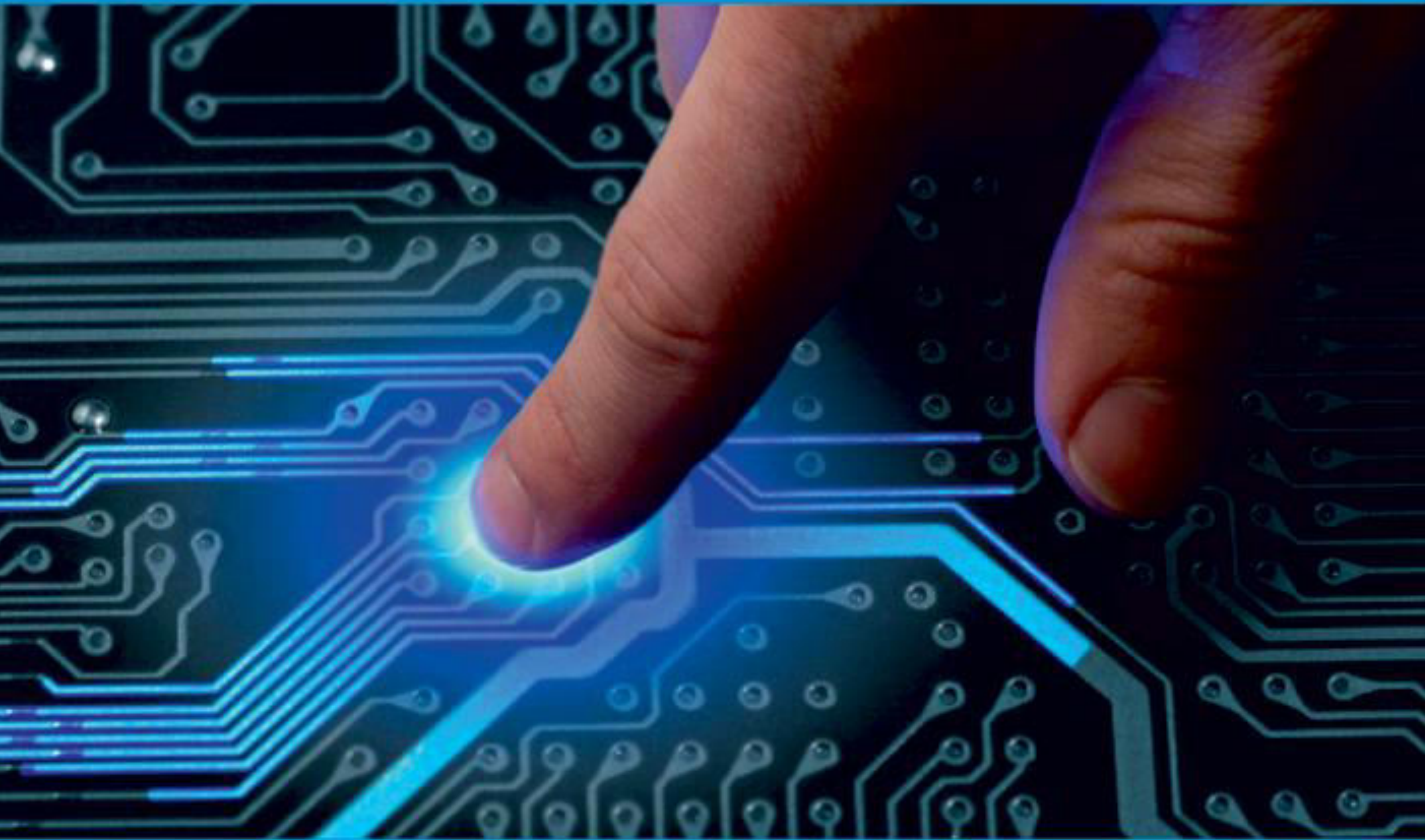
IJIRCCE

e-ISSN: 2320-9801 | p-ISSN: 2320-9798



# INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

## IN COMPUTER & COMMUNICATION ENGINEERING

**Volume 11, Issue 6, June 2023**

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

**Impact Factor: 8.379**

International Journal of Innovative Research in Computer and Communication Engineering

