AI-based system for detecting and locating brain tumors on cranial magnetic resonance imaging

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***Abstract*—Brain tumors or growths of abnormal cells in the brain tissue is a problem that is becoming more and more common in the population. Generally, the most common symptoms are headaches, personality changes (depression, anxiety, or uninhibitedness), loss of balance, and trouble concentrating. Therefore, a fusion between Artificial Intelligence (AI) and Neuroimaging was devised to develop a prototype that can serve as a preventive instrument to detect possible anomalies associated with brain tumors. Besides using some images contained in datasets (3 339 images), some training and validation processes were conducted through *Google Colab*, where the formats of the images are essential when evidencing some anomaly. Furthermore, using pre-trained neural networks with the deep search networks facilitated the training of the AI-based model and increased the accuracy of the results.**

***Index Terms*—artificial intelligence; brain magnetic resonance imaging; convolutional neural networks; resnet; resunet; tumor detection and location.**

I. Introduction

Brain tumors are becoming more and more common in the population. As this disease progresses, the question arises as to how medicine can improve processes to speed up the analysis of cranial Magnetic Resonance Imaging (MRI) and achieve a faster and more accurate diagnosis. Symptoms for people with this condition include headache, personality changes (such as suddenly feeling depressed, anxious, or uninhibitedness), loss of balance, difficulty concentrating, seizures, and incoordination [1]. Nevertheless, the symptoms are very diverse, and not all can end in a type of malignant tumor. That is the motivation to carry out this study and combine artificial intelligence (AI) with medicine, mainly neuroimaging. Analyzing cranial resonances will help health professionals improve decision-making in patients who present abnormalities, achieving a diagnosis and treatment in a shorter period.

The segmentation of brain tumors in MRI directly influences the diagnosis of the type of brain tumor in the patient since many cases can end in a secondary or non-malignant brain tumor. In most processes, focused detection speeds up control and eliminates the tumor in the early stages [1]. Unfortunately, the machines that allow us to perform MRI cannot accurately detect and classify a brain tumor.

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The emergence of AI and deep convolutional neural networks (CNN) has boosted the development of supervised segmentation methods [2], improving and updating diverse techniques for detection and location on image diagnosis, such as ResNet and ResUnet [3]. These techniques allow us to carry out deep searches in multiple layers of an image to be analyzed, leading to the segmentation of medical images with a high degree of precision, facilitating the observation and understanding of the target region to be diagnosed. This provides useful and important information to the health professional or radiologist that can be used to determine the type of tumor according to its magnitude, location, and type that is evidenced in the MRI of each patient, speeding up results and treatments [4]–[7].

Using CNN methods represents a significant advantage. However, it should be noted that this type of method must be trained with a dataset that shares the same image format, and obviously, this becomes a disadvantage since a new training must be performed when changing the MRI image format. For example, if the training was performed with a Tagged Image File Format (`.TIFF`) and the analysis is performed using a Digital Imaging and Communications in Medicine (`.DCM`) format, which is an international standard in medical image analysis, the deterioration in the performance when training the model using the new format and analyzing the MRI is evident.

Training and evaluation of MRI images must be conducted using the same format to achieve results with robust segmentation in all cases. This study integrates supervised CNN methods and AI to exploit this combination's advantages in medical image analysis and overcome its disadvantages with an open dataset. The results demonstrate that our proposed system has great adaptability and robustness and outperforms other supervised segmentation approaches in medical image analysis.

The rest of the paper is organized as follows. Section II presents the preliminaries and performs a review of the related work. Section III describes in detail the proposed AI-based architectures and software development. Section IV presents the two main phases to validate the solution: training and evaluation. Section V describes the conducted experiments and presents the results. Finally, Section VI draws the conclusions and presents the future work.

II. Preliminaries and related work

Brain tumors are a heterogeneous group due to the different cell lines that generate them. However, the authors in [8] mention that they can be classified into i) primary lesions, which affect the central nervous system, and ii) secondary lesions, which originate in other parts of the body and are implanted as metastases in the brain. This disease turns out to be more common, not so much due to an increase in its incidence but due to the increase in life expectancy of the general population and timely diagnoses thanks to technological advances [9].

