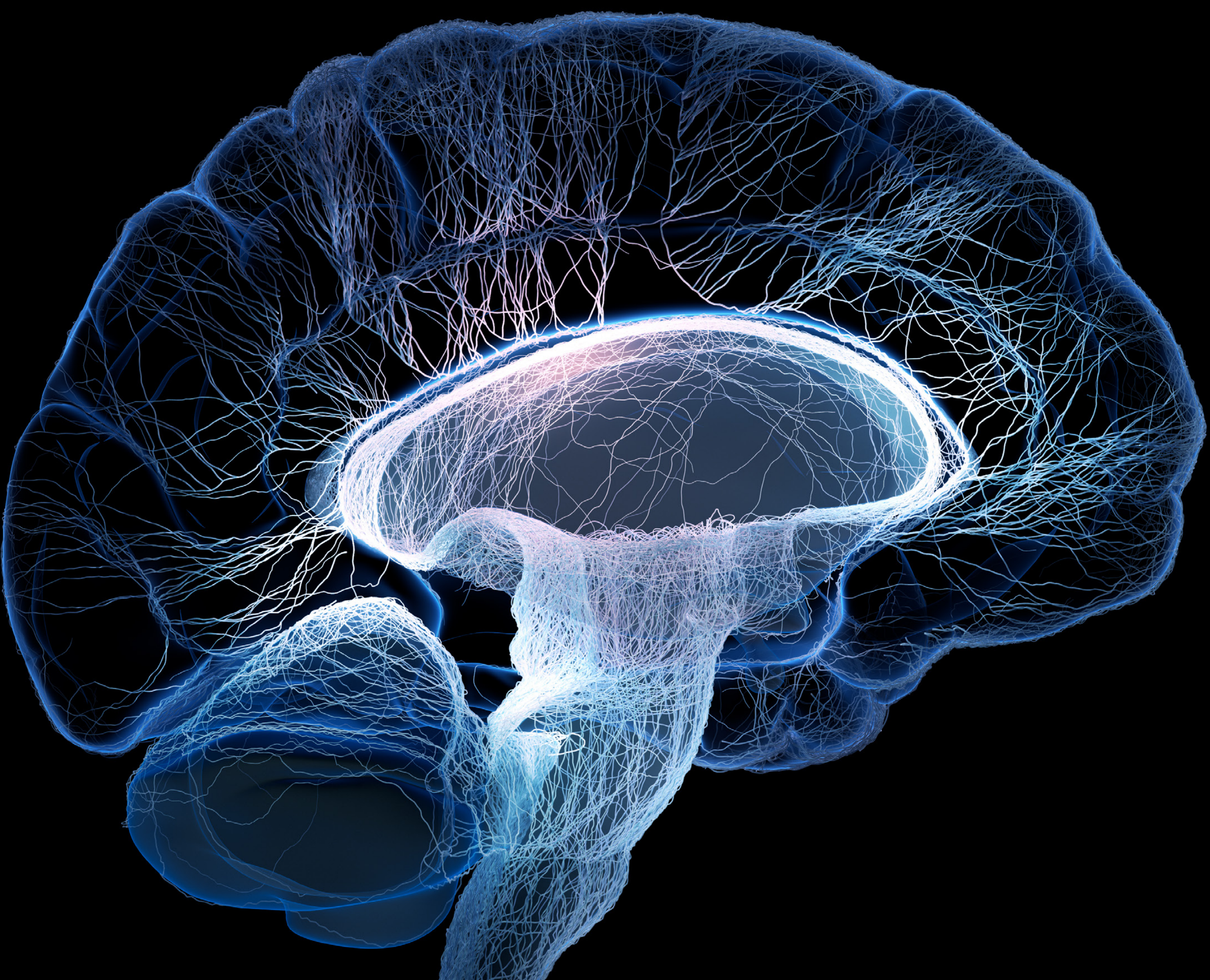
mlangles Predictive AI

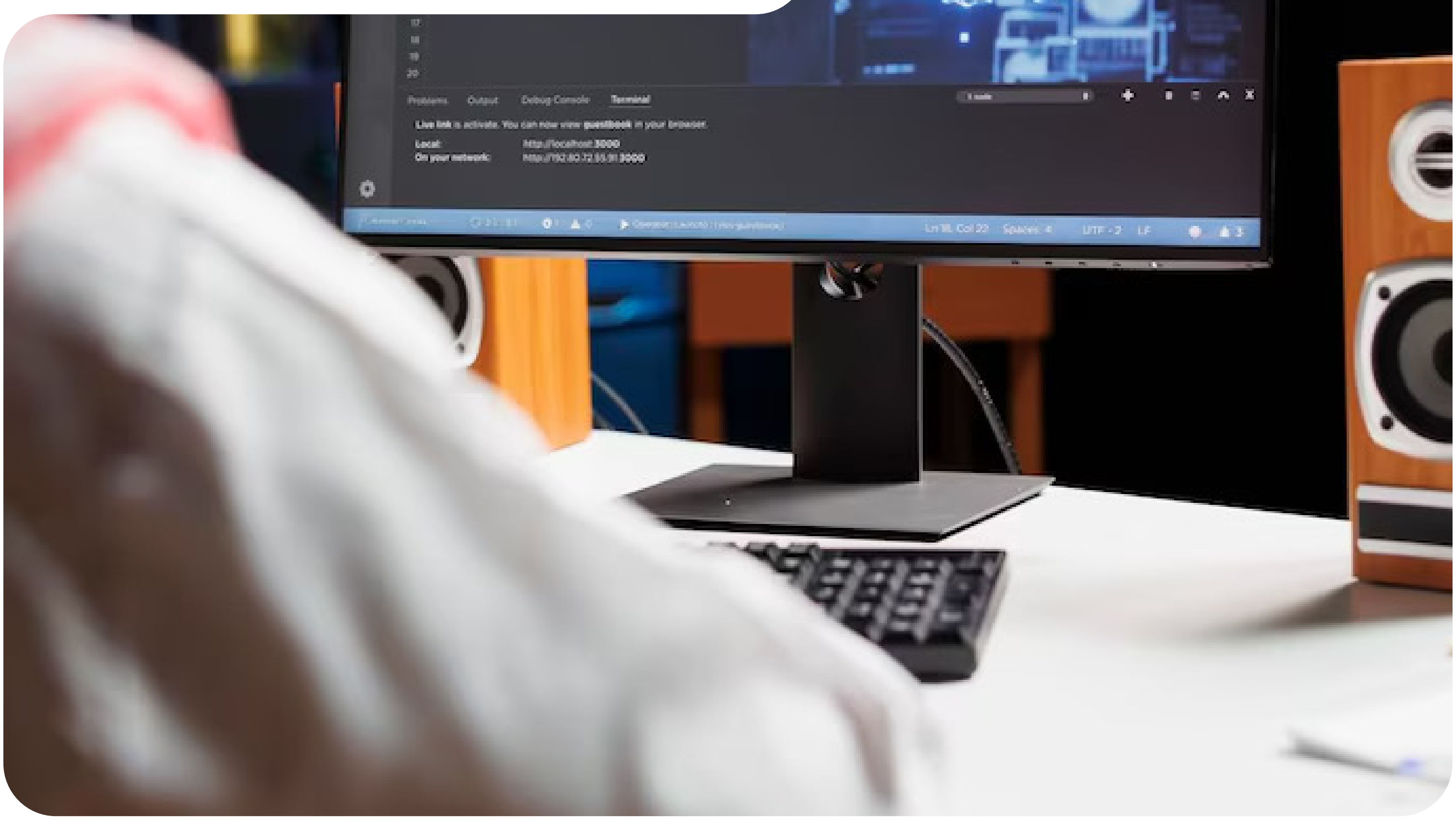
Brain Tumor Classification



About mlangles Predictive AI

mlangles is a comprehensive AI platform designed to manage the lifecycle of data and models, offering streamlined solutions for every stage of the process.

