue window (WW=380; WL=40)	-	GEAD-CAM and GRAD-CAM++ heat maps presented	1. No pre-processing done. 2. Haven't made private dataset public.

With reference to the above table, we can infer some important gaps in the research literature which have to be taken care of while implementing a model for Detection and Classification of Intracranial Brain Hemorrhage into its subtypes. The following are some measures to be taken care of: -

- Adequate pre-processing techniques must be applied before feature extraction and classification because pre-processing techniques help in removing noise, removing not required information from image data, and increasing the quality of the image leading to better feature extraction.
- Saliency or Heat maps of the CT scan image showing the location of the ICH region must be presented. This might help the radiologists in locating the acute ICH region and also proves the credibility of the classification model that it is considering the ICH part in real and not classifying on the basis of some external bias.
- The adjacent slices of a CT scan have almost similar texture composition and have similar characteristics. Thus, while training the classification model one should use this spatial interdependence among slices of CT scan. This leads to better results comparatively.
- Using only a single window of CT scan image cannot help much in the diagnosis of ICH because there might be a case when hemorrhage is present in the bone region of the brain and if only soft tissue windows are being considered then it might not provide clear insights of the hemorrhage. Thus, a combination of different windows of a CT scan image should be preferred for diagnosis.
- If any researcher is preparing or collecting their own private dataset then they should make the dataset publicly available with proper metadata. This motivates the research community to further work in the field.
- Most of the papers published before the year 2019 have either used their private datasets or have used the CQ500 dataset. But almost all works that are being done after 2019 have used RSNA dataset because the RSNA ICH Detection Challenge [22] was launched in the year 2019. Generally, it has been observed that the num-

ber of images in both private datasets and CQ500 are much less than the number of images present in RSNA dataset. Thus, models trained on the RSNA dataset can be considered as more promising on the grounds of generalizability.

- To the best knowledge of the authors, as of now, there is no publicly available dataset for the segmentation and extraction of ICH from CT scan images for its volumetric analysis. For the treatment of ICH, its volumetric analysis is considered as a crucial step and due to lack of publicly available dataset, it becomes difficult for new researchers to work in this field.
- For the purpose of segmentation of the ICH region, the proposed algorithm should be robust to the quality of the input CT scan images. The algorithm should not be trained on any particular types of CT scans like encephalic regions only. It should be able to locate and extract the hemorrhage regions of all subtypes present in all types of CT scan images.

4 Conclusion and Future Work

This study aimed to investigate the problem of detection of Intracranial Brain Hemorrhage and classification into its subtypes. Intracranial Hemorrhage (ICH) is a life-threatening emergency that corresponds to acute bleeding within the skull (cranium). Thousands of people die every year due to the lack of instant treatment of ICH. We have shown the significance of machine learning and deep learning, in the field of diagnosis of ICH. Along with the general insights of Intracranial Hemorrhage and its subtypes, the paper described the existing methods of diagnosis using CT scan and MRI. Our study also explains how AI/ML techniques can be used for the detection and extraction of the ICH region. In the review process of previously done works, the paper consists of a state-of-art ranging from data handling to feature extraction and classification. All these stages in the pipeline were explored and analyzed individually. The works are compared on the basis of various dimensions like application of work, the dataset used, data pre-processing steps included, heat maps presented, AI/ML techniques employed and classifiers used, etc.

We have compared different previously done studies in the field of detection and classification of Intracranial Brain Hemorrhage on the basis of some common parameters. But there are some limitations of this study that need to be addressed in future work. Firstly, we have majorly reviewed works which are using deep learning techniques. This is because it has been observed that the performance of deep learning models is generally much better than that of traditional machine learning methods and algorithms. Almost all studies related to this field done in recent years have employed only deep learning-based CNN models for classification. Secondly, we assumed that the reader is having some prior knowledge about the implementation details of various algorithms and methods presented in this study. That is why we have not shown the working details or theoretical information about these algorithms. Thirdly, some specific parameters like hyperparameters values (batch size, learning rate, number of nodes or layers in customized networks, epochs, kernel size, etc.), number of images in the datasets, information about data splitting, and results of the reviewed works have not been presented. This is because these parameters were differently implemented in different studies and thus, cannot be directly compared. Lastly, we have not implemented any codes for the confirmation of the results claimed in the reviewed studies. Also, we do not guarantee the qualitative results of these studies in real-time applications for the diagnosis of ICH.