An MRI scan on the brain is a non-invasive test used to diagnose diseases. It uses a strong magnetic field, radio waves, and a computer to create detailed images of structures inside the body. In this way, the images can be examined on a computer monitor. Once the patient is positioned on the table, restraints and a bolster are used to help keep the patient immobile and maintain the patient's position. Next, devices containing coils capable of emitting and receiving radio waves will be placed adjacent to the area of the body being scanned.

If contrast material is used, a doctor, nurse, or technologist will insert an intravenous catheter (IV line) into a vein in your arm or hand that will be used to inject the contrast material. The technologist will do the exam while working on a computer located outside the room. When the exam is complete, the patient will be asked to wait while the radiologist reviews the images if more images are needed. The IV line will be removed after the exam is complete. The exam is usually completed in 45 minutes [10].

A radiology expert has traditionally carried out a cranial MRI analysis; in this study, the developed software allows the location of a brain anomaly through training with datasets collected from digital repositories, radiology clinics, and internet images. The proposed AI-based model, uses deep search networks, specifically ResNet for detection and ResUnet for location, which allow us to locate a brain anomaly in each of the images used in the training phase; considering different formats, such as `.jpg`, `.tiff`, `.dicom`, `.png`. By using this diversity of formats, our AI-based model achieve enough knowledge and prior preparation for highly effective results.

Regarding the related works, we only discovered a few studies on the subject. For instance, the authors of [3] detail how MRI can be used to segment brain tumors. Medical practitioners with great experience and much time are normally required for this type of segmentation task. To address these challenges, this research uses a U-Net-based brain tumor segmentation model as well as a complete data processing strategy that includes target magnification and image transformations such as data augmentation and edge contour enhancement. The authors state that they worked with 3D magnetic resonance pictures that were later transformed into 2D images, pointing out that altering the format of each image resulted in three images, providing more data for the model to train on.

This study shares the method used in [11] to be able to classify magnetic resonances into two classes: tumor and non-tumor; CNN technologies are implemented, specifically ResNet models (18, 34, and 52), concluding that ResNet18 with the proposed weighted loss function method achieves the

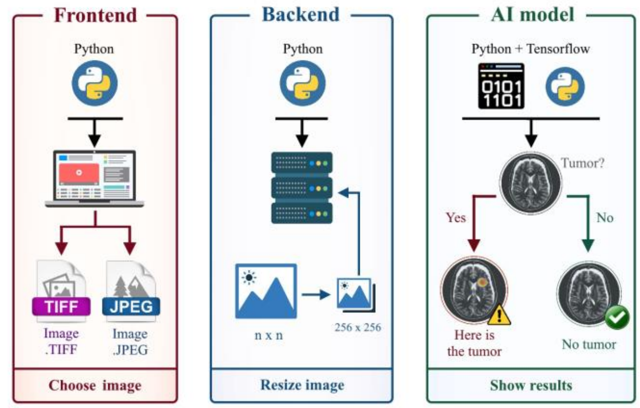

Figure 1. AI-based MRI architecture.

best results to classify benign from malignant anomalies in 3D MRI images. Therefore, it stands out in this article that the models used are the most convenient for classifying purposes. Furthermore, with the accompaniment of more recent models such as ResUnet, favorable results are expected, similar to those obtained in [11] using 3D CNN.

The software developed in this study uses Python as the primary tool and the Visual Studio Code IDE due to its low consumption of resources in a computer. The *Google Colab* [12] was used for the tests carried out with datasets from cloud repositories, which allows any user to write and execute Python code in the browser—being a tool with unique characteristics, machine learning, data analysis, and execution in real-time without excessively consuming computer resources. Note that this type of development is not intended to replace a professional in a specific area; what is sought with these is to provide support for a much faster and more efficient result in situations that require a prompt response in results or analysis.

III. AI-based architecture for detecting and localizing brain tumors in cranial MRI

This section describes the design of the proposed architecture for the development and implementation of the system called AI-based MRI. We first explain in detail the architecture of the AI-based model applied for experimentation; then, we elaborate on the algorithms and datasets used for detecting and locating anomalies on cranial MRI to classify brain images into tumor and non-tumor.

A. *AI-based architecture*

The architecture of the AI-based MRI system is divided into three layers, as illustrated in Fig. 1: frontend, backend, and AI-based model.

Frontend: This layer handles the user's interface when the program is executed. Cranial MRI is required, in `JPEG`, `PNG`, `Gif`, `TIFF` or `DICOM` formats, provided by the user to detect and locate the tumor. A `start` button for loading images allows you to open a file directory on the computer and choose the corresponding image.

