Detecting Intracranial Hemorrhage with Deep Convolutional Neural Networks

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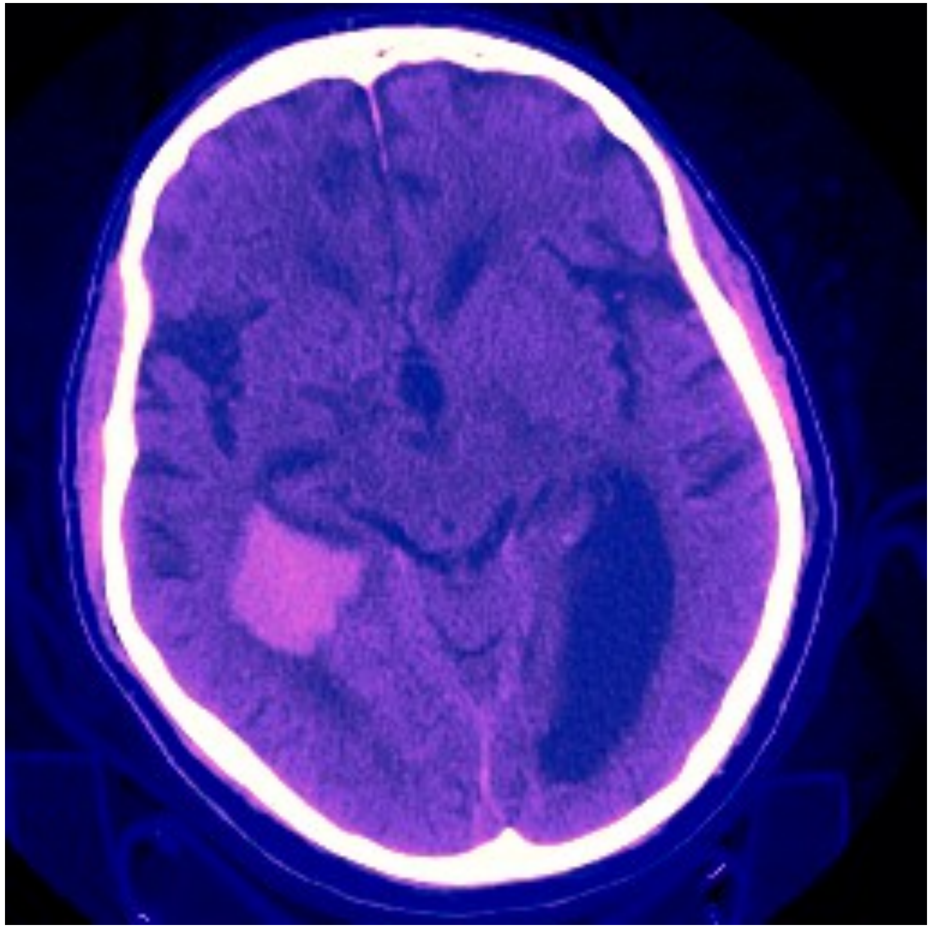
Final presentation, BINF G4006 “Translational Bioinformatics”

Traumatic brain injuries can result in bleeding within the brain – a life-threatening condition that needs fast action

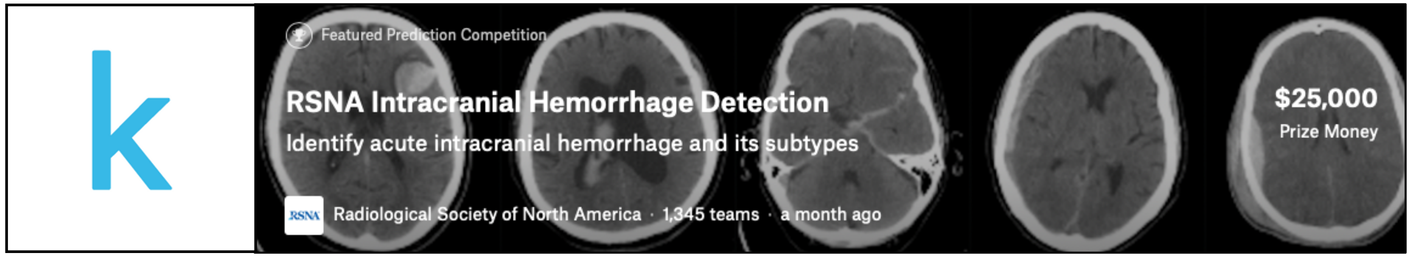


- Intracranial Hemorrhage (ICH) can cause permanent brain damage and is responsible for almost 30% of yearly injury related deaths in the US
- To decide the course of treatment, experienced radiologists are required to quickly identify the presence of an ICH in CT scans
- This is increasingly difficult due to shortage of radiologists, cost pressure, and limited time available to do the time-consuming analysis