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 |

|| Volume 11, Issue 6, June 2023 ||

| DOI: 10.15680/IJIRCCE.2023.1106041 |

# Intracranial Hemorrhage Detection

**Amrutha P, Chandana S R, P D Himani Kaveramma, Shresta H D, Dr. Srinivas Halvi**

UG Students, Dept. of Medical Electronics, Dayananda Sagar College of Engineering, Bengaluru, India

Assistant Professor, Dept. of Medical Electronics., Dayananda Sagar College of Engineering, Bengaluru, India

**ABSTRACT:** When a blood vessel in the brain is ruptured, it can cause an intracranial haemorrhage, which causes severe brain damage or even death. To lessen the severity of brain injury and other problems, an accurate diagnosis of intracranial haemorrhage is crucial. Rapid diagnosis based on a radiologist's examination of CT images is essential for cerebral haemorrhage treatment, as it lowers patient mortality. In this study, we investigate the cerebral haemorrhage detection issue and create a deep learning model to speed up haemorrhage detection. Deep Learning is frequently employed in medical image interpretation and has made promising progress in the diagnosis of brain haemorrhage. By speeding up the time it takes to find them, a deep learning model can aid in this process. We have used ResNet50 pre-trained CNN model and also present a traditional CNN model of architecture for the detection and categorical classification of intracranial brain haemorrhage on CT scans. For classification, we created a convolutional neural network based on Sequential, and for predicting the kind of bleeding, we trained and tested a Sequential-based model. Our model has a 93% accuracy in the precise multiclass prediction.

KEYWORDS: Intracranial haemorrhage, CT images, CNN model

## I. INTRODUCTION

Intracranial haemorrhage (ICH) can be brought on by trauma, stroke, aneurysm, vascular malformations, high blood pressure, illegal drugs, and irregular blood coagulation. Shape, position, and size are used to distinguish various ICH types. In order to reduce patient mortality, early identification of ICH is essential, especially within 24 hours. A head computed tomography (CT) scan is used to diagnose a patient, and the results of the CT are interpreted by a radiologist. To create 3D cross-sectional images of the body's blood, bone, and soft tissue, CT scans combine a series of X-ray images taken from various angles. The application of ML models like neural networks for medical image processing has been broadened thanks to developments in machine learning for image recognition.

Deep learning systems mine large datasets for significant patterns and traits without explicit instructions. They can therefore receive comprehensive training. utilising machine learning to deduce and carry out challenging cognitive tasks, such CT scan analysis, which is typically carried out by a radiologist. To identify and categorise several forms of ICH on unenhanced CT scans, we employed a deep convolutional neural network in this study. Rapid ICH diagnosis and distinction from other strokes and brain illnesses can speed up effective treatment and lower mortality and long-term brain damage. we propose using neural networks to identify and categorise the condition based on the CT scan. The time-distributed convolutional network is implemented in the model architecture. If there is enough data, we suggest observing accuracy exceeding 91% from such an architecture. We suggest additional modifications to our strategy that involve the implementation of federated learning. This would enable the pooling of learnt parameters without impinging on the data's intrinsic privacy.