Backend: This layer handles what we call data cleaning since it is responsible for processing the image obtained in such a way that, using the Python programming language, it resizes its size to 256×256 pixels, which is the appropriate size to be displayed on the screen. Therefore, this layer displays the graphical interface through which the data obtained will be returned. Finally, image data is sent to be processed in the AI-based model layer.

AI-based model: This layer uses transfer learning; in particular, the ResNet model to detect if an image has or does not have a brain tumor. If existence is detected, it proceeds with the ResUnet model that locates the brain tumor and returns `1` thus indicating the backend layer the result obtained and proceeded to display; otherwise, it returns `0` thus indicating to the backend layer the result obtained and proceeds to display. The `softmax` function is used in neural networks that aim to classify data, in this case classifying cranial MRI. The function returns a probability percentage that the images belong to the desired filter (a brain tumor); it is used in the last layer of the CNN. The function is represented as $softmax(k) = e^{z_k} / \sum_{k=1}^{10} e^{z_k}$, where z is the output of the hidden layers and k is the number of classes that our model has. In this study, two classes will be taken, tumor and non-tumor

Once the information has been obtained and processed, the results are displayed using a graphical interface so that the original image that was uploaded is depicted on the left side of the screen, and the result obtained is depicted on the right side.

B. *AI-based Detection and location*

ResNet is an artificial neural network (ANN) based on known constructs of pyramidal cells in the cerebral cortex. Residual neural networks use jump connections or shortcuts to jump over some layers. In Fig. 2, this network with more layers or more profound works similarly to an image with fewer layers to analyze the Residual Convolutional Network (RCN) of the cranial MRI; as they become more profound, gradient fading tends to occur, which negatively affects network performance. The residual neural network includes the "skip connection" function that allows the training of 152 layers without problems of gradient fading. ResNet works by adding "identity maps" on top of the RCN; ImageNet contains 11 million images and 11 000 categories, using it to train the ResNet deep network [13].

Figure 3 illustrates an example of the network architecture for ImageNet. First, we load an image and then apply the residual blocks to the filter size 3×3 and the number of filters (64) to obtain a gradient of the analyzed image.

ResUnet is a fully CNN designed for high performance with fewer parameters, as illustrated in Fig. 4. It is an improvement over the existing UNet architecture. ResUnet leverages both the UNet architecture and Deep Residual Learning. As observed, the UNet backbone architecture is combined with residual blocks to overcome gradient fading problems in deep architectures, based on fully convolutional networks, and it is modified to work well for segmentation tasks [14].

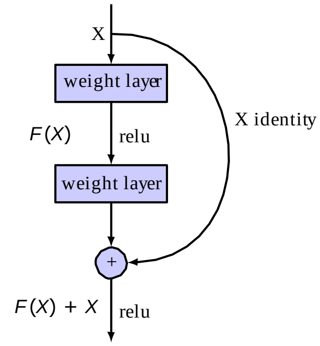

Figure 2. ResNet model.

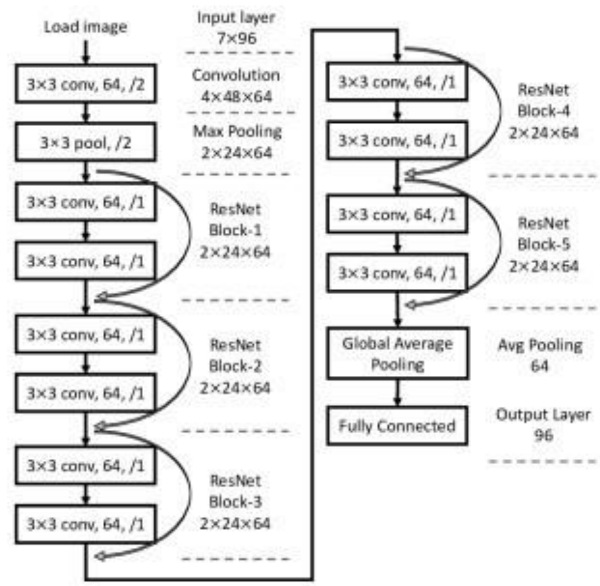

Figure 3. ImageNet architecture.

