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Intracranial Hemorrhage Identification in CT scans Using Deep Neural Networks

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ABSTRACT

Brain Hemorrhage caused by high pressure of blood may erupt the arteries of the brain causing its Bloodless haematoma that may lead to the traumatic brain injury or death. It's the kind of medical emergency in which a doctor must also have years of experience to make an instant diagnosis of the area in the body that is bleeding internally and then begin treatment. In this study the deep learning model Convolutional Neural Network (CNN) is presented for classifying the Brain Hemorrhage. The head CT scan images dataset is employed to enhance the accuracy rate and the computational power of the deep learning models. The purpose of this work is to leverage the abstraction capability of deep learning on lesser number of images since in most critical scenarios large databases are not available on-site. The methods like image augmentation and imbalancing the dataset with CNN model are used to design the architecture and call it Brain Hemorrhage Classification based on Neural Network (BHCNet). The effectiveness of the proposed method is evaluated in terms of accuracy and precision. Moreover, the proposed system results are analyzed using the balanced and imbalanced dataset in terms of the CNN model. Experimental results demonstrate the attention of the proposed model in terms of accurate prediction to save patient's life in the mean time and rapid deployment in real-life conditions.

Keywords: Brain Hemorrhage, CNN, Deep Learning, Accuracy, CT scan.

1. INTRODUCTION

Hemorrhage is a serious medical condition characterized by excessive bleeding, either externally or internally within the body [1], [2]. When this bleeding occurs inside the brain, it is referred to as brain hemorrhage or intracranial hemorrhage [3]. This condition typically results from a sudden blood clot [4] in the arteries that supply oxygen-rich blood to the brain or due to the rupture of those arteries, causing internal bleeding in the surrounding brain tissues [5]–[8]. This internal bleeding damages neurons—the brain's functional nerve cells—which can lead to severe cognitive and physical impairments. Brain hemorrhages often arise from various underlying causes, such as traumatic brain injury [1], uncontrolled high blood pressure [10], aneurysms, abnormalities in blood vessels [11], amyloid angiopathy, blood clotting disorders, and brain tumors [12], [13]. These conditions significantly contribute to mortality and long-term disability across populations.

Brain hemorrhage remains one of the leading causes of death and disability globally. In 2013, it accounted for approximately 30% of deaths in the United States [14], with incidence rates of about 7 per 100,000 people in Western countries and up to 200 per 100,000 in Asia. Furthermore, statistics reveal that women are more vulnerable to this condition than men, with a prevalence ratio of 3:2. Additionally, nearly 80% of individuals are born with inherent weaknesses in the internal carotid and vertebral arteries—the major arteries that supply blood to the brain—making them prone to spontaneous hemorrhage [15].

According to the 2009 report from the World Health Organization (WHO), approximately 15 million people globally suffered from strokes, of which 5 million died and another 5 million were left permanently disabled [16]. Early and accurate diagnosis is critical for saving lives and minimizing damage in such cases. Medical professionals emphasize the importance of timely intervention through fast diagnosis and effective initial treatment to reduce the chances of death and disability in patients [17], [18]. For this purpose, Computed Tomography (CT) scans [19] and Magnetic Resonance Imaging (MRI) [20] are the two primary medical imaging techniques employed to visualize the internal structure of the skull and brain.

Among these, CT scanning is generally favored by healthcare professionals over MRI in emergency scenarios due to its wider availability, lower cost, faster processing time, and high sensitivity to early hemorrhage detection. A CT scan works by combining multiple X-ray images taken from various angles into

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cross-sectional views, creating a 3D representation of the brain's internal structure using computer processing techniques [10]. The CT scanner emits X-ray beams [6], [2] in an arc formation, which allows it to capture detailed images of tissues based on how different structures absorb X-rays. This helps generate comprehensive insights into the internal anatomy, enabling doctors to detect hemorrhages, blood clots, and abnormalities in brain tissue with greater precision [6].

