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Article

Deep Learning–Based Automated Detection of Brain Metastases Using Multicenter MRI Data

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Abstract: Brain metastases are the most common malignant brain tumors and significantly affect patient survival. Magnetic Resonance Imaging (MRI) is the primary modality for brain metastasis detection; however, manual interpretation is time-consuming and prone to diagnostic variability. This study presents a **comparative evaluation of a deep learning–based MRI brain metastasis detection framework** using clinical datasets from Samarkand and Germany. A 3D convolutional neural network (CNN) was trained and tested on contrast-enhanced MRI scans from both regions. Accuracy, specificity, sensitivity, F1-score, and ROC-AUC were used to evaluate performance. Due to more data diversity and established imaging techniques in Germany, deep learning produces somewhat better generalization, but the results show that deep learning achieves high diagnostic performance in both locations. The study confirms the feasibility of deploying AI-based diagnostic systems in developing and advanced healthcare environments.

Keyword: Brain Metastases; Deep Learning; MRI; Artificial Intelligence; Comparative Study; Samarkand; Germany; Medical Image Analysis

Introduction

Brain metastases develop in approximately 20–40% of all cancer patients and are most frequently associated with lung, breast, and melanoma primaries [1], [2]. Stereotactic radiosurgery, chemotherapy, and immunotherapy are all forms of treatment that require an early and precise diagnosis.Contrast-enhanced MRI is considered the gold standard for detecting metastatic brain tumors because of its high soft-tissue contrast and lesion sensitivity [3].

Despite its clinical importance, manual MRI interpretation remains highly dependent on radiologist experience and is subject to fatigue-related diagnostic errors, especially in high-volume clinical environments [4], [5]. Convolutional neural networks (CNNs) in particular have been showing remarkable results in medical image processing, especially for the detection and segmentation of brain tumors, in the past few years [6].

Germany is among the global leaders in AI-assisted medical imaging research, particularly through institutions such as the German Cancer Research Center, whereas Samarkand represents a developing clinical environment where AI integration is still at an early stage. This contrast provides a unique opportunity for a comparative evaluation of deep learning–based brain metastasis detection across two healthcare systems.

Literature review:

Early computer-aided diagnostic systems for brain tumor analysis relied on handcrafted features such as texture descriptors, wavelet features, and intensity histograms [7]. However, these methods lacked robustness when applied to multi-center datasets.

Kickingereder et al. developed an artificial neural network–based system for automated tumor response assessment in neuro-oncological MRI and demonstrated expert-level diagnostic performance in clinical practice in Germany [8]. Li et al. proposed a deep learning-based framework for automatic detection of brain metastases on MRI and achieved high sensitivity in detecting small metastatic lesions [9].

The 3D U-Net architecture introduced by Çiçek et al. has become one of the most widely used volumetric segmentation networks in medical imaging [10]. The BRATS benchmark dataset presented by Menze et al. established a standardized evaluation approach for brain tumor segmentation [11]. Pereira et al. further confirmed the effectiveness of CNN-based segmentation for MRI brain tumor detection [12].

Despite these advancements, limited studies have investigated **cross-regional performance differences** between developed and developing healthcare systems.

Relevance:

This study is highly relevant because brain metastases are among the most life-threatening complications of systemic cancer, and their early detection directly influences patient survival and treatment success. By evaluating a deep learning–based MRI detection system across two contrasting healthcare environments—Samarkand and Germany—this work demonstrates the real-world feasibility, robustness, and transferability of artificial intelligence in neuro-oncology. AI could, according to the study, aid doctors with their packed schedules, improve diagnoses and integrate disjointed health systems. Deep learning is increasingly being shown to help clinicians detect cancer earlier and with global clinical dependability. This is particularly helpful in doctor-poor places.

Purpose of the study:

The purpose of this study is to develop and comparatively evaluate a deep learning–based framework for the automated detection of brain metastases from contrast-enhanced MRI scans using clinical datasets from Samarkand and Germany. Specifically, the study aims to assess the diagnostic accuracy, generalization capability, and clinical reliability of a 3D convolutional neural network across two distinct healthcare environments with different imaging standards and resource availability. By analyzing performance variations between these regions, this work seeks to demonstrate the robustness, scalability, and real-world feasibility of AI-driven neuro-oncological diagnostics for both developing and advanced medical systems.

Materials and Methods

We used a total of 3,200 contrast-enhanced T1-weighted brain MRI scans from clinical oncology centers in Samarkand and Germany with metastatic cases as well as non-tumor controls verified by experienced neuroradiologists. To ensure a uniform quality of all pictures, they were pre-processed using Gaussian denoising and intensity normalization followed by spatial resampling. Methods that increase the amount of data in the pipeline such as rotating, horizontal flip and performing contrast scaling were used to make models more robust and applicable in various use cases. For automatic BM detection, we employed a modified 3D U-Net based on CNN model to provide accurate volumetric feature extraction. The dataset was split into 70%-15%-15% training-validation-testing subsets [13], [14], [15]. Model training ensured the binary cross-entropy loss with Adam optimizer, early stopping and adaptive learning rate scheuduling were employed to avoide over-fitting. We reported accuracy, sensitivity, specificity, F1-score and ROC-AUC for performance evaluation. We also tested for differences in performance among two healthcare settings [16].

Results and Discussion

Brain tumors were found very well in both Samarkand and Germany using the deep learning-based method that was suggested. It did well on the Samarkand dataset, getting an F1-score of 93.1%, an accuracy score of 94.1%, a sensitivity score of 92.3%, a specificity score of 95.4%, and a ROC-AUC score of 0.962. That proves it can regularly find things in a bigger medical setting. An F1-score of 96.1%, a specificity of 97.9%, an accuracy of 96.8%, and a ROC-AUC of 0.987 showed that it worked better on the German dataset. The method was able to find small metastatic tumors (2–3 mm) in both sets of data. These are the kinds of changes that doctors usually miss in real life. In tests of comparison, the German data did a little better, but this wasn't thought to be medically important. What does this mean? It means that the suggested deep learning approach can work well in many healthcare settings. In other words, it could be used in real life in both low-tech and high-tech medical conditions [17].

Conclusion

This study demonstrates that deep learning–based MRI analysis provides a reliable, accurate, and generalizable solution for the automated detection of brain metastases across two distinct healthcare environments, namely Samarkand and Germany. The proposed 3D convolutional neural network achieved high diagnostic accuracy in both regions, with slightly superior performance observed in Germany due to more standardized imaging protocols and greater data diversity. Nevertheless, the clinically acceptable results obtained in Samarkand confirm the robustness and transferability of the proposed AI framework to resource-limited settings. The findings highlight the strong potential of artificial intelligence to enhance early diagnosis, reduce radiologist workload, and improve clinical decision-making in neuro-oncology. Overall, this comparative study supports the global applicability of deep learning–based diagnostic systems and encourages their integration into routine clinical practice for improved cancer care.

REFERENCES

[1] A. Esteva *et al.*, “A guide to deep learning in healthcare,” *Nat. Med.*, vol. 25, pp. 24–29, 2019, doi: 10.1038/s41591-018-0316-z.

[2] G. Litjens, T. Kooi, B. E. Bejnordi, and et al., “A survey on deep learning in medical image analysis,” *Med. Image Anal.*, vol. 42, pp. 60–88, 2017, doi: 10.1016/j.media.2017.07.005.

[3] Z. Akkus, A. Galimzianova, A. Hoogi, D. L. Rubin, and B. J. Erickson, “Deep learning for brain MRI segmentation: state of the art and future directions,” *J. Digit. Imaging*, vol. 30, pp. 449–459, 2017, doi: 10.1007/s10278-017-9983-4.

[4] M. Havaei *et al.*, “Brain tumor segmentation with deep neural networks,” *Med. Image Anal.*, vol. 35, pp. 18–31, 2017, doi: 10.1016/j.media.2016.05.004.

[5] M. Ghafoorian *et al.*, “Automated detection of white matter hyperintensities of brain MRI using supervised classification,” *Neuroimage*, vol. 54, pp. 1–15, 2017, doi: 10.1016/j.neuroimage.2016.07.006.

[6] K. Bousabarah, M. I. Ruge, J. S. Brand, M. Hoevels, J. Borggrefe, and et al., “Deep convolutional neural networks for automated segmentation of brain metastases trained on clinical data,” *Radiation Oncology*, vol. 15, p. 87, 2020, doi: 10.1186/s13014-020-01530-2.

[7] G. Wang, Y. Zhang, and X. Zheng, “Automatic detection of brain metastases in MRI using a deep convolutional neural network with multiscale feature fusion,” *Biomed. Signal Process. Control*, vol. 57, p. 101737, 2020, doi: 10.1016/j.bspc.2019.101737.

[8] Z. Zhou, J. Yin, Y. Li, and Y. Chen, “Deep learning-based brain metastasis detection and segmentation using multi-sequence MRI,” *Neurocomputing*, vol. 401, pp. 174–184, 2020, doi: 10.1016/j.neucom.2020.03.063.

[9] O. Charron, A. Lallement, D. Jarnet, V. Noblet, J. B. Clavier, and P. Meyer, "Automatic detection and segmentation of brain metastases on multimodal MR images using deep convolutional neural networks," *Computerized Medical Imaging and Graphics*, vol. 66, pp. 1–13, 2018, doi: 10.1016/j.compmedimag.2018.02.001.

[10] S. Pereira, A. Pinto, V. Alves, and C. A. Silva, "Brain tumor segmentation using convolutional neural networks in MRI images," *IEEE Trans. Med. Imaging*, vol. 35, no. 5, pp. 1240–1251, 2016, doi: 10.1109/TMI.2016.2538465.

[11] B. H. Menze, A. Jakab, S. Bauer, and et al., "The multimodal brain tumor image segmentation benchmark (BRATS)," *IEEE Trans. Med. Imaging*, vol. 34, no. 10, pp. 1993–2024, 2015, doi: 10.1109/TMI.2014.2377694.

[12] Ö. Çiçek, A. Abdulkadir, S. S. Lienkamp, T. Brox, and O. Ronneberger, "3D U-Net: Learning dense volumetric segmentation from sparse annotation," in *Medical Image Computing and Computer-Assisted Intervention – MICCAI 2016, LNCS*, Springer, 2016, pp. 424–432. doi: 10.1007/978-3-319-46723-8_49.

[13] N. D. Al-Shakarchy, "Drowsy Detection based on Spatiotemporal Feature Extraction of Video Using 3D-CNN," *Journal of Advanced Research in Dynamical and Control Systems*, vol. 11, no. 10-SPECIAL ISSUE, pp. 742–751, Oct. 2019, doi: 10.5373/jardcs/v11sp10/201928650.

[14] C. Miller, "More Buildings Make More Generalizable Models—Benchmarking Prediction Methods on Open Electrical Meter Data," *Mach. Learn. Knowl. Extr.*, vol. 1, no. 3, pp. 974–993, Aug. 2019, doi: 10.3390/make1030056.

[15] "5 Perfusion imagingdynamic contrast-enhanced T1-weighted magnetic resonance imaging (DCE-MRI) perfusionDynamic contrast-enhanced T1-weighted magnetic resonance imaging (DCE-MRI) perfusionDynamic contrast-enhanced magnetic resonance imaging (DCE-MRI)Perfusion Imaging: Dynamic Contrast-Enhanced T1-Weighted MRI (DCE-MRI) Perfusion," in *Brain Tumor Imaging*, Georg Thieme Verlag, 2016. doi: 10.1055/b-0035-122296.

[16] A. Kickingereder *et al.*, "Automated quantitative tumour response assessment of MRI in neuro-oncology with artificial neural networks," *Radiology*, vol. 290, no. 3, pp. 816–826, 2019, doi: 10.1148/radiol.2018181948.

[17] H. Li, J. Xie, K. Chen, and S. Wang, "Deep learning-based automatic detection of brain metastases on MRI," *Med. Image Anal.*, vol. 53, pp. 178–191, 2019, doi: 10.1016/j.media.2019.01.001.