PROCESSING OF MEDICAL IMAGE DATA BY COMPUTER VISION METHODS AND DEEP NEURAL NETWORKS

BY: AHMED LOTFI ALQNATRI

SUPERVISOR: DOC. ING. VANDA BENEŠOVÁ PHD.

GOAL

- Analyze the current state of the issue of the use of computer vision in the processing of visual data in medicine.
- Focus especially on methods using deep neural networks.
- Implement the proposed method with a software prototype using libraries and frameworks suitable for medical data processing.
- Verify the solution by experimenting with real data from medical modalities.
- Evaluate the accuracy, robustness and time efficiency of processing. Compare the results with other published solutions.

MOTIVATION

- Intracranial hemorrhage (ICH) corresponds to bleeding inside the skull caused by a vascular rupture. Speed of diagnosis is crucial because the mortality reaches up to 60% after 30 days and 35% to 52% of patients die before a month after being diagnosed, and approximately half of these deaths occur within the first 24 hours [3].
- This is a reason why ICH is considered a medical emergency and specialists must diagnose it properly and quickly. However, in general medicine emergency rooms, up to 20% of patients with suspected ICH may be misdiagnosed, which is an indicator that bleeding cannot be reliably distinguished without the support of medical imaging techniques.

INTRACRANIAL HEMORRHAGE ICH

There are 5 types of ICH:

1. Epidural
2. Subdural
3. Intraventricular
4. Intraparenchymal
5. Subarachnoid

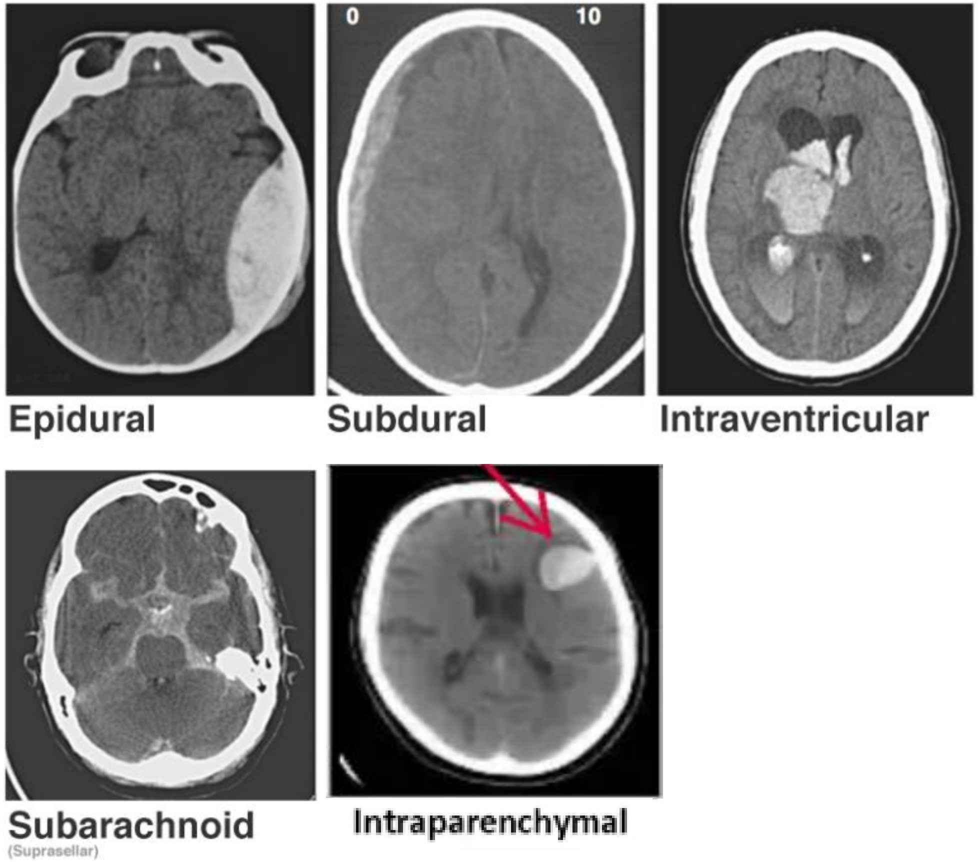


Figure 1. Intracranial hemorrhage subtypes [2]

STATE OF THE ART
SIMILAR WORK STUDY

CONVOLUTIONAL NEURAL NETWORKS FOR DETECTION INTRACRANIAL HEMORRHAGE IN CT IMAGES [4]

- Dataset:
  - The chosen Dataset is known as CQ500 Dataset
  - It has the following characteristics:

Characteristic	CQ500 dataset
No. of scans	491/193.317slices
Mean age	22.43
No. of scans (percentage) with intracranial hemorrhage	205(41.17%)
Intracerebral	162(32.99%)
Subdural	53(10.79%)
Extradural (Epidural)	13(2.64%)
Subarachnoid	60(12.21%)

Table 1. Characteristics of the dataset

STATE OF THE ART
SIMILAR WORK STUDY

CONVOLUTIONAL NEURAL NETWORKS FOR DETECTION INTRACRANIAL HEMORRHAGE IN CT IMAGES [4]

- Image Preprocessing:
  - Remove the background image of all slices
  - Visualize only the brain parenchyma, using windowing
  - The pixel values of each slice in the dataset were normalized between 0 and 1
  - Resizing to 256x256 pixels
  - All preprocessing were done before being passed to the deep learning models

STATE OF THE ART
SIMILAR WORK STUDY

CONVOLUTIONAL NEURAL NETWORKS FOR DETECTION INTRACRANIAL HEMORRHAGE IN CT IMAGES [4]

- CNN Model:
  - Two convolutional layers with ReLu activation and kernel (3x3) and Max-pooling layer for size reduction
  - Two convolutional layers with the same characteristics than previous convolutional layer
  - Followed by a max-pooling layer with kernel(2x2)
  - Flatten layer to prepare the features maps to dense layers.
  - Finally, two fully connected layers for classification were implemented to predict labels with sigmoid activation function