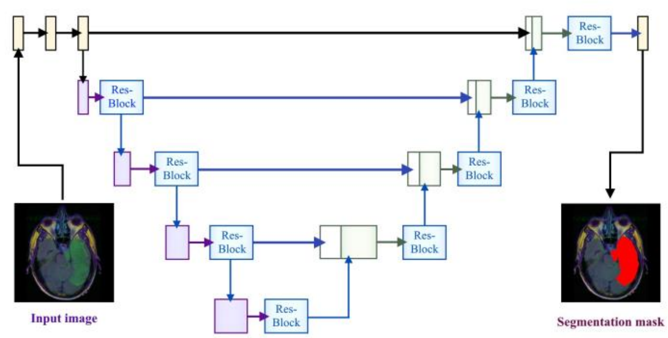

Figure 4. ResUnet architecture.

IV. IMPLEMENTATION

The software was developed using Python and its libraries. It allows the location of brain tumors in MRI, jointly with image identification and image segmentation.

We used the dataset in [15] to evaluate the models, which consists of 7 858 collected brain MRI images corresponding to 110 patients included in The Cancer Genome Atlas (TCGA) [16] lower-grade glioma collection under conditions

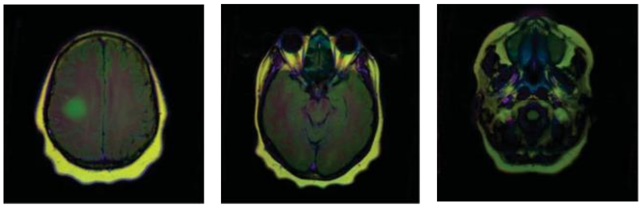

Figure 5. Example of an image set.

of low and high resolution. Image codes were used to recognize whether a tumor or a non-tumor was detected in the filtering process, obtaining 2 556 images with no tumor and 1 373 images with a tumor.

In the search for deep analysis of detail of the construction and training of the AI-based model to detect and locate brain tumors, the ResNets and ResUnet networks (applications in health care) were used.

For the initial development of this software, the Google Colab tool was used, which is freely accessible. Using this tool, we call the libraries, and they will be executed according to our requirements in the developed code, allowing us to link to the dataset in digital repositories [17].

The following Python libraries were used in the development stage: Pandas library for manipulating datasets; Numpy for numerical analysis; Searborn for the treatment of files; OpenCv standard library; Skimage for image processing; Tensorflow 2.0 with keras api; Transfer learning ResNet50 library trained by Google.

V. Experiments and Results

In this section, we evaluate the proficiency of our AI-based MRI system.

A. *Training phase*

For the first training, a dataset obtained from [15] was used, in which brain MRI images for brain tumor detection were selected. It gives us a quantity of 98 images in formats that can be trained by our AI-based model.

In the first training, it is evident that the use of `.jpg` images (Fig. 6) took a long processing time by our model due to each image's weight. Nevertheless, the model had an accuracy of 95%.

For a second training, we consider the images of the previous dataset converted into `.tif` (Fig. 7). This format is one of the lightest for image processing and has the property that it is evidenced with a base of green, purple, and yellow colors, allowing the model a much faster and more accurate analysis with a result of 96.5% accuracy. A dataset obtained from a clinic specialized in magnetic resonance analysis was used for the training and choice of the most accurate image format. They provide us with images in `.Dicom` or `.DCM` format, the same standard format used by clinics specialized in analyzing these images since they have the property of being images with movement and 360 degrees of vision.

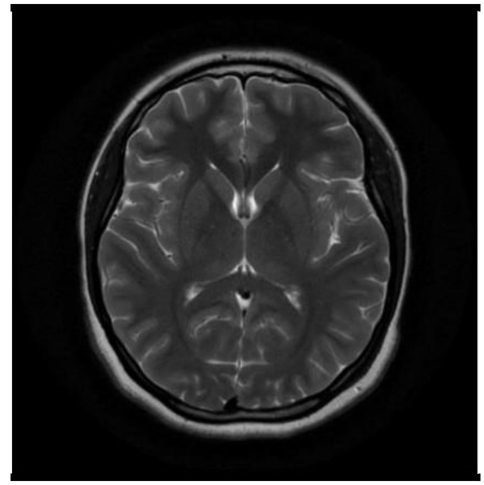

Figure 6. Image sample in `.JPEG` format.