ML techniques present an unprecedented opportunity to support specialists in quick and life-saving decision-making

SOURCE: Carey 2017

A Kaggle Competition by the RSNA tries to solve this problem and provides an excellent data source



- The Radiological Society of North America published a dataset of over 25,000 labeled CT exams to solicit teams to devise machine learning algorithms in order to detect ICH and its 5 subtypes
- The dataset consists of ~700,000 CT scans. The large majority of the scans does not show any hemorrhage and the distribution of subtypes is heavily unbalanced
- GPU usage is available via Kaggle Notebooks but limited and the competition ended mid November

So why not develop the best algorithm, win the price money, and get an "A" in this very class, we thought…

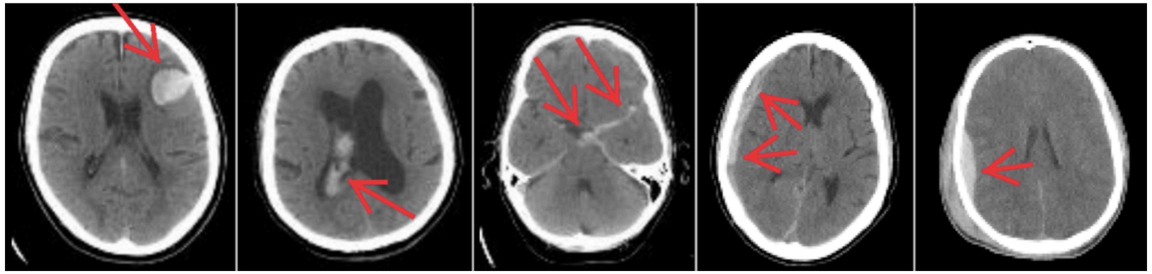
SOURCE: Kaggle Competition 2019

Our approach is aligned along the common steps for machine learning projects

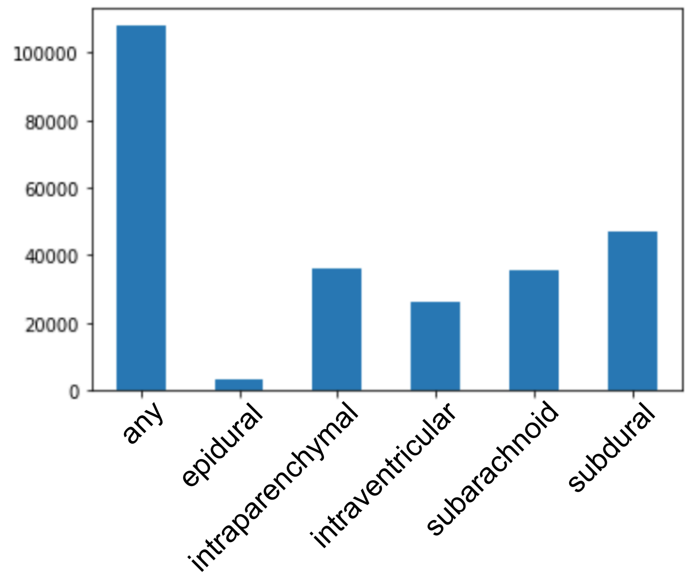
1. Data pre-processing
2. Train, validation, test split
3. Model selection
4. Model training
5. Model evaluation
6. Parameter tuning
7. Final accuracy comparison
8. Application implementation

… but things proved harder than expected: multilabel classification and windowing are just examples