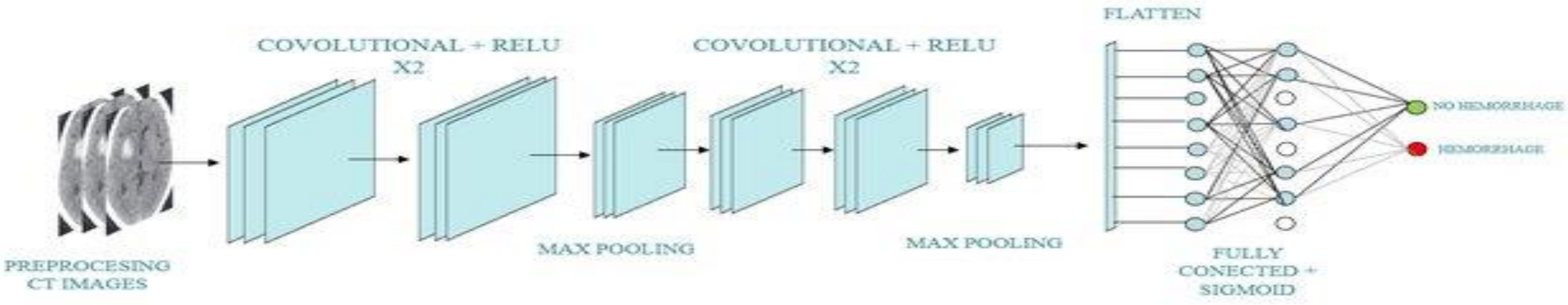


Figure 2. Illustration of the custom CNN model

STATE OF THE ART
SIMILAR WORK STUDY

CONVOLUTIONAL NEURAL NETWORKS FOR DETECTION INTRACRANIAL HEMORRHAGE IN CT IMAGES [4]

- Modified VGG 16:
  - Modification for binary classification (hemorrhage vs no-hemorrhage)
  - 5 blocks (convolutional + pooling)
  - 3 fully connected layers used for the classification task

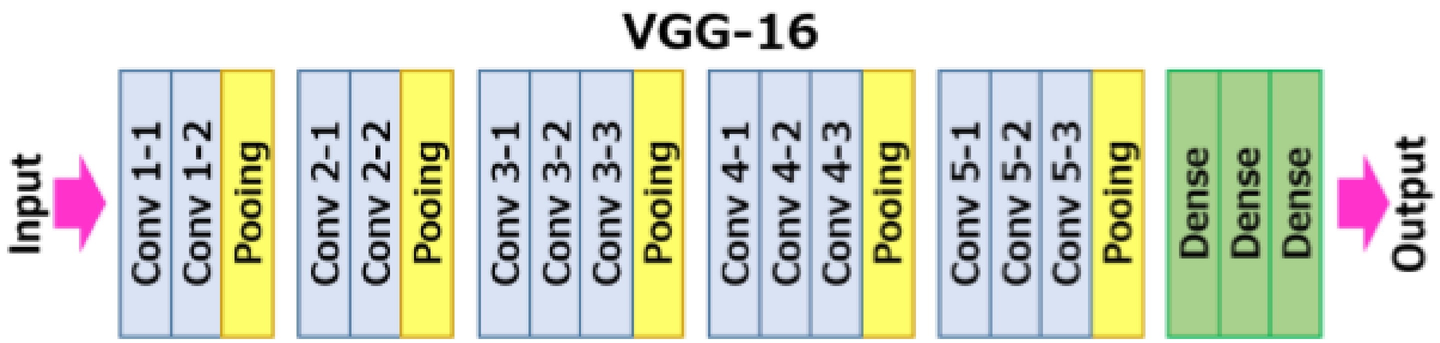


Figure 3. Illustration of the modified VGG-16 model

STATE OF THE ART
SIMILAR WORK STUDY

CONVOLUTIONAL NEURAL NETWORKS FOR DETECTION INTRACRANIAL HEMORRHAGE IN CT IMAGES [4]

- Training and evaluating models:
  - Two methods to train the models were proposed:
    - Slices randomized:

      All slices were randomized to train (0.85) and test(0.15) sets, regardless of independence between subjects

      Slices of a subject could be in the train set and another part of the slices could be in the test set
    - Subject randomized:

      All slices were randomized to train (0.85) and test (0.15) sets, ensuring independence between subjects

      This means all slices of one subject were sent to train or test

STATE OF THE ART
SIMILAR WORK STUDY

CONVOLUTIONAL NEURAL NETWORKS FOR DETECTION INTRACRANIAL HEMORRHAGE IN CT IMAGES [4]

- Training and evaluating models:
  - Dataset was divided as 80% for training and 20% for validation during the training process.
  - Each model was trained for 150 epochs with a batch size of 32
  - The best model was saved to be evaluated with the test set.
  - Binary cross-entropy loss was used to assess performance overtime.
  - Accuracy, recall and F1 measure and ROC curves were also obtained for each of the algorithms “CNN4”, ‘’VGG 16”.

STATE OF THE ART
SIMILAR WORK STUDY

CONVOLUTIONAL NEURAL NETWORKS FOR DETECTION INTRACRANIAL HEMORRHAGE IN CT IMAGES [4]

- Results:
  - Regarding the performance of the networks compared to the state of the art ,it can be determined that the randomized slices method with a recall of 0.974 for the VGG16 and 0.972 for CNN4, is very similar to the performance.

Mode	Accuracy	Recall	F1_measure	Area Under Curve (ROC)
VGG-16				
Slices Randomized	0.968	0.974	0.971	0.989
Subject Randomized	0.707	0.735	0.758	0.783
CNN - 4				
Slices Randomized	0.981	0.972	0.982	0.982
Subject Randomized	0.598	0.721	0.687	0.658

DATASET

- The used Dataset has been obtained from “RSNA Intracranial Hemorrhage Detection, Identify acute intracranial hemorrhage and its subtypes” challenge on Kaggle[1]
- It contains 752 803 DICOM files
- Each file is representing a slice
- The files has diameters (512,512)
- For the data there is CSV file contains annotations for the corresponding DICOM files

ANALYZING DATASET

1. CSV ANNOTATIONS

- CSV has the following Structure:
- It has shape of (4516842, 2)

	ID	Label
0	ID_12cadc6af_epidural	0
1	ID_12cadc6af_intraparenchymal	0
2	ID_12cadc6af_intraventricular	0
3	ID_12cadc6af_subarachnoid	0
4	ID_12cadc6af_subdural	0
5	ID_12cadc6af_any	0
6	ID_38fd7baa0_epidural	0
7	ID_38fd7baa0_intraparenchymal	0
8	ID_38fd7baa0_intraventricular	0
9	ID_38fd7baa0_subarachnoid	0

