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Research Article

Automated Detection of Lower-Grade Gliomas Using Deep Learning with UNet and EfficientNet-B7

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ABSTRACT

Detecting lower-grade gliomas (LGGs) remains a significant challenge in neuro-oncology due to their complex nature and variable clinical behaviors. Accurate identification and classification of LGGs are crucial for devising effective treatment strategies and improving patient outcomes. This study presents an innovative approach to LGG detection leveraging advanced deep learning techniques, outperforming traditional image segmentation methods. The research emphasizes the use of the UNet model, enhanced with an EfficientNet B7 backbone, to achieve superior accuracy in automatic LGG prediction. By integrating these cutting-edge technologies, the proposed framework not only streamlines the detection process but also enhances the precision of diagnosis. This approach provides valuable insights that can significantly aid in the early identification and management of LGGs. Furthermore, the proposed method focuses on overcoming limitations associated with traditional techniques, such as manual segmentation inaccuracies and computational inefficiencies. The adoption of deep learning enhances the model's ability to analyze intricate patterns and subtle variations in medical imaging, leading to more reliable and consistent results. By advancing the automation of LGG detection, this research contributes to the ongoing development of diagnostic tools in neuro-oncology, potentially reducing diagnostic delays and enabling personalized treatment approaches. The findings pave the way for future advancements in integrating artificial intelligence into medical imaging and neuro-oncology practices.

Keywords: EfficientNet B7, U-Net, image segmentation, lower-grade gliomas (LGGs).

INTRODUCTION

Lower-grade gliomas (LGGs), classified as WHO Grade 2 and Grade 3 tumors, present significant challenges in detection and diagnosis compared to Grade 1 brain tumors. LGGs, which grow slowly and arise in the brain's supportive tissue, are part of the broader glioma classification ranging from Grade 1 to Grade 4. Grade 1 tumors, often found in children and young adults, are less aggressive and have a favorable prognosis, while Grade 2 and Grade 3 gliomas are more complex to identify and treat. Accurately predicting patient outcomes for LGGs using histopathological data remains a challenge due to inter-observer variability and the labor-intensive, error-prone nature of manual segmentation. Recently, advanced deep learning methods have transformed image segmentation, yielding higher accuracy and predictive performance.

This study proposes a novel algorithm leveraging deep learning for efficient tumor segmentation. Convolutional Neural Networks (CNNs), including models such as ResNet, U-Net, and EfficientNet, are employed, each with specific strengths. By fine-tuning hyperparameters, an optimal segmentation model is developed to address challenges like inter- and intra-observer inconsistencies. Automated segmentation eliminates subjective variability and enhances reproducibility. Furthermore, it is cost-effective and significantly faster, achieving an impressive average Dice coefficient of 92%, comparable to expert human performance.

In this research, we utilize state-of-the-art CNN architectures like ResNetX50 and EfficientNet-B7 to improve LGG classification and diagnosis accuracy. By harnessing the capabilities of these modern models, our approach outperforms traditional methods. Rigorous experimentation and optimization highlight the algorithm's effectiveness, achieving enhanced diagnostic precision for early detection and treatment of LGGs, ultimately improving patient outcomes.

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The proposed method excels in its robustness in identifying diverse tumor regions, ease of training, and superior effectiveness. This paper provides comprehensive insights into the methodology and experimental outcomes, underscoring the system's potential to revolutionize LGG diagnosis and treatment. Figure 1 shows image with the corresponding tumour mask