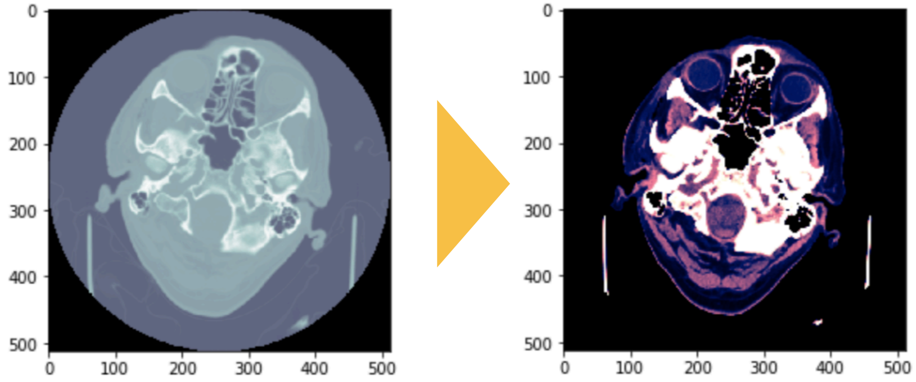
Hemorrhage Types



Intra-parenchymal | Intra-ventricular | Subarachnoid | Subdural | Epidural



Windowing

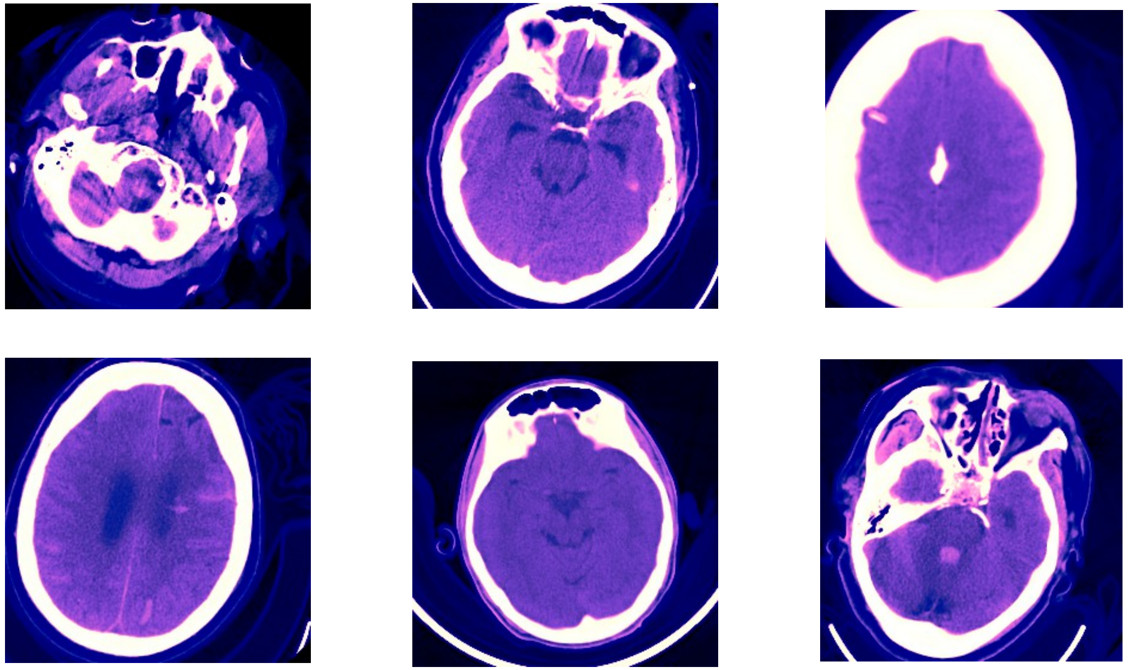


- 16-bit DICOM image values range from -32,768 to 32,767, whereas an 8-bit greyscale image stores values from 0 to 255. DICOM range correlates with Hounsfield Scale
- Radiologists use windowing to increase the contrast of images across particular bands of Hounsfield Units
- Windowing in DICOM ML algorithms is mostly recommended but highly debated, since computers don't have problems with perceiving the entire value range

SOURCE: Howard on Kaggle 2019, Allunia on Kaggle 2019

To avoid further GPU and RAM issues, we drew on a preprocessed dataset of 200k CT scans as JPEGs

- Corrected RescaleIntercept
- Images with little useful information removed (e.g. they don't actually contain brain tissue)
- Resampled with 2/1 split of with/without hemorrhage
- Images cropped to just contain the brain
- JPEG 256x256 px images with histogram rescaling



Out of this dataset, we create a training set containing 20,000 images without hemorrhage and 6,547 images with hemorrhage present

SOURCE: Howard on Kaggle 2019

For this project, we implement three different Neural Network architectures and compare their performance

Overview of different NN architectures implemented to detect ICHs

Simple NN

- 2 basic layers
- ReLU & Sigmoid activation functions
- Adadelta optimizer
- “binary_crossentropy” loss
- 25,166,081 trainable parameters

Deep CNN

- Mix of 2D convolutional and 2D max pooling layers
- ReLU & Sigmoid activation functions
- Adadelta optimizer
- “binary_crossentropy” loss
- 30,536,385 trainable parameters