CT scans are particularly valuable in emergency settings for diagnosing conditions such as infections, tumors, traumatic brain injuries [2], and hemorrhagic strokes, all of which may be difficult to detect without imaging [14]. Because of its speed and reliability, CT scanning is generally the first choice in life-threatening cases that require immediate diagnosis and treatment. However, despite advancements in medical imaging, accurately identifying the presence and exact location of brain hemorrhages is a complex task. Internal bleeding may be subtle, and interpreting CT images correctly often requires years of clinical experience and expertise [8]. The life of a patient often depends on early and accurate detection, making every second and every decision critically important.

Previous research efforts have attempted to develop reliable automated systems to identify hemorrhagic regions within the brain. However, these systems often fell short due to slow processing times, inadequate calibration methods, and insufficient diagnostic accuracy—failing to consistently deliver results that could save lives in real-time emergencies.

Stroke continues to rank as the second leading cause of death worldwide and remains a substantial burden for individuals as well as healthcare systems. Encouragingly, many of the risk factors for stroke are potentially modifiable, including hypertension, cardiac disease, diabetes, glucose metabolism disorders, smoking, poor diet, and other lifestyle-related issues.

To address these challenges, this study aims to utilize deep learning algorithms trained on large medical datasets to improve the prediction and detection of strokes, especially hemorrhagic types. By analyzing both brain imaging data and patient risk factors, deep learning models can recognize subtle patterns that may go unnoticed by human experts. This approach has the potential to significantly accelerate diagnosis, improve treatment planning, and ultimately reduce mortality and long-term disability in stroke patients.

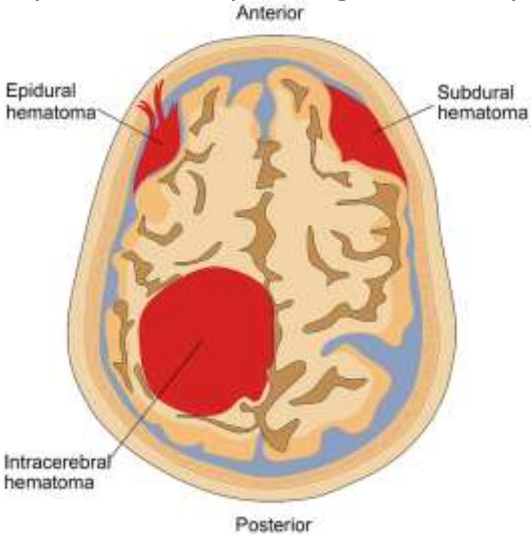

Figure 1. Types of Intracranial Hemorrhage of brain

The main objectives of this work are:

- To collect CT scan dataset of intracranial brain hemorrhage.
- Development of Deep learning-based CNN classification model using the ResNet-50 architecture, which detects and distinguish between Intraparenchymal Hemorrhage, Subdural Hemorrhage and Epidural Hemorrhage in brain CT scans.
- Features extraction- usage of ResNet-50 for extraction of more distinctive features in hemorrhage types to achieve more accurate and dependable diagnosis.
- To enhance the accuracy in recognizing Epidural Hemorrhage which is usually difficult to differentiate from other hemorrhages.
- To increase the speed of detection and lower error rate.

2. RELATED WORKS

Intracranial hemorrhage (ICH) is a critical condition requiring rapid and accurate detection for effective medical intervention [1]. The proposed SVM-LSTM framework represents a significant

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step towards automated and reliable ICH detection, offering a powerful tool to assist radiologists and improve patient outcomes. The paper [2] emphasized importance of precise classification and diagnosis of brain hemorrhages as it has proven to be important in detecting early and one of the preventable causes of mortality. In this article, they consider the challenging problem of Computer-Based Diagnosis (CBD), which aims to achieve the automatic diagnosis of clinical conditions without human supervision. The system returns the detected type of brain hemorrhage as the result, which can be helpful in validating the expert opinions for other diagnostic tools and also can work as an efficient teaching aide for radiology students to prevent misdiagnosis. The authors used the Backpropagation Network (BPN) that is very good for pattern recognition problems. Computationally, a multi-layer perceptron feed-forward artificial neural network was used to discriminate initial brain hematomas.

