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Supervised Soft Attention Network For Accurate Classification Using Intracranial Hemorrhage From Ct Scan

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Abstract: Intracranial bleeding is a critical medical issue caused by blood flow within the skull or nearby spaces due to factors like high blood pressure, head injuries, or blood vessel ruptures. Prompt and accurate diagnosis is essential for better patient outcomes. To address this challenge, we employ powerful pre-trained models such as ResNet 101 and Inception V3 to identify crucial features in medical images, enhancing the model's ability to pinpoint key areas. The classification process utilizes a diverse range of machine learning and deep learning algorithms like AdaBoost and Logistic Regression, each with its unique strengths. By combining these methods, we can more precisely detect instances of intracranial bleeding. Evaluating our methodology with measures like accuracy, sensitivity, specificity, and F1-score ensures the effectiveness and dependability of our tool for detecting brain hemorrhages.

***Index Terms* - ResNet-101, Inception-V3, Adaboost, Logistic Regression.**

I. INTRODUCTION

In recent years, the prompt and accurate diagnosis of Intracranial Hemorrhage (ICH) has emerged as a critical medical concern due to its potential for life-threatening consequences. Intracranial hemorrhage refers to bleeding within the skull, which can arise from various causes such as trauma, hypertension, vascular malformations, or coagulation disorders. Given the urgency of the condition, timely identification and classification of different types of ICH are paramount for effective patient management and improved outcomes. Computed Tomography (CT) scans have become essential instruments in diagnosing ICH, providing in-depth insights into the location, size, and characteristics of hemorrhagic brain lesions. These scans allow medical professionals to differentiate between various types of ICH, such as intraparenchymal hemorrhage (IPH), intraventricular hemorrhage (IVH), subarachnoid hemorrhage (SAH), subdural hemorrhage (SDH), and epidural hemorrhage (EDH). However, the manual interpretation of CT scans by radiologists is arduous and time consuming, especially considering the intricate and nuanced nature of these images.

The problem is made more difficult by the lack of qualified radiologists, especially in areas with limited resources and developing countries. The elevated death rates linked to ICH situations are partly caused by this shortage of qualified people, which exacerbates delays in diagnosis and treatment. In addition, several barriers to prompt intervention and patient treatment include inequities in healthcare access, excessive wait periods for CT scans, and restricted access to healthcare resources.

This paper introduces a novel automated system that combines advanced deep-learning methods and machine-learning algorithms to tackle urgent challenges. By utilizing cutting edge convolutional neural networks (CNNs) such as ResNet101 and Inception V3, the system aids in extracting features from CT scans with unparalleled accuracy and speed. These CNNs adept at capturing intricate details and subtle variations in medical images, enhancing the precision of diagnosing ICH subtypes. Additionally, an attention mechanism is integrated into the system to improve sensitivity, directing the model's focus toward specific areas in CT scans where hemorrhages are more likely to be present. This inclusion of an attention mechanism greatly enhances the model's capacity to identify even the smallest or subtlest hemorrhages, thereby increasing the overall accuracy of diagnostics.

This automated system represents a significant advancement in the medical imaging and diagnosis field, specifically in detecting ICH. By simplifying the analysis of CT scans and providing quick and accurate diagnoses, the system has the potential to greatly improve patient outcomes, especially in areas lacking access to expert radiologists and healthcare resources. Furthermore, the incorporation of advanced AI technologies offers promising solutions to global healthcare challenges, including disparities in medical knowledge and resource distribution.

II. LITERATURE REVIEW

In this section, the research on intracranial hemorrhage classification in recent years can be summarized. It can be grouped based on machine learning, the Internet of Things, and deep learning to classify and detect particular subtypes.

A. ICH Detection Using Machine Learning:

Majeed et al. [8] propose standard machine learning techniques to automatically detect ICH from two-dimensional CT scans. It includes a pre-processing pipeline to remove skull bones, feature extraction, and PCA-based feature selection to enhance model performance. The final step involves training and testing a Random Forest classifier, achieving an accuracy of 92.5.Shayan Fazeli et al.[6] has developed a reliable system for supervised techniques to classify ICH segmentation using a mixed model. By recognizing unique distributions of hemorrhagic and healthy tissues, their algorithm employs an Expectation-Maximization process to dynamically segregate them and determine the number of clusters required to identify the disease.Ushani Balasooriya et al.[3] have proposed a system for diagnosing brain hemorrhages employing artificial neural networks.