## II. RELATED WORK

In [1] authors developed a deep learning strategy that imitates the radiologists' interpretation process and incorporates a 2D CNN model and two sequence models. Their deep learning algorithm can accurately classify the acute ICH and its five subtypes with AUCs of 0.988 (ICH), 0.984 (EDH), 0.992 (IPH), 0.996 (IVH), 0.985 (SAH), and 0.983 (SDH), respectively, reaching the accuracy level of expert radiologists. In [2] Authors developed a intracranial haemorrhage (ICH) and categorise its subtypes detector without using a convolutional neural network (CNN). The area under the ROC curve (AUC) for the detection of ICH using the summing of all computed tomography (CT) images for each patient was 0.859, and the sensitivity and specificity were 78.0% and 80.0%, respectively. Based on the intracranial

International Journal of Innovative Research in Computer and Communication Engineering

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 |

|| Volume 11, Issue 6, June 2023 ||

| DOI: 10.15680/IJIRCCE.2023.1106041 |

height, CT scans were split into 10 subdivisions for the purpose of ICH localization. In [3] Two convolutional neural networks were trained and assessed to classify haemorrhage or non-haemorrhage using a total of 491 CT studies. The suggested CNN networks have 98% accuracy, 97% recall, and 98% F1 score. In [4] Authors have used ResNet-50, transfer learning , and the performance of linear and sigmoid windowing is examined. In order to produce a more evenly distributed training dataset, an under sampling strategy was used due to the substantial imbalance in the number of examples that were available. The three windows of interest that were combined with sigmoid windowing had the highest F1 score as a result. The correlation between intracranial haemorrhage subtype and diagnosis was found to be unclear through error analysis, and the next step is to split the architecture into two steps, with the first step diagnosing intracranial haemorrhages and the second step classifying subtype within the positively diagnosed examples.

## III. PROPOSED ALGORITHM

### 1. DATA COLLECTION:

Data collection is the act of acquiring and measuring information on variables of interest in a systematic and defined manner. Data collection for our study comprises gathering CT scans of cerebral haemorrhages. The dataset was labelled by professionals and is from the Kaggle RSNA Intracranial Haemorrhage Classification competition round. The pictures were in the DICOM (Digital Imaging and Communications in Medicine) format, which is a typical way to handle medical pictures.

### 2. DATA PREPROCESSING:

Preparing raw data to be used with a machine learning model is known as data pre-processing. In order to build a machine learning model, it is the first and most important stage. It is not always the case that we come across the clean and prepared data when developing a machine learning project. Additionally, any time you work with data, you must clean it up and format it. Therefore, we use a data pre-processing task for this.

### 3. APPLYING CNN MODEL:

Convolution can be defined as the action between two functions having a real value parameter and is frequently represented as follows:

$$S(t)=(x*w)(t)$$

The first argument (x) is known as the input in CNN parlance, and the second argument (w) is known as the kernel. A feature map is typically used to describe the outcome.

A convolutional neural network normally consists of three stages: the first stage includes convolutional layers with activations similar to ReLUs (rectified linear units), the second stage includes a pooling layer for size reduction, usually max-pooling. Lastly, a layer that is flattened before becoming fully connected for classification.

### 4. TRAINING AND TESTING:

The sequential CNN model is trained and tested using each image in the database. The model is trained using the machine learning concept of supervised learning. Models are trained in this way using labelled datasets so that the model may learn about various types of data. Following completion of the training procedure, the model is evaluated using test data (a subset of the training set), which predicts the result.

Each model undergoes ten training epochs, with the top model being preserved for comparison with the test set. The performance over time is evaluated using a weighted logistic loss function. In order to evaluate how well CNN performs in classifying ICH, some metrics will be collected.

### 5. PREDICTION:

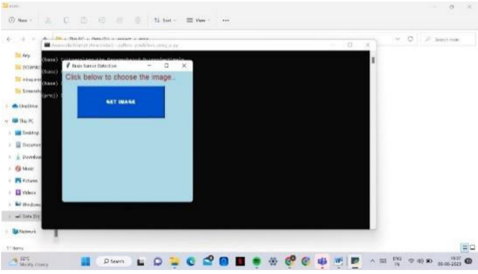
The category classifier, a component of the convolution neural network, is used to carry out the final prediction.