In [3], the authors address the challenge of brain hemorrhage identification, a task that is particularly difficult for radiologists during the early onset of hemorrhaging. To overcome this challenge, a deep learning approach was employed, using Convolutional Neural Networks (CNNs). The study utilized the well-known AlexNet architecture and a modified version of AlexNet integrated with a Support Vector Machine (SVM) classifier, referred to as AlexNet-SVM. These models were trained to classify brain CT images into hemorrhagic and non-hemorrhagic categories. The experimental results demonstrated that knowledge learned from natural image datasets could be successfully transferred to medical image classification. Furthermore, the proposed AlexNet-SVM model outperformed both the original AlexNet and a CNN model built from scratch in identifying brain hemorrhages.

The study in [4] focuses on medical imaging for understanding internal body structures and physiological functions of organs and tissues. The primary objective of the system is to detect the presence of hemorrhages and classify their type upon detection. CT images were utilized to identify hemorrhagic areas. The system achieved an impressive average classification accuracy of 98% across three types of brain hemorrhages, showcasing its effectiveness in diagnostic applications.

In paper [5], the authors aim to detect acute intracranial hemorrhages and their subtypes using Artificial Neural Networks (ANNs). The system leverages a combination of watershed algorithms and deep learning techniques to enhance the accuracy of detection. This hybrid approach demonstrates promise in improving the robustness of hemorrhage classification systems.

Study [6] introduces a deep Convolutional Neural Network (CNN) architecture that jointly learns both feature extraction and classification, thereby eliminating the need for multiple hand-engineered processing steps. Model performance was further improved by averaging outputs over multiple rotated versions of each input image. Postprocessing techniques were applied to refine CNN outputs, significantly increasing specificity. The dataset used comprised 134 CT cases (totaling 4,300 images), divided into 60 cases for training, 5 for validation, and 69 for testing. Each case typically contained multiple hemorrhages. On the test set, the model achieved 81% sensitivity per lesion (34 out of 42 lesions detected) and 98% specificity per case (45 out of 46 cases). Although the sensitivity was comparable to existing methods on other datasets, the achieved specificity was substantially higher. The study also offers insights into further performance improvements as the dataset is expanded. Medical imaging plays a pivotal role in diagnosing various medical conditions by providing visual insights into the human body's interior [7]. Computer-aided detection and diagnosis (CAD) systems have gained prominence in clinical practice, particularly in fields like mammography and colonoscopy. However, the development of CAD systems for brain-related conditions remains relatively underexplored compared to other areas. This paper introduces a CAD system designed to analyze brain computed tomography (CT) scans for detecting fresh intracranial hemorrhages. The system employs advanced image processing techniques, including noise reduction, morphological operations, and segmentation algorithms. Experimental results highlight its robust performance, achieving a sensitivity and specificity of 94.4%, a precision rate of 91.259%, and an overall classification accuracy of 88.89%. Intracranial Hemorrhage (ICH) is a critical condition characterized by bleeding within the brain or skull, posing significant risks due to the potential for increased intracranial pressure [8]. This study focuses on simultaneously detecting and classifying ICH with high precisionThe study concludes that integrating CNN and RNN architectures, such as LSTM and GRU, enhances ICH

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detection, identification, and classification, reducing diagnostic errors and improving clinical outcomes. This approach holds significant promise for advancing automated ICH diagnosis in medical imaging.

Timely detection of brain hemorrhages is crucial in medical diagnostics, as delays in identifying and treating this condition can lead to irreversible brain damage or even death [9]. This research introduces a CNN-based method for detecting cerebral hemorrhages using computed tomography (CT) scans. The results highlight the remarkable performance of the CNN-based model, achieving an impressive overall accuracy of 95.6% and a specificity of 97.8%.

Detecting brain hemorrhages accurately and efficiently is vital for timely medical intervention, as delays can result in severe complications or fatalities [10]. This study proposes an ensemble learning method for the automatic detection of brain hemorrhages using Magnetic Resonance Imaging (MRI). By integrating multiple learning models, the proposed method reduces diagnostic errors and enhances the robustness of brain hemorrhage detection.