Through its MLOps component, mlangles provides a suite of tools to navigate efficiently through each phase of AI project development, encompassing data engineering, development, deployment, and monitoring. It facilitates continuous integration, continuous deployment,continuous training, continuous monitoring (CI-CD-CT-CM), enabling enterprises to effectively manage their AI initiatives.

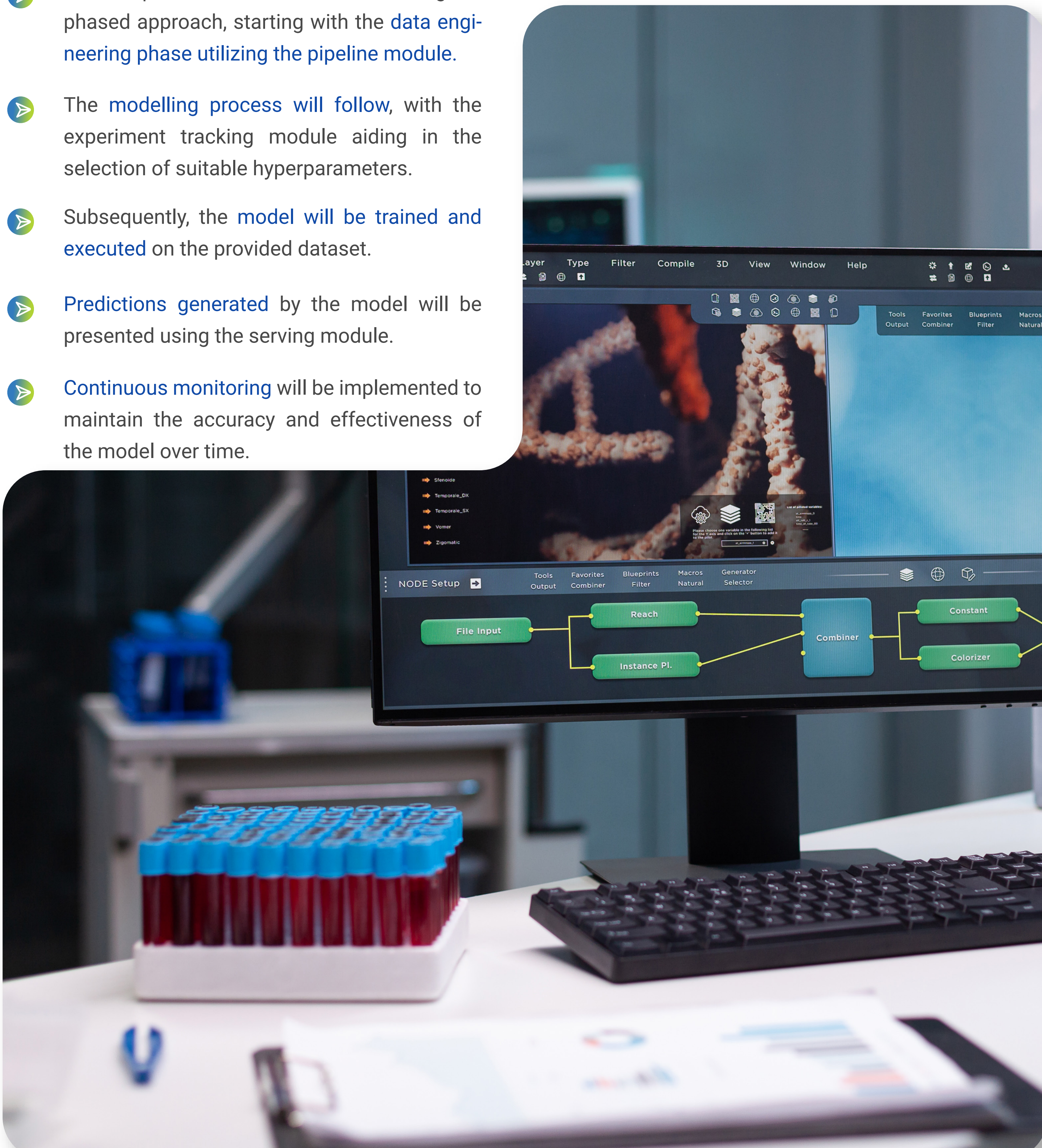


Objective of the use case:

To develop a deep learning model capable of accurately predicting the presence and types of brain tumors from MRI images, with the goal of assisting healthcare professionals in early diagnosis and treatment planning.

working of the use case

- The AI problem will be tackled through a phased approach, starting with the data engineering phase utilizing the pipeline module.
- The modelling process will follow, with the experiment tracking module aiding in the selection of suitable hyperparameters.
- Subsequently, the model will be trained and executed on the provided dataset.
- Predictions generated by the model will be presented using the serving module.
- Continuous monitoring will be implemented to maintain the accuracy and effectiveness of the model over time.



Explanation of the use case

Brain tumor is one of the aggressive diseases affecting children and adults, constituting most primary Central Nervous System (CNS) tumors. Each year, approximately 11,700 individuals receive a brain tumor diagnosis, with a 5-year survival rate of around 34% for men and 36% for women with cancerous brain or CNS tumors. These tumors are categorized into types such as benign, malignant, and pituitary tumors. Effective treatment planning and accurate diagnostics are crucial for improving patient life expectancy.

Magnetic Resonance Imaging (MRI) is the preferred technique for detecting brain tumors, generating substantial image data for examination by radiologists. However, manual examination of these images is prone to errors due to the complexities involved in brain tumors and their characteristics. Automated classification techniques utilizing Machine Learning (ML) and Artificial Intelligence (AI) have consistently demonstrated higher accuracy rates compared to manual classification methods. Therefore, the development of a system utilizing Deep Learning techniques such as Transfer Learning (TL) holds promise in aiding doctors worldwide by automating the detection and classification of brain tumors.

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The dataset obtained in kaggle for the use case consists of about 100 images (in jpg format) from each of the 3 categories of tumors which are glioma, meningioma, pituitory along with similar number of images of the brain with no tumors.

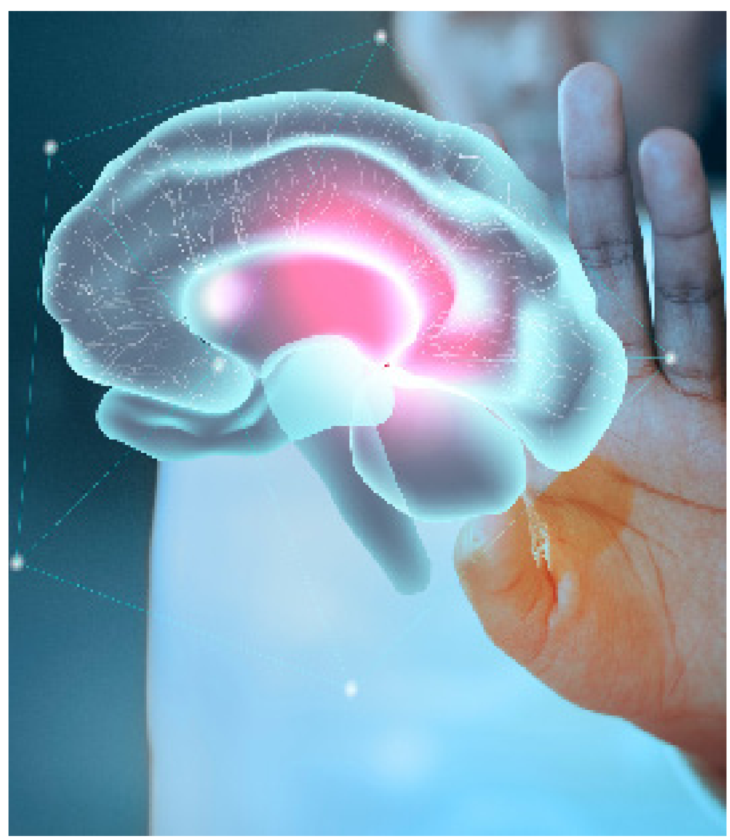
Step 1: Data Engineering & pipeline creation

Install Dependencies: The required packages and libraries are installed.