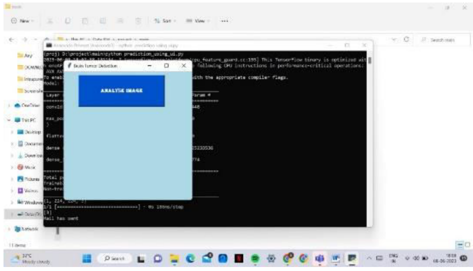
| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 |

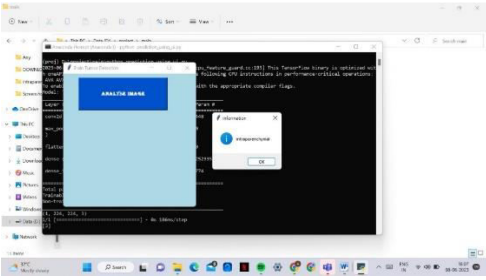
|| Volume 11, Issue 6, June 2023 ||

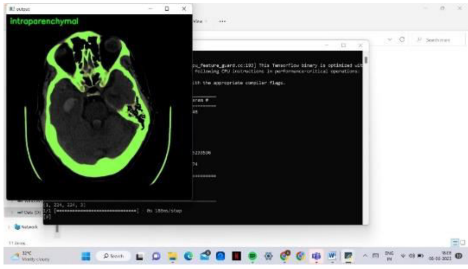
| DOI: 10.15680/IJIRCCE.2023.1106041 |

## IV. SIMULATION RESULTS

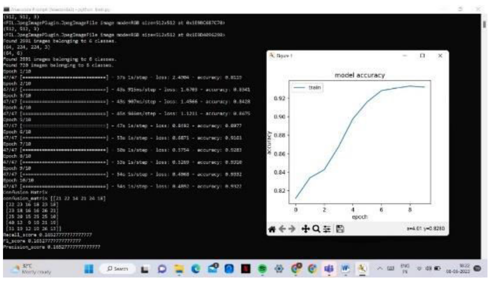


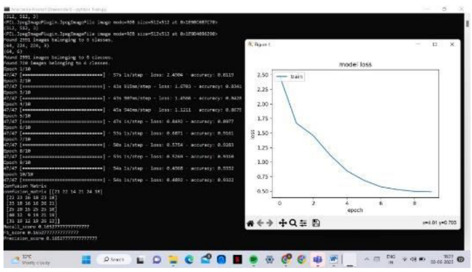


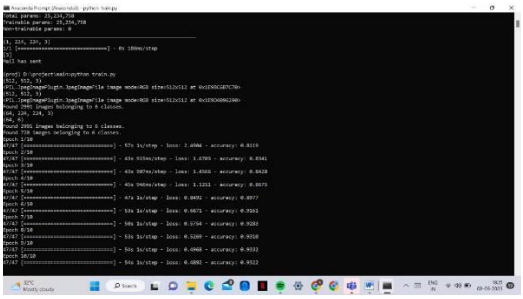





The dataset was collected from Kaggle RSNA, and the experiment was conducted using a PC with an i5 processor running at 1.1 GHz, 8 GB of RAM, and 20 GB of SSD disc storage. In addition, we used Python 3.7 and important libraries as Tensorflow, Keras, Numpy, Matplotlib, and OpenCV.



The weights overfitted to the training set after three epochs when using 10 steps per epoch, and the validation loss did not go below 0.4.The steps per epoch was increased after that, and it was discovered that 10 epochs had the lowest validation loss.

Based on the CT scan, a neural network technique is employed to identify and categorise the condition. With sufficient data, we observe accuracy of more than 92% with such an architecture. This strategy entails sending the analysis report via email to the client or another consultant.

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 |

|| Volume 11, Issue 6, June 2023 ||

| DOI: 10.15680/IJIRCCE.2023.1106041 |

## V. Conclusion and Future Work

Intracranial haemorrhage is a potentially fatal medical condition that requires prompt, frequent, and intensive medical care. However, because to the challenge of interpreting minor signals for the bleeding regions and the increased workload for radiologists in clinical practise, misdiagnosis and missed diagnosis continue to occur.