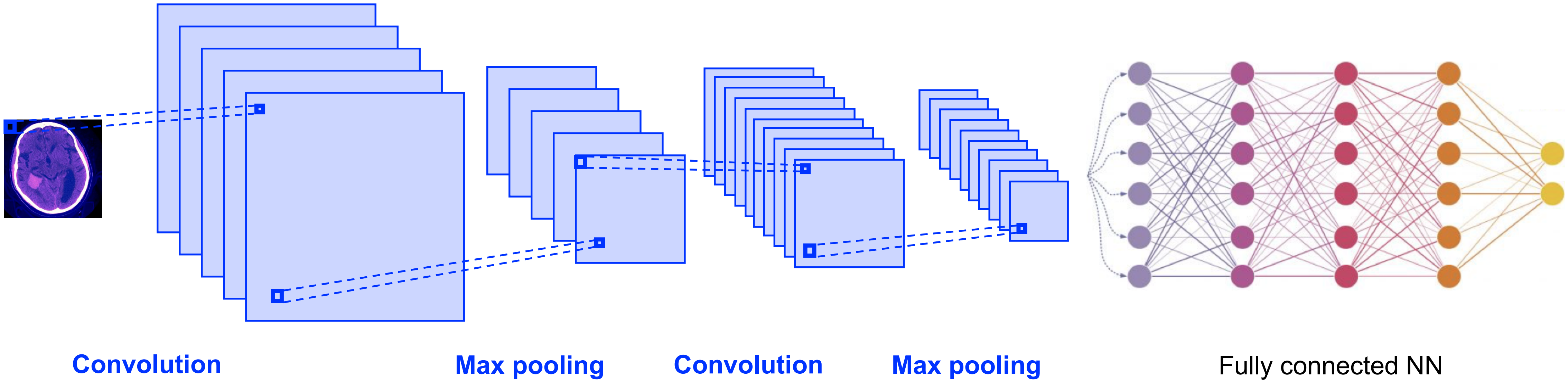
ResNet50

- Winner of the ImageNet challenge in 2015
- Available with pretrained weights (we didn’t use them)
- Mix of 2D convolutional, batch normalization, and different pooling layers
- Much deeper than others
- 23,538,690 trainable parameters

SOURCE: Own depiction

Reminder: CNNs are Neural Networks with a special pattern detection mechanism for spatial interactions

Simplified overview of a feedforward CNN



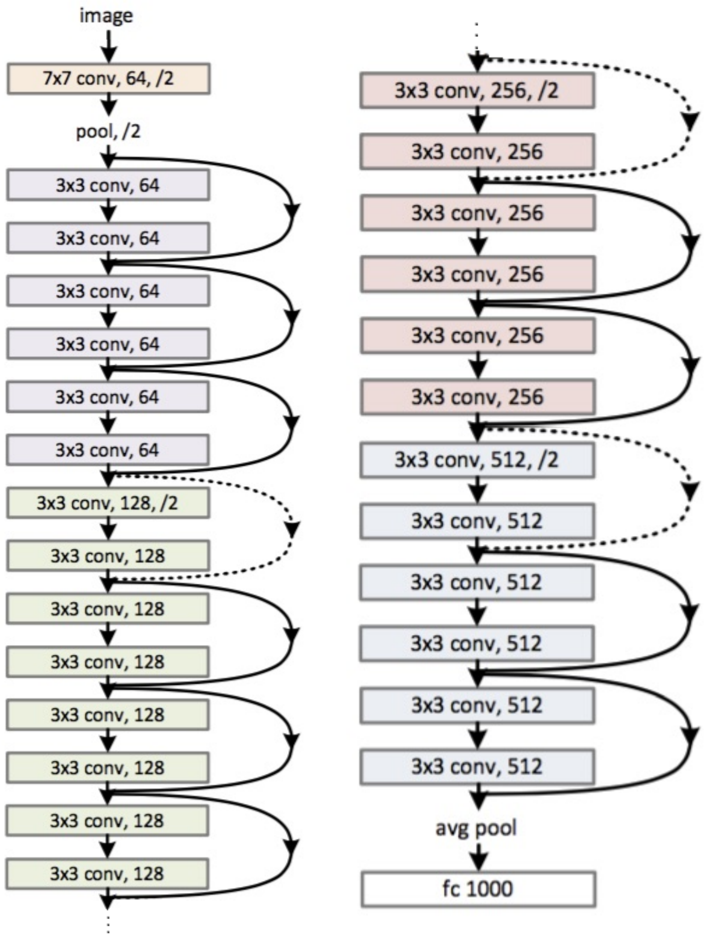
“We look for many simple patterns!”

