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Original Article

Development of an artificial intelligence-based convolutional neural network for sellar barrier classification using magnetic resonance imaging

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ABSTRACT

Background: This study aims to develop an artificial intelligence (AI) model using convolutional neural networks and transfer learning to classify sellar barriers as strong, mixed, or weak based on magnetic resonance imaging (MRI). Accurate classification is essential for surgical planning in endoscopic endonasal approaches for pituitary adenomas, as variations in the sellar barrier can lead to complications such as cerebrospinal fluid leaks.

Methods: The dataset consisted of 600 MRI images of sellar barriers obtained from coronal sections and evenly distributed among the three classes. The EfficientNetB0 architecture was employed, leveraging transfer learning to optimize performance despite the small dataset. The model was implemented and trained on Google Colab using TensorFlow, with techniques such as dropout and batch normalization to improve generalization and reduce overfitting. Performance metrics included accuracy, recall, and F1-score.

Results: The AI model achieved a classification accuracy of 96.33%, with individual class accuracies of 98% for strong barriers, 95% for mixed barriers, and 96% for weak barriers. These results demonstrate the model's high capacity to accurately classify sellar barriers and identify their specific characteristics, ensuring reliable preoperative assessment.

Conclusion: The proposed AI model significantly enhances the preoperative classification of sellar barriers, contributing to improving surgical planning and reducing complications. While the "black box" nature of AI poses challenges, integrating explainability modules and expanding datasets can further increase clinical trust and applicability. This study underscores the transformative potential of AI in neurosurgical practice, paving the way for precise and reliable diagnostics in managing pituitary lesions.

Keywords: Artificial intelligence, Convolutional neural networks, Medical imaging, Pituitary adenomas, Sellar barrier classification

INTRODUCTION

The endoscopic endonasal approach is one of the most utilized techniques for the resection of pituitary lesions, primarily indicated in patients with endocrinological alterations or neurological deficits.[26] This approach provides direct access to the sellar region, where pituitary macroadenomas often exhibit a vertical growth pattern, displacing and compressing surrounding glandular tissues.[31] The interface formed by the tumor, arachnoid, and the sellar diaphragm is defined as the sellar barrier, whose precise classification into strong, mixed, or weak is essential to prevent surgical complications such as cerebrospinal fluid (CSF) leaks[32,33] [Figures 1-3].

This complication arises due to anatomical variations in the sellar barrier, which may not always provide sufficient resistance to prevent CSF escape during surgical manipulation, regardless of whether the technique used is microscopic, endoscope-assisted, or purely endoscopic.[6,22]

In clinical practice, the classification of the sellar barrier is currently based on the evaluation of magnetic resonance imaging (MRI) and intraoperative observations.[31,32,35] However, anatomical variations and the heterogeneous consistency of tumors can complicate this task. In addition, subjective interpretation and inter-observer variability increase the risk of diagnostic errors, highlighting the need for an automated and precise tool for this process.

