ICVEE **ICVEE 2022**
2022 The Fifth International Conference on Vocational Education and Electrical Engineering (ICVEE)

UNESA IEEE ComSoc IEEE Communications Society

CERTIFICATE

NO. 57228/UN38.I/DL.01.02/2022

THIS CERTIFICATE OF APPRECIATION IS AWARDED TO

Hapsari Peni Agustin T

as

Presenter

In The Fifth International Conference on Vocational Education and Electrical Engineering (ICVEE) 2022

THE FUTURE OF ELECTRICAL ENGINEERING, INFORMATICS, AND EDUCATIONAL TECHNOLOGY THROUGH THE FREEDOM OF STUDY IN THE POST-PANDEMIC ERA

Surabaya, 10-11 September 2022

VICE RECTOR FOR ACADEMICS AFFAIRS

KEMENTERIAN PENDIDIKAN, KEBUDAYAAN, RISET DAN TEKNOLOGI UNIVERSITAS NEGERI SURABAYA UNESA

Prof. Dr. Bambang Yulianto, M. Pd.

CONFERENCE CHAIR

ICVEE

Dr. Rr. Hapsari Peni Agustin T, S.T., M.T.

Brain Tumor Classification Using Deep Neural Network Based on MRI Images

1st Hapsari Peni Agustin Tjahyaningtijas
Department of Electrical Enginieering
Universitas Negeri Surabaya
Surabaya, Indonesia
hapsaripeni@unesa.ac.id

2nd Laras Suciningtyas
Department of Electrical Enginieering
Universitas Negeri Surabaya
Surabaya, Indonesia
laras20025@mhs.unesa.ac.id

3rd Andi Kurniawan Nugroho
Department of Electrical Engineering
Universitas Semarang
Semarang, Indonesia
andikn@usm.ac.id

4th Cucun Very Angkoso
Informatics Department,
University of Trunojoyo Madura
Bangkalan, Indonesia
cucunvery@trunojoyo.ac.id

5th Lusia Rakhmawati
Department of Electrical Enginieering
Universitas Negeri Surabaya
Surabaya, Indonesia
lusiarakhmawati@unesa.ac.id

6th Naim Rokhmawati
Department of Informatics Engineering
Universitas Negeri Surabaya
Surabaya, Indonesia
naimrokhmawati@unesa.ac.id

2022 Fifth International Conference on Vocational Education and Electrical Engineering (ICVEE) | 978-1-6654-7581-5/22/$31.00 ©2022 IEEE | DOI: 10.1109/ICVEE57061.2022.9930354

***Abstract*—Deep learning is a part of machine learning that has been shown to address challenges in the artificial intelligence field. To express complicated relationships, traditional machine learning methods such as Support Vector Machine (SVM and k-Nearest Neighbor (kNN) require a high number of nodes. In this study, we employ Deep Neural Network (DNN) as a brain tumor classification approach since it can efficiently handle difficult problems without the usage of a large number of nodes like SVM and kNN. This research used MRI scans from the BraTS data set with a total of 112 low grade glioma (LGG) and high grade glioma (HGG). The study was divided into four stages: segmentation applied the U-Net-based segmentation approach, image feature extraction using gray level co-occurrence matrix (GLCM), gray level run length matrix (GLRLM), and gray level size zone matrix (GLSZM) in the second stage, in the third stage we applied the Max-Min normalization method, in the fourth stage we utilized info gain ratio as a scoring method. Finally, the DNN classification approach is compared to the SVM classification method. The classification approach with DNN has a greater accuracy value of 2.75 percent than SVM.**