To use limited medical resources and enhance patient care, an automatic computer-aided diagnosis (CAD) system with high accuracy and reliable performance can serve as a second reader and patient triage tool more effectively. Traditional machine learning techniques would rely on manually defined image features to tackle the ICH classification problem; however, designing such features necessitates a substantial amount of algorithmic and clinical domain expertise. Additionally, because typical classification methods have a finite capacity, handling huge shape and appearance variations of ICHs in real data is challenging. Using this more recent technology, we created an artificial intelligence (AI) system for automatic acute ICH detection and classification in this work.

## References

[1] Kaggle and RSNA, "Intracranial hemorrhage detection dataset," 2019. [Online]. Available: https://www.kaggle.com/c/rsna-intracranialhemorrhage-detection/data

[2] T. Lewicki, https://github.com/tomek-l/brain, [Online].

[3] K. He, X. Zhang, S. Ren, and J. Sun, "Delving deep into rectifiers: Surpassing human-level performance on imagenet classification," CoRR, vol. abs/1502.01852, 2015. [Online]. Available: http://arxiv.org/abs/1502.01852

[4] G. J. S. Litjens, T. Kooi, B. E. Bejnordi, A. A. A. Setio, F. Ciompi, M. Ghafoorian, J. A. W. M. van der Laak, B. van Ginneken, and C. I. Sanchez, "A survey on deep learning in medical image analysis," ´ Medical Image Analysis, vol. 42, pp. 60–88, 2017. [Online]. Available: https://doi.org/10.1016/j.media.2017.07.005

[5] P. Rajpurkar, A. Y. Hannun, M. Haghpanahi, C. Bourn, and A. Y. Ng, "Cardiologist-level arrhythmia detection with convolutional neural networks," CoRR, vol. abs/1707.01836, 2017. [Online]. Available: http://arxiv.org/abs/1707.01836

[6] S. Chilamkurthy, R. Ghosh, S. Tanamala, M. Biviji, N. Campeau, V. Venugopal, V. Mahajan, P. Rao, and P. Warier, "Deep learning algorithms for detection of critical findings in head ct scans: a retrospective study," The Lancet, vol. 392, 10 2018.

[7] X. W. Gao, R. Hui, and Z. Tian, "Classification of CT brain images based on deep learning networks," Computer Methods and Programs in Biomedicine, vol. 138, pp. 49–56, 2017. [Online]. Available: https://doi.org/10.1016/j.cmpb.2016.10.007

[8] L. V. Fulton, D. Dolezel, J. Harrop, Y. Yan, and C. P. Fulton, "Classification of alzheimer's disease with and without imagery using gradient boosted machines and resnet-50," Brain Sciences, vol. 9, no. 9, 2019. [Online]. Available: https://www.mdpi.com/2076-3425/9/9/212

[9] M. Talo, O. Yildirim, U. B. Baloglu, G. Aydin, and ¨ U. R. Acharya, "Convolutional neural networks for multiclass brain disease detection using MRI images," Comp. Med. Imag. and Graph., vol. 78, 2019. [Online]. Available: https://doi.org/10.1016/j.compmedimag.2019.101673

[10] J. E. Barnes, "Characteristics and control of contrast in ct." RadioGraphics, vol. 12, pp. 825–37, 1992.

[11] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," CoRR, vol. abs/1512.03385, 2015. [Online]. Available: http://arxiv.org/abs/1512.03385

[12] D. P. Kingma and J. Ba, "Adam: A method for stochastic optimization," 2014, cite arxiv:1412.6980Comment: Published as a conference paper at the 3rd International Conference for Learning Representations

INNO SPACE
SJIF Scientific Journal Impact Factor
Impact Factor: 8.379

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

# INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING