Industrial Engineering Journal
ISSN: 0970-2555
Volume : 52, Issue 7, July : 2023

IDENTIFICATION OF INTRACRANIAL HEMORRHAGE FROM CT IMAGES USING CONVOLUTIONAL NEURAL NETWORKS

K.Saraswathi, Student, Department of ECE , Vemu Institute of Technology, P.Kothakota
Dr S.Leela Lakshmi , Professor ,Department of ECE , Vemu Institute of Technology, P.Kothakota

Abstract

Intracranial hemorrhage (ICH) detection from CT images is an important task in medical imaging that aims to identify and localize bleeding within the brain using computed tomography (CT) scans. This task is crucial for timely diagnosis and treatments planning in cases of traumatic brain injury, stroke, aneurysm rupture, or other intracranial conditions.There are several approaches to intracranial hemorrhage detection from CT images, ranging from traditional machine learning techniques to more advanced deep learning methods. Among all the available methods, deep learning-based models provide precise solution for the prognosis of intracranial hemorrhage due to the automatic feature learning ability. Based on this idea, in this work we adopted the concept of residual networks. All these experiments were carried out on the CT images which are collected from Kaggle repository and analyzed through well-known evaluation measures such as sensitivity, specificity, precision, F1-score, AUC, and accuracy.

Keywords: Intracranial hemorrhage, computed tomography, deep learning, and evolution measures

1. Introduction

According to Urden et al. [1], intracranial hemorrhages account for roughly 10% of strokes in the United States. Although hemorrhagic strokes are less frequent than ischemic strokes (87%), the former ones present a higher mortality rate. Indeed, it seems that between 37% and 38% of hemorrhagic strokes result in death within 30 days. With approximately 795,000 strokes per year in the United States alone, the number of yearly death cases caused by intracranial hemorrhage is in the range of 30,000. Therefore, intracranial hemorrhage is considered one of the most critical health conditions, demanding rapid intervention and intensive post-traumatic healthcare. Severe headache or loss of consciousness is neurological symptoms often associated with intracranial hemorrhage. When a patient shows such symptoms, highly trained radiologists typically analyze Computed Tomography (CT) scans of the patient’s brain to find and determine the type of hemorrhage.

Intracranial hemorrhage is a potentially life-threatening neurological condition. It results in a significant burden on health resources. It can happen in many different causes such as due to increased blood pressure, hemorrhage secondary to infarct, trauma, tumor hemorrhage, and many more (Figure 1). One of the common causes of intracranial hemorrhage is traumatic brain injury [2]. When the blood from trauma is in contact with adjacent brain tissues, it irritates and causes swelling. This is known as cerebral edema. The pool of blood within the brain parenchyma is called a hematoma. This causes increased pressure on the adjacent brain tissues which leads to reduced blood flow and kills the brain cells s [3].

There are six types of intracranial hemorrhage in trauma characterized by the extravascular accumulation of blood within different intracranial spaces. There are extradural hemorrhage (EDH), subdural hemorrhage (SDH), subarachnoid hemorrhage (SAH), and contusional hemorrhage, Intraparenchymal hemorrhage (IPH), and Intraventricular hemorrhage (IVH) [4], and they are shown in Figure 2. Extradural hemorrhage is also known as epidural hemorrhage which is a collection of blood in between the inner surface of the skull and the outer surface of the dura. This is usually associated with a skull fracture. The Source of bleeding is usually from the artery, most commonly the middle meningeal artery. Subdural hemorrhage is a collection of blood within the subdural spaces which is the potential space between the dura and arachnoid of meninges around the brain. Prognosis varies widely depending on the size and chronicity of the hemorrhage. Subarachnoid hemorrhage (SAH) is a type of extra-axial intracranial hemorrhage located within the subarachnoid spaces. Besides trauma, other causes that can lead to subarachnoid hemorrhage are ruptured aneurysm, venous infarction, cerebral vasculitis, and dural arteriovenous malformation. Contusional hemorrhage is a type of intra-axial intracranial hemorrhage which is commonly seen in the setting of significant head injury. It is characterized by foci of hemorrhage in the brain parenchymal which frequently happens in the frontal lobes.