Keywords—Support Vector Machine, GLCM, GLRLM, GLSZM, Max-min normalization

I. Introduction

Brain tumors can strike anyone at any age. The effects of a brain tumor on the body vary depending on the type and severity. Glioma is a type of brain tumor that develops from glial cells. According to the World Health Organization, gliomas are classified into four types, namely tumor types I through IV [1]. Type I tumors are typically found in children and have a texture similar to glial cells. Type II tumors have a large tumor area with little change in texture. Type III tumors are usually malignant. Oligodendrogliomas are among the type III brain tumors. Oligodendrogliomas are a type of brain tumor that combines oligoastrocytoma and anaplastic oligodendroglioma. Glioblastoma, or GBM, is a type IV brain tumor. GBM is the most severe type of brain tumor, with a tumor texture that can be distinguished even with the naked eye[2]. Types I and II tumors are categorized as benign tumors or low grade glioma (LGG), while type III and IV tumors are categorized as malignant tumors or GBM. Type III and IV brain tumors grow very quickly in brain cells and will affect healthy parts, particularly the spinal cord. Treatment of brain tumors becomes very difficult, dangerous, and incurable. The medical field requires early detection of brain tumors so that the development of early-type tumors can be detected quickly and the chance of recovery is increased. Because the human brain has a very complex structure, diagnosing brain tumors is a difficult task. Doctors urgently need improved brain tumor imaging methods to observe and track the growth of brain tumor areas at various stages of severity, so that a diagnosis can be made based on the imaging results.

There are numerous computer-based methods for imaging brain tumors. Medical Resonance Imaging (MRI) and Computed Tomography (CT) were used to obtain brain tumor imaging modalities [3]. Because it is non-invasive, has good contrast, high spatial resolution, and requires slight exposure to harmful radiation, MRI is becoming more widely used in the diagnosis of brain tumors [4]. In this study, we classified brain tumors using MRI image modalities T1, T1-CE, T2, and fluid-attenuated inversion recovery (FLAIR).

Experts believe that proper brain tumor classification is critical. A better computer-aided diagnostic (CAD) method is required due to the subjectivity and timing of visual diagnosis [5]. The most recent methods developed in medical image processing are machine learning and deep learning..

Machine learning (ML) technology is a machine designed to learn on its own without human intervention. Machine learning is built on other disciplines such as statistics, mathematics, and data mining in order for machines to learn by analyzing data without having to be reprogrammed or ordered. There are two types of ML algorithms: supervised and unsupervised. Supervised learning is an approach to AI creation. It is called "supervised" because in this approach, machine learning is trained to recognize patterns between input data and output labels. Not only that, machine learning is also trained to identify the relationship that underlies the connection of input data with output labels. Supervised learning methods in ML used in computer vision include K-Nearest Neighbors (KNN) [6], k-means, Support Vector Machine (SVM) [7], and Artificial Neural Network (ANN) [8]. Unsupervised learning is a technique used by machine learning to create artificial intelligence. In this approach, you don't need to train computer algorithms to recognize the patterns that make up the AI. The model is designed to be "self-study" in gathering information, including recognizing unlabeled data. It is called “unsupervised” because the model in this approach does not need to be trained. Unsupervised methods that have been developed include using Fuzzy C-Means [9] and Self-Organization Map (SOM) [10].

Praveen et al. [11] conducted research on brain tumor classification. Praveen et al. classified brain tumors into three stages in their study using the SVM classification algorithm. The initial stage involves skull stripping and noise filtering. The second stage involves segmenting the brain tumor image with a fast bounding box and extracting features with GLCM. The least-squares support vector machines (LS-SVM) classification algorithm was used to classify brain tumors in the third stage. Genetic algorithm SVM (GA-SVM) was also proposed as a method for determining probabilities in tumor grade, and GA-ANN was used to check accuracy [10]. Ansari et al. [12] presented a rational method for detecting brain tumors. They revolve around noise reduction, GLCM-based key feature extraction, and ultimately, brain tumor segmentation using Discrete Wavelet Transformation (DWT) to boost output and reduce complexity. Morphology actions for noise reduction have been established as a result of the segmentation procedure. SVM was used to classify brain tumor detection.

The K-Nearest Neighbor approach has been used as a classification methodology to classify brain tumors [13]. Both methods, the k-Nearest Neighbor (kNN) and the Support Vector Machine (SVM) are used to categorize tumors as benign or malignant. The accuracy of the SVM classifier is higher than that of the kNN classifier. On the other hand, the system specificity value of the kNN approach is larger than that of the SVM method [14].

However, in recent decades, Support Vector Machines (SVM) and Neural Networks (NN) have become popular techniques for high performance [10]. Deep architectures may efficiently express complicated connections without having as many nodes as shallow designs such as SVM and K-nearest neighbors (KNN). As a result, they are making a significant contribution in a variety of health informatics domains.