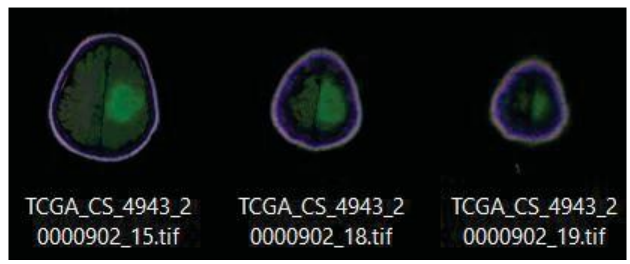

Figure 7. Image sample in `.TIF` format.

Figure 8. Image sample in `.DCM` format.

```
[ ] from sklearn.model_selection import train_test_split

    train, test = train_test_split(brain_df_train, test_size = 0.15)
```

Figure 9. Training and validation procedure.

Additionally, the software Horos Project was used for debugging images, allowing us to work with `DCM` images and simulating IOS to handle and process MRI images.

Through the Google Colab platform, the training and validation of the model were carried out (Fig. 9); specifically, 3 339 images were used from the dataset for training the model and 590 images for its validation.

Subsequently, the ResNet50 model was used to train the

```
[ ] basemodel = ResNet50(weights = 'imagenet', include_top = False, input_tensor = Input(shape=(256, 256, 3)))

[ ] headmodel = basemodel.output
    headmodel = AveragePooling2D(pool_size = (4,4))(headmodel)
    headmodel = Flatten(name= 'flatten')(headmodel)
    headmodel = Dense(256, activation = "relu")(headmodel)
    headmodel = Dropout(0.3)(headmodel)
    headmodel = Dense(256, activation = "relu")(headmodel)
    headmodel = Dropout(0.3)(headmodel)
    headmodel = Dense(2, activation = 'softmax')(headmodel)

    model = Model(inputs = basemodel.input, outputs = headmodel)
```

Figure 10. Training phase with ResNet50.

```
[ ] from sklearn.metrics import accuracy_score

    accuracy = accuracy_score(original, predict)
    accuracy

    0.9791666666666666
```

Figure 11. System evaluation and accuracy.

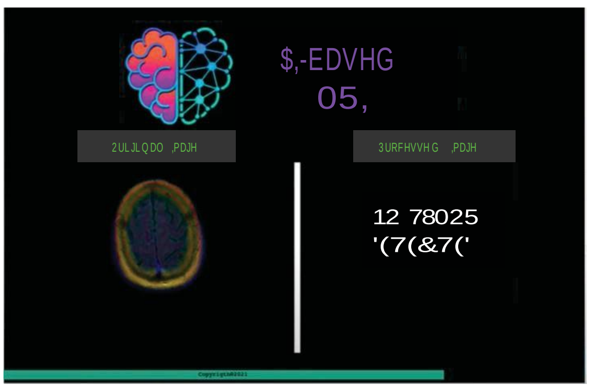

Figure 12. Cranial MRI without tumor.

model with the number of images previously mentioned, as illustrated in Fig. 10.

B. Evaluation phase

After the training phase, the model was saved in a `.json` file so that each time it is needed, the `.json` file is called directly, and there is no need to retrain the model. As a next step, the evaluation of the model was carried out, and through Python functions, it was possible to verify that the model has a success rate of `0.9791` (Fig. 11), which is an acceptable result.

Analyzing images with no tumors, we obtained high accuracy in all the analyses performed, as shown in Fig. 12.

For the final analysis, images with a positive diagnosis of brain tumors in MRI were used; the AI-based model had an excellent success with all the images inserted in the software used for this analysis, as evidenced in Fig. 13.

Different tests were conducted in two operating systems: Windows and macOS, as shown in [18]. This evidences that our developed software is multi-platform and can be executed on any machine with the previous installation of Python packages for its analysis.

Figure 13. Cranial MRI with tumor.

In the case of the macOS, we trained the model using real data, since the dataset was obtained from a clinic specialized in this type of MRI, so in this version it was refined both the user interface and the different formats of images that the user can insert. Table I summarizes the main features of the image formats tested and compares their performance regarding accuracy, processing time, and acceptance.

C. Processing time

For the percentage of success, it was possible to show that each training is dependent on the type of image that is inserted in the software so that it performs the corresponding analysis. For example, when analyzing images in `.jpg` format or `.png` format, the waiting time and precision were 48 seconds and 95%, respectively. At its highest time, when performing the analysis with images of the same extension but that do not have a positive result or random images, the time in all the analyses is optimal and acceptable.