When a patient comes to the hospital after trauma. The emergency department will assess the patient. The detailed neurological examination must be completed after primary and secondary surveys were done. Not all trauma cases need a CT scan due to radiation risk. NICE (national institute for health and care excellence) has made a guideline to choose which patient requires a CT scan done as the benefit outweighs the risk of radiation [5]. Once the CT scan is done, the radiology doctor will review the case. In normal situations, not all cases are being reviewed at the same time the scan was done as they need to handle other modalities in the radiology department. The primary team is the one who usually sees the scan first. In some of the cases, subtle intracranial hemorrhage may be missed by them. This is due to the highly variable appearance of intracranial hemorrhage, depending on its age and location. The most common types of intracranial hemorrhage that were missed were subdural and subarachnoid hemorrhage occurring in 39% and 33% of the cases, respectively. The most common location for missed subdural hemorrhage was either parafalcine or frontal [6].

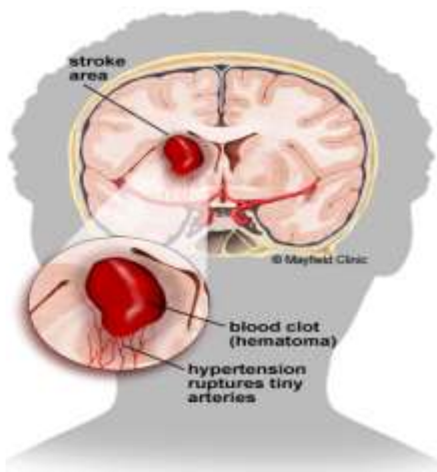

Figure 1: An intracerebral hemorrhage (ICH) is usually caused by rupture of tiny arteries within the brain tissue (left). As blood collects, a hematoma or blood clot forms causing increased pressure on the brain.

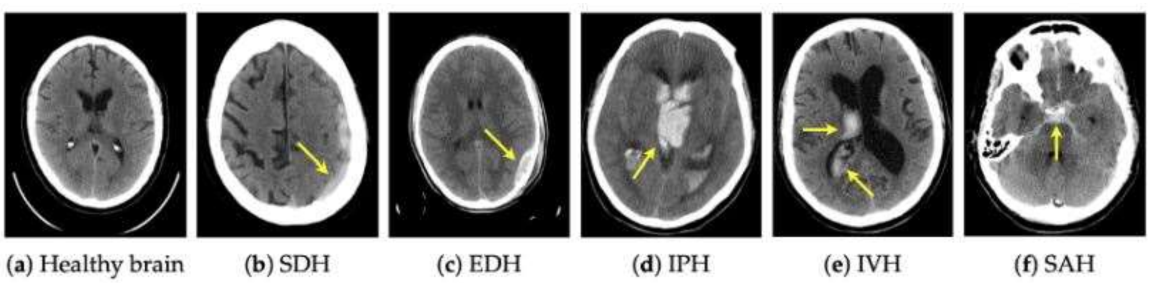

Figure 2: Non-contrast CT sub types of intracranial hemorrhage yellow arrows point to bleeding regions

Rapid diagnosis and management of patients with intracranial hemorrhage are important because early deterioration is common in the first few hours after intracranial hemorrhage onsets. More than 20% of patients will experience a decrease in the Glasgow Coma Scale (GCS) of 2 or more points between the prehospital emergency medical services (EMS) assessment and the initial evaluation in the emergency department (ED) [7]. It is critical for deciding on the need and approach for emergent surgical intervention. The surgical intervention aims to prevent herniation, reduce the intracranial pressure and reduce the pathophysiological impact of the hematoma on the surrounding tissue. This is achieved by reducing the mass effect cellular toxicity of the blood product [8]. Recognizing intracranial hemorrhage in head CT is also essential for allowing safe administration of thrombolytic therapy in acute ischemic stroke. Since “time is brain”, increased speed and reduced error in these clinical settings would constitute life-saving innovations.

