[1] V. PavaniChandra*

[2] Dr. S. PrinceMary

[3] Sangepu Nagaraju

[4] Dr.Nandam.Gayatri

A Comprehensive Review on Deep Learning Approach for Intracranial Haemorrhage Detection and Analysis of Multimodal Dataset

Journal of Electrical Systems

Abstract: - The process of creating visual representations of every internal part and constructing the physiological functions of the body as well as organs functioning is known as medical imaging. For medical support and therapy, the medical pictures are retrieved using a variety of procedures, including MRI (Magnetic Resonant Imaging) and CT (Computed Tomography). Intracranial hemorrhages (ICH) can result from severe brain injury. The term "intracranial hemorrhage" refers to a blood clot inside the skull. If it has not been adequately detected, this disease may cause considerable impairment or maybe death. The proposed study aims to analyze the supervised DL models to determine whether there is a hemorrhage in CT brain images.Convolution neural networks are particularly helpful for identifying patterns in images and for enabling scenarios to contain objects and faces. In the first phase, a pre-processing step is performed. The images endure pre-processing procedures to prepare them for additional processing. CNN eliminates the requirement for manual extraction of features by classifying pictures directly from image data using patterns or samples. This method has the benefit of producing findings with a clear range of errors and is extremely efficient in high-dimensional settings. This article demonstrates the processing of CT brain images for cerebral bleeding identification using a variety of approaches including region-based growth. This research highlights the superior hemorrhage results in DL models, including GoogleNet, ResNet-50, and AlexNet methods. These methods offer more precise findings for detecting ICH on CT scans and when analyzing multimodal medical imaging datasets.

Keywords:- Anxiousness, Haemorrhage, Detection and Analysis of Haemorrhage.

I. INTRODUCTION

Brain injury from trauma, tumors, anxiousness, vascular abnormalities, arteriovenous defects, and smoking are a few causes of ICH in the skull. The elevated mortality rate of ICH, which ranges from 35% to 52% in the first 30 days, is one of the main causes of worry. The survivors also have to deal with challenges including disabilities, epilepsy, vascular problems, blood clotting, memory loss, and eyesight loss [1,2]. With the seriousness of damage ratings, which often incorporate clinical severity (for example, Glasgow Coma Scale) and neuroimaging (for example, hematoma volume), patient outcomes following ICH can be predicted. To lower the elevated death rate of ICH, a quick and precise method is needed to administer medical care at the first stage. The most significant risk factors for illness of an ICH are hypertension, weak arteries, exterior head trauma, drug use, and leakage into the veins attached to the ICH [3,4]. Epidural, subdural, subarachnoid, intraventricular, and intraparenchymal hemorrhages are the four main categories of ICHs. Physicians use a variety of imaging methods, including CT of the head, MRI, and angiography (CTA), to assess abnormalities. One of the best medical techniques for detecting brain hemorrhages is computed tomography (CT). This reputation is due to a variety of benefits, such as its outstanding sensitivity to blood, brief scanning time, and capacity to disclose bleeding spots [5,7]. To help physicians recognize brain hemorrhages, measure the quantity of the bleeding, and determine where it is located within the patient, CT provides accurate and reliable data. By quickly and reliably analyzing enormous amounts of CT image data, the use of artificial intelligence approaches has considerably benefited specialists, medical professionals, and patients. In turn, this makes it much easier to precisely identify and locate different kinds of ICH. While CT is used for the first head scan following a catastrophic injury, MRI is becoming important for the age evaluation of an ICH and for the identification of severe bleeding in patients who experience rapid changes in consciousness, particularly when anticoagulant therapy is involved. In recent years, AI algorithms have attained

[1] Research Scholar, Satyabhama Institute of Science and Technology, Chennai, Tamil Nadu, India. vpavanic@gmail.com

[2] Associate Professor, Satyabhama Institute of Science and Technology, Chennai, Tamil Nadu, India. princemary.cse@satyabama.ac.in

[3] Associate Professor, Kakatiya Institute of Technology and Science Warangal, Telangana, India. sn.cse@kitsw.ac.in

[4] Assistant Professor, Kakatiya Institute of Technology and Science Warangal, Telangana, India. ng.cse@kitsw.ac.in

* Corresponding Author Email: vpavanic@gmail.com

effective results and quick speeds. DL models have demonstrated more effective generality for resolving complicated medical issues, such as analyzing and detecting medical images, identifying diseases, and spotting internal organs. It has also been demonstrated that these models are highly precise in recognizing signs of ICH and can identify hyper-dense imperfections on head CT scans.DL models have received a lot of interest recently for the classification and segmentation of images. Typically, a CT scan is a collection of two-dimensional slices arranged in three dimensions [8,10]. As a result, the likelihood that an image voxel would work is high; however, it may require complicated processing. Calculating slices independently or using a 3D context in a simpler format are two ways to avoid this kind of situation. In recent years, several DL and ICH detections have been developed.