Further, for the future works to be done, it would be suggested for aiming to implement several pipelines for the detection and classification of ICH using CT scans. In these pipelines, one can implement different pre-processing techniques like skull removal methods, head cropping methods, enhancing the medical image quality by applying CLAHE, Gamma correction or Histogram equalization, etc., and different image data augmentation techniques. Then compare the results obtained from these pipelines to get the best pre-processing and augmenting techniques to be followed for achieving the best results. For the classification purpose, it would be suggested to use pre-trained CNN models for feature extraction and Bi-LSTM network layers on top to use the interdependency among slices in a CT scan. As classifiers, one can train both traditional machine learning algorithms like SVM, KNN, XGBoost, and Random Forest on top of CNN models and softmax activated final output layer. Along with the combination of CNN and Bi-LSTM, one can also use the 3D-CNN model for classification purposes. Saliency heat maps for the visualization of the location of the Hemorrhage region in the CT scan image should be presented in work.

This study has certain limitations, but it also provides insightful information about the problem and suggests several solutions to overcome the current challenges related to the field. We think it will motivate other researchers who would like to contribute in the future to this field. The role of radiologists and neurologists cannot be replaced by the intelligence of machine learning and deep learning models. We have presented support to the healthcare workforce. The primary aim for this study is to bridge the gap between AI/ML experts and trained medical staff so that they cooperate proactively with each other. In the near future, it is hoped that AI/ML techniques will be accurate and reliable enough to be used in the diagnosis of Intracranial Brain Hemorrhage in real-time so that we can together win over this life-threatening disease.

References

1. Brain Bleed, Hemorrhage (Intracranial Hemorrhage). https://my.clevelandclinic.org/health/diseases/14480-brain-bleed-hemorrhage-intracranial-hemorrhage. Last accessed 2021/12/10.
2. Pandian J. D., Sudhanb P.: Stroke Epidemiology and Stroke Care Services in India. Elsevier Public Health Emergency Collection. DOI: 10.5853/jos.2013.15.3.128. (2013).
3. Thayyil J., Jeeja M. C.: Issues of creating a new cadre of doctors for rural India. In: International Journal of Medicine and Public Health. Jan-Mar 2013 Vol 3 Issue 1. (2013).
4. Kumar A., Nayar R. K., Koyac S. F.: COVID-19: Challenges and its consequences for rural health care in India. Elsevier Public Health Emergency Collection. DOI: 10.1016/j. puhip.2020.100009. (2020).

