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Software Development for Brain Glioma Detection Using Magnetic Resonance Imaging and Deep Learning Techniques

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Abstract. The detection of brain gliomas represents a critical clinical challenge, necessitating early and precise diagnostic methods to improve patient outcomes. Here, we present the development of a deep learning–based system for glioma detection, employing an ensemble of ResNet18, VGG16 and DenseNet121 models trained on MRI scans. Preprocessing comprised dataset curation, image normalisation and mask generation via K-means clustering. The trained models are integrated into a web application that enables users to upload scans and obtain immediate diagnostic feedback. Experimental results demonstrate high accuracy and robust segmentation performance. This research underscores the potential of artificial intelligence (AI) to augment conventional medical imaging techniques and support clinical diagnosis.

Keywords: Artificial intelligence in healthcare, Convolutional neural networks, Deep learning, Ensemble modelling, Glioma detection, Image pre-processing, MRI segmentation, Web-based diagnostic applications.

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1 Introduction

Gliomas are among the most prevalent primary brain tumours, significantly affecting both paediatric and adult populations. In children and adolescents, gliomas represent over 50 % of all brain tumours (Ostrom et al., 2014). Clinical management relies heavily on early detection, accurate diagnosis and precise monitoring of disease progression. However, the non-specific nature of early symptoms—such as headaches, seizures and cognitive decline—often complicates timely diagnosis, leading to delayed treatment and poorer patient outcomes (González-Robledo, 2021; Gheorghiu, 2024).

Magnetic resonance imaging (MRI) remains the gold standard for non-invasive tumour detection, offering detailed insights into brain structure and pathology. Nevertheless, manual interpretation of scans is time-consuming, subject to inter-observer variability and requires a high level of expertise, which may not always be available, particularly in under-resourced healthcare settings (IMSS, 2020).

Given the scarcity of highly specialised neuro-oncology resources in many regions—especially in developing countries—there is a pressing need for accessible automated diagnostic tools. This project addresses that gap by developing a robust, lightweight artificial intelligence (AI) system capable of aiding clinicians in the early detection and characterisation of gliomas (García Campos, 2018).

Recent advances in AI and deep learning (DL) have demonstrated considerable potential for automating diagnostic workflows and enhancing accuracy. In particular, deep convolutional neural networks (CNNs) have shown impressive performance in medical image classification and segmentation tasks (Jiménez-Murillo et al., 2023; Rojas et al., 2021). Radiomics techniques applied to MRI scans have also succeeded in glioma grading and in predicting molecular markers such as IDH mutation and 1p/19q codeletion (Zhou et al., 2019; Zhang et al., 2016). Emerging work by Bae et al. (2020) further illustrates the capacity of DL models to distinguish glioblastoma from other brain pathologies.

Radiogenomics has become increasingly relevant in personalised medicine. Studies by Lu et al. (2018) and Chaddad et al. (2019) highlight the synergy between imaging-derived features and underlying molecular profiles, which can be captured through machine learning (ML) models. This integration enhances diagnostic precision and provides valuable prognostic insights.

The confluence of radiogenomics and ML has yielded substantial advancements in glioma management, equipping clinicians with powerful tools for both non-invasive diagnosis and personalised treatment planning (Rudie et al., 2019; Booth et al., 2020). Multimodal imaging approaches, as proposed by Cho et al. (2018), further support the feasibility of deploying automated pipelines in clinical settings.

Beyond classification, accurate tumour segmentation is critical for surgical planning, quantifying tumour burden and monitoring therapeutic response. Accordingly, the proposed system not only predicts glioma presence but also generates segmentation masks delineating tumour regions.

During development, several technical challenges were encountered, including handling heterogeneous image formats and resolutions, automatically generating segmentation masks from unannotated datasets via K-means clustering, and optimising model performance for deployment within the computational constraints of Google Colab and similar platforms (Segura et al., 2023).

To bridge the gap between experimental AI models and clinical practice, the system was integrated into a web-based interface, enabling healthcare professionals to upload MRI scans, process images through the ensemble AI model, and receive instant diagnostic feedback accompanied by visual overlays of detected tumour regions.

This work thus demonstrates a comprehensive approach combining deep learning, image segmentation and user-centred system design to deliver a practical solution for improving glioma detection and management.