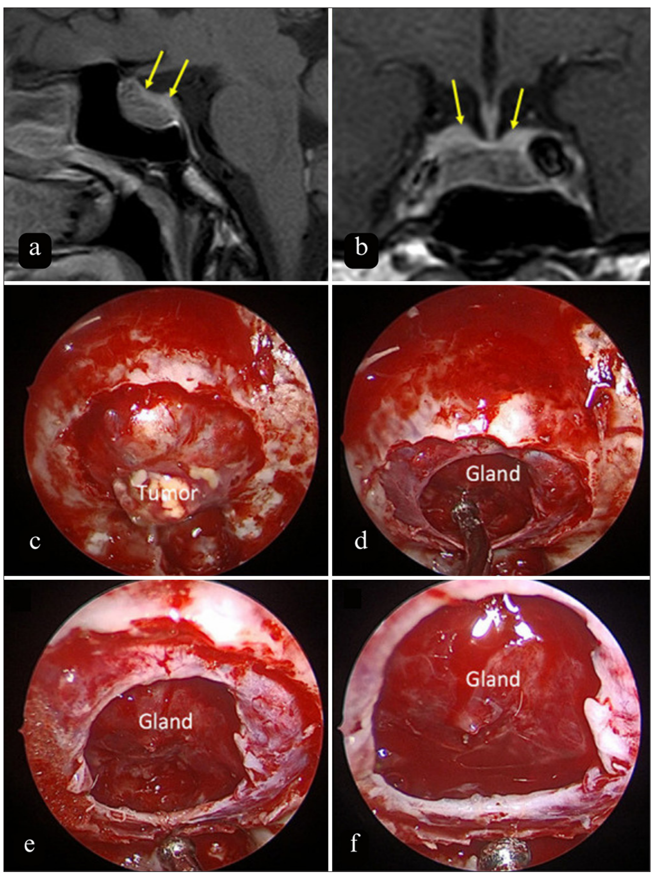

Figure 1: Strong sellar barrier. A 42-year-old male patient with growth hormone produce macroadenoma. (a and b) Preoperative magnetic resonance imaging: the yellow arrows indicate the barrier that captures contrast with a thickness >1 mm. (c-f) Intraoperative images: the barrier constituted by the gland can be seen.

To address these limitations, this study proposes an artificial intelligence (AI) model based on convolutional neural networks (CNNs). Using MRI images and transfer learning techniques, the model automatically classifies sellar barriers into three categories, achieving an accuracy of 97%. This solution aims to optimize the preoperative identification of sellar barriers, contributing to surgical planning and reducing associated complications.[1,3,6,10,14,16,22,29,38]

MATERIALS AND METHODS

Code

The complete code is available for review at the following link. This repository provides full access to the implementation, allowing for in-depth analysis and reproducibility of the methods described in this study:

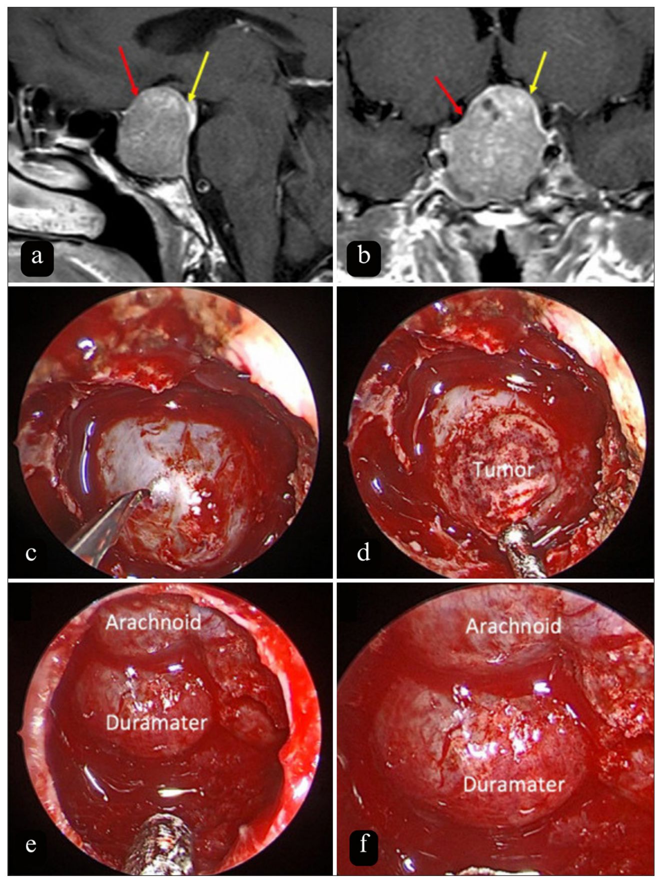

Figure 2: Mixed sellar barrier. A 59-year-old female patient with a PRL produced macroadenoma. (a and b) Preoperative magnetic resonance imaging: the yellow arrows indicate the barrier that captures contrast with a thickness >1 mm, and the red arrows indicate the barrier that captures contrast with a thickness <1 mm. (c-f) Intraoperative images: the barrier constituted by dura mater and arachnoid can be seen. PRL: Prolactin

https://colab.research.google.com/drive/1AyNB1wUoV6IGAZLvhJ4mxCRPCRsZRqBa?usp=drive_link

Dataset

Preoperative MRI scans of patients with pituitary adenomas were used. The MRI scans consisted of coronal sections.