II. Analysis Of Multimodal Dataset

To increase the precision of detecting and categorizing ICH, multimodal datasets for intracranial hemorrhage disease are datasets that comprise many types of data, such as CT scans, MRI scans, and other clinical data. Ischemic intracranial hemorrhage illness multimodal datasets are included below:

2.1 RSNA 2019 Brain CT Hemorrhage Challenge:

More than 25,000 head of CT data are included in this database, which includes 6types of brain hemorrhages: epidural, intraparenchymal, intraventricular, subarachnoid, subdural, and any existing hemorrhage. DICOM files are used to store the dataset [11]. The example RSNA dataset pictures for hemorrhage are displayed in Fig. 1 below.

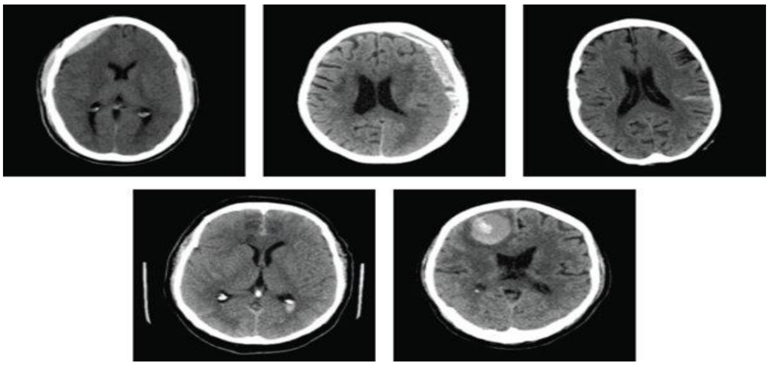

Fig.1 Sample RSNA dataset images

2.2 Intracerebral Hemorrhage:

This dataset employs a multimodality strategy to enhance ICH results. It consists of MRI and CT scans as well as other clinical information [12]. The set of data for ICH is shown in Fig. 2 below.

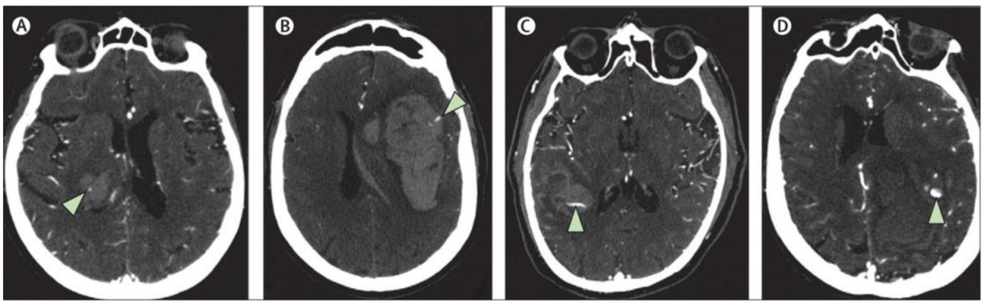

Fig.2 Intracerebral Hemorrhage dataset

2.3 Brain CT Images with Intracranial Hemorrhage Masks:

Head CT pictures in jpg format make up this collection. For 82 individuals, there are 2,500 pictures from the brain windows and 2500 from the bone windows [13]. The brain hemorrhage CT scan picture utilizing mask RCNN is shown in Fig. 3 below.

Fig.3 Brain Hemorrhage CT scan image using mask RCNN

III. Analysis Of Deep Learning Methods

The objective of DL, a kind of ML is to train artificial neural networks to carry out tasks automatically. To automatically recognize and describe patterns and characteristics in data, deep neural networks with several layers are used [14]. The DL model's fundamental principle of operation is shown in Fig.4 below.