The convolution applies a windowed filter to the picture and max pooling reduces the dimensionality of the data by summarizing the output

SOURCE: Karpathy (Stanford CS231n) 2019, Rensu Theart 2017

ResNets are CNNs that skip connections and feature heavy batch normalization

Overview of a ResNet



- ResNets ease the training of networks that are substantially deeper than those used previously
- They have commonly double- or triple- layer skips that contain ReLU and batch normalization in between
- Shortcut connections avoid problem of vanishing gradient in Deep Learning

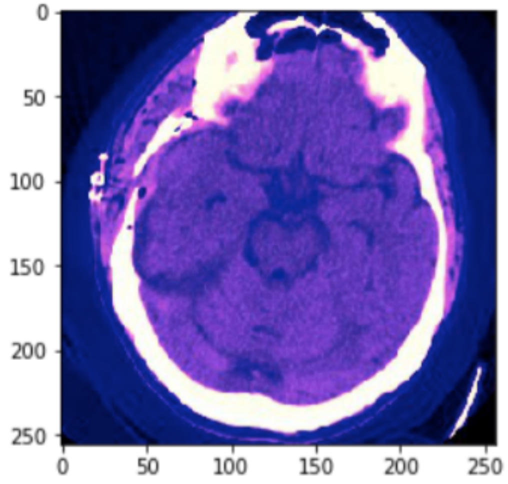
Residual Neural Networks have recently proven very successful: they are easier to optimize, and can gain accuracy from considerably increased depth

SOURCE: He et al. 2015

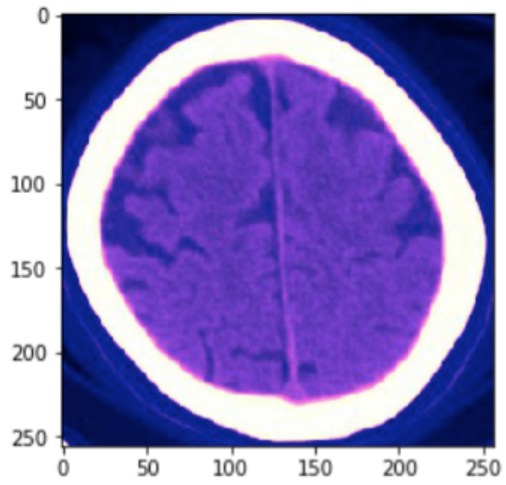
Our first results on identifying different subtypes showed a very low accuracy – but some images have multiple labels

- Trying to identify different subtypes was largely unsuccessful
- We decided to subset training data with either 1+, 2+ or 3+ ICHs present
- This heavily improved the performance of the different NNs deployed