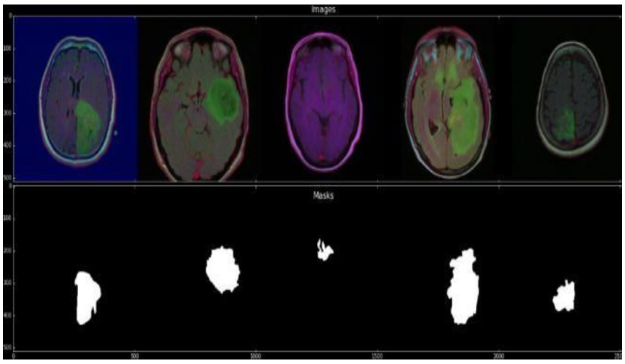

Figure 1: Input image with the corresponding tumour mask

II. LITERATURE SURVEY

This paper, authored by Mateusz Buda, Ashirbani Saha, and Maciej A. Mazurowski [1], is among the first to employ deep learning approaches for identifying lower-grade gliomas (LGGs). The study reveals that automatically extracted imaging features from LGG cases exhibit a moderate association with tumor molecular subtypes determined via genomic analysis. Utilizing deep learning algorithms for tumor segmentation, the research acknowledges that while current radiogenomic models show moderate predictive capabilities, they are not yet sufficient to replace genomic analysis completely. However, the study emphasizes that imaging data can still provide valuable preliminary insights, aiding in early treatment decisions, especially for patients who do not immediately undergo surgical excision or have incomplete resections. Imaging-based models, despite their moderate accuracy, can assist in prioritizing patients for genomic tests.

Accurate tumor segmentation is critical for consistent assessment of imaging features. Using the U-Net model in their research, the authors achieved an 82% mean Dice coefficient, addressing variability between observers and ensuring reliable tumor quantification. This study underscores the potential of imaging-based models to complement existing treatment approaches for LGG patients, offering valuable insights into tumor biology and aiding personalized therapeutic strategies. It also explores various deep learning methodologies for brain tumor segmentation, highlighting fully convolutional neural networks (FCNNs) as a more efficient alternative to traditional sliding-window approaches by reducing computational overhead through single-pass image processing. The U-Net architecture used incorporates skip connections between the encoder and decoder, enhancing segmentation capabilities. Other models such as ResNet, Inception, and DenseNet have been explored in segmentation tasks, with optimization functions like Dice similarity coefficient-based loss proving effective in handling imbalanced datasets. This research, while employing the standard U-Net architecture, suggests that accuracy could improve with alternative deep learning models and optimization techniques.

Another study by Mohamed A. Naser and M. Jamal Deen highlights the potential of MRI for non-invasive brain imaging, enabling automated tumor segmentation and grading to enhance treatment planning [2]. Their work emphasizes the promise of deep learning, particularly using the U-Net architecture, for this purpose. Additionally, they discuss the application of transfer learning through pre-trained VGG16 models for glioma grading, concluding that segmentation, detection, and grading of tumors are essential for clinical utility and represent significant advancements in neuroimaging and patient care. They found that for high-resolution, multi-varied data, traditional classification methods like multilayer perceptron, decision trees, and support vector machines often fall short in delivering high accuracy.

Deep learning models like CNNs, specifically U-Net and transfer learning with pre-trained VGG16, were utilized in tumor segmentation, detection, and grading tasks, achieving a mean Dice coefficient of 0.84, tumor detection accuracy of 0.82, and grading accuracy of 0.83 at both image and patient levels. The research suggests combining segmentation algorithms to detect tumors in different spatial orientations, such as axial, coronal, and sagittal, to improve accuracy in predicting LGGs.

A survey conducted by Farhana Sultana, Abu Sufian, and Paramartha Dutta [3] offers an extensive review of CNN-based image segmentation techniques. It provides a taxonomy of methods and details their architectures, training

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processes, and hyperparameter tuning, facilitating performance comparisons across diverse datasets. The survey emphasizes the importance of CNN-based models for advancing medical image analysis and identifies U-Net-based models as particularly effective due to their ease of training and high accuracy. The study suggests that combining architectures like ResNetX50 and EfficientNet-B7 with U-Net could further enhance performance for LGG prediction.

A study focusing on the challenges of MRI-based brain tumor segmentation highlights the criticality of segmenting gliomas and glioblastomas due to their diffuse and variable appearances. The study, presented by the Association of University Radiologists Radiology Research Alliance Task Force, explores deep learning's role in radiology, particularly its application to semantic scene segmentation [4]. Techniques such as Fluid-attenuated Inversion Recovery (FLAIR) imaging sequences are discussed as valuable tools for improving segmentation. Finally, an innovative Eff-UNet architecture, combining EfficientNet as an encoder with U-Net for fine-grained segmentation maps, achieved remarkable performance in semantic scene segmentation challenges [6]. Though developed for driving datasets, the model's principles could be applied to LGG datasets for higher accuracy. Another study proposes a fully automatic deep convolutional neural network (DCNN) approach, utilizing multiscale processing inspired by the human visual system to classify and segment brain tumors across various spatial orientations, achieving tumor classification accuracy of 0.973 [7].