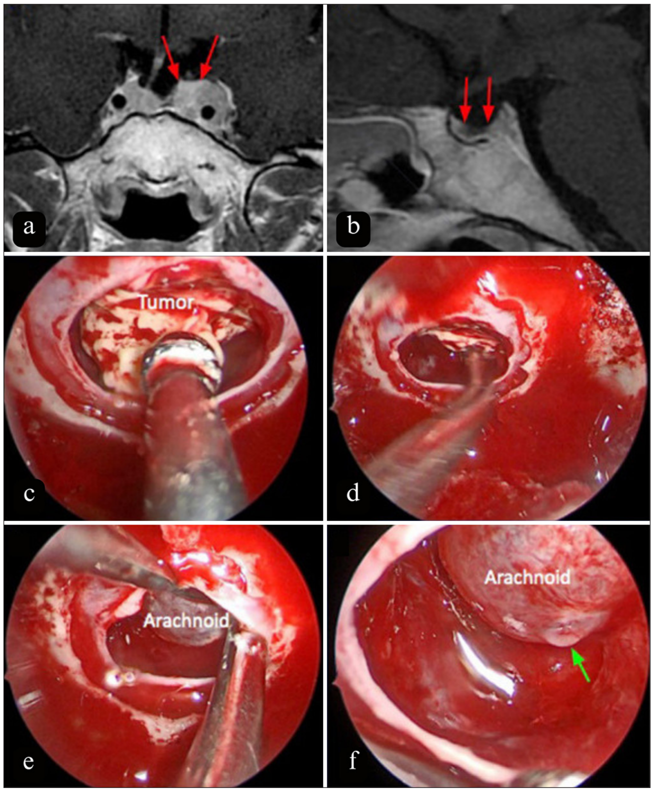

Figure 3: Weak sellar barrier. A 31-year-old female patient with an adrenocorticotropic hormone produced macroadenoma. (a and b) Preoperative magnetic resonance imaging: the red arrows indicate the barrier that captures contrast with a thickness <1 mm. (c-f) Intraoperative images: the barrier constituted only with arachnoid can be seen. The green arrow marks the cerebrospinal fluid leak.

A total of 200 images were included for each type of sellar barrier (strong, mixed, and weak). The images were standardized to a resolution of 150 × 150 pixels to ensure data uniformity. However, the system also supports the upload of images in other resolutions, as the code includes a module for automatic rescaling to the required format, ensuring compatibility and consistency across the dataset [Figure 4].

CNN architecture

CNNs are a type of deep learning model specifically designed for processing structured grid data, such as images. These networks excel automatically and adaptively, learning spatial hierarchies of features, from low-level edges to high-level patterns, directly from raw input data. This capability makes CNNs particularly well-suited for tasks like image classification and medical imaging analysis[2,5,7-9,11-13,17,19-21,24,25,28,30,36,37,39-43] [Figure 5].

In this study, the EfficientNetB0 architecture was employed, given its optimal balance between performance and computational efficiency. EfficientNetB0 utilizes a compound scaling approach that uniformly scales the depth, width, and resolution of the network, resulting in a model that achieves high accuracy with fewer parameters. This architecture was pretrained on the ImageNet dataset, a widely recognized benchmark comprising millions of labeled images across 1,000 categories, providing a robust starting point for transfer learning.