The goal of this research is to use deep learning to automatically classify and measure brain tumors using MRI images. Using brain MRI images, the suggested approach tries to distinguish between Low-Grade Glioma (LGG) and Glioblastoma (GBM) tumors. The proposed methodology supports a feature set obtained from segmented brain MRI images using Gray level co-occurrence matrix (GLCM), gray level run length matrix (GLRLM), and gray level size zone matrix (GLSZM) methods.

This paper is divided into five sections: section 1 contains background and previous research that supports the research, section 2 contains the basic ideas and deep learning architecture expressed in a method. Section 3 contains the method approach steps that were implemented as a result of experimental findings and discussions, while Section 4 is a conclusion and proposal for future research.

II. Proposed Methods

A vital aspect of the segmentation process is determining the characteristics of the health system and tumors. In this segmentation section, we used our previous method for brain segmentation called modified U-Net (mU-Net) [14] compared with the original U-Net architecture. mU-Net is a modified U-Net architecture by adding a DO layer at the 4th convolution layer (512) and the 5th convolution layer (1024). The proposed methodology for classifying the brain tumors in brain MRIs is as follows:

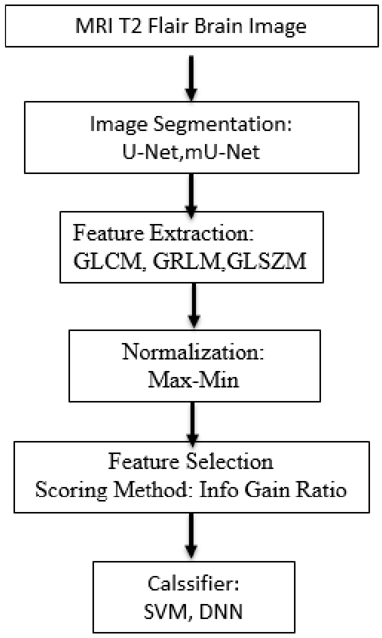
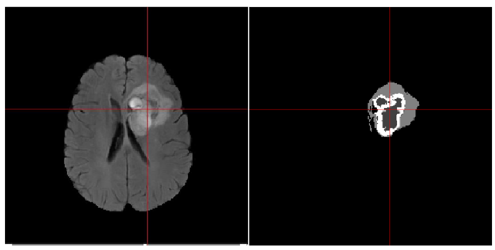


Fig. 1. Proposed method on brain tumor classification using DNN

A. Dataset

This study uses a dataset obtained from Brain Tumor Segmentation. The dataset used in this experiment was collected from Brain Tumor Segmentation (BraTS) 2018 [15][16]. Given that the BraTS data set comes from several institutions with different annotations, the labeling of the data set must still be consistent and comply with the protocol. Data sets are synchronized by board-certified neuroradiologists with over 15 years of experience. The BraTS data set was manually segmented by one to four assessors following a protocol defined by an expert and approved by an experienced neuroradiologist. The BraTS data set has also undergone a preprocessing stage, namely skull stripping, normalization, and synchronization by interpolating the same isotropic resolution to the same anatomical framework of the brain. Since the beginning of its publication, the BraTS dataset is open and has become a benchmark for brain tumor research because it has undergone a preprocessing stage. The results of manual segmentation covered the entire tumor area, tumor enhancing, necrosis, and edema with four multi-sequence MRIs namely T1, T1Gd, T2, and T2 FLAIR. Fig. 1 (a) shows a segment of the BraTS dataset and (b) an expert's ground truth manual.



(a) (b)

Fig. 2. (a) A segment of the BraTS dataset and (b) an expert's ground truth manual

B. Segmentation

A vital aspect of the segmentation process is determining the characteristics of the health system and tumors. In this segmentation section, we used our previous method for brain segmentation called modified U-Net (mU-Net) [17] compared with the original U-Net architecture. mU-Net is a modified U-Net architecture by adding a Drop Out (DO) layer at the 4th convolution layer (512) and the 5th convolution layer (1024).

Many architectural configurations were devised to improve segmentation performance, Overfitting will become more common as performance settings get more complex. One method for reducing overfitting is to use a DO layer. DO is a regulatory mechanism that can pick unused neurons at random throughout the training process. Using the DO method, more exact results may be obtained. mU-Net used DO to reduce overfitting and it is applied to improve system performance with a limited amount of data.