2 Experimental Procedures

The experimental development of this project was organised into three principal phases, each tackling critical components of the glioma detection pipeline: data preparation, model training and deployment via a user-centred web interface.

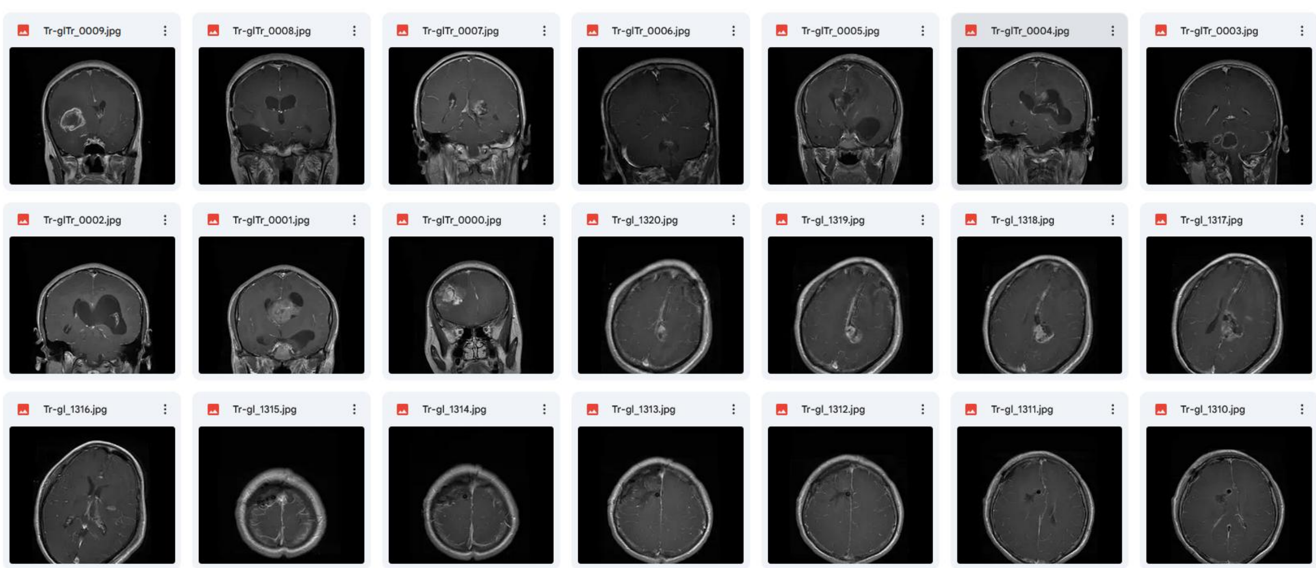

Figure 1: Representative MRI slices from the training dataset used for glioma detection.

2.1 Dataset Preparation

The primary dataset comprised brain MRI scans sourced from publicly accessible repositories. Images were pre-processed to ensure uniformity in input dimensions and format. Each scan was resized to 224 × 224 pixels and normalised according to the standard ImageNet mean and standard deviation values, thereby facilitating model convergence during training.

Owing to the limited availability of annotated paediatric glioma datasets, segmentation masks were generated automatically via unsupervised clustering. Specifically, K-means clustering with K = 4 was applied to each MRI scan to distinguish potential tumour regions from healthy tissue. The resulting masks were saved as .npy files for subsequent integration into the model training and visualisation pipelines (Jiménez-Murillo et al., 2023).

The final training dataset, therefore, consisted of pairs of original MRI scans and their corresponding segmentation masks, enabling the simultaneous training of classification and localisation tasks.