To adapt EfficientNetB0 for this study's specific task of classifying sellar barrier types, the top layer of the network – originally designed for 1,000-class classification – was replaced with a fully connected dense layer. This layer includes a SoftMax activation function, which outputs a probability distribution over the predefined categories (strong, mixed, and weak sellar barriers). The replacement process involves fine-tuning the pretrained weights while retraining the final layer to specialize the

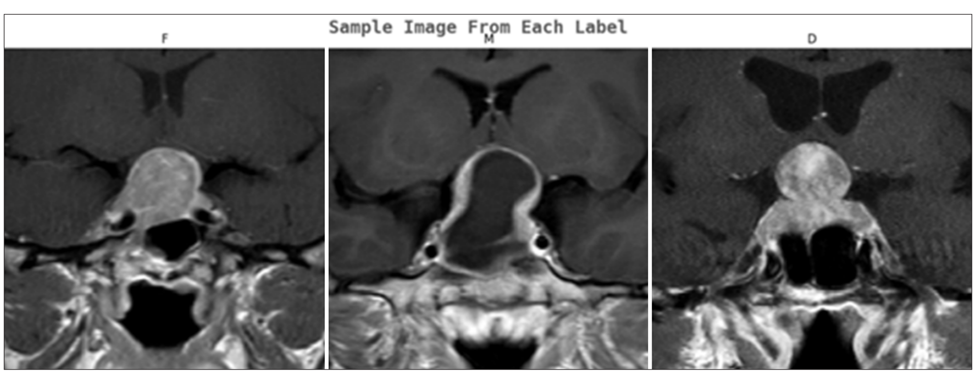

Figure 4: Samples from each category in Google Colab, with the corresponding rescaled coronal magnetic resonance imaging images. Labels are F (Strong), M (Mixed), and D (Weak).

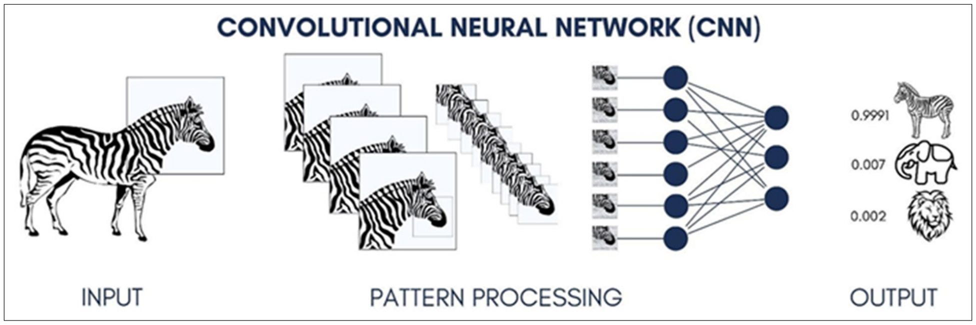

Figure 5: Labeled datasets are provided, such as 1,000 images of zebras, 1,000 of lions, and 1,000 of elephants. During training, the network learns to recognize key features that define each category. Once trained, the system can accurately identify an entirely new and different image (one it has never seen before) based solely on the features it has learned. This process is similar to human learning: after observing various examples of tables, we can identify a table we've never encountered, even if it differs in size, shape, or design. Similarly, a convolutional neural network processes millions of parameters (over 4 million in this case) to make precise decisions in just milliseconds.

model for the sellar barrier classification task, leveraging the previously learned hierarchical features from ImageNet.

- Key Layers
  - Convolutional layers: Extract local patterns from the images, such as edges, textures, and shapes, using filters that traverse the image. These layers are essential for identifying specific and relevant structures in the visual data.
  - Batch normalization layers: Regulate activations in intermediate layers by normalizing the values, reducing oscillations during training, and enabling faster and more stable convergence
  - Dropout layers: Randomly deactivate a percentage of neurons during training, forcing the model to learn more generalizable features and reducing excessive dependence on specific patterns, thereby minimizing the risk of overfitting.

Transfer learning

Transfer learning is a powerful technique in deep learning where a model pretrained on a large dataset is adapted to perform a related but distinct task. This process capitalizes on the knowledge encoded in the pretrained model's layers, especially its ability to extract generic features such as edges, textures, and patterns from images, applying it to new data with minimal retraining[4,18,27] [Figure 6].

In this study, this approach enabled excellent results, even with a small dataset. Training a model from scratch with only 600 images, as in this case, would have yielded suboptimal performance due to insufficient data for learning complex patterns. However, using a pretrained model trained on thousands of images and fine-tuning these 600 images not only drastically reduced training time and resource consumption but also significantly improved performance.