Machine learning has become popular over the past few years, particularly deep learning which is a branch of machine learning that employs multi-layered neural networks. It has shown huge potential in extracting important information from medical images. Deep learning has been involved in a few medical fields which include grading of detection of metastases in histologic sections of lymph nodes [9], classification of images of skin cancer [10], and diabetic retinopathy on retinal funds photographs [11] with high accuracies. It has proved to be accurate in image classification and processing tasks, mainly using convolutional neural networks (CNN) [12]. The same method will be implemented in the head CT scan image. It will involve image segmentation and the processed image will be trained by a deep learning approach to detect hemorrhage in the scan which is classified into cases with hemorrhage and cases without hemorrhage with great accuracy.

Deep learning transforms the dataset by mapping them with high dimension space. For image classification, the convolutional neural network in deep learning will provide huge support with advanced techniques [13]. CNN extracts the semantic features and network-fused features of the dataset to classify the images [14]. Due to the deep nature of the network, high-resolution image classification is well supported by the convolutional neural network. This is important as most of the medical data must be in high-quality resolution to prevent missed diagnosis of diseases that could harm the patient as this will delay the management [15].

2. Literature Review

Chan et al. [16] adapted midline detection techniques using CT images. Burduja et al. [17] presented a systematic approach for hemorrhage detection based on the CNN for ICH detection using CT images. However, this technique requires more time for training and produced limited accuracy in the image data evaluation platform. Chen et al. [18] provided hemorrhage detection schemes based on IoT smart intelligent systems. Tong et al. [19] presented SVM-based feature detection techniques. Shuchi et al. [20] mentioned the important parameters and analyzed the CT image slicing techniques like ML-based Statistical Analysis (MLSA), watershed, and Expectation Maximization (EM) methods. Raja et al. [21] presented DL algorithms for the detection of ICH.

Agata et al. [22] proposed intensity windows and consecutive slicing of the image for the detection of a brain hemorrhage. Additionally, this approach performed primary Region of Interest

(ROI) extractions to prepare the data for the analysis. Chithra et al. [23] presented the various image processing techniques for considering the image parameters such as color, texture, size, and shape image sections. Kamnitsas et al. [24] suggested an effective computational method to overcome the burden of 3D image data analysis schemes. Schmitz et al. [25] presented baseline margin techniques with CNN architectures for detecting brain issues (CNNDS).

Peng et al. [26] provided the DL-based brain age prediction model that used weighted structural Magnetic Resonance Imaging (MRI) data and CNN-based classification models. For improving the quality of this DL model, the authors investigated the lightweight data analysis schemes and data regularizing schemes in the diagnosis architectures. Nonetheless, these schemes produced significant error rates. Arbabshirani et al. [27] included 46,583 inpatients, outpatients and emergency patients NCTCs for ICH detection with a five-layer and two fully connected-layer CNN architecture.

A two-fold study was conducted by Chang et al. [28] with an examination training cohort and test cohort of 10,159 NCTCs and 682 NCTCs, respectively. The training cohort was used to develop a custom hybrid 3D/2D mask-based CNN architecture and the trained network was applied for the external validation data. Clinical reports were used to identify ICH positive cases (IPH, EDH/SDH, and SAH) in both cohorts based on the assessment done by one board-certified radiologist.

Chilamkurthy et al. [29] retrospectively included patients with ICH (IPH, EDH/SDH and SAH) in the Qure25k data and CQ500 dataset with 21,095 and 419 scans, respectively. ResNet18 CNN network with slight modifications was used for detection of ICH subtypes based on the electronic clinical reports for the Qure25k dataset and consensus by three radiologists for the CQ500 dataset. Patients younger than 7 years were removed from the Qure25k dataset and the rest was used for training.

Two hospitals were used to obtain a dataset of 329 NCTCs for training, validation and testing by Grewal et al. [30]. Their final Recurrent Attention DenseNet (RADnet) architecture was used to binary classify NCTC with or without ICH. A web-based annotation tool was applied for reference standard labelling of the training and validation dataset at slice-level. This was done with the consensus of two senior radiologists, in correlation to patient’s medical history.

During a 7-years period, Kuo et al. [31] constructed a dataset consisting of 4,396 CT scans with pixelwise labels for ICH confirmed by two American Board of Radiology-certified radiologists. Data preprocessing consisted of removing skull and face bones, while retaining the intracranial structures for

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 52, Issue 7, July : 2023

network training. 200 CT scans where external validation and performed over a two-month period to test the fully trained CNN.