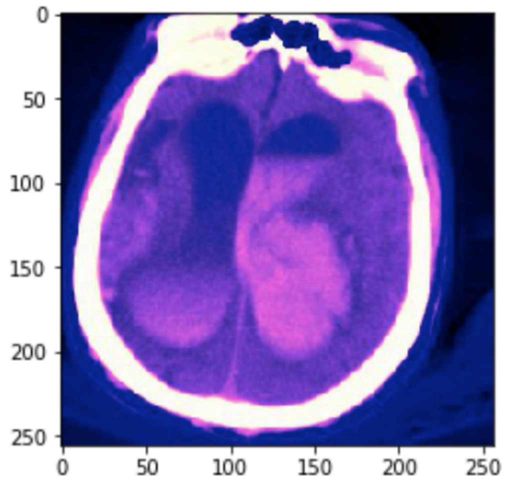
subdural



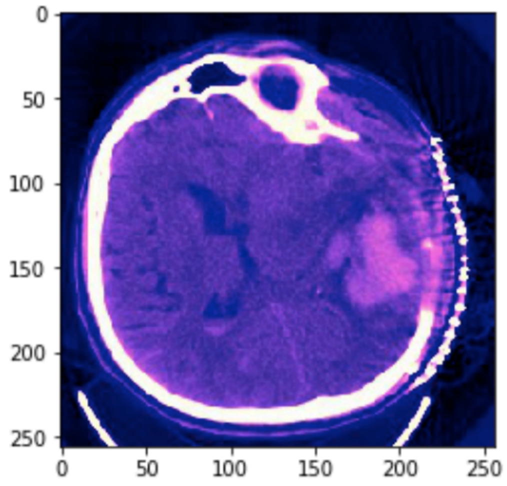
subdural



3+ ICHs



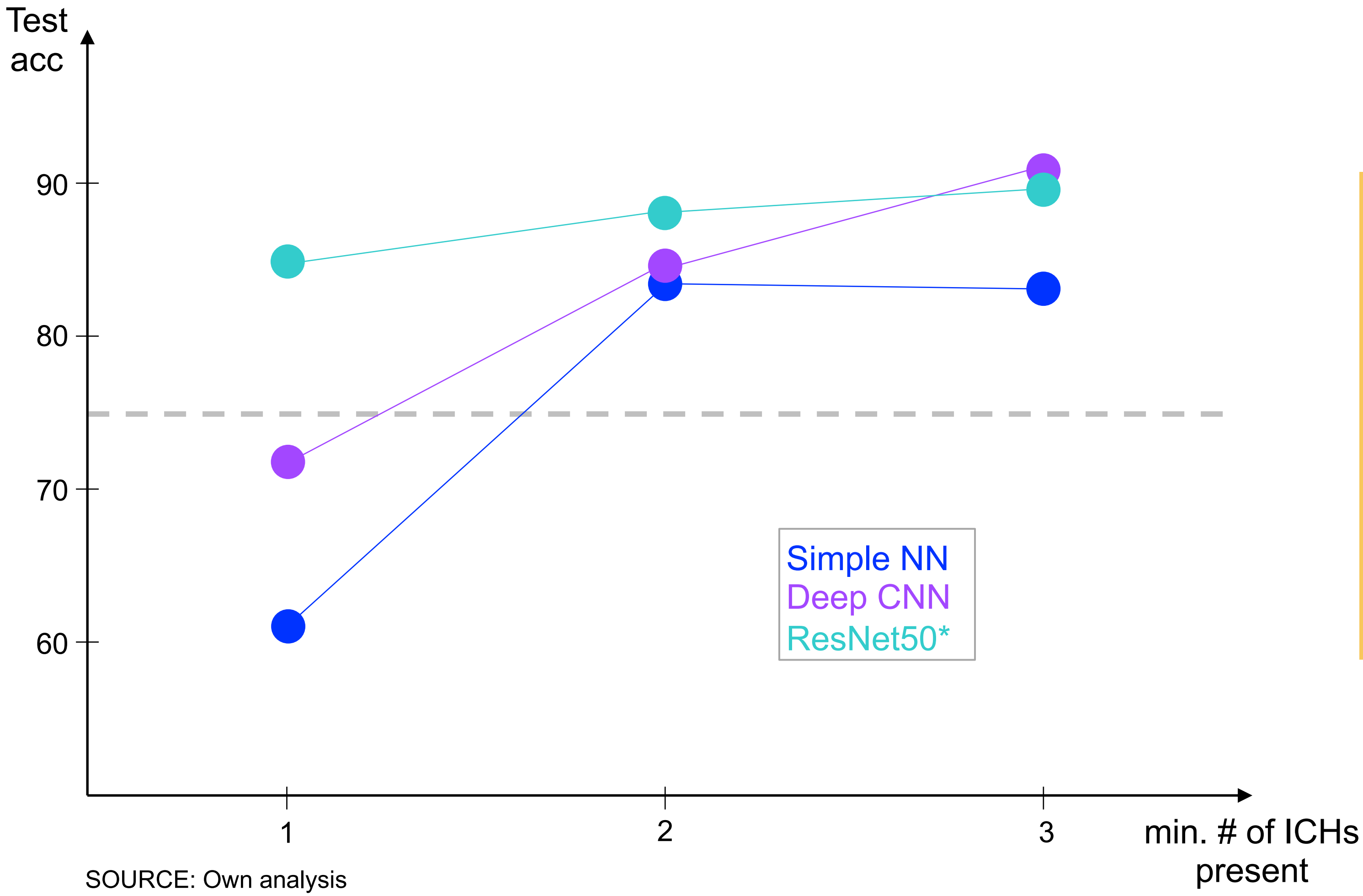
3+ ICHs



SOURCE: Own analysis

After an intense process of model tuning, we find that performances of different architectures vary