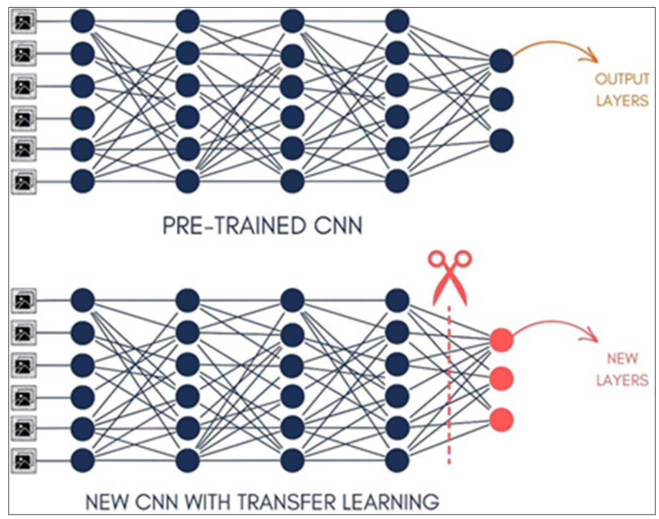

Figure 6: Transfer Learning is a technique where a pre-trained Convolutional Neural Network (CNN), which has already learned to recognize general features from a large dataset, is reused for a new task. As shown in the image, the initial layers (in dark blue) are kept because they capture basic features like edges and shapes. Then, the final layers (indicated by the orange arrow) are replaced with new layers (highlighted in red), which are trained on a smaller, task-specific dataset. This approach saves time, requires less data, and still achieves high performance.

The lower layers of the EfficientNetB0 architecture, which specialize in capturing fundamental visual features, were frozen to retain their pretrained weights obtained from the ImageNet dataset. This allowed the model to leverage pre-learned representations, minimizing the data and computational resources required for training. The upper layers were replaced and retrained using images of the sellar barrier, fine-tuning the model to identify critical characteristics such as barrier thickness, irregularities, and contrast differences. This process involved optimizing weights in the newly added layers to enable accurate classification into the categories of strong, mixed, or weak sellar barriers.

The model processes over 4 million parameters per image, enabling it to capture complex anatomical nuances critical for high-precision classification. By leveraging transfer learning, this study achieved a substantial reduction in training time while maintaining robust performance, even with limited data. This strategy ensured that the pretrained model's generalization capabilities were effectively adapted to the specific task of sellar barrier analysis [Figure 7].

Implementation

The programming and training were conducted on Google Colab, a cloud-based platform that allows users to write and execute Python code in a notebook environment. Google Colab is particularly suitable for deep learning tasks, as it provides free access to graphics processing unit (GPUs) and tensor processing unit (TPU), significantly accelerating processing.

The main libraries used included:

- TensorFlow: Utilized for building, training, and deploying deep learning models, offering advanced tools for CNNs

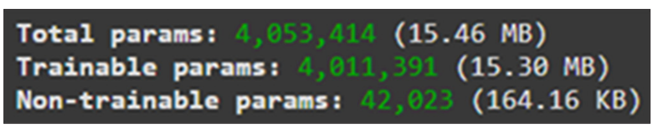

Figure 7: Architecture parameters directly extracted from the Google Colab programming environment using the function "model.summary()".

- NumPy: Essential for numerical calculations, matrix management, and structured data manipulation
- Pandas: Used for organizing, analyzing, and cleaning data, facilitating dataset preparation for the model
- Matplotlib: Used for visualizing data and training results, such as loss curves and accuracy metrics, to monitor the model's performance during training
- Scikit-learn: Provided tools for preprocessing data, splitting datasets, and evaluating model performance with metrics such as precision, recall, and F1 score
- OpenCV: Assisted in image preprocessing tasks such as resizing, normalization, and augmentation to enhance the robustness of the model.