5. Saini S. and Prof. V.K. Banga: A Review: Hemorrhage Intracranial Segmentation in Ct Brain Images. In: International Journal of Engineering Research & Technology (IJERT). ISSN: 2278-0181. Vol. 2 Issue 10, October – 2013. (2013).
6. Shahangian B., Pourghassem H.: Automatic Brain Hemorrhage Segmentation and Classification in CT scan Images. In: IEEE 8th Iranian Conference on Machine Vision and Image Processing (MVIP). DOI: 10.1109/IranianMVIP.2013.6780031. (2013).
7. Liu R., Tan C. L., Leong T. Y., Lee C. K., Pang B. C., Lim C. C. T., Qi Tian, Tang S., Zhang Z.: Hemorrhage Slices Detection in Brain CT Images. In: IEEE 19th International Conference on Pattern Recognition. DOI: 10.1109/ICPR.2008.4761745. (2008).
8. Mahmoud A. A., Alawad D., Khaldun A. D., Inad A. J.: Automatic Detection and Classification of Brain Hemorrhages. WSEAS TRANSACTIONS on COMPUTERS. Issue 10, Volume 12, October 2013. (2013).
9. Salehinejad H., Kitamura J., Ditkofsky N., Lin A., Bharatha A., Suthiphosuwan S., Lin H., Wilson J. R., Mamdani M., Colak E.: A Real-World Demonstration of Machine Learning Generalizability: Intracranial Hemorrhage Detection on Head CT. Scientific Reports. Article number: 17051 (2021).
10. Sage A., Badura P.: Intracranial Hemorrhage Detection in Head CT Using Double-Branch Convolutional Neural Network, Support Vector Machine, and Random Forest. Applied Sciences MDPI. Appl. Sci. 2020, 10, 7577; doi:10.3390/app10217577. (2020).
11. He, J.: Automated Detection of Intracranial Hemorrhage on Head Computed Tomography with Deep Learning. In: ICBET 2020: Proceedings of the 2020 10th International Conference on Biomedical Engineering and Technology. 117–121 (2020).
12. Anaya. E, Beckinghausen, M: A Deep Learning Approach to Classifying Intracranial Hemorrhages. CS230: Deep Learning, Fall 2019, Stanford University, CA. (2019).
13. Castro J.S., Chabert S., Saavedra C., Salas R.: Convolutional neural networks for detection of intracranial hemorrhage in CT images. In: Proceedings of the 4th Congress on Robotics and Neuroscience. Vol - 2564. (2019).
14. Lewicki T., Kumar M., Hong R., Wu W.: Intracranial Hemorrhage Detection in CT scans using Deep Learning. In: 2020 IEEE Sixth International Conference on Big Data Computing Service and Applications (Big Data Service). DOI: 10.1109/BigdataService49289 .2020.00033. Page 169-172. (2020).
15. Patel A., SIL. C. Van De, Prokop M., Ginneken B. V, Manniesing R.: Image Level Training and Prediction: Intracranial Hemorrhage Identification in 3D Non-Contrast CT. IEEE Access. Digital Object Identifier 10.1109/ACCESS.2019.2927792. (2019).
16. Nguyen N. T., Tran D. Q., Nguyen N. T., Ha Q. Nguyen.: A CNN-LSTM Architecture for Detection of Intracranial Hemorrhage on CT scans. Medical Imaging with Deep Learning 2020. arXiv:2005.10992v3 [cs.CV]. (2020).
17. Burduja M., Ionescu R. T., Verga N.: Accurate and Efficient Intracranial Hemorrhage Detection and Subtype Classification in 3D CT scans with Convolutional and Long Short-Term Memory Neural Networks. In: Sensors MDPI. Sensors 2020, 20, 5611; doi:10.3390/s20195611. (2020).
18. Hoon K., Chung H., Lee H., Lee J.: Feasible Study on Intracranial Hemorrhage Detection and Classification using a CNN-LSTM Network. In: 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC). DOI: 10.1109/EMBC44109.2020.9176162. (2020).
19. Davis V. and Dr. Devane S.: Diagnosis & Classification of Brain Hemorrhage. In: IEEE International Conference on Advances in Computing, Communication and Control (ICAC3). DOI: 10.1109/ICAC3.2017.8318764. (2017).

20. Majumdar A., Brattain L., Telfer B., Farris C., Scalera J.: Detecting Intracranial Hemorrhage with Deep Learning. In: Annu Int Conf IEEE Eng Med Biol Soc 2018 Jul. 2018:583-587. DOI: 10.1109/EMBC.2018.8512336. (2018).
21. RSNA Intracranial Hemorrhage Detection Identify acute intracranial hemorrhage and its subtypes. Competition on Kaggle By RSNA.https://www.kaggle.com/c/rsna-intracranial-hemorrhage-detection/data. Last accessed 2021/12/10.
22. RSNA Intracranial Hemorrhage Detection Challenge (2019).https://www.rsna.org/ education/ai-resources-and-training/ai-image-challenge/rsna-intracranial-hemorrhage-detection-challenge-2019. Last accessed 2021/12/10.
23. Usachev D. :10 Use Cases of Machine Learning for Medical Diagnosis. Fayrix. (2020)
24. Chilamkurthy S., Ghosh R., Tanamala S., Biviji M., Campeau N. G., Venugopal V. K.: In: Deep learning algorithms for detection of critical findings in head CT scans: a retrospective study. The Lancet Journal. Articles Volumes 392, Issue 10162, P2388-2396. (2018).
25. Anam C., Budi W.S., Haryanto F., Fujibuchi T., Dougherty G.: A novel multiple-windows blending of CT images in red-green-blue (RGB) color space: Phantom's study. Scientific Visualization. volume 11, number 5, pages 56 - 69, DOI: 10.26583/sv.11.5.06. (2019).
26. CQ500 Head CT scan dataset. http://headctstudy.qure.ai/dataset. Last accessed 2021/12 /10.