B. ICH Detection Using Internet Of Things:

G. Revathy et al.[9] have designed a system to detect brain hemorrhage utilizing Internet of Things sensors. This project presents an IoT-centered approach employing deep learning algorithms for accurate brain hemorrhage diagnosis, outperforming conventional techniques such as naive Bayes, KNN and K-medoids.The employment of SVM and Recurrent Neural Networks demonstrates remarkable performance, providing valuable insights for expert verification and radiologist training.Yixuan Chen et al.[4] proposed a system for detecting intracranial hemorrhage using an MIT sensor. An open planar MIT sensor array equipped with gradiometers enhances the detection of intracranial hemorrhages, showcasing superior efficiency compared to Bx sensors. This advancement facilitates precise reconstruction and offers encouraging spatial resolutions suitable for real-world applications. **C. ICH Detection Using Deep Learning:**

Asif Muhammad et al.[6] has proposed system detecting for deep conventional models and boosting mechanism.Due to workload and staff constraints, an intelligent system combining ResNet101-V2, Inception-V4, and boosting achieves 97.7 accuracy, outperforming benchmarks for ICH detection, proving its significance for real-time use.Li Xiangyu et al.[7] introduced a system focused on segmenting intracranial hemorrhages while also estimating uncertainties. The SLEX-Net model combines hematoma expansion with contextual information transfer to improve segmentation accuracy, continuity, and uncertainty estimation, outperforming existing techniques for detecting intracranial hemorrhages.Lakshmi Prasanna et al.[8] proposed a system for multiclass classification of intracranial hemorrhages through a transfer learning approach. By utilizing DenseNet121 for transfer learning, this system enhances the classification of intracranial hemorrhages by leveraging complex features from medical images and pretrained weights, providing a valuable solution for precise clinical diagnosis.Shifat E. Arman et al.[9] developed a method for classifying intracranial hemorrhages using deep learning and Bayesian optimization. Their automatic approach for identifying intracranial hemorrhages from CT scans involves optimizing Dense Net through Bayesian Optimization, ensuring dependable diagnoses to support patient care. Wu Dasheng et al.[10] has proposed a system for automatic brain midline surface. Integrating advanced image processing and AI, this technology precisely maps the brain's midline surface in 3D CT images, significantly enhancing intracranial hemorrhage diagnosis and improving patient outcomes, revolutionizing neuroimaging and critical care medicine.

III. METHODOLOGY

This section includes data collection, pre-processing, model training, classification and model evaluation. The goal is to develop a comprehensive medical image classification solution, leveraging supervised learning algorithms, pre-trained models like ResNet-101 and Inception V3 for feature extraction, and AdaBoost with Logistic regression for accurate detection and classification of intracranial hemorrhages, optimizing project success. Based on the learned features during training, the trained model categorizes comments into offensive or non offensive categories, as depicted in Figure 1