RESULTS

The model was trained and evaluated over 20 epochs to optimize learning. In deep learning, an epoch refers to one complete pass through the entire training dataset by the model. Multiple epochs are typically used to refine the model's performance as it iteratively adjusts its internal parameters to minimize error. In this study, the core of the pretrained EfficientNetB0 architecture, which contains the convolutional layers responsible for extracting fundamental visual features, was left unaltered. Only the final dense layers were retrained, allowing the model to specialize in classifying sellar barrier types. This approach drastically reduced training time and computational resources while retaining the rich feature representations learned from the large ImageNet dataset [Figure 8].

Twenty epochs provided sufficient iterations to achieve convergence without overfitting, balancing computational efficiency and learning quality.

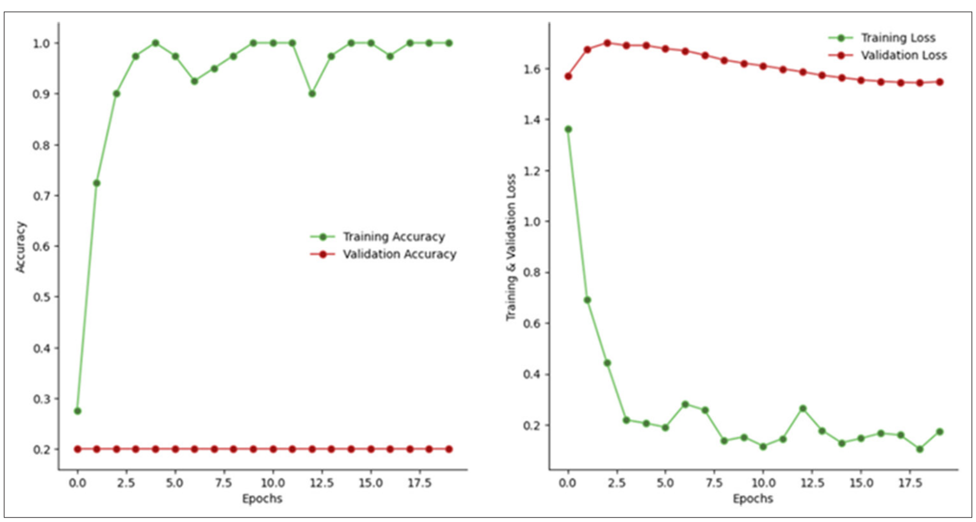

Figure 8: The graph shows the relationship between epochs and the model's performance. Accuracy represents the correctness of predictions, while loss indicates the prediction error. Training metrics reflect how well the model fits the training data, while validation metrics assess its generalization on unseen data.

Table 1: The table presents the numerical data corresponding to the text above, including class, accuracy, recall, and F1-score.

Class	Accuracy	Recall	F1-Score
Strong	98.0	97.0	98.0
Mixed	95.0	94.0	94.0
Weak	96.0	96.0	96.0
Macro average	96.33	95.67	96.0

In this context, accuracy measures the percentage of correct predictions among all made, while recall reflects the proportion of correctly identified positive cases among all real positive cases, representing the model's sensitivity to detect all relevant instances. The F1-score combines both metrics, providing a harmonic meaning that is especially useful in scenarios with imbalanced data.

The model achieved an overall accuracy of 96.33%. In detailed class analysis, strong barriers reached 98% accuracy, 97% recall, and a 98% F1-score. Mixed barriers achieved 95% accuracy, 94% recall, and a 94% F1-score, while weak barriers obtained 96% accuracy, 96% recall, and a 96% F1-score. These results demonstrate the model's high capacity to accurately identify and differentiate the specific characteristics of each type of sellar barrier, even in complex clinical scenarios [Table 1].