Results of different NN architectures per amount of ICHs present in the data



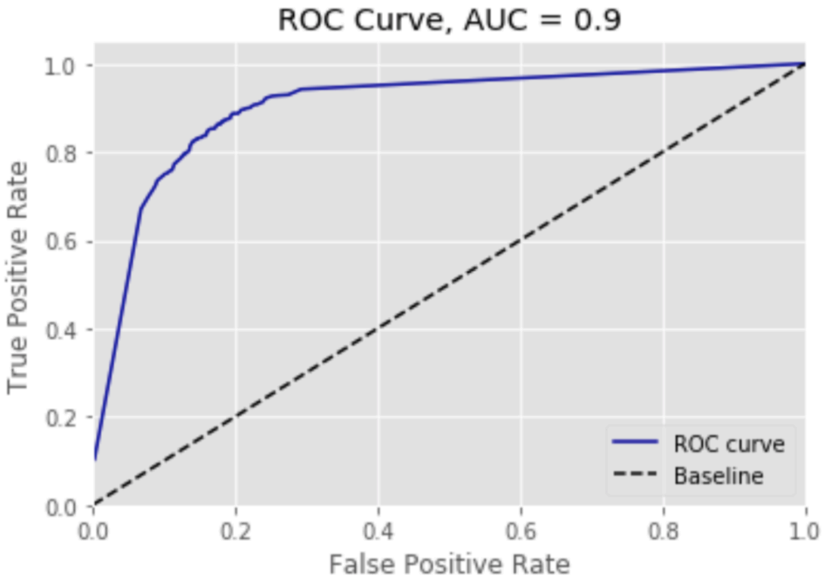
Although the ResNet50 outperforms the other architectures in cases of fewer ICHs present, the less expensive architectures achieve similar results in more obvious cases of ICH

SOURCE: Own analysis

In terms of Area Under Curve and Receiver Operating Characteristics, the ResNet50 outperforms the others

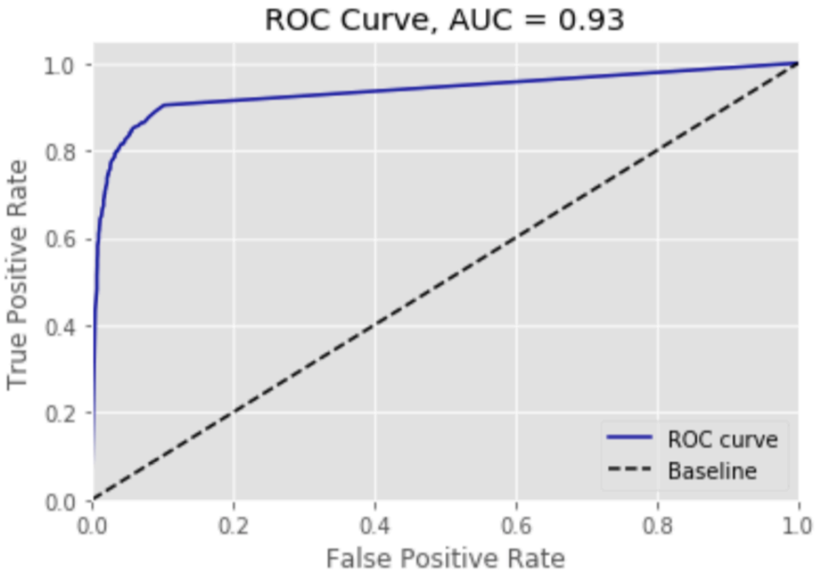
AUROC of different NN architectures with 3+ ICHs present