3. Proposed Method

Figure 3 shows the flow-diagram of the proposed model, which includes data collection, CNN, and transfer learning.

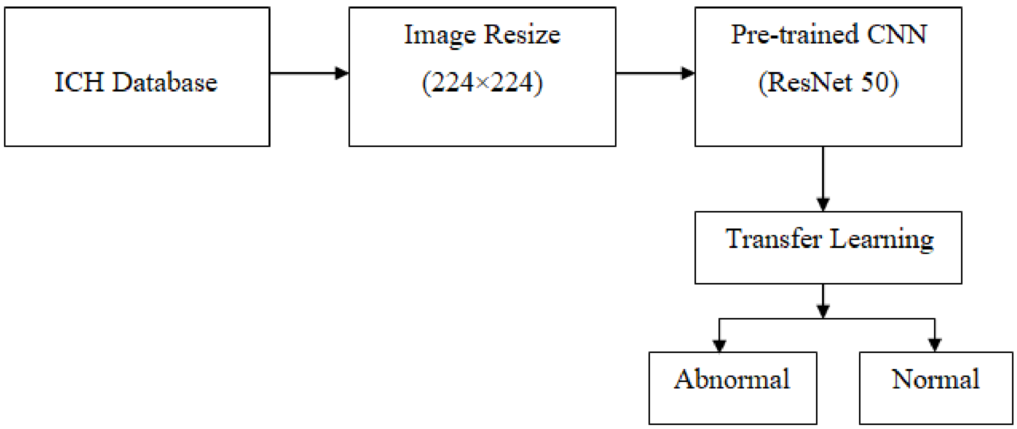

Figure 3: Block diagram of the proposed model

3.1.Dataset

This was a cross-sectional study using secondary data, in which the 200 data was collected from public datasets. This dataset is owned by Abdul Kader Helwan, academic staff at Al-Manar University of Tripoli, Lebanon [32]. Permission to use the dataset for this research was officially obtained from the owner. All of the samples had been anonymized into secondary data.

The study population consisted of all adult patients who underwent head CT scan with intracranial hemorrhage and without intracranial hemorrhage from public datasets. Inclusion criteria include both genders, CT brain of all types of ICH, CT brain of normal findings, CT of ICH with a formal report which is categorized by the dataset provider. The exclusion criteria include CT brain without anonymization into secondary data, CT brain with artifacts, lowquality CT brain images which is not suitable for making a diagnosis.

The CT brain with radiological findings of intracranial hemorrhage and without intracranial hemorrhage was classified by the dataset provider. A total of 100 CT brain with hemorrhage and another 100 CT brain without hemorrhage were put in two different folders. The dataset was classified based on a formal report of the CT scan.

3.2.ResNet-50

ResNet-50 is a deep convolutional neural network architecture that was proposed by researchers at Microsoft Research in 2015. It is part of the ResNet (short for "Residual Network") family, which introduced the concept of residual learning and achieved significant improvements in training deep neural networks. The "50" in ResNet-50 refers to the number of layers in the network. ResNet-50 consists of a total of 50 layers, including convolutional layers, pooling layers, fully connected layers, and shortcut connections.

The key innovation in ResNet is the introduction of residual blocks. A residual block is a building block of the network that allows the network to learn residual mappings instead of directly trying to learn the desired underlying mapping. This is achieved by adding shortcut connections that bypass one or more layers, allowing the network to learn residual functions. These shortcut connections enable the network to effectively propagate gradients and alleviate the vanishing gradient problem, making it easier to train very deep networks.

ResNet-50 has been widely used and proven to be highly effective in various computer vision tasks, such as image classification, object detection, and image segmentation. It has achieved state-of-the-art performance on benchmarks like the ImageNet dataset. Each layer in ResNet-50 performs a set of operations, typically including convolution, batch normalization, activation (e.g., ReLU), and pooling. The network gradually reduces spatial dimensions while increasing the number of channels. The final layers of ResNet-50 typically consist of global average pooling, fully connected layers, and softmax activation for classification.