C. Classification

The classification stage was carried out with a segmentation-based classification. Following that, the segmentation results will be subjected to a feature extraction step. GLCM, GRLM, and GLSZM are the image features extracted. For each image, there are a total of 24 features. The feature selection step follows the feature extraction stage, and the methods used to pick features at this stage include the info gain ratio. The DNN approach is then used to classify the data by comparing classification with SVM.

Fig.3 shows a block diagram of the classification approach using DNN. The DNN is given a set of features collected from 112 LGG and HGG brain tumor images in the brain tumor image data set. These characteristics have been normalized using the max-min approach. The data should then be partitioned into 80 % training data and 20 % percent test data. The validation data is 20 % of the training data [18]. The next stage is to use DNN to classify brain tumors. Fig. 4. shows the DNN modeling algorithm. The architecture of DNN shown in Fig. 5 consists of 1 input layer, 3 hidden layers, and 1 output layer.

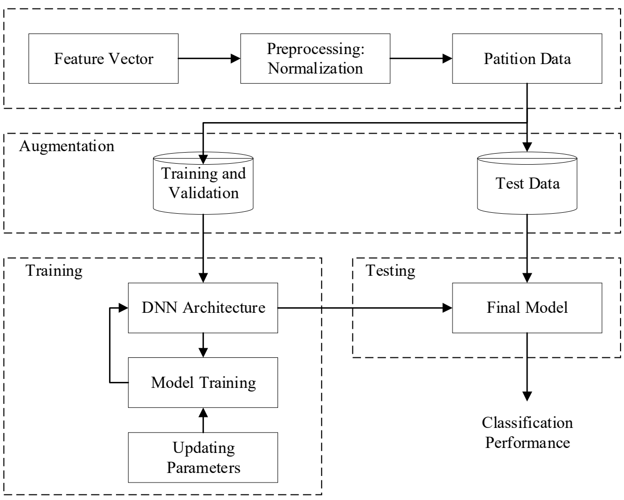


Fig. 3. Block diagram of brain tumor MRI image classification using DNN

Algorithm 1. Building the DNN model
<u>Training Algorithm</u>
Input: Feature vector, label
Output: Trained model

1. Define the epoch number
2. Define the input shape of the network
3. Initialize number of layers
4. For each number of layers
   Do nonlinearity operation with Relu layer
5. Get output class through a softmax layer
6. For each epoch
   Update the weights and loss

Algorithm 2. Classification algorithm for DNN
<u>Testing Algorithm</u>
Input: Feature vector, label
Output: Prediction Result

1. Feed the test set with n number of data to the trained network
2. Get prediction score
3. For each test data
   If prediction score > 0.5
      prediction result is "HGG"
   Else
      prediction result is "LGG"

Fig. 4. Pseudo-code classification algorithm with DNN

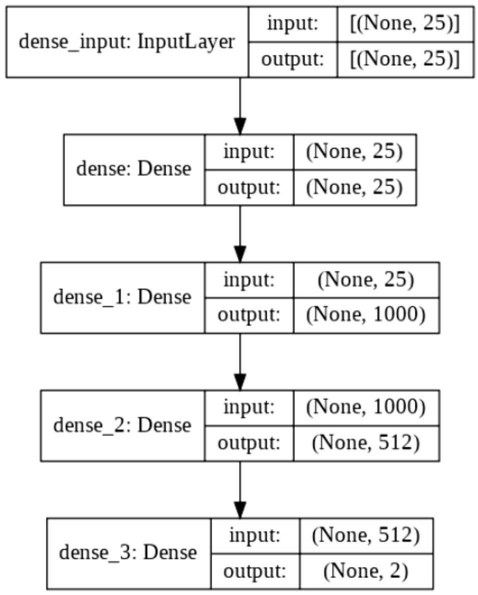


Fig. 5. DNN architecture for brain tumor classification

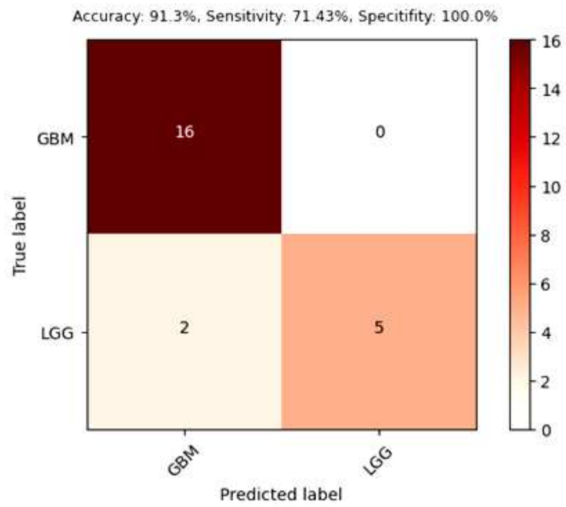
III. Result And Discussion

The testing process is carried out using the DNN architecture that has been developed in Fig. 5, and the results of the testing accuracy for the classifier methods are listed in Table 1.