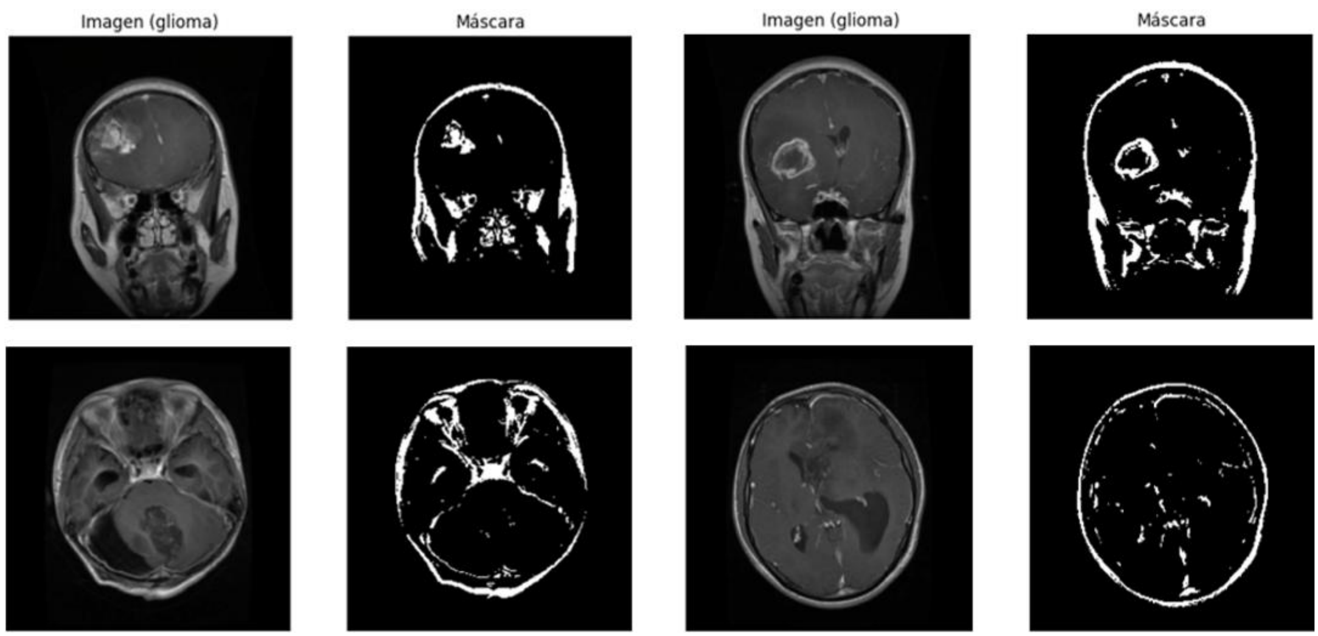

Figure 2: Result of mask segmentation by K-means (Cluster=5)

2.2 First Stage: Image Conversion and Preprocessing

All scans were processed via a custom PyTorch Dataset class, ensuring:

- Loading and conversion from JPEG/PNG formats into tensors.
- Application of resizing and normalisation transforms.
- Generation of red-highlighted masks for glioma regions where applicable.

An initial exploratory analysis then validated image quality, mask coherence and the statistical distribution of tumour versus non-tumour scans.

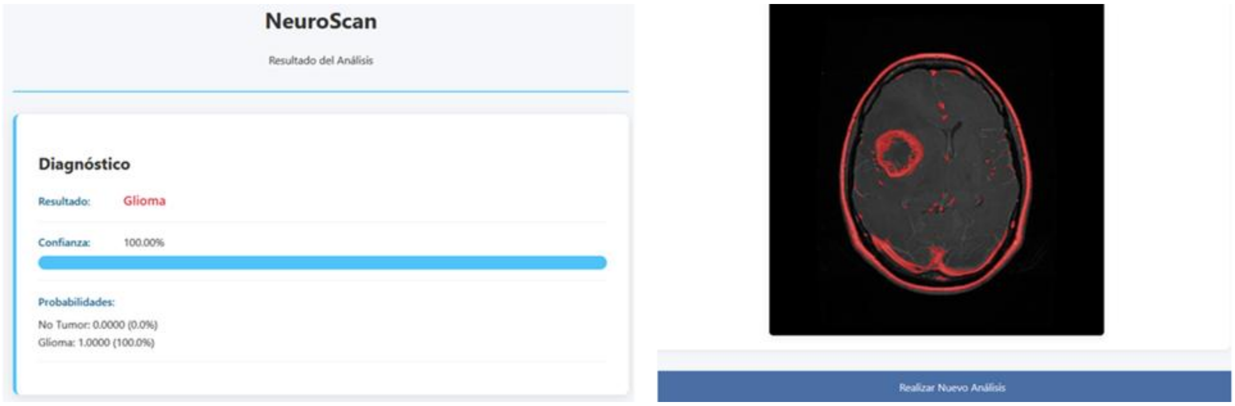

Figure 3: Example of K-means mask generation (In Spanish).