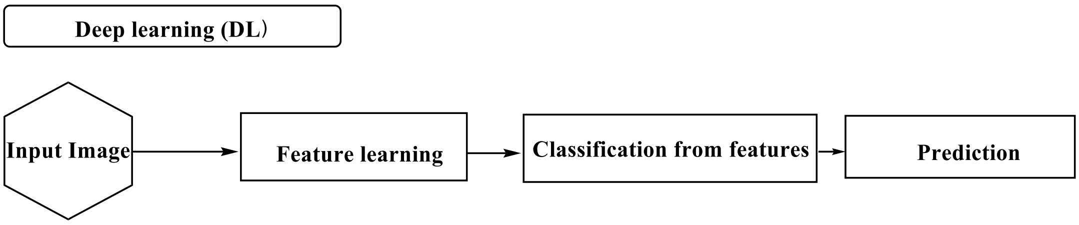

Fig.4 The general functioning mechanism of the DL model

In the below section, we discuss some more existing related works**.** For the automated identification and classification of acute ICH and its categories in head CT images, the author of [15] introduced a deep learning strategy that includes a 2D CNN model with two sequential models. A 3D volume including long-distance spatial relationships is captured by the first sequential model, a GRU-based RNN. Another RNN, the second sequential model averages weighted models and corrects prior prediction mistakes. The 2019-RSNA Brain CT Haemorrhage Competition dataset is used to train and evaluate the algorithm. A DL-based method for segmentation and 3D visualization of ICH using CT images is presented in the research in [16]. Pre-processing the CT images, developing several pre-trained models, and choosing the U-Net model with DenseNet201 are all steps in the approach. To detect cerebral hemorrhage and classify its subtypes in 3D CT images, the author of [17] introduced a compact DNN architecture that utilizes a CNN with an LSTM network. The dataset from the RSNA 2019 Brain CT Haemorrhage is used to assess the system's efficiency. The research [18] proposes a DL-based model for the classification and diagnosis of ICH utilizing the Inception system's best image segmentation technique. The model entails NIfTI files being turned into JPEG format, Kapur's thresholding with an EHO algorithm being used for image segmentation, the Inception v4 network being used as a feature extractor, and an MLP being employed for categorization. A Dense U-net architecture is used in research [19] to present a deep learning-based pipeline for the identification of ICH in unenhanced head CT images. The pipeline has three key steps: the recognition of landmarks, the removal of the brain, and the identification of hemorrhages. In a retrospective dataset, the algorithm's performance is assessed.In [20], the author shows how well an AI program performs when used to analyze emergency CT images for ICH. Using commercially available ICH detection software, it examined a total of 4946 non-contrast head CT images from 18 institutions. A blinded neuroradiologist reviewed the differences between the AI analysis and the initial RR to ascertain the number of additional ICHs detected and assess the causes of errors. The findings revealed that the AI algorithm detected an additional 29 instances of ICH while missing 12.4% of ICH and overcalling 1.9%.Using two parallel routes and an enhanced approach, the author of [21] describes the recognition and subtype categorization of ICH. ResNet101-V2 is used in the first path to extract potential characteristics from displayed slices, while Inception-V4 is used in the second path to gather important spatial data. Using the results of ResNet101-V2 and Inception-V4, the identification and subtype categorization of ICH are carried out employing the LGBM. Three approaches are presented in [22] by the author for the quick identification of cerebral hemorrhages in CT scans. The first approach uses DL models that have already been trained for identification. The subsequent system uses the SVM classification technique in conjunction with feature maps that were obtained using DL models. The third technique employs ANNs built using DL model characteristics for the quick diagnosis of cerebral hemorrhages. The author of [23] describes a deep learning-based CAD method to increase doctors' ability to diagnose cerebral bleeding when utilizing CT images. The CAD system was created using the head CT scans of 433 patients, and it uses U-Net and a false-positive elimination technique based on machine learning to generate probability heat maps of hemorrhage regions. The CAD system significantly enhances the diagnostic results of all doctors, improving accuracy and cutting down on the time required for reading. The author presents the wisdom of crowd vs. laissez-faire in [24] while discussing Crowd-Sourced Deep Learning for ICH Identification. Clinical head CT scans from 134 individuals, that had been deidentified, were included in this retrospective analysis. Every part was labeled with either "no-intracranial hemorrhage" or "intracranial hemorrhage," and 70 convolutional neural network models were used to identify them. The research was conducted on four ensemble learning techniques, and their accuracy, receiver operation characteristic curves, and associated areas under the curve were compared to those of individual CNNs. Applying a hybrid input consisting of brain CT scans and other clinical characteristics, the author of [25] presented a DL model for predicting the prognosis following ICH. The model was trained to classify patients into bad predictions and favorable prognoses. Then, compare it to two other designs, one trained just with pictures (I-model) and the other using tabular data (D-model), respectively.For the identification and classification of ICH using CT images, the author of [26] presents a hybrid deep learning strategy that combines CNN and LSTM techniques. The model uses a Systematic Windowing approach with Conv-LSTM and is tested on the RSNA dataset. It first establishes the presence of hemorrhage and, if present, establishes the kind of hemorrhage(s). For the identification and classification of in [27], an AI technique is presented for exploiting brain CT images to diagnose AIH. Nine reviewers with varying degrees of competence participated in retrospective research and assessed 12,663 slices of brain CT images both with and without AI support. In diagnosing acute intracranial hemorrhage (AIH), the brain CT interpretation with AI helps dramatically improve the precision of diagnosis, particularly for non-radiologist physicians, board-certified radiologists, and to some extent, neuroradiologists.The identification and classification of To detect cerebral hemorrhages in head CT images, the study [28] offers a technique using deep learning, namely a CNN. This strategy tries to address the issue of missed hemorrhage identifications;this can lead to a major impact.