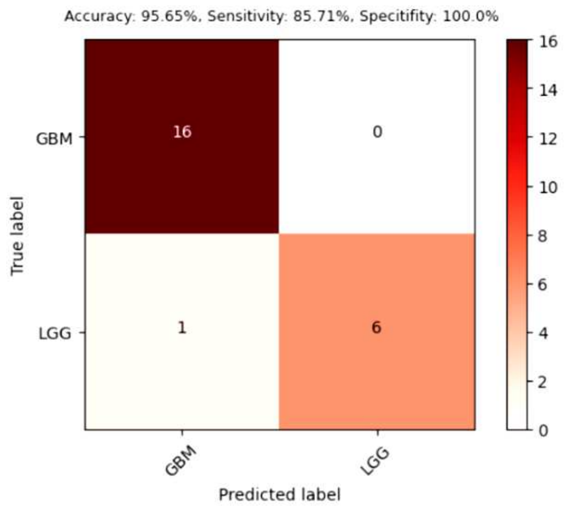
TABLE I. PERFORMANCE OF CLASSIFIER ACCORDING TO THE SEGMENTATION METHODS

Segmentation Method	Classifier	Accuracy (%)	Sensitivity (%)	Specificity (%)
U-Net	SVM	85.7	85.7	86.9
	DNN	91.3	71.43	100
mU-Net	SVM	92.9	92.9	92.8
	DNN	95.65	85.71	100

Table 1 shows that the accuracy of the classification technique using DNN is 91.3 %, which is higher than the accuracy of SVM when utilizing the U-Net segmentation method. The DNN classification method employing the mU-Net segmentation approach has a greater accuracy value of 2.75% than the SVM classification method. Fig. 6 shows the results of the confusion matrix Classification of brain tumors using DNN



(a)



(b)

Fig. 6. Confusion matrix of brain tumor classification using DNN based on the segmentation methods (a) U-Net and (b) mU-Net

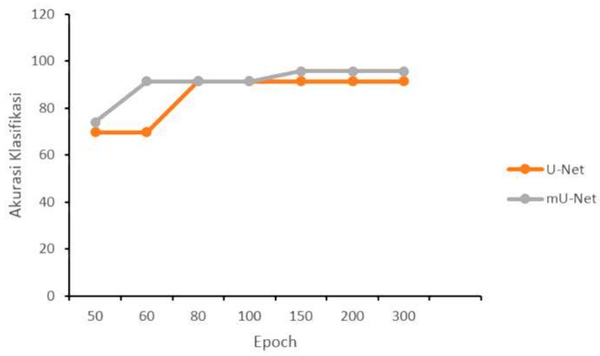


Fig. 7. Brain tumor classification accuratcy using DNN according to the epoch variation.

Meanwhile, based on the epoch values for two distinct segmentation approaches, the accuracy performance of the DNN method can be shown in Fig. 7. The DNN classification approach employing mU-Net segmentation has a greater accuracy value than U-Net segmentation. The accuracy of brain tumor classification using the mU-Net segmentation method is fixed at 95.65%, even though the epoch continues to increase, but the DNN classification method using the U-Net segmentation method has a fixed accuracy value of 91.3 %.

The image characteristics collected from both U-Net and mU-Net segmentation techniques may be inferred that the classification approach utilizing DNN has a higher classification accuracy value than SVM.

IV. CONCLUSION

In this paper, we propose a method for classifying brain tumor images into two classes LGG and HGG that combines a deep learning-based classification method, DNN, with a U-Net-based segmentation method. Compared to SVM, the experimental findings suggest that classification using DNN produces higher accuracy outcomes. As a result, future research should focus on expanding the use of CNN-based classification methods by combining them with U-Net-based segmentation methods.