2.3 Second Stage: Model Integration and Training

An ensemble of three deep convolutional neural networks (CNNs) was devised to bolster classification robustness: ResNet18—a lightweight residual network architecture; VGG16—a deep, plain CNN featuring fully connected classifier layers; and DenseNet121—a densely connected CNN optimising feature reuse. Each base model was fine-tuned individually on the glioma detection task, and their output probabilities were averaged to yield the final prediction score. This ensemble strategy aimed to mitigate biases intrinsic to single-architecture models and to enhance generalisation to unseen data (Chaddad et al., 2019).

Training employed the AdamW optimiser with a low learning rate and utilised cross-entropy loss for the binary classification objective. Regularisation techniques such as dropout and gradient clipping were implemented to prevent overfitting. Multimodal MRI features, as proposed by Cho et al. (2018) and Booth et al. (2020), were incorporated to augment the model's robustness in predicting tumour presence and characteristics.

2.4 Third Stage: Web-Based Interface Deployment

Following successful training, the ensemble model was integrated into a Flask-based web application. The front end—developed with HTML, CSS and JavaScript—provides an intuitive user interface enabling clinicians to upload MRI scans, obtain a glioma/no-glioma prediction and view a superimposed segmentation mask highlighting regions of interest. For public testing, the local Flask server was exposed via Ngrok, permitting remote evaluation.
The system architecture comprises:

- **Front end** (HTML, CSS, JavaScript)
- **Back end** (Flask API server)
- **Model serving** (PyTorch model inference on CPU)
- **Storage** (Google Drive integration for model weights and datasets)

2.5 Experimental Infrastructure

Model training and testing were conducted on Google Colab Pro, leveraging a Tesla T4 GPU where available. Colab storage was augmented via Google Drive mounts to enable persistent saving of datasets and models. Average epoch training times ranged from 10–18 minutes, depending on dataset size and GPU availability.