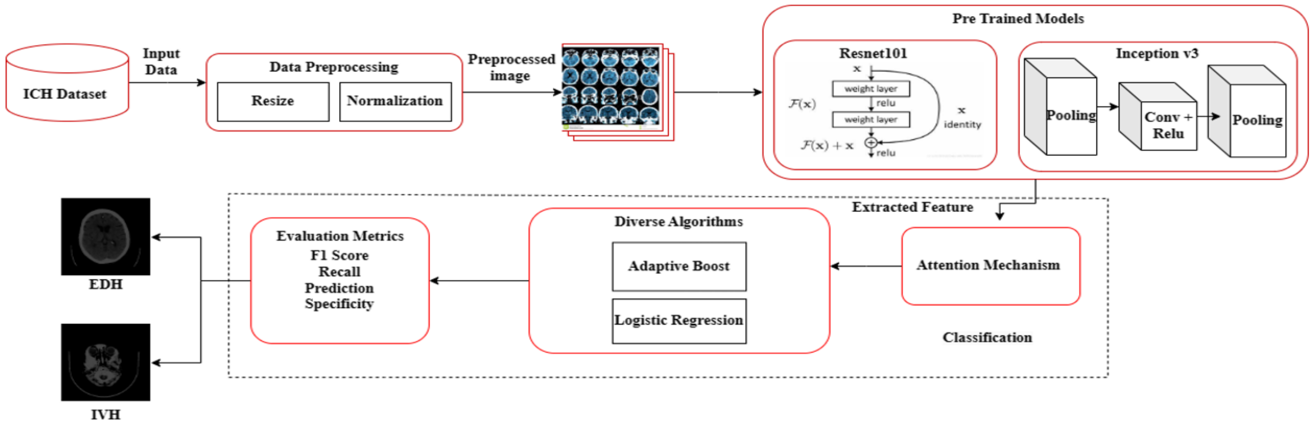

Fig. 1. Proposed architecture

A. Dataset Description:

The dataset comprises training and test data in DICOM format. The "train.csv" file includes image ID and target information, labeling five subtypes of hemorrhage. "submission.csv" illustrates the prediction format for test set images, necessitating predictions on hemorrhage presence and subtype. See Table 1 for details.

- ID:An image ID corresponding to a unique image, presented with underscores.
- LABEL: It can be represent the five distinct multiple hemorrhage subtypes.

Table 1: Labeled Data

ID	LABEL
0	epidural_hemorrhage
0	subdural_hemorrhage
1	any
2	intraventricular_hemorrhage

B. Data Pre-processing:

Pre-processing serves as critical phase in preparing data for machine learning models. In the context of medical image analysis, common pre-processing tasks include standardizing image dimensions and normalizing pixel intensities.

- Resize the image to a fixed size of 224x224 pixels. You can use various libraries like OpenCV for this purpose.
- After resizing, convert the image to an array format. Normalize the pixel values by dividing the overall total value. Since you mentioned dividing by 255, this step involves scaling the values between 0 and 1. This can be done element-wise for the entire array.

C. Feature Extraction:

Utilizing pre-trained CNNs such as ResNet-101 and Inception v3 significantly enhances feature extraction for detecting intracranial hemorrhages. These architectures are combined to form a comprehensive image representation, leveraging ResNet-101's deep structure and Inception v3 multi-scale feature extraction capabilities.

Algorithm 1 Feature Extraction Of ResNet-101 and Inception-V3

Input: Pre-processing Brain CT Scan
Output: Both training and evaluating the model

Step1: Prepare the training data
Step2: Define the pre-trained model architecture
Step3: Initialize the model weights
Step4: Train the model
Step5: Evaluate the model

Incorporating attention mechanisms further improves interpretability city by dynamically prioritizing relevant image regions, Crucial for accurate diagnosis. Transfer learning fine-tunes this mod- els on medical data, adapting their learned features to specific tasks. Overall, this approach enhances diagnostic accuracy by capturing intricate patterns and prioritizing important regions within medical images.