Table 2. Original table

	any	epidural	intraparenchymal	intraventricular	subarachnoid	subdural
filename						
ID_000039fa0	0	0	0	0	0	0
ID_00005679d	0	0	0	0	0	0
ID_00008ce3c	0	0	0	0	0	0
ID_0000950d7	0	0	0	0	0	0
ID_0000aee4b	0	0	0	0	0	0
...	...	...	...	...	...	...
ID_ffff73ede	0	0	0	0	0	0
ID_ffff80705	0	0	0	0	0	0
ID_ffff82e46	0	0	0	0	0	0
ID_ffff922b9	1	0	0	1	0	0
ID_fffff9393	0	0	0	0	0	0

Table 3. Modified table

- After modifying it to be used efficiently It has shape of (674257,6)
- From the number of rows on the modified CSV we notice that there are 78 546 DICOM file without annotation.

ANALYZING DATASET
1. CSV ANNOTATIONS

- After applying EDA on the Dataset “Figure 4”, we noticed that there are a lot more slices of ICH negative than ICH positive
- In Figure 5. we can see the ratio difference between each ICH subtype

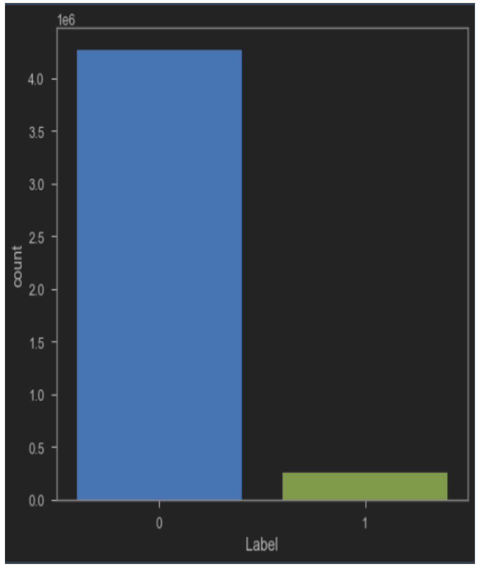


Figure 4. Graph of ICH positive and negative cases

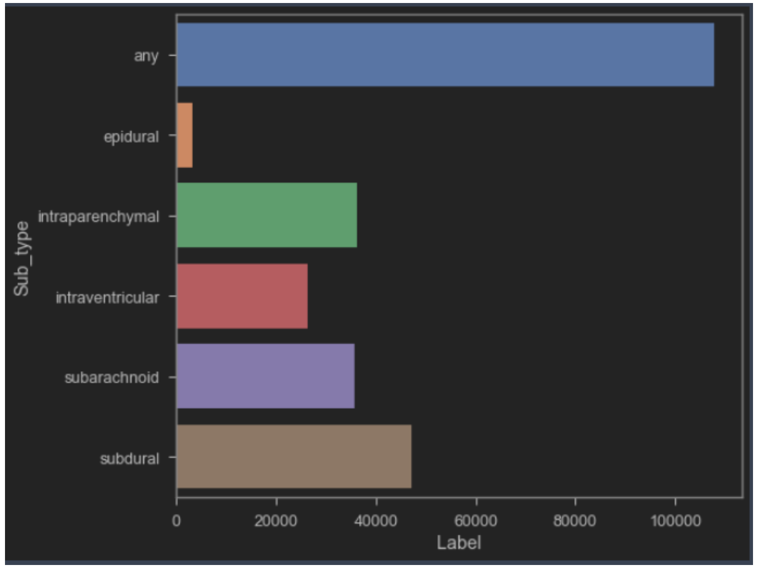


Figure 5. Graph of ICH subtypes

ANALYZING DATASET
1. CSV ANNOTATIONS

- Total representation of the ICH Subtypes
- Labels for both of ICH positive and ICH negative