Overall, ResNet-50 has played a significant role in advancing deep learning research and applications in computer vision and has become a widely adopted architecture for various image-related tasks.

3.3.Transfer Learning (TL)

Transfer learning in deep learning refers to the technique of leveraging pre-trained models on a source task and applying that knowledge to a new, related task. Instead of training a deep neural network from scratch, transfer learning allows us to take advantage of the knowledge learned by a model on a large dataset and apply it to a different but related problem, even when the new dataset is relatively small.

The basic idea behind transfer learning is that deep neural networks learn hierarchical representations of data, where lower layers capture generic features like edges and textures, while higher layers capture more abstract and task-specific features. These learned representations can be reused and adapted to new tasks, potentially saving time and computational resources.

The typical workflow of transfer learning involves the following steps:

1. **Pre-training:** A deep neural network model, such as a Convolutional Neural Network (CNN), is trained on a large-scale dataset, typically on a source task with a large amount of labeled data. This pre-training phase allows the model to learn useful and general feature representations from the source task.
2. **Fine-tuning:** After pre-training, the pre-trained model is used as a starting point for the new task. The final layers of the pre-trained model, which are typically task-specific, are replaced or retrained with new layers suitable for the target task. The new layers are initialized randomly, and the entire model is fine-tuned on the target task's dataset. Alternatively, some layers of the pre-trained model can be frozen, meaning their weights are not updated during fine-tuning, while the remaining layers are trained.

By using transfer learning, several benefits can be gained:

1. Reduced training time: Since the initial layers of the pre-trained model have already learned generic features, they can be directly used for the new task. Training only the final layers or a subset of the layers reduces the overall training time.
2. Improved generalization: Transfer learning allows the model to leverage knowledge from a large, diverse dataset. This helps in situations where the target task's dataset is small, preventing overfitting and improving generalization performance.
3. Handling data scarcity: In scenarios where labeled data is limited, transfer learning enables the model to learn from the source task's data, which may have a larger labeled dataset. This provides more training examples and enhances the model's performance on the target task.
4. Transferring domain-specific knowledge: Pre-trained models trained on a specific domain (e.g., medical imaging) can transfer their knowledge to related domains (e.g., histopathology) that share similar underlying features.

However, it is important to consider the similarity between the source and target tasks. The effectiveness of transfer learning depends on the relatedness of the tasks and the similarity of the datasets. If the tasks are vastly different, or the datasets are dissimilar, the transfer learning approach may not yield significant benefits.

Overall, transfer learning is a powerful technique in deep learning that allows us to leverage pre-existing knowledge and accelerate the training process while improving generalization and performance on new tasks with limited data.

3.4.Evolution Criteria

The performance of the suggested approach is evaluated using various well-known measures such as true positive rate (TPR), true negative rate (TNR), positive predictive value (PPV), F-score, accuracy, and the area under the curve (AUC). TPR estimates the percentage of the accurately identified ICH cases, while TNR measures the rate of precisely recognized non-ICH patients. PPV calculates the fraction of correctly identified CT images flagged as ICH. F-score is the weighted average or harmonic mean of PPV and TPR. AUC is an effective way of quantifying the overall performance of the test. Accuracy represents the percentage of correctly classified CT images, including ICH and non-ICH, over the total number of images. The mathematical interpretations of all these parameters are described as follows:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{3.1}$$

$$\text{True Positive Rate (TPR)} = \frac{TP}{TP + FN} \tag{3.2}$$

$$\text{True Negative Rate (TNR)} = \frac{TN}{TN + FP} \tag{3.3}$$

$$\text{Positive Predictive Value (PPV)} = \frac{TP}{TP + FP} \tag{3.4}$$

$$\text{F-Score} = 2\left(\frac{PPV \times TPR}{PPV + TPR}\right) \tag{3.5}$$

$$\text{Area Under Curve (AUC)} = \frac{TPR + TNR}{2} \tag{3.6}$$

Where, TP = True Positive; FN = False Negative; FP = False Positive and TN = True Negative.

4. Results and Discussions

This paper developed a CNN model for effectively detecting ICH in brain from CT images. To analyze the performance of the proposed model, we split the dataset into 80% training and 20% testing.