3. METHODOLOGY

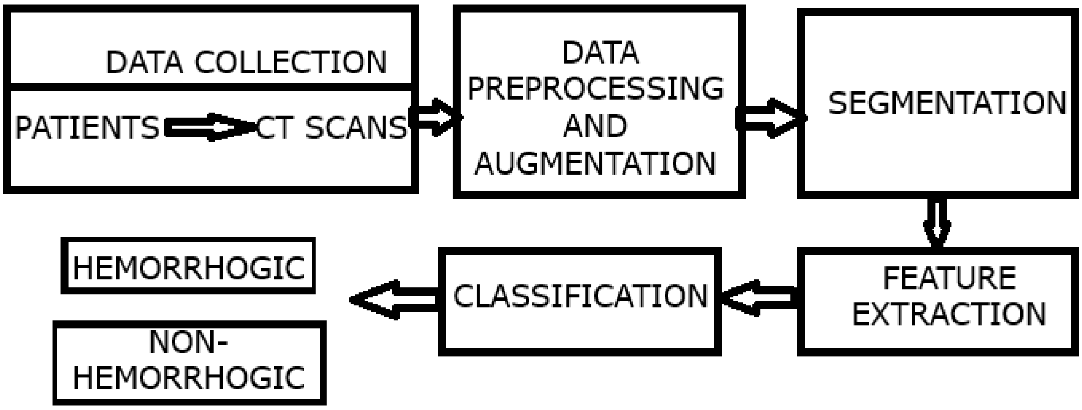

Figure 2. Block diagram depicting brain hemorrhage detection process

Dataset Collection:

In the era of advancing research and technology publicly available datasets plays a vital role. The required data is taken from Kaggle Platform that is Labeled CT scan images (hemorrhage and non-hemorrhage).

Types of Intracranial Brain Hemorrhage (IBH) dataset

1. Epidural hematoma
2. Subdural hematoma
3. Intraparenchymal hematoma

Input CT Scan Image

From the above block diagram, the primary input is the brain CT scan image, collected from a medical imaging device

Preprocessing

Preprocessing involves Resizing, Noise Removal and Contrast Enhancement. During this stage images are resized to match the input size required by the model (e.g., 224x224 for CNNs). After this artifact are removed using Gaussian or median filters. This is followed by improve of visibility of abnormalities by adjusting brightness/contrast.

Segmentation (ROI segmentation**)**

Thresholding or U-Net-based segmentation methods are used isolates areas potentially containing a hemorrhage.

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Feature Extraction

Features extracted like intensity levels, texture patterns, or statistical measures helps in distinguishing hemorrhagic regions.

Classification

This is prediction of presence or absence of a hemorrhage based on extracted features. A trained CNN model (ResNet) performs this task.

Post-processing

If hemorrhage is detected, the system overlays bounding boxes or masks on the input image to mark the affected regions.

Output

This block produces the classification result and annotated CT scan images, supporting medical professionals in diagnosis.

The key innovation in ResNet-50 is the introduction of residual learning, which allows information to bypass multiple layers using skip connections (or shortcut connections). This helps in preserving gradients during backpropagation, allowing the network to be trained effectively even with increased depth.

ResNet-50 is a 50-layer deep network that consists of:

- 1 convolutional layer
- 16 residual blocks
- A fully connected Layer

It is a scaled-down version of the larger ResNet architectures, such as ResNet-101 and ResNet-152, but still maintains high accuracy and efficiency.

Working of ResNet-50 Architecture:

The architecture consists of five major stages, each contributing to extracting hierarchical image features. These stages include convolutional layers, residual blocks, pooling layers, and a final classification layer.

The model follows this sequence:

1. Input Image → Preprocessing
2. YOLO Weights → Feature Extraction
3. ResNet-50 v2 → Deep Residual Learning
4. Feature Pooling & Flattening → Dimensionality Reduction

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5. Classification Output → Final Prediction

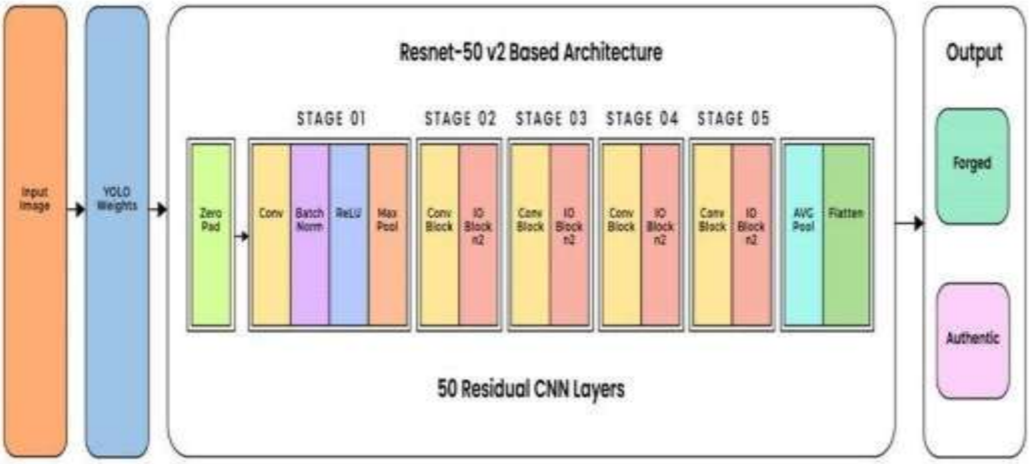

Figure 3. Architecture of ResNet 50 [8]

4. RESULTS AND DISCUSSION

Medical image processing is crucial in healthcare, particularly in diagnostic imaging, treatment planning, and research. The provided image illustrates various image processing techniques applied to medical images, particularly brain CT scans. These techniques help enhance image quality, remove noise, sharpen features, and perform segmentation for further analysis. The training process of a CNN involves feeding labeled data through the network, which performs convolutions to extract features. The output is compared to the actual label, and the error is calculated using a loss function. The network weights are updated using backpropagation and optimization techniques like gradient descent. The final training loss is approximately 0.8–0.9, while the validation loss is also close to 0.9. Final accuracy at epoch 100 is around 85-90% for training and 83-88% for validation, indicating good generalization and minimal overfitting.

GUI-based intracranial hemorrhage detection system is developed using Python in Visual Studio Code (VS Code). The system efficiently processes CT scan images, extracts important features, and predicts all the three types of intracranial hemorrhage that is epidural, subdural and intraparenchymal using deep learning. The model's accuracy indicates how confident it is in the prediction. Based on the diagnosis, medical treatment and dietary recommendations are provided to assist doctors and patients in decision-making.

Figure 4. Created user login page

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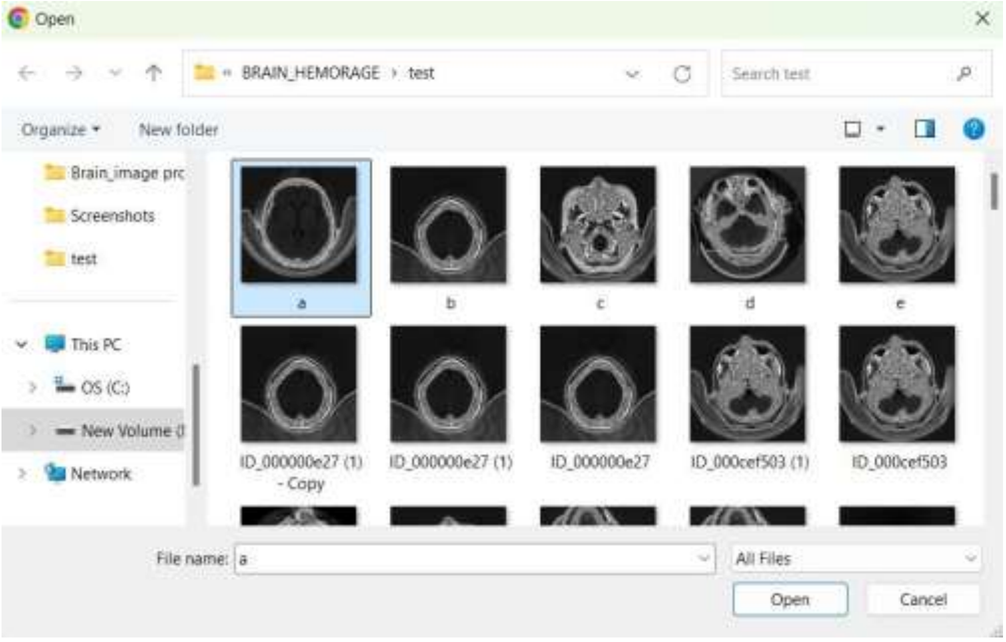

Figure 5. Selected CT Scan Image for Analysis

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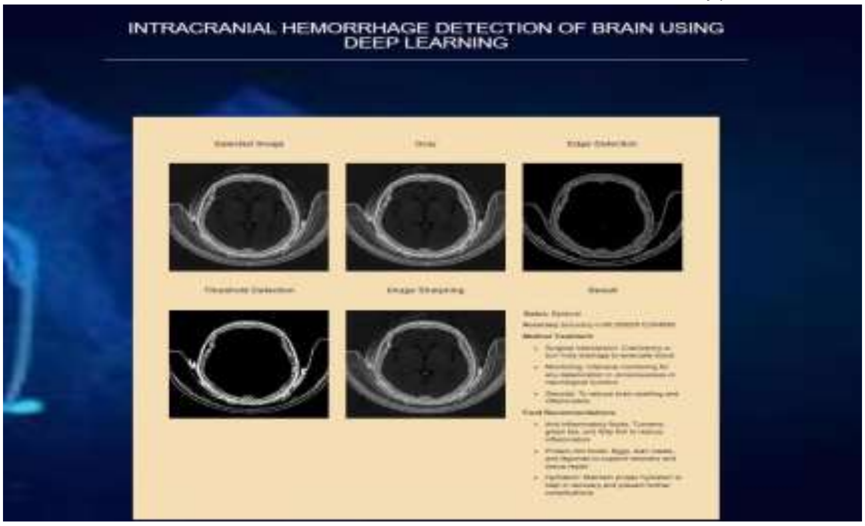

Figure 6. Epidural output displayed on the user interface

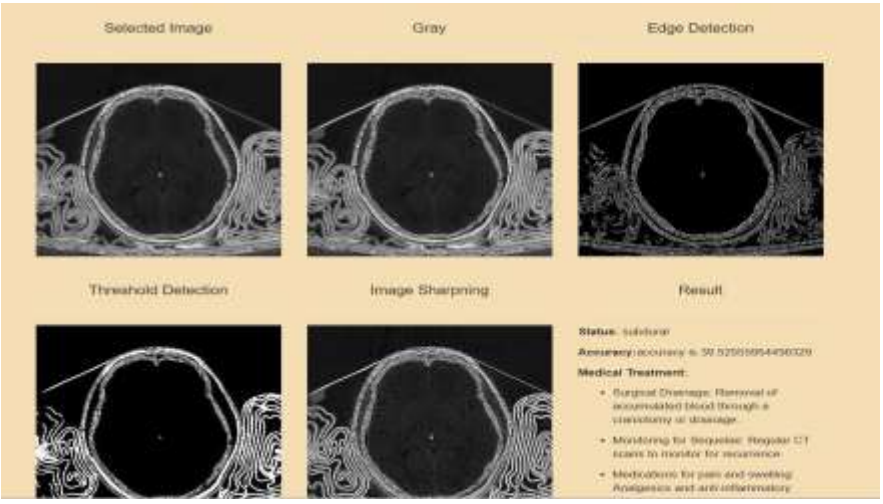

Figure 7. Subdural output displayed on the user interface

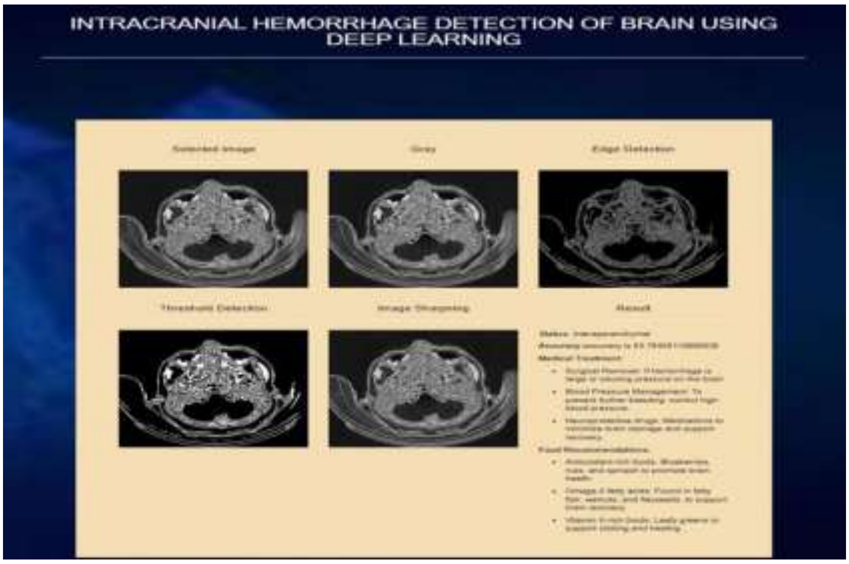

Figure 8. Intraparenchymal output displayed on the user interface

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5. CONCLUSION

Deep Learning based Intracranial Brain Hemorrhage (IBH) detection, specifically the ResNet-50 network, has shown great potential in clinical diagnosis for the classification and analysis of hemorrhagic cases in CT scan imaging. The deep learning model processes medical images quickly, detects hemorrhagic patterns and subsequently classifies these patterns as Epidural, Subdural and Intracerebral, classified with reasonably good accuracy. The model achieved in the resulted test set was able to detect all three types of IBH in these results, demonstrating that it can extract and evaluate significant features from CT images. The utilizing of preprocessing methods consisting of the grayscale conversion, the edge detection, threshold and image sharpening plays an important role in highlighting the hemorrhagic region for the model. ResNet-50 architecture utilizing deep Residual learning and skip connections for better feature extraction and classification enhances convergence speed and diminishes overfitting when dealing with complex medical image analysis. While the model's accuracy can be improved with more work like fine-tuning, more augmentation and training with a larger dataset. The application of this deep learning method to clinical practice offers a useful tool for radiologists to diagnose early and avoid human error, which can be beneficial for patients.

REFERENCES

[1] X. Ma, Y. Cheng, R. Garcia, and J. Haorah, ''Hemorrhage associated mechanisms of neuroinflammation in experimental traumatic brain injury,'' J. Neuroimmune Pharmacol., vol. 15, no. 2, pp. 181–195, Jun. 2020.

[2] A. Barman, V. Lopez-Rivera, S. Lee, F. S. Vahidy, J. Z. Fan, S. I. Savitz, S. A. Sheth, and L. Giancardo, ''Combining symmetric and standard deep convolutional representations for detecting brain hemorrhage,'' Proc. SPIE, vol. 11314, Mar. 2020, Art. no. 113140D.

[3] M. Fallenius, M. B. Skrifvars, M. Reinikainen, S. Bendel, S. Curtze, G. Sibolt, N. Martinez-Majander, and R. Raj, ''Spontaneous intracerebral hemorrhage,'' Stroke, 2019.

[4] M. Otterskog, N. Petrovic, and P. O. Risman, ''A multi-layered head phantom for microwave investigations of brain hemorrhages,'' in Proc. IEEE Conf. Antenna Meas. Appl. (CAMA), Oct. 2020, pp. 1–3.

[5] V. Anand, S. Gupta, D. Koundal, S. R. Nayak, P. Barsocchi, and A. K. Bhoi, "Modified U-NET architecture for segmentation of skin lesion," Sensors (Basel), vol. 22, no. 3, p. 867, 2022.