Analyzing images with `.tif` or `.tiff` extension, the processing times were much shorter and with slightly higher accuracy, with average values of 24 seconds and 96.5% accuracy; so we can say that this is a format that can be considered for the analysis of MRI images or, failing that, for the analysis of medical images.

Finally, the AI-based model allows the location and segmentation of medical images in magnetic resonances, using a `.DICOM` or `.DCM` format, a standard format used for analyzing this type of procedures. A success rate of 97.9% was obtained with a relatively low processing time of 15 seconds. Figure 14 summarizes the processing time for each image format tested.

It is worth mentioning that we obtain low processing times, around 4 seconds, when analyzing images without tumor and 5 seconds when analyzing images that are not related with MRI or any type of it. These results where 100% accurate, showing that the model is working properly.

VI. Conclusions

We developed an AI-based software to detect and locate brain anomalies in MRI through training with data sets collected from digital repositories, radiology clinics, and internet

Table I
IMAGES FORMAT COMPARISON ON PERFORMANCE.

Image format	Uses	Compression	Size	Colors' quantity	Transparency	Animation	Compatibility	Optimization	Training	Accuracy(%)	Time (s)	Acceptance (%)
JPEG	Web, photo, or print	With loss	Pictures, light or heavy	Millions	No	No	High	Alter image quality	First	95	48	65
PNG	Web, print, and video	Lossless	Drawings, light or heavy	Millions	Yes	No	Low	Reduce color palette and more	First	95	48	30
GIF	Web	Lossless	Light	Up to 256	Yes	Yes	High	Reduce color palette and more	First	95	48	20
TIFF	Store images (MRI, X-ray, Ultrasounds)	Lossless	heavy	Millions	Yes or No	No	Specific SW (Radiology)	Almost all color spaces	Second	96.5	24	85
DICOM (DMC)	World standard medical digital imaging (MRI, X-ray, Ultrasound, CT)	Lossless	heavy	Millions	Yes or No	Yes	Specific SW (Radiology)	Ideal for re-touching	Third	97.9	5	99

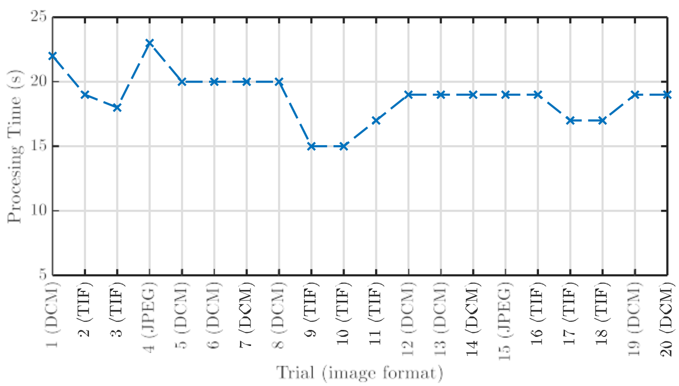

Figure 14. Processing time vs. trials using different image formats.

images. Prior to the training of our AI, which uses deep search networks, specifically ResNet for detection and ResUnet for location, the same ones that will allow us to locate a brain anomaly in each of the images used for training, these images will have different formats. Considering this diversity of formats, our AI-based model will have enough knowledge and prior preparation for providing highly effective results. The use of pre-trained neural networks with the deep search networks facilitated the training of the AI model and the accuracy of the results. Finally, the training of deep search networks such as Res-Net and ResUnet allows us to scale the types of formats used in MRI images and multi-platform management with Windows and macOS operating systems, allowing us to process images with formats such as `.Dicom` and `.tif`. These results can be improved with the recommendations obtained by the staff of a radiology clinic.

REFERENCES

[1] X. Wang, C. Guo, and X. Zhou, "Robust Segmentation of 3D Brain MRI Images in Cross Datasets by Integrating Supervised and Unsupervised Learning," in *2020 10th International Conference on Information Science and Technology (ICIST)*. IEEE, 2020, pp. 194–201.

[2] R. S. y. S. S. A.-N. A. Saleh, "Brain tumor classification using deep learning," in *Proceedings of the International Conference on Assistive and Rehabilitation Technologies (iCareTech)*, 2020, pp. 131–136.