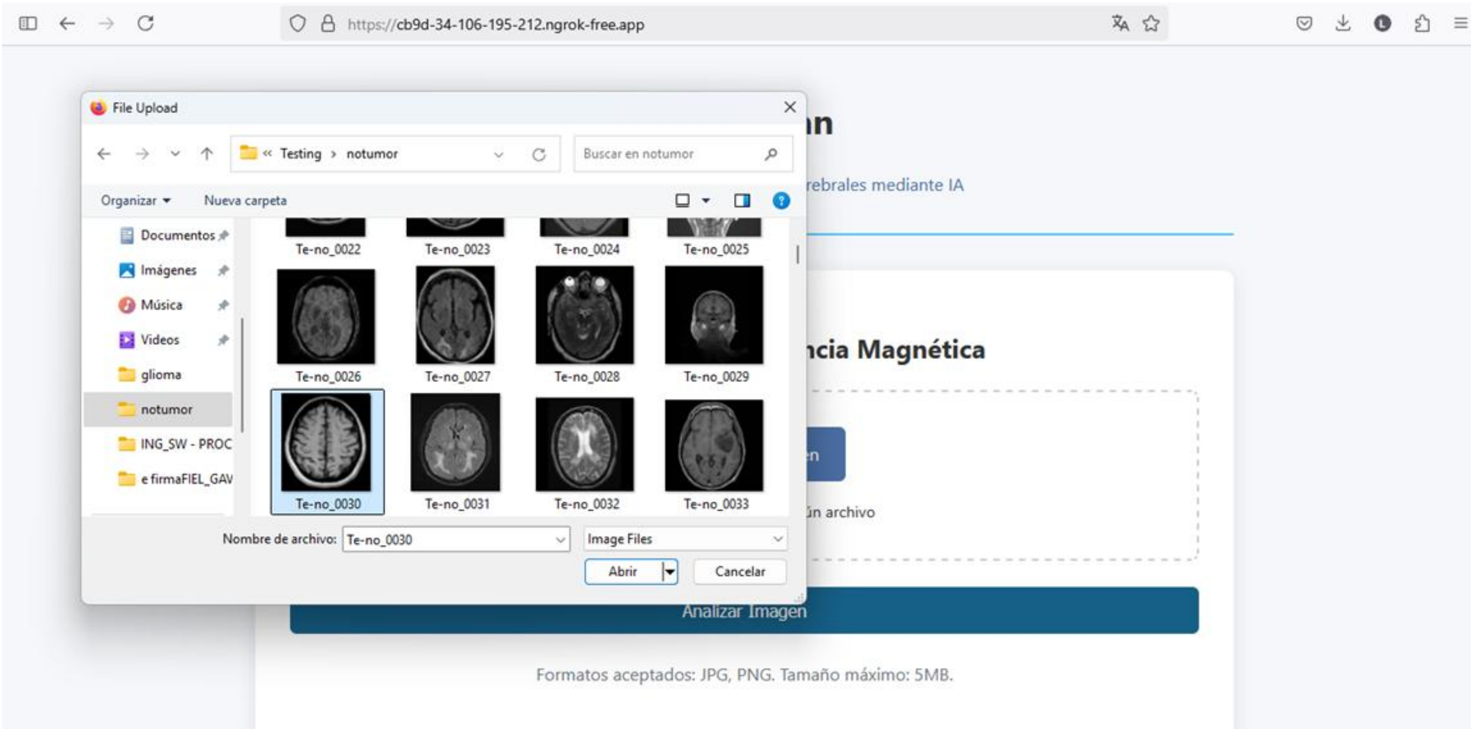

Figure 4: Web interface for uploading MRI images (In Spanish).

3 Results

The developed system demonstrated promising results across all experimental stages, confirming the viability of an ensemble-based, web-accessible glioma detection platform.

3.1 Model Performance

During training, the ensemble model achieved stable convergence after approximately ten epochs. Key training metrics were as follows:

- Training accuracy: 88.7%
- Final training loss: 0.315

The combination of ResNet18, VGG16 and DenseNet121 facilitated diverse feature extraction, addressing MRI variability and tumour heterogeneity (Booth et al., 2020; Chaddad et al., 2019). Ensemble averaging reduced prediction variance and enhanced overall robustness, in line with findings from multimodal MRI applications in glioma classification (Zhang et al., 2016; Zhou et al., 2019).

Table 1. Training Metrics Summary

Metric	**Value**
Training Accuracy	88.7%
Final Training Loss	0.315
Number of Epochs	10
Batch Size	8 (with GPU usage)
Optimiser	AdamW

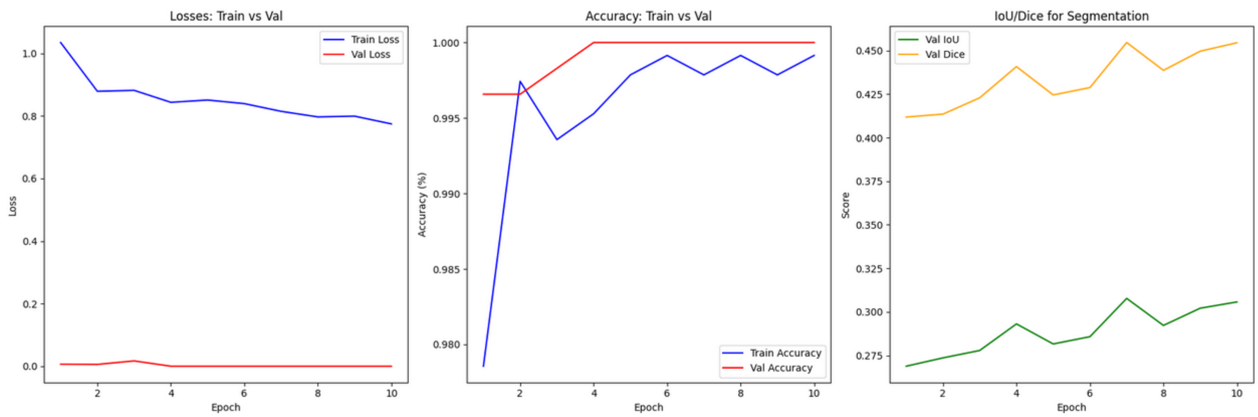

Figure 5: Training loss and accuracy curves.

3.2 Visual Output Analysis

The system produced visual outputs comprising:

- an original MRI scan
- a red segmentation mask overlay delineating the detected tumour area
- a prediction label ('Glioma' or 'No tumour') accompanied by its confidence score

These outputs corresponded with anticipated tumour localisations in the majority of cases, thereby reinforcing the system's interpretability and its potential clinical utility. Similar methodologies employing red overlay masks have been validated in related deep learning segmentation studies (Jiménez-Murillo et al., 2023; Segura et al., 2023).