[6] V. Davis and S. Devane, ''Diagnosis & classification of brain hemorrhage,'' in Proc. Int. Conf. Adv. Comput., Commun. Control (ICAC), Dec. 2018, pp. 1–6.

[7] R. Mahajan and P. M. Mahajan, ''Survey on diagnosis of brain haemorrhage by using artificial neural network,'' Int. J. Sci. Res. Eng. Technol., vol. 5, no. 6, pp. 378–381, 2018

[8] J. A. Caceres, and J. N. Goldstein, "Intracranial hemorrhage," Emergency medicine clinics of North America, vol. 30, no. 3, pp. 771, 2019.

[9] T. Vedin, S. Svensson, M. Edelhamre, M. Karlsson, M. Bergenheim, and P.-A. Larsson, "Management of mild traumatic brain injury–trauma energy level and medical history as possible predictors for intracranial hemorrhage," European Journal of Trauma and Emergency Surgery, vol. 45, no. 5, pp. 901-907, 2019.

[10] Y.-H. Li, L. Zhang, Q.-M. Hu, H.-W. Li, F.-C. Jia, and J.-H. Wu, "Automatic subarachnoid space segmentation and hemorrhage detection in clinical head CT scans," International journal of computer assisted radiology and surgery, vol. 7, no. 4, pp. 507-516, 2018.

[11] Ji Young Lee, Jong Soo Kim, Tae Yoon Kim, and Young Soo Kim, "Detection and classification of in tracranial haemorrhage on CT images using a novel deep-learning algorithm," Sci. Rep., vol. 10, no. 1, pp. 20546, Nov. 2020.

[12] Xiyue Wang, Tao Shen, Sen Yang, Jun Lan, Yanming Xu, Minghui Wang, Jing Zhang, and Xiao Han, "A deep learning algorithm for automatic detection and classi f ication of acute intracranial hemorrhages in head ct scans," NeuroImage: Clinical, vol. 32, pp. 102785, 2021.

[13] H. Ko, H. Chung, H. Lee, and J. Lee, "Feasible study on intracranial hemorrhage detection and classification using a CNN-LSTM network," Annu. Int. Conf. IEEE Eng. Med. Biol. Soc., vol. 2020, pp. 1290–1293, 2020.

[14] N. Bhat, V. G. Biradar, A. K. S. Mallya, S. S. Sabat, M. S., and P. K. Pareek, "Identification of Intracranial Hemorrhage using ResNeXt Model," in 2022 IEEE 2nd Mysore Sub Section International Conference

10.48047/jocaaa.2024.33.08.160

(MysuruCon), 2022.

[15] M. Altuve and A. Pérez, "Intracerebral hemorrhage detection on computed tomography images using a residual neural network," Phys. Med., vol. 99, pp. 113–119, 2022.

[16] G. Zhu, H. Chen, B. Jiang, F. Chen, Y. Xie, and M. Wintermark, "Application of deep Learning to ischemic and hemorrhagic stroke computed tomography and magnetic resonance imaging," Semin. Ultrasound CT MR, vol. 43, no. 2, pp. 147–152, 2022.

[17] X. Zhang, K. P. Rane, I. Kakaravada, and M. Shabaz, "Research on vibration monitoring and fault diagnosis of rotating machinery based on internet of things technology," Nonlinear Engineering, vol. 10, no. 1, pp. 245–254, 2021.

[18]] S. Bharany et al., "Energy efficient fault tolerance techniques in green cloud computing: A systematic survey and taxonomy," Sustain. Energy Technol. Assessments, vol. 53, no. 102613, p. 102613, 2022.

[19] M. Yang, P. Kumar, J. Bhola, and M. Shabaz, "Development of image recognition software based on artificial intelligence algorithm for the efficient sorting of apple fruit," Int. J. Syst. Assur. Eng. Manag., vol. 13, no. S1, pp. 322–330, 2022.

[20] Sakshi and V. Kukreja, "A retrospective study on handwritten mathematical symbols and expressions: Classification and recognition," Eng. Appl. Artif. Intell., vol. 103, no. 104292, p. 104292, 2021.