Simple NN



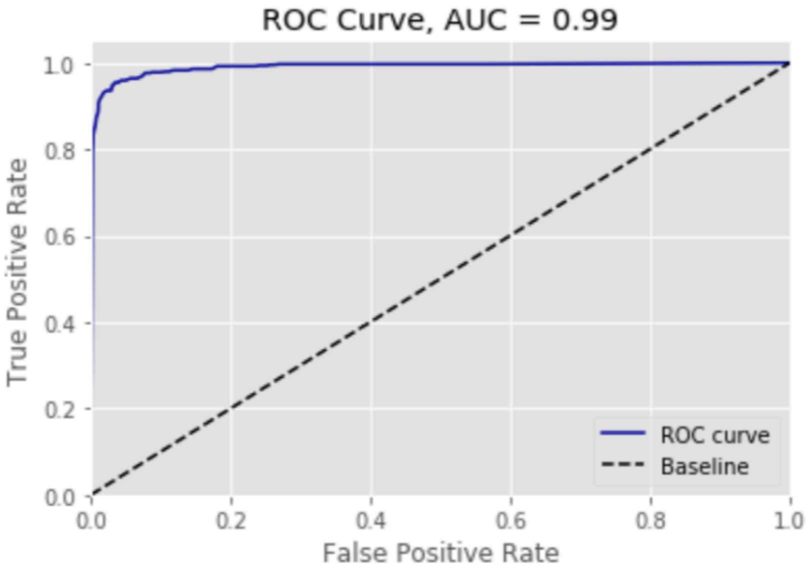
Test accuracy: 84.11%
Test MSE: 0.137

Deep CNN



Test accuracy: 92.17%
Test MSE: 0.0663

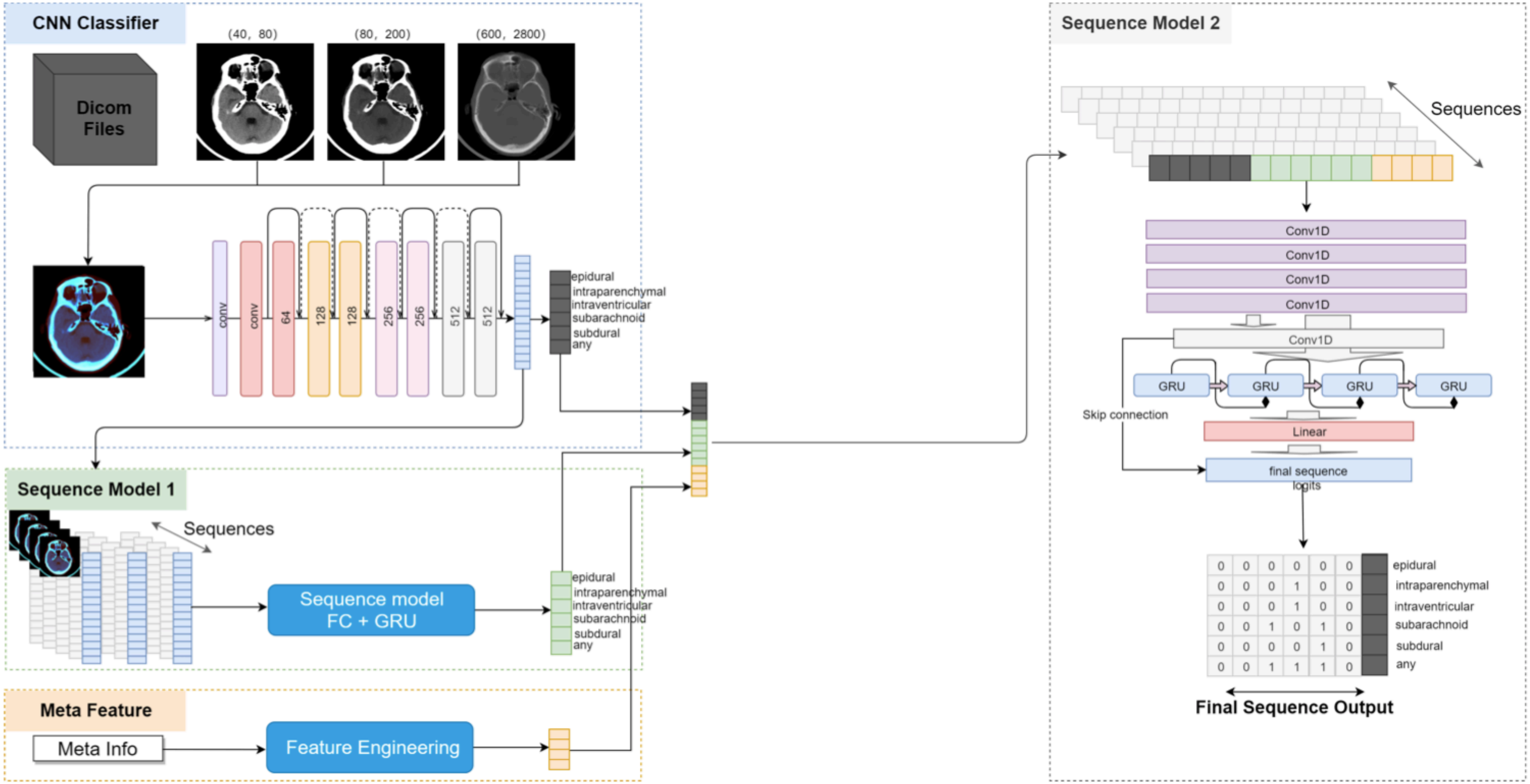
ResNet50



Test accuracy: 89.91%
Test MSE: 0.0694

SOURCE: Own analysis

The winning solution of the Kaggle Competition combined several models and included DICOM meta information



SOURCE: SeuTao on Kaggle

Thank you!

Github Repo