This research addresses the challenges associated with brain tumors and underscores the critical importance of precise classification and early detection. Brain tumors, defined as abnormal cell growth in the brain, affect fewer than 2% of the global population but contribute significantly to morbidity and mortality [9]. These tumors are categorized into primary and secondary types, with gliomas being the most prevalent. They vary in grades from benign to highly malignant. The paper emphasizes that accurate classification and timely detection of brain tumors are vital for effective treatment planning. However, traditional manual classification methods can be complex and time-consuming, highlighting the need for novel computer-aided diagnostic (CAD) systems powered by machine learning (ML) algorithms. The research further asserts that segmentation plays a crucial role in medical imaging, where it helps divide images into meaningful segments. However, the focus of this study is more on classification techniques, particularly those that utilize transfer learning.

Deep learning (DL), specifically convolutional neural networks (CNNs), is identified as a powerful tool in image analysis. CNNs are capable of autonomously extracting features from images, making them highly suitable for tasks such as brain tumor classification. Several CNN architectures, including VGG, GoogLeNet, and AlexNet, have been successfully applied to medical imaging. Despite their advantages, CNNs encounter challenges such as vanishing gradients and optimization difficulties. The ResNet (Residual Network) architecture addresses these issues and has demonstrated significant improvements in recognition accuracy.

The research introduces a brain tumor detection method based on the ResNet50 architecture, which delivers highly accurate results. By leveraging transfer learning, this model is designed to classify brain tumors both accurately and efficiently. The study highlights the growing role of deep learning techniques in enhancing medical image analysis, particularly in improving the accuracy of brain tumor classification and detection. The paper also observes a surge in interest around machine learning, particularly with the rise of deep artificial neural networks since 2009, which have consistently outperformed other models across various benchmarks. Deep learning models are now at the forefront of machine learning, with applications across diverse domains such as image analysis, natural language processing, and healthcare. These advancements hold significant potential for transforming medical imaging technology, data analysis, diagnostics, and healthcare systems.

The research focuses on recent developments and challenges in the application of machine learning to medical image processing, with a particular emphasis on deep learning techniques in MRI. The goals of the study are threefold: first, to provide an overview of deep learning with key references; second, to showcase how deep learning has been integrated into various stages of the MRI processing pipeline, including acquisition, segmentation, disease prediction, and image retrieval; and third, to offer guidance for individuals interested in contributing to this field, providing resources such as educational materials, open-source code, and medical imaging datasets.

Overall, the research aims to offer a comprehensive view of the current state of deep learning in medical imaging, serving as a valuable resource for those interested in exploring and advancing this rapidly evolving field. In conclusion, these studies collectively demonstrate the potential of deep learning models in advancing LGG segmentation, detection, and grading, providing valuable insights and avenues for further improvement

III. PROPOSED METHODOLOGY

A) Overview:

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A deep learning model is employed for precise pixel-wise segmentation of images, utilizing a U-Net-based architecture with EfficientNet-B7 as its backbone. The U-Net model, in combination with various other machine learning models, is explored in this study to enhance accuracy and identify the optimal model for testing data. Additionally, the study investigates how different models perform with the provided dataset. The primary segmentation process is carried out using a fully convolutional neural network built on the U-Net architecture [5], which offers higher accuracy and better generalization. This approach is applied for the detection of lower-grade gliomas, aiding in tumor growth prevention. Manual segmentation is utilized as the ground truth for training the model.

The primary goal of detecting lower-grade gliomas is to support early intervention and potentially prevent the tumor from advancing to higher-grade levels, such as Grade 4, as well as to avoid dementia progression.

B) U-Net based architecture:

The U-Net architecture, as illustrated in Figure 2, is employed for efficient segmentation, with EfficientNet-B7 serving as its backbone. This model is trained on the Cancer Imaging Archive (TCIA) dataset, where it functions as a lightweight structure for initializing weights, which can be further enhanced by adding a backbone to improve accuracy. FLAIR images, along with their associated tumor masks from the TCIA, are utilized to accurately identify the tumor's location, offering a wide range of potential applications [4]. Magnetic Resonance Imaging (MRI) is commonly used for diagnosing brain tumors. However, manual segmentation of MRIs is both time-consuming and costly, highlighting the need for more reliable methods. This could facilitate quicker diagnoses and treatment of neurological conditions such as Alzheimer's disease (AD), schizophrenia, and dementia.

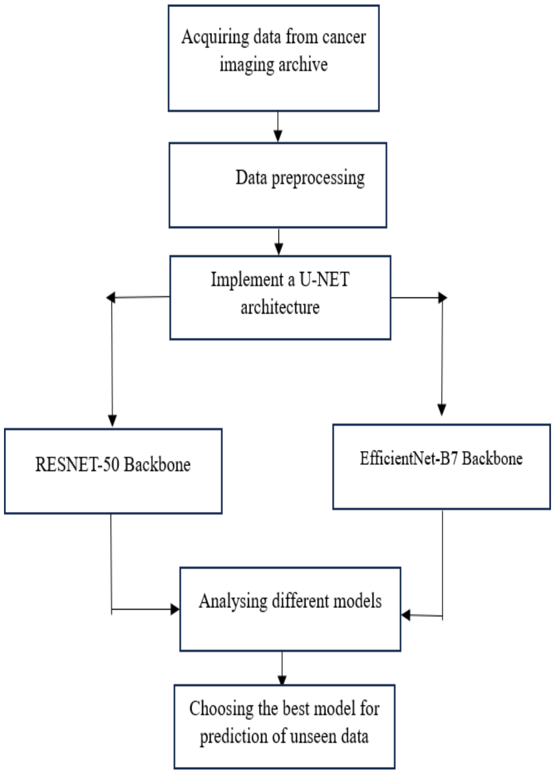

Figure 2: Workflow of Architecture

C) Segmentation:

The segmentation process involves the use of various models, including the basic U-Net model, U-Net combined with FPN, U-Net with ResNet50 as the backbone, and U-Net with EfficientNet-B7 as the backbone. This approach was employed to determine the optimal parameters for training the model and to identify the best-performing model.

D) Combination of Models:

The analysis reveals that incorporating ResNet-50 or EfficientNet-B7 as backbones into the U-Net architecture significantly improves image segmentation performance compared to the standard U-Net model. EfficientNet-B7, the most advanced variant in the EfficientNet family, employs a compound scaling technique to systematically adjust the model's depth, width, and resolution, achieving an optimal balance between accuracy and model size. The findings indicate that combining U-Net with ResNet-50 or EfficientNet-B7 backbones delivers superior results for identifying lower-grade gliomas (LGGs) in FLAIR images. Selecting the most effective model ensures high accuracy and reliability, providing medical professionals with robust tools for the automated detection and segmentation of LGGs.

E) Prediction Model:

The U-Net model with an EfficientNet-B7 backbone was selected as the primary predictive model for evaluating unseen test data. This configuration demonstrated superior accuracy compared to ResNet-50 and other models evaluated in this study.

F) Tools and Frameworks Used in the Study:

1. Convolutional Neural Networks (CNNs):

For image segmentation, the study leverages advanced CNN architectures, specifically ResNet-50 and EfficientNet-B7, known for their robust feature extraction capabilities.

2. Google Colab:

Google Colab, a cloud-based platform offering powerful hardware resources, was utilized for executing deep learning algorithms. It simplifies Python code execution and supports libraries essential for machine learning. TIFF images were uploaded using Python libraries like OpenCV, PIL, and scikit-image, enabling seamless integration and processing in the Colab environment.

3. Python and Libraries:

Python, with its rich ecosystem, played a central role in model development. Libraries such as TensorFlow, PyTorch, and scikit-learn facilitated efficient deep learning workflows:

a) TensorFlow: This framework, developed by Google, supported the implementation of architectures like U-Net and ResNet, offering tools for building and training deep neural networks. Its high-level API, TensorFlow Keras, enabled rapid prototyping and model iteration.

b) Keras: A user-friendly API that simplifies deep learning, Keras allowed quick experimentation with different architectures and hyperparameters, essential for tasks like LGG detection.

c) Scientific Libraries: Tools like NumPy and Pandas supported data manipulation and analysis.

4. Computer Vision Libraries:

OpenCV was employed for video-related tasks such as frame extraction, color space conversion, and resizing, ensuring high-quality preprocessing for image segmentation.

5. Machine Learning Framework:

PyTorch, renowned for its dynamic computation graphs and flexibility, was used to implement deep learning models. It streamlined tasks such as automatic differentiation and model training, contributing significantly to the research's success.

These tools collectively enhanced the study's ability to design and evaluate CNN-based models for accurate segmentation and detection.

IV. RESULTS AND DISCUSSION

The dataset utilized in this study was sourced from The Cancer Imaging Archive (TCIA) and The Cancer Genome Atlas (TCGA). It comprises preoperative imaging and genomic data from 110 patients across five institutions, all diagnosed with lower-grade gliomas (LGGs). This dataset includes imaging data paired with manually annotated segmentation masks, which were used to train the models for accurately predicting tumour regions in the testing dataset as shown in figure 3.

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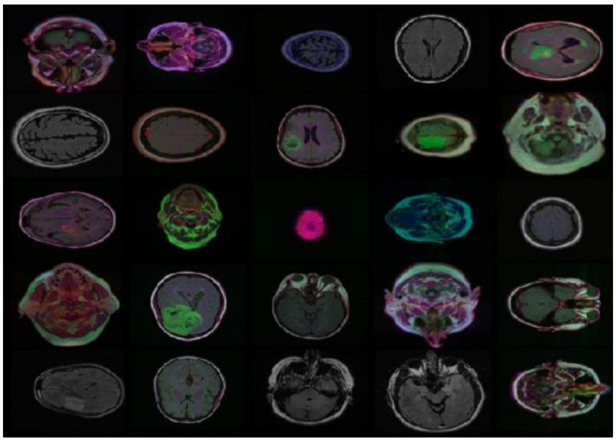

Figure 3: Dataset Used

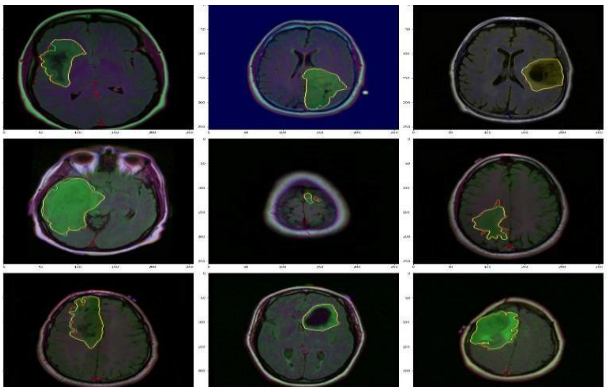

Figure 4: Image representing the ground truth and prediction regions obtained with the above models of Unet and EfficientNetB7 as Backbone

Table 1: Comparison of different results obtained after testing with two main models

Vanilla U-Net	IOU SCORE- 82%	Dice Coeff- 84%
U-Net with ResNet50 Backbone	IOU SCORE- 85%	Dice Coeff- 90%
U-Net with EfficientNet-B7 backbone	IOU SCORE- 90%	Dice Coeff- 92%

For this segmentation task, the Intersection over Union (IoU) score is employed as a metric to measure the overlap between the ground truth and the predicted regions. IoU provides a numerical value representing the extent of agreement between these two regions.

Given the highly imbalanced nature of the dataset, Dice Loss is utilized as a loss function. This metric calculates the intersection between true and predicted segmentation values by summing them up and dividing by the combined total of the true and predicted values, resulting in the Dice Similarity Coefficient.