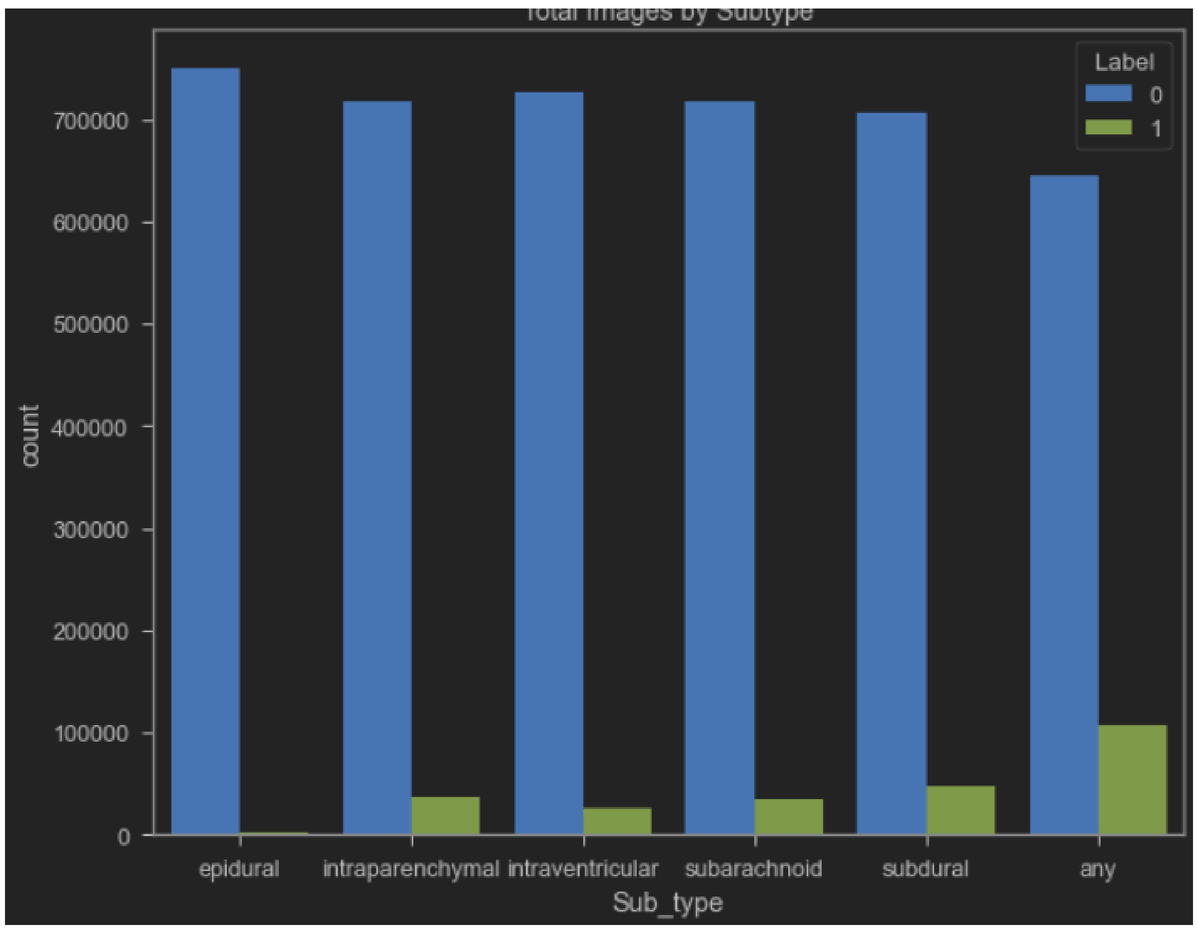


Figure 6. Graph of ICH subtypes and labels

ANALYZING DATASET

2. DICOM FILES

- One pixel array of a file is corrupted "**ID_6431af929.dcm**".
- 78 546 out of 752 803 DICOM file without annotation "Out of use".

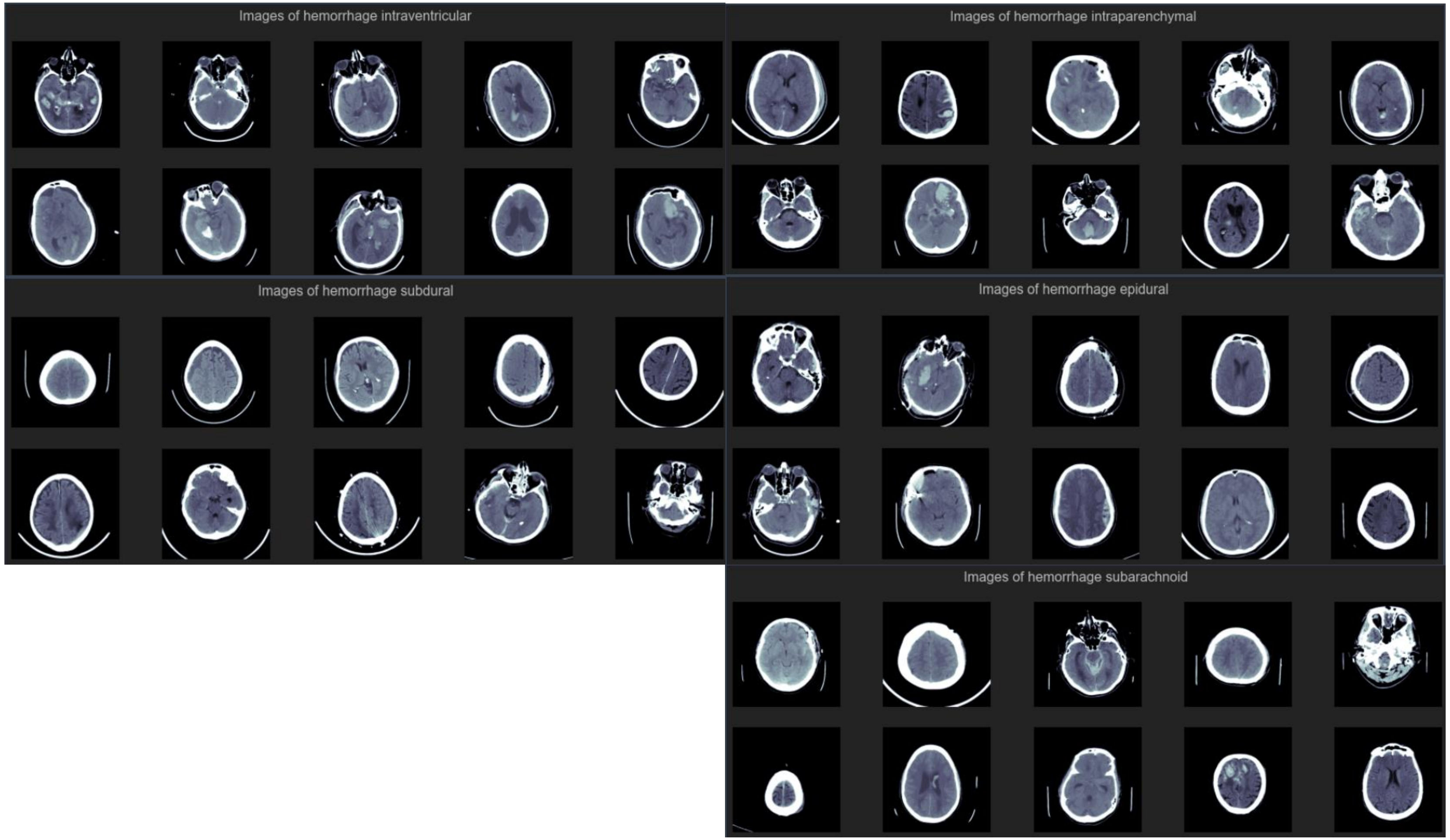


Figure 7. Some examples of ICH cases in our Dataset

OUR SOLUTION

BINARY CLASSIFICATION
EXPERIMENT NO.1

- **Image Preprocessing**
  - Remove the background image of all slices
  - The pixel values of each slice in the dataset were normalized between 0 and 1
  - Pixel Standardization to scale pixel values to have a zero mean and unit variance.
  - All preprocessing were done before being passed to the deep learning models

- **Training and Validating**
  - Choosing randomly 10 000 slices
  - split the dataset randomly 80% for training and 20% Validating
  - 50 epochs, batch size of 32 and learning rate of 1e-3

OUR SOLUTION
BINARY CLASSIFICATION
EXPERIMENT NO.1

- **Model Architecture**

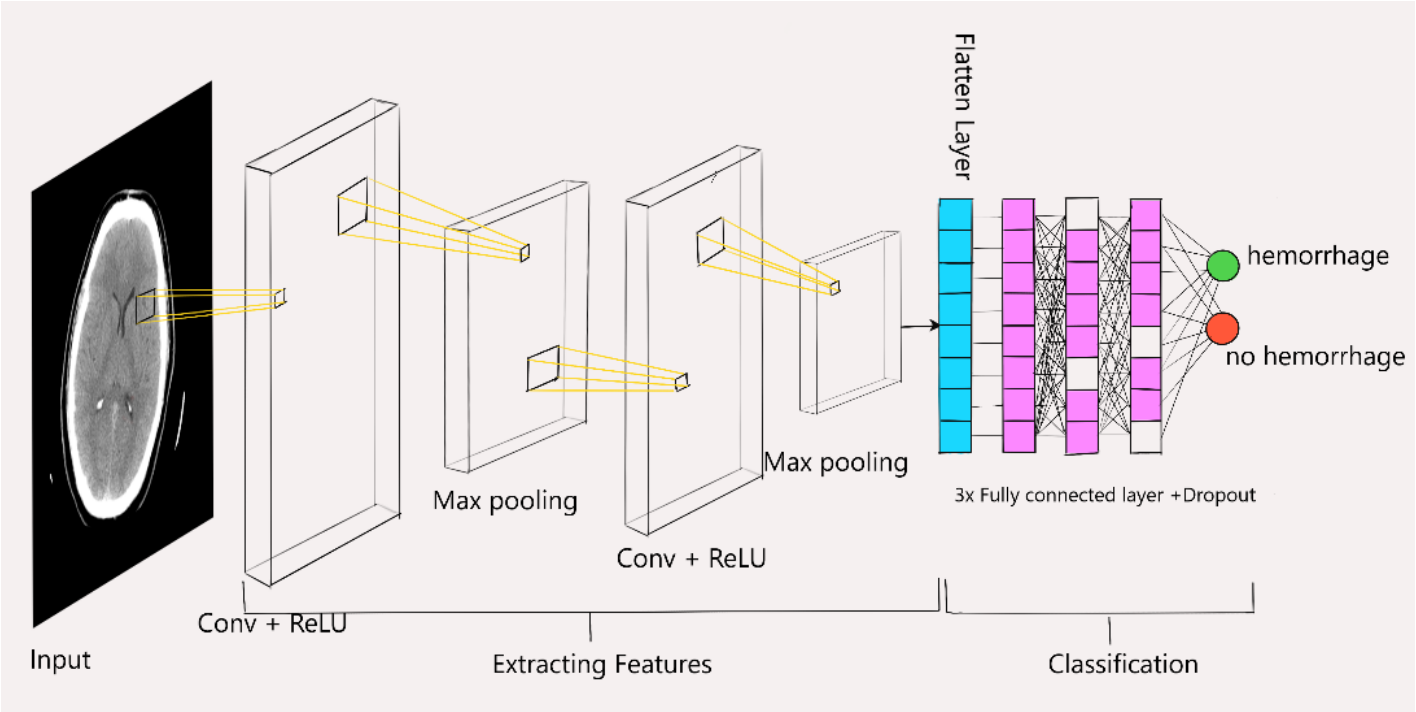


Figure 8. Our CNN model architecture for binary classification

OUR SOLUTION
BINARY CLASSIFICATION
EXPERIMENT NO.1

Accuracy	Recall	F1 measure	ROC
0.636	0.67	0.71	0.761

- **Results**
  - BCEWithLogistLoss as loss function
  - Adam Optimizer as an optimizer

OUR SOLUTION
EXPERIMENT NO.2

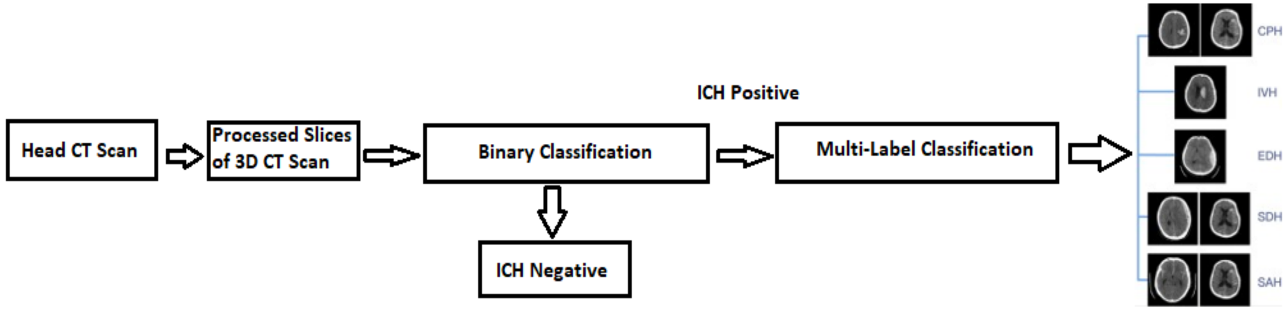


Figure 9. Illustration of the workflow of the Solution

- Dataset
  - Because of the extreme variation of the dataset, we choose the middle slices to train our model
  - Creating 2 datasets

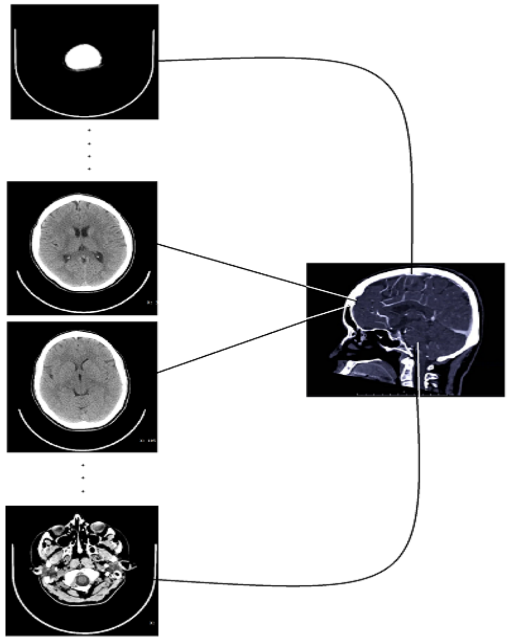


Figure 10. Illustration of choosing the slices to create clean dataset

	Train Dataset	Test Dataset
Binary classification Dataset	78116	19529
Multi-label Classification Dataset	22501	5756

Table 4. Details of both datasets

OUR SOLUTION
EXPERIMENT NO.2

- Image Preprocessing:
  - Resampled to 512x512 pixels and then downscaled to 256x256 pixels, followed by random cropping 224x224
  - Apply windowing of three layers (Bone, Brain, Subdural) and stack them to create 3 channels image

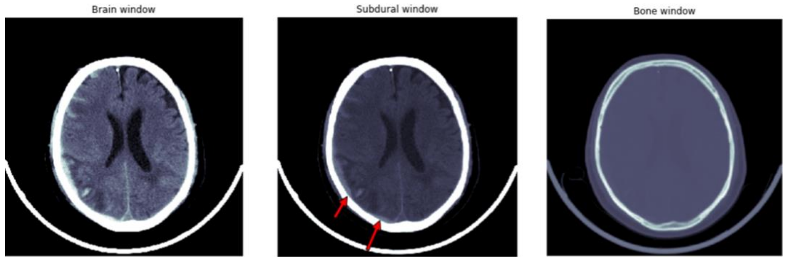


Figure 11. Bone, Brain, Subdural Windows

- Balancing datasets
  - Using class weights
  - Hyper method between down sampling and up sampling

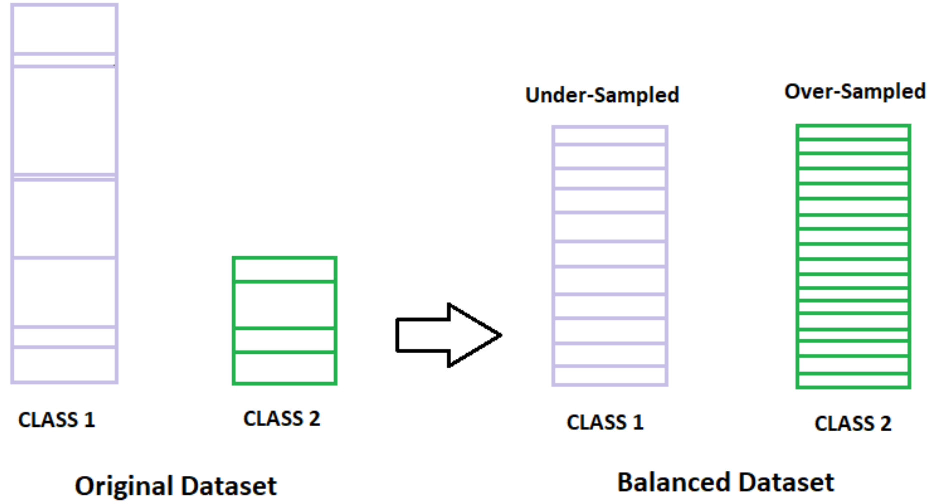


Figure 12. Illustration of data-based approaches, which includes a hybrid method of under-sampling, over-sampling

OUR SOLUTION EXPERIMENT NO.2

- Models
  - We modified ResNet-152 for Both of Binary classification and Multi-classification task
  - For Multi-label classification model, we made 5 parallel layers for each ICH subtype

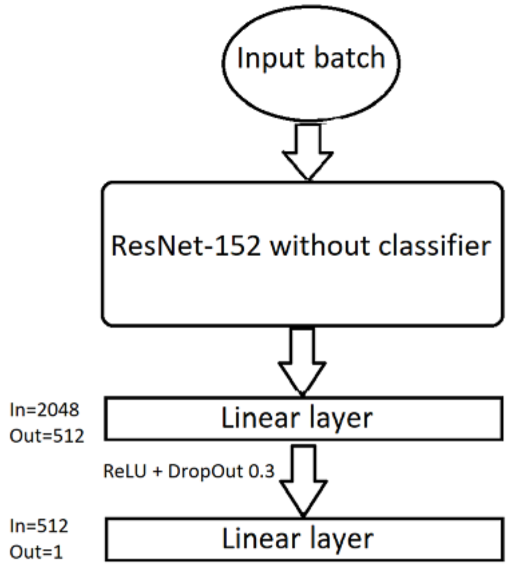


Figure 13. Illustration of Binary classification model

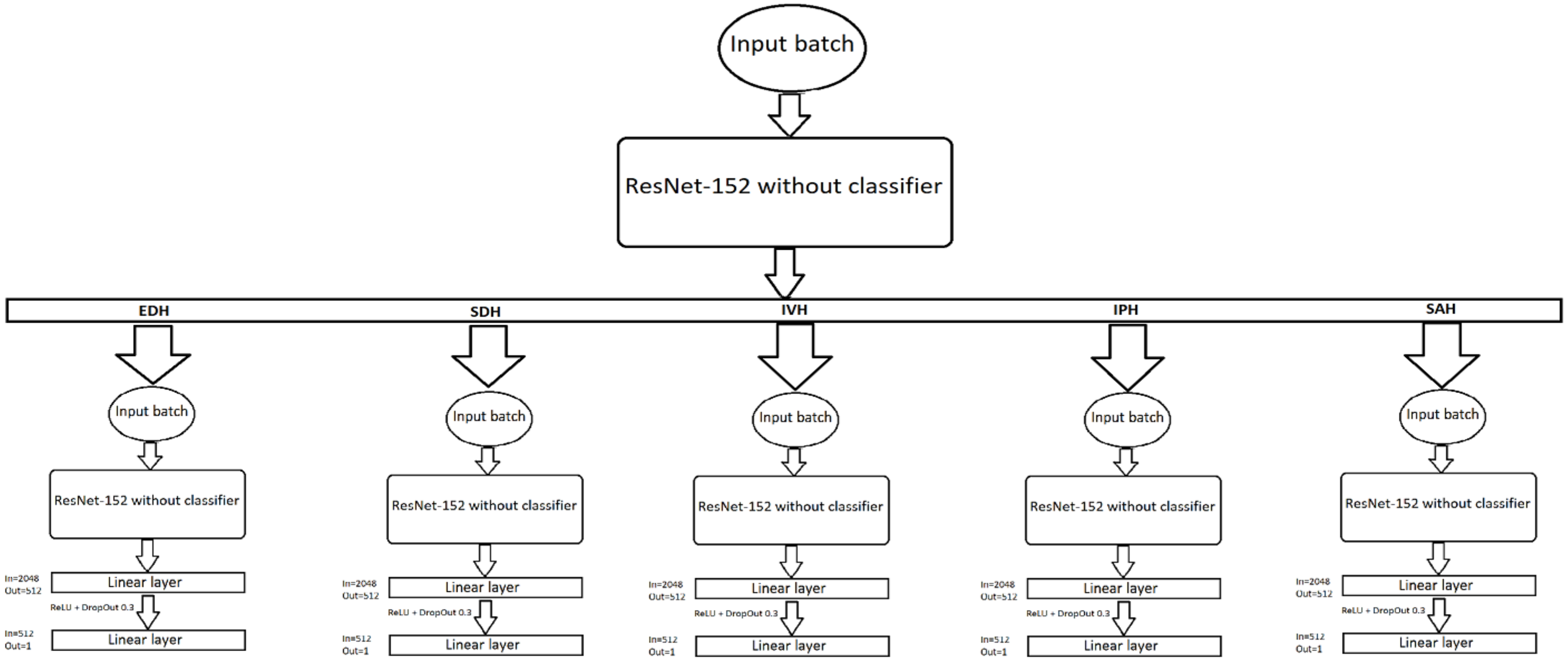


Figure 14. Illustration of Multi classification model

OUR SOLUTION
BINARY CLASSIFICATION EXPERIMENT NO.2

Name	Train Batch Size	Test Batch Size	Epoch	Learning Rate	Momentum	Optimizer
Value	32	32	50	1e-3	0.9	SGD

- Training and validating:
  - Has been trained with the shown hyperparameters
  - Got an accuracy of 84%.

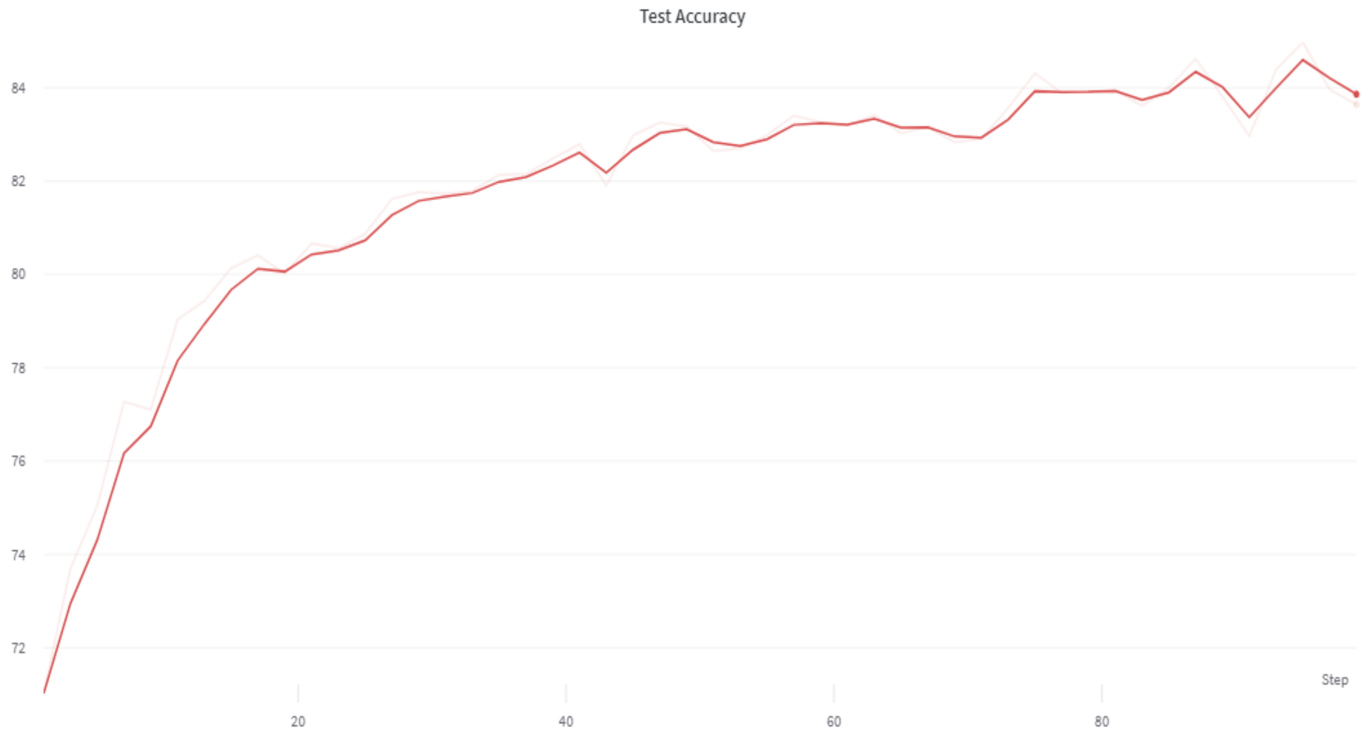


Figure 15. Test accuracy score on testing data after each epoch

OUR SOLUTION

MULTI-CLASS CLASSIFICATION EXPERIMENT NO.2

Name	Train Batch Size	Test Batch Size	Epoch	Learning Rate	Momentum	Optimizer
First Run	32	32	150	1e-4	0.9	SGD
Second Run	32	32	100	1e-3	0.9	SGD
Third Run	32	32	50	1e-2	0.9	SGD

- Training and validating:
  - Has been trained with the 3 different set of hyperparameters
  - Auto adjust LR when validation loss stopped decreasing
  - Got an accuracy of 84% of average across all classes.