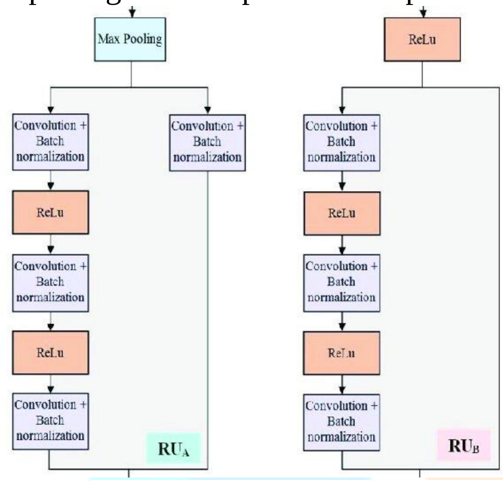

Fig.2. ResNet-101

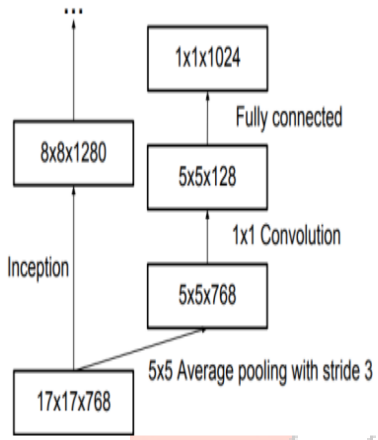

Fig.3. Inception-V3

D. Attention Mechanism:

Feature-enriched data, augmented with attention-aware representations plays a pivotal role in optimizing the classification pipeline for medical images by prioritizing important regions within the images, thereby enhancing efficiency and accuracy.This approach facilitates a deeper understanding of crucial features for diagnosis, streamlining the classification process and enabling clinicians to make more informed decisions based on highlighted regions of interest.. In clinical settings, this refined categorization pipeline serves as a valuable tool, aiding healthcare professionals in swiftly and accurately diagnosing medical conditions.

Algorithm 2 Attention Mechanism

Input: Combined ResNet-101 and Inception-V3 Model
Output: Initialized weight for specific task

Step1: Initialize the combined ResNet-101 and Inception-V3 model.
Step2: Prepare the input data for the model.
Step3: Forward passes the input data through the combined model to obtain feature maps.
Step4: Compute weights based on feature maps.
Step5: Apply the attention weights to the feature maps to obtain the attended features.
Step6: Initialize the weights for the specific task using the attended features.
Step7:Output the initialized weights for the specific task.

. Moreover, the utilization of attention mechanisms ensures the efficiency and reliability of the diagnostic process by global and local information to capture subtle nuances in the images.

```
[ 59414852.   54585256.   -983395.2 ...  21797108.    3524398.8
 -39719044. ]
[ 59414852.   54585256.   -983395.2 ...  21797108.    3524398.8
 -39719044. ]
...
[ 59414852.   54585256.   -983395.2 ...  21797108.    3524398.8
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[ 59414852.   54585256.   -983395.2 ...  21797108.    3524398.8
 -39719044. ]
[ 59414852.   54585256.   -983395.2 ...  21797108.    3524398.8
 -39719044. ]]
```

Fig.4. Attention Weight Value

```
1/1 [==============================] - 5s 5s/step
Final Predictions:
[[0. 0. 0. 0. 1. 0. 0.]
 [0. 0. 0. 0. 1. 0. 0.]
 [0. 0. 0. 0. 1. 0. 0.]
 [0. 0. 0. 0. 1. 0. 0.]
 [0. 0. 0. 0. 1. 0. 0.]
 [0. 0. 0. 0. 1. 0. 0.]
 [0. 0. 0. 0. 1. 0. 0.]
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 [0. 0. 0. 0. 1. 0. 0.]
 [0. 0. 0. 0. 1. 0. 0.]
 [0. 0. 0. 0. 1. 0. 0.]
 [0. 0. 0. 0. 1. 0. 0.]
 [0. 0. 0. 0. 1. 0. 0.]
```

Fig.5. Attention Final Prediction

E. Classification:

The final classification model integrates a features attention mechanism and an AdaBoost classifier, both meticulously trained on a labeled dataset specifically curated for predicting intracranial hemorrhages and their various types. The features attention mechanism serves to highlight relevant features within medical images, enabling the model to focus on crucial areas for diagnosis. Meanwhile, the AdaBoost classifier harnesses the collective power of weak learners, enhancing the model's predictive capabilities. This holistic approach maximizes the model's ability to discern subtle patterns indicative of hemorrhagic conditions, thereby significantly improving its accuracy and efficacy in medical image analysis.

IV. RESULT AND ANALYSIS

In this section, we present the final prediction results and evaluation metrics of the implemented modules and model. Model evaluation such as recall, F1 score, sensitivity, and precision showed promising performance, indicating the robustness of the developed models.The high accuracy suggests that the models effectively differentiated between images with and without intracranial hemorrhages, crucial for timely and accurate diagnosis in clinical settings.Furthermore, the balanced F1 score, sensitivity, and precision metrics indicate the model's ability to minimize false positives and negatives, essential for reducing misdiagnosis rates and ensuring patient safety. Overall, the results highlight the effectiveness of integrating pre-trained models like ResNet-101 and Inception V3 with attention mechanisms and classification algorithms like AdaBoost and logistic regression for accurate classification of multi-hemorrhage in medical imaging. Moreover, the analysis of the attention mechanism impact revealed their importance in enhancing the model's interpretability and diagnostic accuracy.