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 52, Issue 7, July : 2023

Table 2 represents the hyperparameters used in our work to train the model. These experiments are carried out on Intel (R) Core (TM) i3-5005U CPU @ 2 GHz using MATLAB 2022b. Figure 4 represents the training progress of the suggested CNN model and corresponding confusion matrix is shown in Figure 5. With the suggested model, we obtain 80% sensitivity, specificity, precision, F1-score, AUC, and accuracy.

Table 1: Hyperparameters used in the suggested work

Parameter	Name/Value
Optimizer	Adam
Batch Size	16
Learning Rate	0.0001
Epochs	30

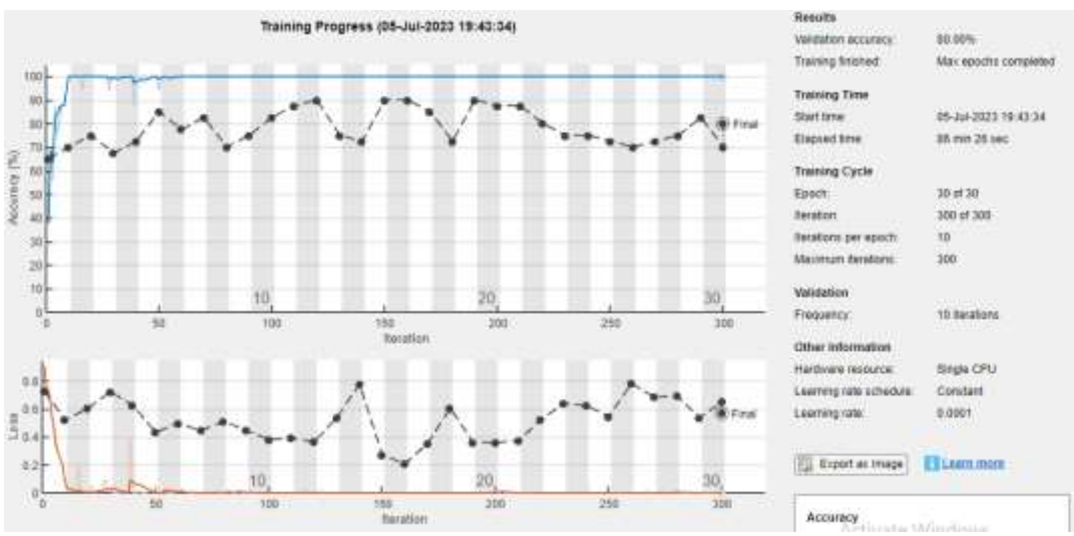

Figure 4: Training progress of the suggested CNN model

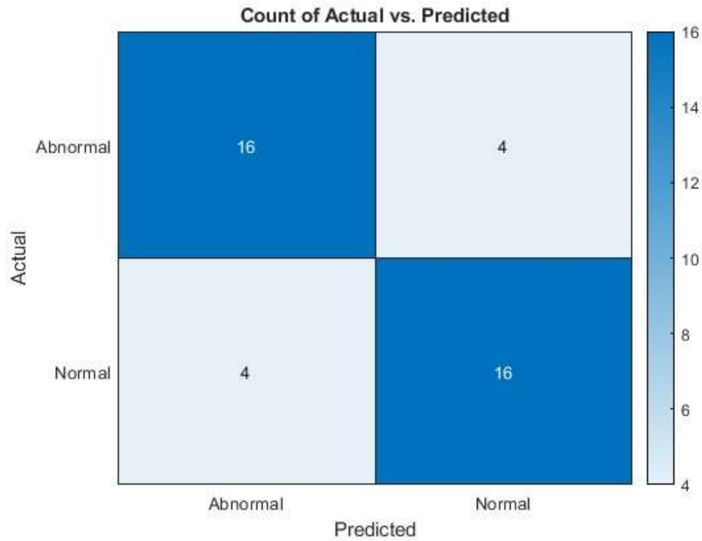

Figure 5: Confusion matrix of the presented approach

5. Conclusion and Future Scope

In this work we proposed a deep learning-based architecture for prediction of ICH in brain from CT images. Here, initially, the collected CT images are converted in to 224×224 dimensions into 3 channels with matrices of floating-point numbers normalized in (0, 1) range. To train our model with limited bias for the disproportionate independent hemorrhage classes, a categorical cross entropy loss function was used for binomial classification. The suggested model, we obtain 80% sensitivity, specificity, precision, F1-score, AUC, and accuracy.

Future improvements include evaluating the system with different convolutional base architectures, such as deeper versions of ResNet (ResNet-101 and ResNet-152) and DenseNet.

References

1. Urden, L.D.; Stacy, K.M.; Lough, M.E. Priorities in Critical Care Nursing, 8th ed.; Elsevier Health Sciences, 2019.

2. K. Blennow et al., “Traumatic brain injuries,” Nature Reviews Disease Primers, vol. 2, pp. 1–19, 2016.

3. J. Borsch, “Ovulationshemmer oder abtreibungspille? So wirken notfallkontrazeptiva,” Deutsche Apotheker Zeitung, vol. 153, no. 9, pp. 32–33, 2013.

4. A. M. Naidech, “Intracranial hemorrhage,” American Journal of Respiratory and Critical Care Medicine, vol. 184, no. 9, pp. 998–1006, 2011.

5. G. Rath and B. Ray, “Head Injury: Assessment and Early Management,” Practice Guidelines in Anesthesia, no. January 2014, pp. 53–53, 2016.

6. W. M. Strub, J. L. Leach, T. Tomsick, and A. Vagal, “Overnight preliminary head CT interpretations provided by residents: Locations of misidentified intracranial hemorrhage,” American Journal of Neuroradiology, vol. 28, no. 9, pp. 1679–1682, 2007.

7. J. S. Moon et al., “Prehospital neurologic deterioration in patients with intracerebral hemorrhage,” Critical Care Medicine, vol. 36, no. 1, pp. 172–175, 2008.

8. J. C. Hemphill et al., “Guidelines for the Management of Spontaneous Intracerebral Hemorrhage: A Guideline for Healthcare Professionals from the American Heart Association/American Stroke Association,” Stroke, vol. 46, no. 7, pp. 2032–2060, 2015.

9. B. E. Bejnordi et al., “Diagnostic assessment of deep learning algorithms for detection of lymph node metastases in women with breast cancer,” JAMA - Journal of the American Medical Association, vol. 318, no. 22, pp. 2199–2210, 2017.

10. A. Esteva et al., “Dermatologist-level classification of skin cancer with deep neural networks,” Nature, vol. 542, no. 7639, pp. 115– 118, 2017.

11. V. Gulshan et al., “Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs,” JAMA - Journal of the American Medical Association, vol. 316, no. 22, pp. 2402–2410, 2016.

12. Y. Lecun, Y. Bengio, and G. Hinton, “Deep learning,” Nature, vol. 521, no. 7553, pp. 436–444, 2015.

13. C. Tang, Q. Zhu, W. Wu, W. Huang, C. Hong, and X. Niu, “PLANET: Improved Convolutional Neural Networks with Image Enhancement for Image Classification,” Mathematical Problems in Engineering, vol. 2020, 2020.

14. A. Usha Ruby, P. Theerthagiri, I. Jeena Jacob, and Y. Vamsidhar, “Binary cross entropy with deep learning technique for image classification,” International Journal of Advanced Trends in Computer Science and Engineering, vol. 9, no. 4, pp. 5393–5397, 2020.