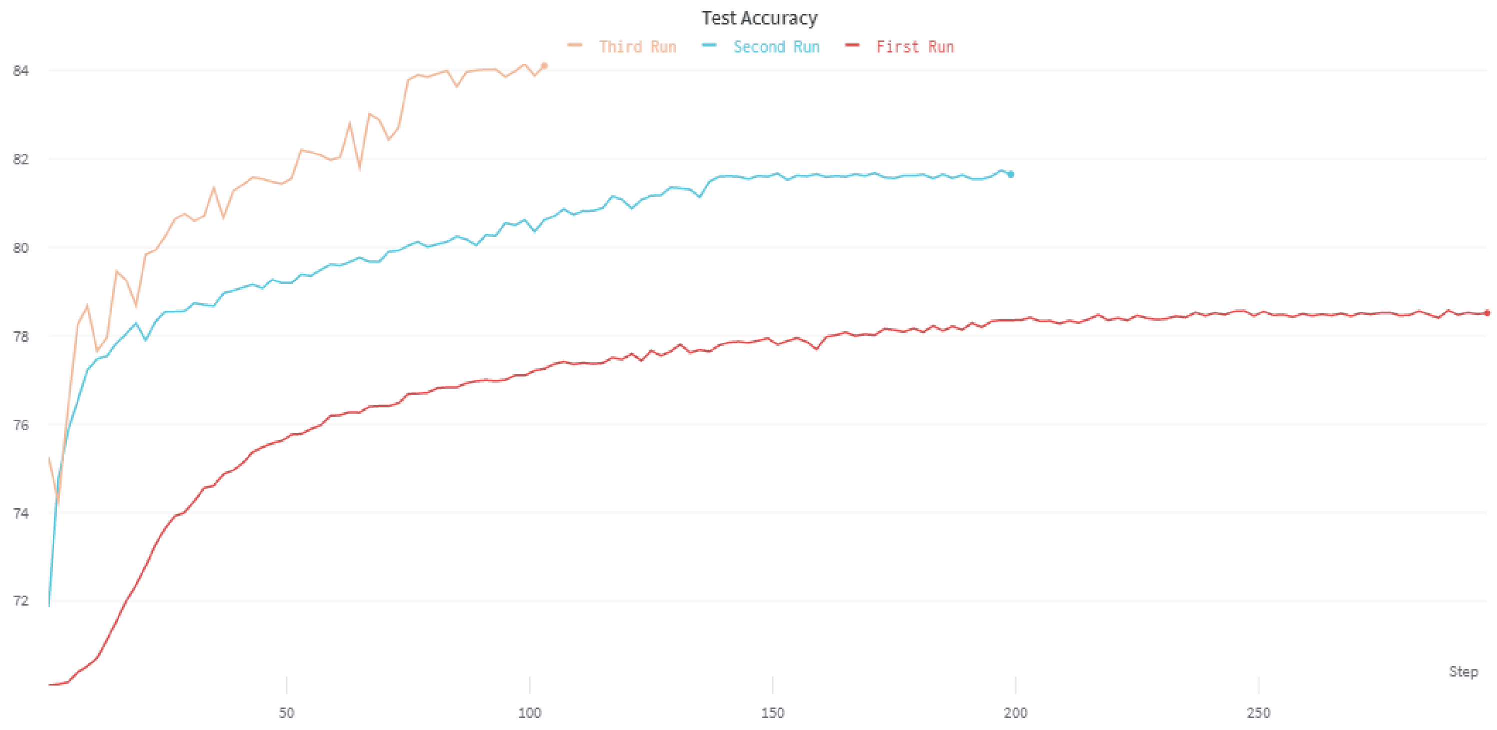
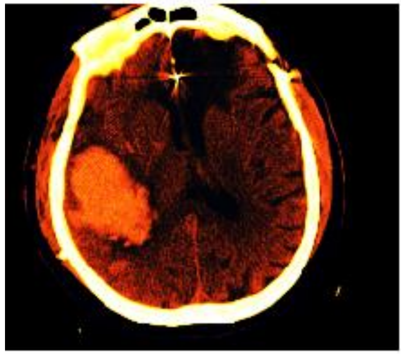


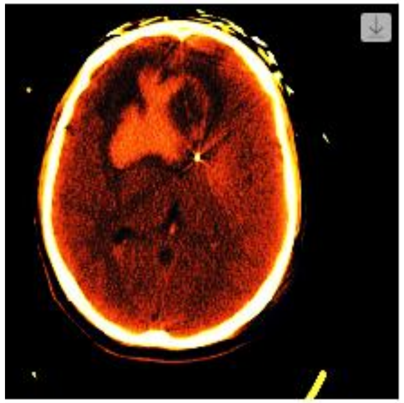
Figure 16. Test accuracy score on testing data after each epoch

OUR SOLUTION MULTI-LABEL CLASSIFICATION

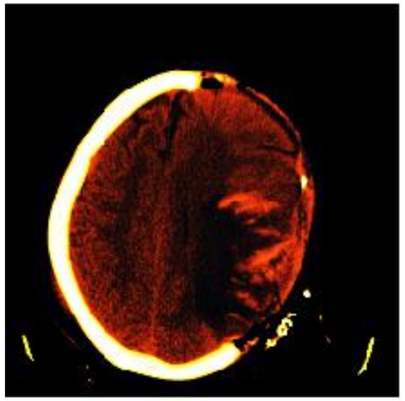
- Examples



Pred: intraparenchymal/intraventricular/ Truth: intraparenchymal/



Pred: intraparenchymal/ Truth: intraparenchymal/



Pred: intraparenchymal/subdural/ Truth: intraparenchymal/subdural/

RESOURCES:

- [1] https://www.kaggle.com/c/rsna-intracranial-hemorrhage-detection/data
- [2] Sage, A.; Badura, P. Intracranial Hemorrhage Detection in Head CT Using Double-Branch Convolutional Neural Network, Support Vector Machine, and Random Forest. *Appl. Sci.* **2020**, *10*, 7577.
- [3] Caceres JA, Goldstein JN. Intracranial hemorrhage. Emerg Med Clin North Am. 2012 Aug;30(3):771-94. doi: 10.1016/j.emc.2012.06.003. PMID: 22974648; PMCID: PMC3443867.
- [4] *(10) (PDF) Convolutional neural networks for detection intracranial hemorrhage in CT images*. Available from: https://www.researchgate.net/publication/339795647_Convolutional_neural_networks_for_detection_intracranial_hemorrhage_in_CT_images [accessed Dec 14 2020].
- [5] YE, HAI and GAO, FENG, 2019, Precise diagnosis of intracranial hemorrhage and subtypes using a three-dimensional joint convolutional and recurrent neural network. European Radiology. 2019. Vol. 29, no. 11, p. 6191-6201. DOI 10.1007/s00330-019-06163-2. Springer Science and Business Media LLC