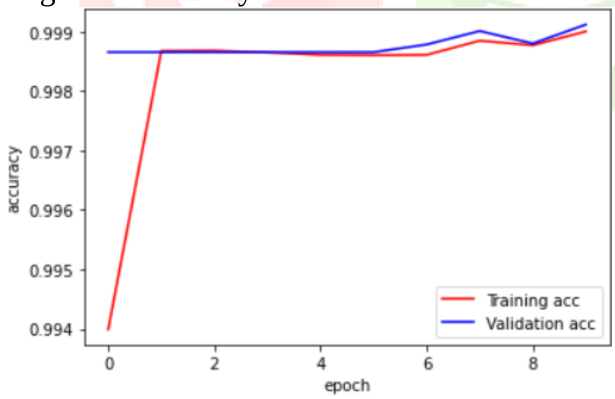

Fig.6.Training and Validation accuracy

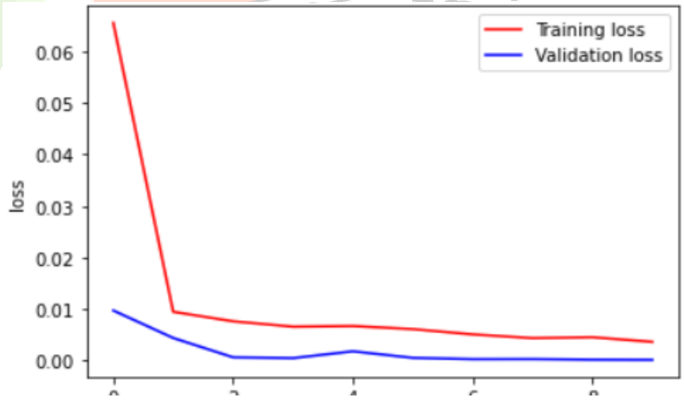

Fig.7. Model Loss

By dynamically prioritizing important image regions, the attention mechanisms guided the models to focus on relevant features associated with intracranial hemorrhages, effectively improving the models' performance. This attention-driven approach not only improved classification accuracy but also provided valuable insights into the regions of interest within medical images, aiding clinicians in their decision-making process. The successful integration of attention mechanisms with pre-trained models and classification algorithms underscores the potential of attention-based techniques in enhancing medical image analysis tasks, offering a promising avenue for further advancements in diagnostic accuracy and patient care.