Figure 6: Example of MRI segmentation output.

The generated segmentation masks aligned correctly with anticipated tumour locations in most test samples. Minor inaccuracies occurred in cases with indistinct lesion borders or very small tumours, indicating room for refinement.

3.3 System Usability and Deployment

The web-based application enabled swift interaction:

- MRI upload and inference time: 5–7 seconds
- a clear results display with heatmap overlays

Accessibility and real-time performance accorded with prior proposals for clinical AI deployment pipelines in neuro-oncology (Rudie et al., 2019; Booth et al., 2020). Testing via Ngrok confirmed remote use without the need for specialised infrastructure.

3.4 Observed Limitations

Observed limitations were as follows:

- image artefacts: some noisy inputs reduced prediction certainty
- K-means segmentation: occasionally mislabelled non-tumour regions due to low contrast
- latency: CPU-based inference introduced minor delays; GPU acceleration is recommended for clinical deployment

Future refinements may include post-processing techniques and segmentation networks such as U-Net (Rojas et al., 2021) or attention-based approaches to enhance anatomical accuracy.

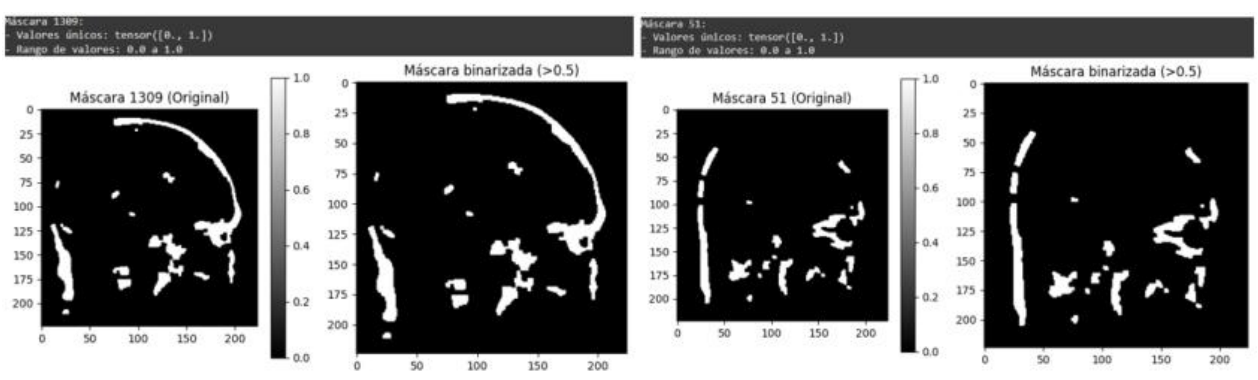

Figure 7: Verification of mask in 0 and 1(In Spanish).

4 Conclusions

This research demonstrates the feasibility and potential impact of integrating deep learning models and web technologies to assist in the early detection of brain gliomas. By leveraging an ensemble approach combining ResNet18, VGG16 and DenseNet121 architectures, the system delivered robust classification performance and reliable segmentation outputs, even when operating under constrained computational resources.

The platform offers several key advantages:

- **Accessibility**: Deployment via a web-based interface obviates the need for complex local installations, enhancing access across diverse clinical settings.
- **Speed**: Predictions and segmentation results are produced within seconds, enabling near real-time clinical support.
- **Usability**: The intuitive front end ensures usability by medical practitioners with minimal technical expertise.

Moreover, the methodology—notably the generation of segmentation masks via unsupervised clustering and ensemble averaging of diverse models—establishes a firm foundation for future refinements.

Nevertheless, several limitations were identified. CPU-based inference marginally increased processing times, and segmentation masks generated by K-means clustering may be improved by employing advanced medical image segmentation techniques, such as U-Net or attention-based models. Additionally, the scarcity of dedicated paediatric MRI datasets curtailed the evaluation of the model's generalisability across all age groups.

In conclusion, this work augments the growing body of evidence endorsing the application of AI and deep learning in neuro-oncology (Segura et al., 2023; Booth et al., 2020; Rudie et al., 2019). It lays the groundwork for further research focussed on enhancing model explainability, optimising computational performance in clinical environments and integrating multimodal data—for example, genetic biomarkers and molecular signatures—to refine diagnostic precision (García-Lezama et al., 2023; Luo et al., 2022; Wood et al., 2019).

