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Initial Experience in MRI-Based Brain Metastases Detection Using Deep Learning

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INTRODUCTION

- Machine and deep learning for detection and segmentation of tumors and contouring of healthy organs is a relevant and fast growing topic in the scientific community that has the potential to become a relevant aid for clinicians.
- Oftentimes, deep learning approaches are based on in-house developed tools that cannot be fully replicated, are not publicly available or have been tailored to an specific dataset.
- In this study we used a 3D U-NET Convolutional neural network that is freely available online and can be easily be adapted to work on different datasets.

AIM

- To evaluate the use of an established 3D U-Net convolutional neural network (CNN) framework for automatic detection and segmentation of brain metastases in MR images.

METHODS

- Eighty-nine MRI datasets from patients with at least one brain metastasis and no previous irradiation from our institution were retrospectively employed.
- Patients were imaged using an MRI protocol that included a T1-weighted (T1w) post-gadolinium contrast agent image and a T2-weighted (T2w) image.
- Metastases were either contoured or reviewed on MRI by an expert neurosurgeon.

The complete analysis workflow was:

1. Bias field correction of MRI images.
2. Resampling of T2w image to T1w image resolution and registration of T2w to T1w.
3. Random split of the dataset on training set (n=72) and validation set (n=17).
4. Training of the CNN using both sets of images (as different channels) and a binary mask of the brain metastases.
5. Running the trained model on the validation set.

The model was trained for a maximum of 500 epochs using a high-performance computing cluster.

RESULTS

- Predicted metastases by the deep learning CNN were stratified based on size to establish a threshold for high sensitivity.
- Using a lesion volume threshold of 65 mm^3 (5 mm equivalent sphere diameter) the sensitivity was 90.3% (28/31) and the false positive ratio per predicted lesion was 15.2% (5/33).
- Decreasing the lesion volume threshold to 14 mm^3 (3 mm equivalent sphere diameter), the sensitivity dropped to 54.7% (29/53), and the false positive ratio per predicted lesion increased to 35.6% (16/45).

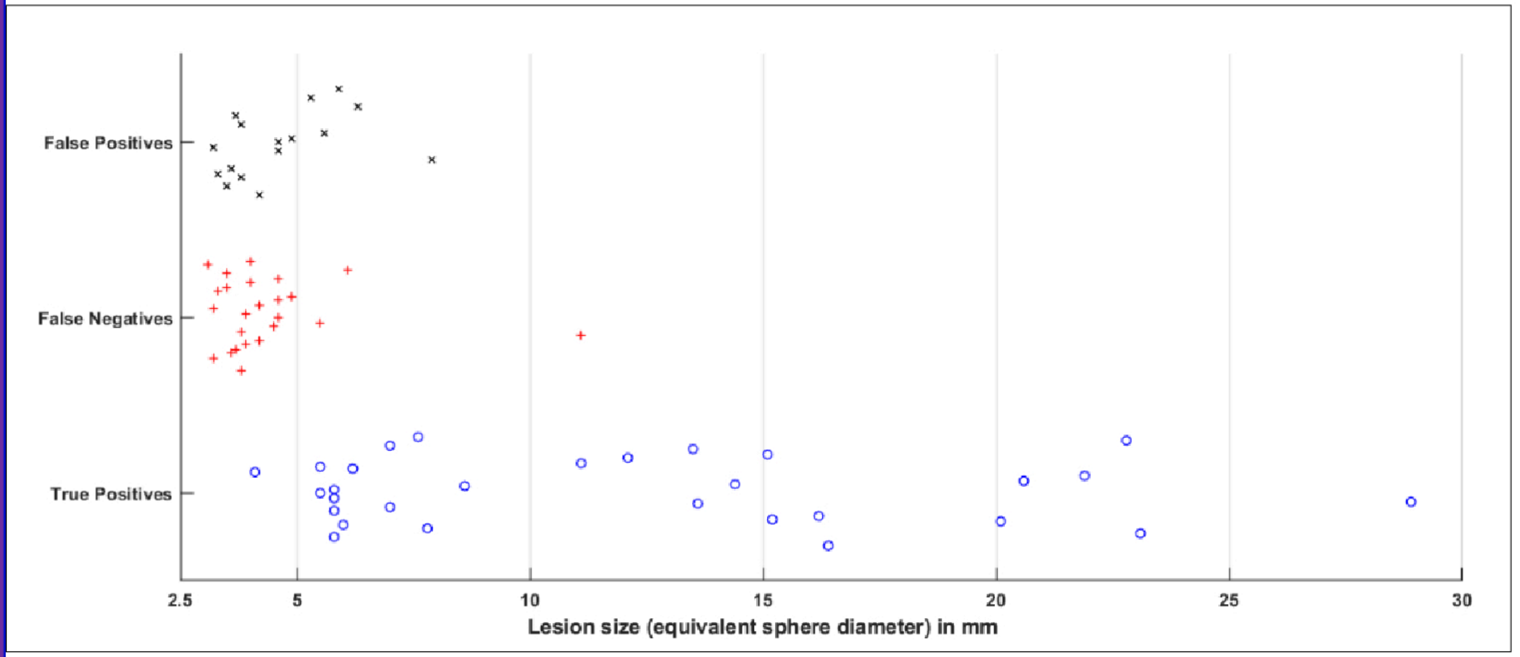

Figure 1. Scatterplot showing metastases detected by the model (True Positives), metastases missed by the model (False Negatives), and lesions created by the model (False Positives) as a function of size.

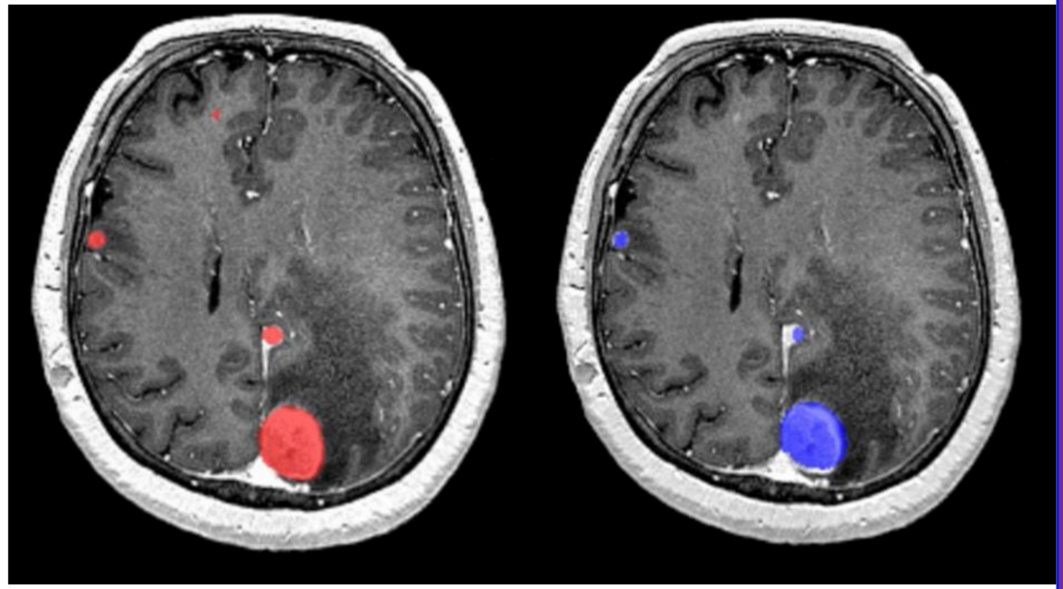

Figure 2. Left: Ground truth contours showing four brain metastases. **Right:** Contours created by the deep learning model. Three brain metastases were accurately detected and contoured by the CNN. The smaller frontal lobe lesion was missed by the trained model.

CONCLUSIONS

- Deep learning holds promise for automatic detection and segmentation of brain metastases.
- A high detection rate and a low false positive ratio can be obtained for metastases that are at least 5 mm in size using the method presented here.
- Lesion size is a determining factor for brain metastases detection using the presented method as demonstrated by the large cluster of false positives and false negatives under 5 mm.

REFERENCES

1. 3DUnet CNN code available at https://github.com/ellisdg/3DUnetCNN. Accessed 6/22/2020.

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