REFERENCES

[1] D. N. Louis *et al.*, "The 2007 WHO classification of tumours of the central nervous system," *Acta Neuropathologica*, vol. 114, no. 2. Springer, pp. 97–109, Aug. 2007.

[2] L. M. DeAngelis, "Medical progress: Brain tumors," *New England Journal of Medicine*, vol. 344, no. 2, pp. 114–123, 2001.

[3] G. Mohan and M. M. Subashini, "MRI based medical image analysis: Survey on brain tumor grade classification," *Biomedical Signal Processing and Control*, vol. 39, pp. 139–161, Jan. 2018.

[4] S. C. Thust, M. J. van den Bent, and M. Smits, "Pseudoprogression of brain tumors," *Journal of Magnetic Resonance Imaging*, vol. 48, no. 3, pp. 571–589, Sep. 2018.

[5] J. E. Villanueva-Meyer, M. C. Mabray, and S. Cha, "Current clinical brain tumor imaging," *Clinical Neurosurgery*, vol. 81, no. 3, pp. 397–415, Sep. 2017.

[6] P. Thanh Noi and M. Kappas, "Comparison of Random Forest, k-Nearest Neighbor, and Support Vector Machine Classifiers for Land Cover Classification Using Sentinel-2 Imagery," *Sensors (Basel)*, vol. 18, no. 1, Dec. 2017.

[7] M. Alfonse and A.-B. M. Salem, "An Automatic Classification of Brain Tumors through MRI Using Support Vector Machine," 2016.

[8] A. I. Khan and S. Al-Habsi, "Machine Learning in Computer Vision," *Procedia Computer Science*, vol. 167, pp. 1444–1451, 2020.

[9] M. Alfonse and A.-B. M. Salem, "An Automatic Classification of Brain Tumors through MRI Using Support Vector Machine," 2016.

[10] H. P. Bahareh Shahangian, "Automatic brain hemorrhage segmentation and classification algorithm based on weighted grayscale histogram feature in a hierarchical classification structure," *Biocybernetics and Biomedical Engineering*, vol. 36, no. 1, pp. 217–232, Jan. 2016.

[11] G. B. Praveen and A. Agrawal, "Hybrid approach for brain tumor detection and classification in magnetic resonance images," *International Conference Communication, Control and Intelligent Systems, CCIS 2015*, pp. 162–166, Mar. 2016.

[12] M. A. Ansari, R. Mehrotra, and R. Agrawal, "Detection and classification of brain tumor in MRI images using wavelet transform and support vector machine," vol. 23, no. 5, pp. 955–966, Jul. 2020.

[13] R. H. Ramdlon, E. Martiana Kusumaningtyas, and T. Karlita, "Brain Tumor Classification Using MRI Images with K-Nearest Neighbor Method," in *IES 2019 - International Electronics Symposium: The Role of Techno-Intelligence in Creating an Open Energy System Towards Energy Democracy, Proceedings*, Sep. 2019, pp. 660–667.

[14] H. J. Motlak, "MRI Technique Based Detection and Classification of Brain Tumor Using Support Vector Machine (SVMM) and k-Nearest Neigbor (kNN)," *Journal of Engineering and Applied Sciences 14*, vol. 14, no. 11, pp. 3625–3629, 2019.

[15] B. Menze, M. Reyes, A. Jakab, E. Gerstner, J. Kirby, and K. Farahani, "Proceedings of the MICCAI Challenge on Multimodal Brain Tumor Image Segmentation (BRATS) 2013," *MICCAI Challenge on Multimodal Brain Tumor Image Segmentation*, vol. 57, 2013.

[16] B. H. Menze *et al.*, "The Multimodal Brain Tumor Image Segmentation Benchmark (BRATS)," *IEEE Transactions on Medical Imaging*, vol. 34, no. 10, pp. 1993–2024, Oct. 2015.

[17] H. Peni, A. Tjahyaningtijas, A. K. Nugroho, C. V. Angkoso, K. E. Purnama, and M. H. Purnomo, "Automatic Segmentation on Glioblastoma Brain Tumor Magnetic Resonance Imaging Using Modified U-Net," *EMITTER International Journal of Engineering Technology*, vol. 8, no. 1, pp. 2443–1168, 2020.

[18] M. J. Willemink *et al.*, "Preparing Medical Imaging Data for Machine Learning," *Radiology*, vol. 295, no. 1, p. 4, 2020.