15. A. Pinto, “Spectrum of diagnostic errors in radiology,” World Journal of Radiology, vol. 2, no. 10, p. 377, 2010.

16. T. Chan, "Computer aided detection of small acute intracranial hemorrhage on computer tomography of brain," Computerized Medical Imaging and Graphics, vol. 31, no. 4-5, pp. 285–298, 2007.
17. M. Burduja, R. T. Ionescu, and N. Verga, "Accurate and efficient intracranial hemorrhage detection and subtype classification in 3D CT scans with convolutional and long short-term memory neural networks," Sensors, vol. 20, no. 19, p. 5611, 2020.
18. H. Chen, S. Khan, B. Kou, S. Nazir, W. Liu, and A. Hussain, "A smart machine learning model for the detection of brain hemorrhage diagnosis based internet of things in smart cities," Complexity, vol. 2020, Article ID 3047869, 10 pages, 2020.
19. H.-L. Tong, M. F. Ahmad Fauzi, and S.-C. Haw, "Automated hemorrhage slices detection for CT brain images," in Proceedings of the International Visual Informatics Conference, pp. 268–279, Springer, Berlin, Heidelberg, 2011.
20. S. Saini and V. K. Banga, "A review: haemorrhage intracranial segmentation in ct brain images," International Journal of Engineering Research and Technology, vol. 2, no. 10, pp. 2022–2026, 2013.
21. M. Raja Suguna and A. Kalaivani, "A review of intracranial hemorrhage detection by deep learning techniques," International Journal of Advanced Science and Technology, vol. 29, no. 7, pp. 104569–110574, 2020.
22. A. Sage and P. Badura, "Intracranial hemorrhage detection in head CT using double-branch convolutional neural Network, support vector machine, and random forest," Applied Sciences, vol. 10, no. 21, p. 7577, 2020.
23. P. L. Chithra and P. Bhavani, "A study on various image processing techniques," International Journal of Emerging Technology and Innovative Engineering, vol. 5, no. 5, pp. 316–322, 2019.
24. K. Kamnitsas, C. Ledig, V. F. J. Newcombe et al., "Efficient multi-scale 3D CNN with fully connected CRF for accurate brain lesion segmentation," Medical Image Analysis, vol. 36, pp. 61–78, 2017.
25. R. Schmitz, F. Madesta, M. Nielsen et al., "Multi-scale fully convolutional neural networks for histopathology image segmentation: from nuclear aberrations to the global tissue architecture," Medical Image Analysis, vol. 70, Article ID 101996, 2021.
26. H. Peng, W. Gong, C. F. Beckmann, A. Vedaldi, and S. M. Smith, "Accurate brain age prediction with lightweight deep neural networks," Medical Image Analysis, vol. 68, Article ID 101871, 2021.

27. S. Chilamkurthy, R. Ghosh, S. Tanamala, M. Biviji, N.G. Campeau, V.K. Venugopal, V. Mahajan, P. Rao, P. Warier, Deep learning algorithms for detection of critical findings in head CT scans: a retrospective study, Lancet 392 (10162) (2018) 2388–2396.

28. M. Grewal, M.M. Srivastava, P. Kumar, S. Varadarajan, RADnet: Radiologist level accuracy using deep learning for hemorrhage detection in CT scans. I: Proceedings - International Symposium on Biomedical, Imaging. (2018).

29. W. Kuo, C. Häne, P. Mukherjee, J. Malik, E.L. Yuh, Expert-level detection of acute intracranial hemorrhage on head computed tomography using deep learning, Proc. Natl. Acad. Sci. USA 116 (45) (2019) 22737–22745.

30. H. Lee, S. Yune, M. Mansouri, M. Kim, S.H. Tajmir, C.E. Guerrier, S.A. Ebert, S. R. Pomerantz, J.M. Romero, S. Kamalian, R.G. Gonzalez, M.H. Lev, S. Do, An explainable deep-learning algorithm for the detection of acute intracranial haemorrhage from small datasets, Nat. Biomed. Eng. 3 (3) (2019) 173–182.

31. H. Ye, F. Gao, Y. Yin, D. Guo, P. Zhao, Y.i. Lu, X. Wang, J. Bai, K. Cao, Q.i. Song, H. Zhang, W. Chen, X. Guo, J. Xia, Precise diagnosis of intracranial hemorrhage and subtypes using a three-dimensional joint convolutional and recurrent neural network, Eur. Radiol. 29 (11) (2019) 6191–6201.

32. A. Helwan, G. El-Fakhri, H. Sasani, and D. Uzun Ozsahin, “Deep networks in identifying CT brain hemorrhage,” Journal of Intelligent and Fuzzy Systems, vol. 35, no. 2, pp. 2215–2228, 2018, doi: 10.3233/JIFS-172261.