[3] T.-W. Ho, H. Qi, F. Lai, F.-R. Xiao, and J.-M. Wu, "Brain Tumor Segmentation Using U-Net and Edge Contour Enhancement," in *Proceedings of the 2019 3rd International Conference on Digital Signal Processing*, 2019, pp. 75–79.

[4] H. Etienne, S. Hamdi, M. Le Roux, J. Camuset, T. Khalife-Hocquemiller, M. Giol, D. Debrosse, and J. Assouad, "Artificial intelligence in thoracic surgery: past, present, perspective and limits," *European Respiratory Review*, vol. 29, no. 157, 2020.

[5] N. Yakubova, A. Sriram, J. Zbontar, M. Rabbat, A. Defazio, M. Tygert and L. Zitnick, "FastMRI breakthrough shows AI-accelerated MRIs interchangeable with traditional MRIs," August 2020. [Online]. Available: https://ai.facebook.com/blog/fastmri-breakthrough-shows-ai-accelerated-mris-interchangeable-with-slow-traditional-mris/

[6] R. Liao, D. Moyer, M. Cha, K. Quigley, S. Berkowitz, S. Horng, P. Golland, and W. M. Wells, "Multimodal representation learning via maximization of local mutual information," in *International Conference on Medical Image Computing and Computer-Assisted Intervention*. Springer, 2021, pp. 273–283.

[7] T. A. Retson, E. M. Masutani, D. Golden, and A. Hsiao, "Clinical performance and role of expert supervision of deep learning for cardiac ventricular volumetry: a validation study," *Radiology: Artificial Intelligence*, p. e190064, 2020.

[8] J. Arbizu, P. Domínguez, R. Diez-Valle, C. Vigil, R. García-Eulate, J. Zubieta, and J. Richter, "Neuroimagen de los tumores cerebrales," *Revista Espanola de Medicina Nuclear*, vol. 30, no. 1, pp. 47–65, 2011.

[9] F. Molina, E. Pujá, R. Vera, M. Marcos, M. Tejedor, and J. Albistur, "Factores pronósticos en los tumores cerebrales," in *Anales del Sistema Sanitario de Navarra*, vol. 24, 2001, pp. 63–72.

[10] M. Vázquez, E. Santos, I. Rodriguez, A. Pato, M. Vilar, J. C. Arias, R. Fernández, I. Costas, A. Ghioldi, M. Sanmartin *et al.*, "Valoración mediante resonancia magnética cerebral de embolias clínicamente silentes en pacientes con fibrilación auricular sometidos a cardioversión eléctrica," *Revista Española de Cardiología*, vol. 65, no. 2, pp. 139–142, 2012.

[11] X. Chen, Y. Chen, C. Ma, X. Liu, and X. Tang, "Classification of pancreatic tumors based on mri images using 3d convolutional neural networks," in *Proceedings of the 2nd International Symposium on Image Computing and Digital Medicine*, 2018, pp. 92–96.

[12] G. Inc., "Colaboratory by Google," March 2022. [Online]. Available: https://colab.research.google.com/

[13] Y. Li, H. Zhang, X. Xue, Y. Jiang, and Q. Shen, "Deep learning for remote sensing image classification: A survey," *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, vol. 8, no. 6, p. e1264, 2018.

[14] F. I. Diakogiannis, F. Waldner, P. Caccetta, and C. Wu, "ResUNet-a: A deep learning framework for semantic segmentation of remotely sensed data," *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 162, pp. 94–114, 2020.

[15] M. Buda, "Brain MRI segmentation," May 2019. [Online]. Available: https://www.kaggle.com/mateuszbuda/lgg-mri-segmentation

[16] M. Buda, E. A. AlBadawy, A. Saha, and M. A. Mazurowski, "Deep Radiogenomics of Lower-Grade Gliomas: Convolutional Neural Networks Predict Tumor Genomic Subtypes Using MR Images," *Radiology: Artificial Intelligence*, vol. 2, no. 1, p. e180050, 2020.

[17] T. S. Gunawan, A. Ashraf, B. S. Riza, E. V. Haryanto, R. Rosnelly, M. Kartiwi, and Z. Janin, "Development of video-based emotion recognition using deep learning with google colab," *TELKOMNIKA*, vol. 18, no. 5, pp. 2463–2471, 2020.

[18] E. Landazuri, J. Changoluiza, L. Tello-Oquendo and F. Tapia, "AI-based MRI system operation," March 2022. [Online]. Available: https://bit.ly/3sBlCaG