IV. Discussion

In this segment, an all-encompassing examination of published literature concerning ICH detection, classification, segmentation, multimodal datasets, and identification/prediction is presented. Figure 5 below illustrates the number of papers incorporated in our analysis of detection, segmentation, identification, prediction, and multimodal datasets.

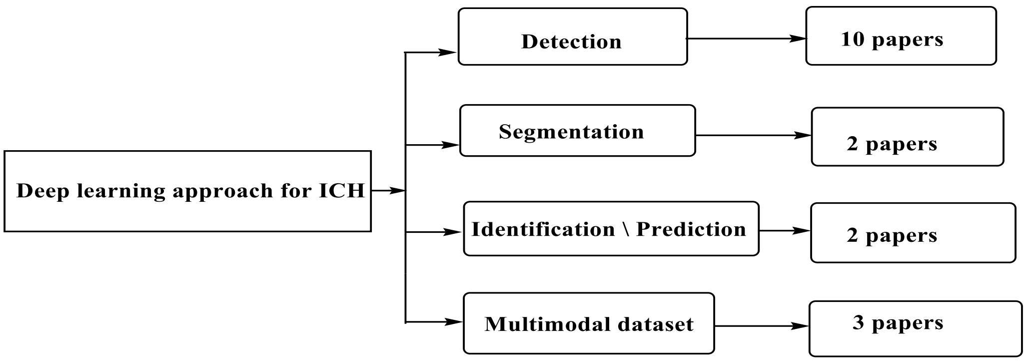

Fig.5 The distribution of the evaluated articles for the multimodal dataset for ICH detection, segmentation, and prediction.

Table1 Review of the methods proposed for the ICH

S. No	Author	Year	Techniques	Accuracy
1	Wang et al [15]	2021	2D CNN model	99.06%
2	Khan et al [16]	2023	U-Net model with a DenseNet201 pre-trained encoder	98.59%
3	Burduja et al [17]	2020	CNN and an LSTM network	weighted mean log loss of 0.04989
4	Mansour et al [18]	2021	Kapur's thresholding	95.06%
5	Gruschwitz et al [19]	2021	Dense U-net architecture	91.00%
6	Kundisch et al [20]	2021	AIDOC	sensitivity of 89-95% and a specificity of 94-99%
7	Asif et al [21]	2023	ResNet101-V2 and Inception-V4	97.70%
8	Mohammed et al [22]	2022	GoogLeNet, ResNet-50, and AlexNet	99.20%
9	Watanabe et al [23]	2021	Deep learning-based computer-assisted detection	83.7% to 89.7%
10	Hofmeijer et al [24]	2023	convolutional neural networks	95%
11	Perez del Barrio et al [25]	2023	Hybrid Deep learning technique	95%
12	Rajagopal et al [26]	2023	deep neural network approach	-
13	Yun et al [27]	2023	DL-based automatic detection algorithm	97.03%
14	Tharek et al [28]	2022	convolutional neural network	95.00%

This observation helps in the study of effective deep-learning strategies and their benefits for our future work. The aforementioned Table 1 illustrates the numerous techniques employed in existing works, overall accuracy, and the year of the article.

V. Conclusion And Future Works

The portion of the brain was detected by the study of ICH using CT brain images using various segmentation, detection, and prediction approaches, including the 2D CNN model, neural network, thresholding, GoogLeNet, ResNet-50, AlexNet, and convolutional neural networks. Pretrained DL models like GoogleLeNet, ResNet-50, and AlexNet provide accuracy scores of 99.2% when compared to other approaches. followed by the U-Net model with a DenseNet201 already trained encoder value of accuracy 98.59%, followed by the 2D CNN model, a sort of convolutional neural network, which provides accuracy values of 99.06%.The proposed findings are encouraging and frequently achieve the best data set with extremely high-quality images directly from the CT scanner, which has higher accuracy for the classification challenge. Additionally, different feature extraction kinds and techniques are frequently used to improve system performance. To improve accuracy in the future, an ensemble of several tools, including the Simulink toolbox, statistics, machine learning toolbox, and optimization for detection and classification, will be taken into consideration. This treatment will enable the longer term to be successful on a significant scale, enabling it to be advantageous for any medical establishment dealing with brain hemorrhages.

Abbreviations	Description
CAD	Computer-Assisted Detection
RNN	Recurrent Neural Network
CT	Computer Tomography
ICH	Intracranial hemorrhage

CNN	Convolution Neural Network
GRU	Gated Recurrent Unit
RR	Radiology Report
EHO	Elephant Herd Optimization
MLP	Multilayer Perceptron
ANNs	Artificial Neural Networks
LSTM	Long-Short Term Memory
MRI	Magnetic Resonant Imaging
ML	Machine Learning

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