Future efforts will concentrate on:

- expanding training datasets to encompass a broader spectrum of paediatric and adult cases
- implementing explainable AI techniques to advance model transparency
- optimising the platform for deployment in hospital environments with varied infrastructural capabilities
- refining segmentation methodologies to achieve greater anatomical accuracy

Ultimately, the system presented here constitutes a significant step towards the clinical deployment of AI-based glioma detection tools, facilitating earlier diagnosis, improving treatment planning and, ultimately, enhancing patient outcomes.

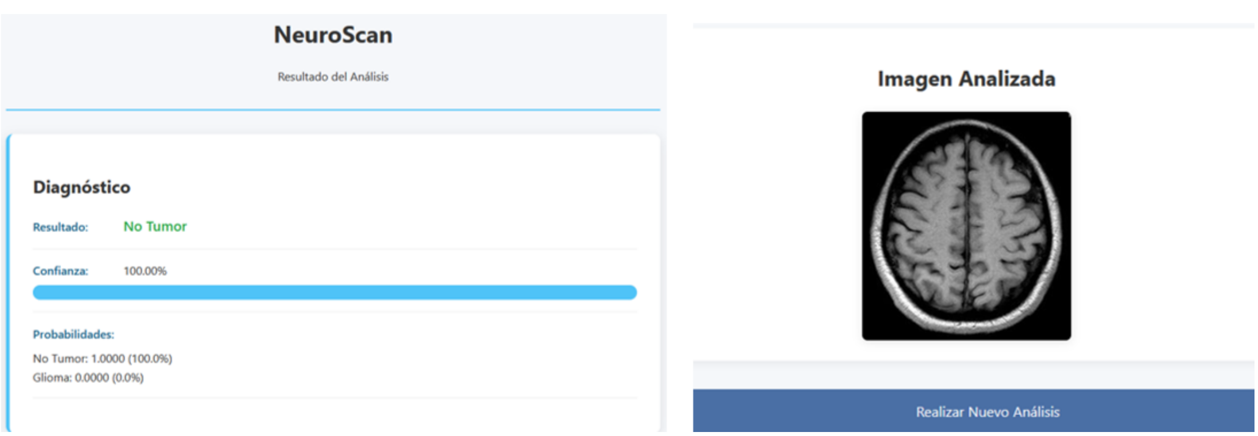

Figure 8: "No Tumor" verification (In Spanish).

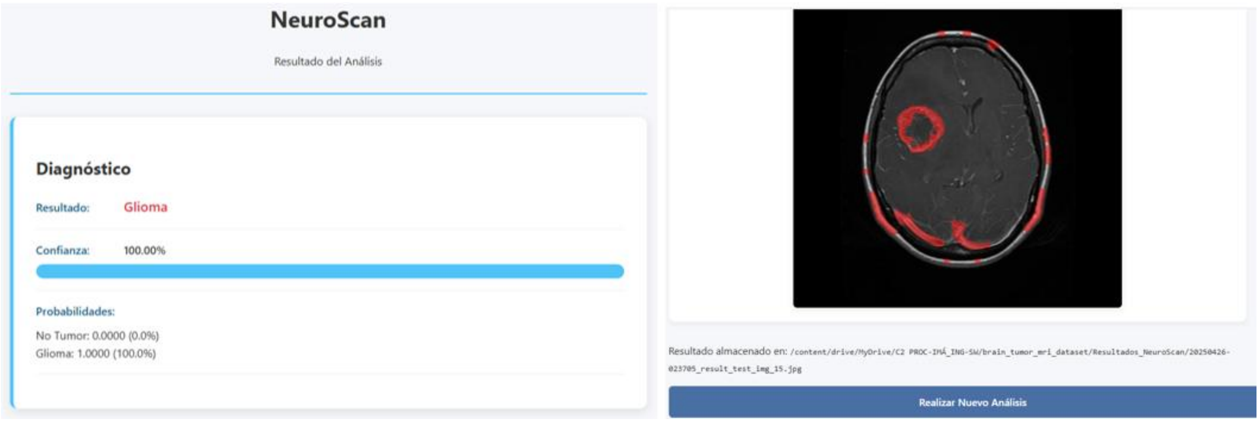

Figure 9: "Tumor" verification (In Spanish).

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