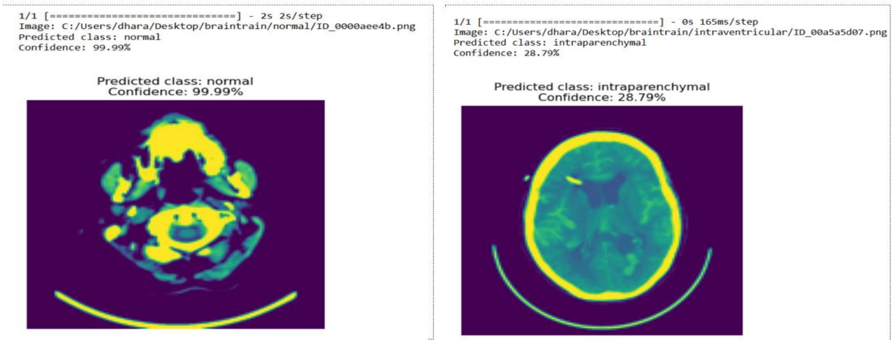

Fig.8. Final Result

Table 2 Model evaluation for Resnet-101

ResNet-101	ACCURACY	PRECISION	F1 SCORE	SUPPORT
0	100	99	99	300
1	99	99	100	300

Table 3 Model evaluation for Inception v3

INCEPTION-V3	ACCURACY	PRECISION	F1 SCORE	SUPPORT
0	80	82	80	300
1	80	79	81	300

Table 4 Model evaluation for Adaboost

ADABOOST	ACCURACY	PRECISION	F1 SCORE	SUPPORT
0	98	98	99	89
1	98	98	98	79

Table 5 Model evaluation for Logistic Regression

LOGISTIC REGRESSION	ACCURACY	PRECISION	F1 SCORE	SUPPORT
0	77	80	77	944
1	77	76	79	-

V. CONCLUSION

In conclusion, the integration of ResNet-101 and InceptionV3 with an attention mechanism significantly enhances feature representation in intracranial hemorrhage detection. AdaBoost refinement of the classifier, along with Logistic regression incorporation, underscores the efficacy of ensemble model in improving predictive performance and semantic segmentation, respectively. This holistic approach showcases the potential of combining deep learning and traditional machine learning methodologies for comprehensive medical image analysis. By leveraging the strengths of both approaches, this integrated strategy offers promising advancements in intracranial hemorrhage detection systems, enhancing diagnostic accuracy in clinical settings.

VI. FUTURE WORK

In the future, expanding the project by integrating advanced algorithms such as transformers and LSTMs would further enhance accuracy in intracranial hemorrhage detection. This expansion would entail incorporating transformer models to capture intricate relationships in medical images, potentially outperforming the current ResNet-101 and InceptionV3 combination. Simultaneously, leveraging the temporal dependencies in sequential data using LSTM networks would provide more nuanced insights into the evolution of intracranial hemorrhages over time. This comprehensive approach not only aims for superior diagnostic accuracy but also enables precise localization of the disease. Additionally, developing a user friendly website to facilitate seamless interaction with the models and presenting results in an interpretable manner.