Additionally, the Categorical Cross-Entropy function is applied as a loss function. It combines SoftMax activation with cross-entropy loss, making it suitable for multiclass classification tasks.

$$total\ loss = dice\ loss + 1 * focal\ loss$$

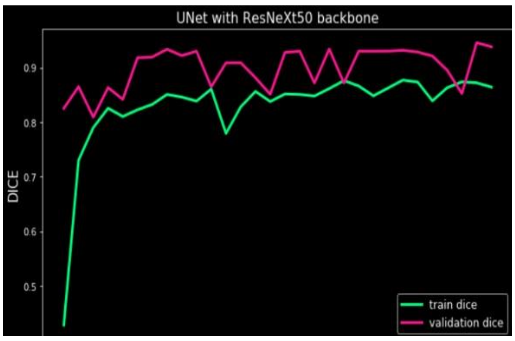

Figure 5: Graph representing the dice coefficient for Unet with Resnet50

V. CONCLUSION

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For accurate segmentation and effective detection of regions impacted by lower-grade tumours, the integration of EfficientNet-B7 as the backbone for the U-Net model demonstrates significant advantages over ResNet-50. This configuration delivers enhanced performance metrics, such as higher Dice coefficient and Intersection over Union (IoU) scores. The model's accuracy is particularly critical for precisely delineating the subtle and irregular boundaries associated with lower-grade tumours. This improvement is highlighted by the substantial alignment observed between predicted abnormality regions and the corresponding ground truth. These results reinforce the importance of leveraging EfficientNet-B7 to enhance segmentation precision, thus advancing medical imaging analysis and improving diagnostic capabilities in detecting lower-grade tumours.

Looking ahead, the developed model for detecting lower-grade gliomas (LGG) can be further expanded to include detection of other types of brain tumours, such as meningiomas, pituitary tumours, or higher-grade gliomas. This extension could involve fine-tuning hyperparameters and modifying the architecture to meet the specific requirements of each tumour type. Employing ensemble models or leveraging additional pre-trained CNN architectures may further enhance accuracy and robustness, especially for datasets with diverse characteristics.

Future studies could also explore the model’s resilience by testing it with images superimposed with noise or subjected to super-resolution techniques to simulate various imaging conditions. Incorporating domain adaptation methods to generalize the model's performance across different MRI scanners and institutions could further improve its clinical applicability. Additionally, integrating advanced feature extraction techniques and multimodal imaging data, such as combining FLAIR and T1-weighted MRI sequences, could improve tumour characterization. By addressing these areas, the model's utility in broader clinical and research settings can be significantly enhanced, contributing to better patient outcomes through precise and early diagnosis.

REFERENCES

[1] M. Buda, A. Saha, and M. A. Mazurowski, "Association of genomic subtypes of lower-grade gliomas with shape features automatically extracted by a deep learning algorithm," Computers in Biology and Medicine, vol. 109, pp. 42–49, 2019.

[2] M. A. Naser and M. J. Deen, "Brain tumor segmentation and grading of lower-grade glioma using deep learning in MRI images," Computers in Biology and Medicine, vol. 121, 2020.

[3] F. Sultana, A. Sufian, and P. Dutta, "Evolution of image segmentation using deep convolutional neural networks: A survey," Knowledge-Based Systems, vol. 204, 2020.

[4] M. Havaei, A. Davy, D. Warde-Farley, A. Biard, A. Courville, Y. Bengio, C. Pal, P.-M. Jodoin, and H. Larochelle, "Brain tumor segmentation with deep neural networks," Medical Image Analysis, vol. 35, pp. 18–31, 2022.

[5] "Deep Learning in Radiology," Academic Radiology, vol. 25, no. 11, 2020.

[6] B. Baheti, S. Innani, S. Gajre, and S. Talbar, "Eff-UNet: A Novel Architecture for Semantic Segmentation in Unstructured Environment," in Proceedings of Center of Excellence in Signal and Image Processing, SGGSIET, Nanded, India, 2022.

[7] F. J. Díaz-Pernas, M. Martínez-Zarzuela, M. Antón-Rodríguez, and M. González-Ortega, "A deep learning approach for brain tumor classification and segmentation using a multiscale convolutional neural network," 2021.

[8] J. Walsh, A. Othmani, M. Jain, and S. Dev, "Using U-Net network for efficient brain tumor segmentation in MRI images," Healthcare Analytics, vol. 2, 2022.

[9] "Brain tumor classification using the modified ResNet50 model based on transfer learning," Biomedical Signal Processing and Control, vol. 86, part C, 2023.

[10] A. S. Lundervold and A. Lundervold, "An overview of deep learning in medical imaging focusing on MRI," Zeitschrift für Medizinische Physik, 2020.