DISCUSSION

The sellar barrier is an important parameter to consider in the assessment of the risk of intraoperative CSF leakage. A prospective cohort study that included 155 cases of patients with supradiaphragmatic pituitary adenomas operated through an endoscopic approach demonstrated the correlation between the type of sellar barrier in MRI, and its *in vivo* characteristics observed during surgery, also detecting the differences between patients who developed an intraoperative CSF leak and those who did not.[34]

In this context, which validates the concept of the sellar barrier as a predictor of intraoperative CSF leakage, it motivates the creation of predictive models with the help of radiomics, which converts images into exploitable data to be subsequently analyzed for decision-making based on AI that includes algorithms capable of modeling themselves and improving accuracy through the analysis of data sets.[15,23]

The results obtained demonstrate the exceptional capability of the CNN model in accurately classifying sellar barriers in MRI images, even with a limited dataset. This success is primarily due to the transfer learning approach, which makes it possible to harness the knowledge embedded in pretrained models to address challenges associated with small datasets. In addition, techniques like dropout significantly reduced the risk of overfitting, enhancing the model's ability to generalize effectively to unseen data.

The findings of this study underscore the potential of CNNs and transfer learning in addressing critical challenges in medical imaging and surgical planning. By achieving a classification accuracy of 97% for sellar barriers, the proposed model demonstrates its capacity to enhance preoperative diagnostics and mitigate complications, such as CSF leaks, in endoscopic endonasal approaches for pituitary adenomas.

This precise classification of sellar barriers carries critical clinical implications. By offering surgeons detailed predictions about the likelihood of CSF leaks, the model supports more informed surgical planning and facilitates the selection of appropriate reconstruction strategies. Such predictive power has the potential to improve surgical outcomes and reduce postoperative complications.

However, a notable concern among clinicians remains the "black box" nature of AI systems. This model, for example, operates using over 4 million parameters, making it nearly impossible to articulate its decision-making process transparently fully. While this complexity is fundamental to achieving high precision, it also creates challenges in building trust among medical professionals. To mitigate these concerns, the integration of an explainability module could be invaluable. Such a system would highlight the primary factors influencing the model's decisions, offering clinicians a clearer understanding of its rationale and thereby fostering greater confidence in its outputs.

Expanding the dataset used for training is another avenue for improvement. By incorporating a broader and more diverse range of anatomical variations, the model's robustness and generalizability could be further enhanced. This would not only increase its reliability across different clinical scenarios but also solidify its utility in real-world applications.

It is essential to emphasize that these AI systems are not intended to replace medical professionals. Instead, it will be the physicians who adopt and leverage these technologies who will replace those who do not. Furthermore, technology is an unstoppable force; resisting its adoption not only delays progress but often works against those who oppose it, highlighting the importance of embracing innovation for collective advancement.

Despite the challenges related to system opacity, the demonstrated ability of this model to deliver high-precision classification with minimal data and computational demands underscores its transformative potential in modern neurosurgery. Continued efforts to validate and refine such models in practical clinical environments will be crucial to ensuring their widespread adoption and their role in addressing complex surgical challenges.

Limitations

However, the study also highlights challenges, such as the “black box” nature of AI models, which can hinder clinician trust. Future work should focus on incorporating explainability modules to elucidate the decision-making processes of these models. Expanding the dataset to include diverse anatomical variations will further enhance the model’s generalizability and clinical applicability.

CONCLUSION

The use of the EfficientNetB0 architecture, coupled with transfer learning, proved effective in overcoming the constraints of small datasets. This approach maximizes performance while maintaining computational efficiency. Moreover, the high accuracy and precision across all barrier categories highlight the model’s robustness and its ability to generalize well to new data.

The clinical implications of this work are significant. Providing surgeons with reliable predictions about the integrity of the sellar barrier equips them to make informed decisions, optimizing surgical outcomes and patient safety. In addition, this methodology offers a pathway to integrate AI-powered tools seamlessly into clinical workflows, improving diagnostic accuracy and reducing variability.

The proposed AI model represents a promising step toward the integration of advanced machine learning techniques in neurosurgical practice, paving the way for more precise, reliable, and patient-centered approaches to managing pituitary lesions.

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Conflicts of interest: There are no conflicts of interest.
Use of artificial intelligence (AI)-assisted technology for manuscript preparation: The authors confirm that there was no use of artificial intelligence (AI)-assisted technology for assisting in the writing or editing of the manuscript and no images were manipulated using AI.

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