REFERENCES

[1] Asif, Muhammad, Munam Ali Shah, Hasan Ali Khattak, Shafaq Mussadiq, Ejaz Ahmed, Emad Abouel Nasr, and Hafiz Tayyab Rauf. ”Intracranial Hemorrhage Detection Using Parallel Deep Convolutional Models and Boosting Mechanism.” VOL 4,pp. 652 (2023).
[2] Arman, Shifat E., Sayed Saminur Rahman, Niloy Irtisam, Shamim Ahmed Deowan, Md Ariful Islam, Saadman Sakib, and Mehedi Hasan. ”Intracranial Hemorrhage Classification From CT Scan Using Deep Learning and Bayesian Optimization.” IEEE (2023).
[3] Balasooriya, Ushani, and MU S. Perera. ”Intelligent brain hemorrhage diagnosis using artificial neural networks.”IEEE Business, Engineering Industrial Applications Colloquium (BEIAC). IEEE (2022).
[4] Chen, Yixuan, Chao Tan, Shu Zhao, and Feng Dong. ”Intracranial hemorrhage detection by open MIT sensor array.” IEEE Transactions on Instrumentation and Measurement.vol.71,pp.1-11 (2022).
[5] Kothala, Lakshmi Prasanna, and Sitaramanjaneya Reddy Guntur. ”MultiClass Classification of Intracranial Hemorrhages in a 3-Channel CT image by using a Transfer Learning based DenseNet121 model.” International Conference on Smart Generation Computing, Communication and Networking (SMART GENCON).pp. 1-5, IEEE (2022).
[6] Kimmo, Shayan Fazeli, and Majid Sarrafzadeh. ”Unsupervised acute intracranial hemorrhage segmentation with mixture models.”IEEE 9th International Conference on Healthcare Informatics (ICHI). IEEE (2021).
[7] Li, Xiangyu, Gongning Luo, Wei Wang, Kuanquan Wang, Yue Gao, and Shuo Li. ”Hematoma expansion context guided intracranial hemorrhage segmentation and uncertainty estimation.” IEEE Journal of Biomedical and Health Informatics.vol.26, no. 3, pp.1140-115 (2021).
[8] Majeed, Mohammad A. Abdul, Omar Munthir Al Okashi, and Azmi Tawfeq Alrawi. ”Intracranial hemorrhage detection and classification from CT images based on multiple features and machine learning approaches.”15th International Conference on Developments in eSystems Engineering (DeSE). IEEE (2023).
[9] Revathy, G., Durga Karthik, and B. Sreedevi. ”IoT Sensors Empowered with Deep Learning for Brain Depletion Recognition.” International Conference on Inventive Computation Technologies (ICICT). IEEE (2022).
[10] Wu, Dasheng, Haoming Li, Jianbo Chang, Chenchen Qin, Yihao Chen, Yixun Liu, Qinghua Zhang et al.”Automatic Brain Midline Surface Delineation on 3D CT Images With Intracranial Hemorrhage.” IEEE Transactions on Medical Imaging.vol.41, no. 9,pp.2217-2227 (2022).
[11] C. Tan, Y. X. Chen, Y. R. Wu, and F. Dong, “A modular magnetic induction tomography system for low-conductivity medium imaging,” IEEE Trans. Instrum. Meas., vol. 70, pp. 1–8 (2021).
[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 classification of acute intracranial hemorrhages in head ct scans,” NeuroImage: Clinical, vol. 32, pp. 102785 (2021).
[13] C. Tan, Y. X. Chen, Y. R. Wu, and F. Dong, “A modular magnetic induction tomography system for low-conductivity medium imaging,” IEEE Trans. Instrum. Meas., vol. 70, pp. 1–8(2021).
[14] H. Zhang et al., “Resnest: Split-attention networks,” arXiv preprint arXiv:2004.08955 (2020).
[15] Mihail Burduja, Radu Tudor Ionescu, and Nicolae Verga, “Accurate and efficient intracranial hemorrhage detection and subtype classification in 3D CT scans with convolutional and long Short-Term memory neural networks,” Sensors (Basel), vol. 20, no. 19 (2020).
[16] Alex Sherstinsky, “Fundamentals of recurrent neural network (rnn) and long short-term memory (lstm) network,” Physica D: Nonlinear Phenomena, vol. 404, pp. 132306 (2020).
[17] M. Oziel, R. Korenstein, and B. Rubinsky, “Non-contact monitoring of temporal volume changes of a hematoma in the head by a single inductive coil: A numerical study,” IEEE Trans. Biomed. Eng., vol. 66, no. 5, pp. 1328–1336(2019).
[18] X. Li et al., “Selective kernel networks,” in Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 510– 519(2019).
[19]] N. Abraham and N. M. Khan, “A novel focal tversky loss function with improved attention u-net for lesion segmentation,” in 2019 IEEE 16th International Symposium on Biomedical Imaging (ISBI 2019). IEEE, pp. 683–687(2019).

[20] H Ye et al., “Precise diagnosis of intracranial hemorrhage and subtypes using a three-dimensional joint convolutional and recurrent neural network,” European Radiology (2019).
[21] A Majumdar et al., “Detecting intracranial hemorrhage with deep learning,” Conf. Proc. IEEE Eng. Med. Biol. Soc., pp. 583–587(2018).
[22] J Heit, M Iv, and M Wintermark, “Imaging of Intracranial Hemorrhage,” Journal of Stroke, vol. 19, no. 1, pp. 11–27(2017). [23] O. Semyachkina-Glushkovskaya, A. Pavlov, J. Kurths, E. Borisova, A. Gisbrecht, O.Sindeeva, A. Abdurashitov, A. Shirokov, N. Navolokin, E. Zinchenko, A. Gekalyuk, M. Ulanova, D. Zhu, Q. Luo, V. Tuchin, “Optical monitoring of stress-related changes in the brain tissues and vessels associated with hemorrhagic stroke in newborn rats,” Biomedical Optics Express, vol. 6(10), pp. 1364(2015).
[24] S.N. Gupta, A.M. Kechli, U.S. Kanamalla, “Intracranial hemorrhage in term newborns: management and outcomes,” Pediatr Neurol, vol. 40, pp. 1-12(2009).
[25] Bruce Lee and Andrew Newberg, “Neuroimaging in traumatic brain imaging,” NeuroRx, vol. 2, no. 2, pp. 372–383(2005).