Data Extraction: The data is loaded from the source (in this case the source is s3 bucket).

Data Visualization: One sample image from each of the 3 types of tumors which are glioma, meningioma, pituitory are displayed along with a sample image with no tumor.

Data Transformation: A series of image transformations is performed on the input images. These transformations include resizing the image to 256x256 pixels, cropping the center to 224x224 pixels, converting the image to a PyTorch tensor, and normalizing the image with predefined mean and standard deviation values. The transformed images are used to create the dataset which is stored to perform the training tumor.

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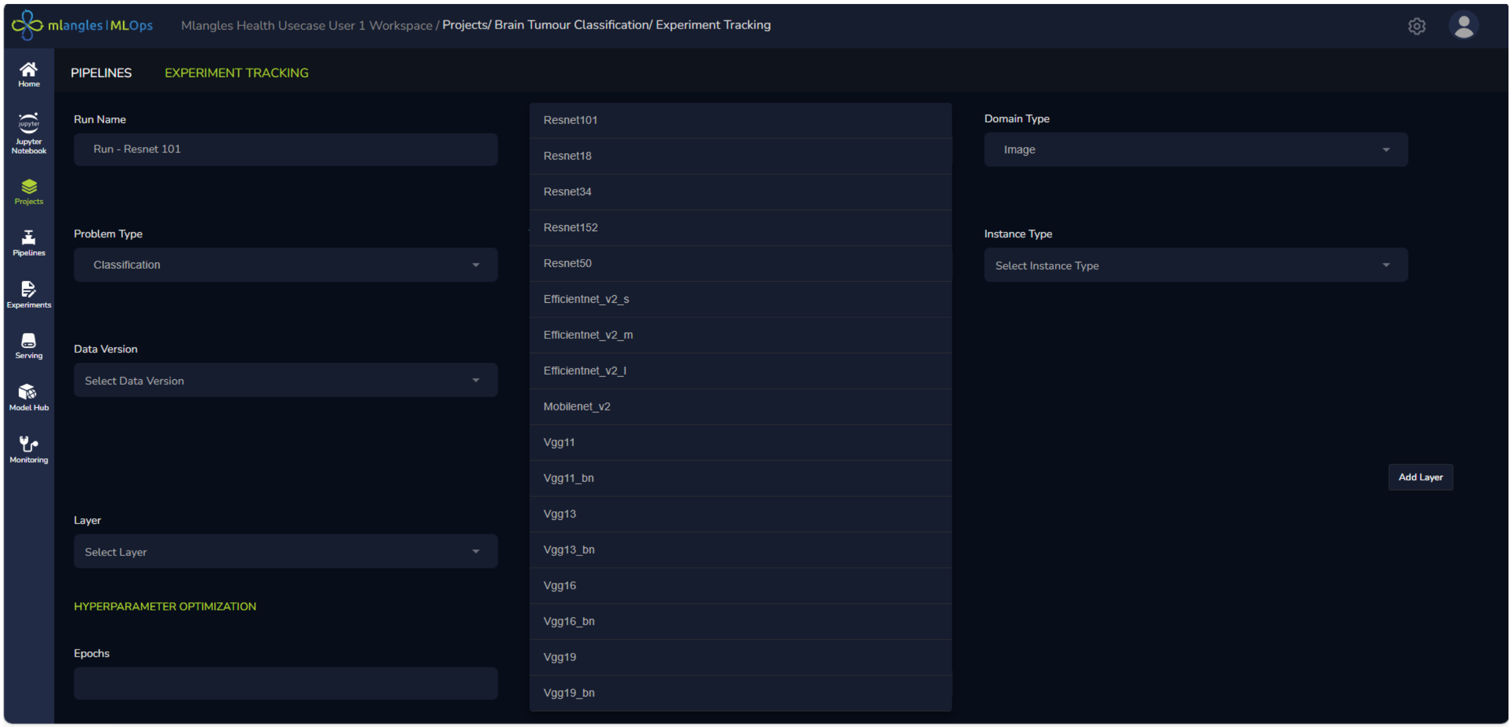
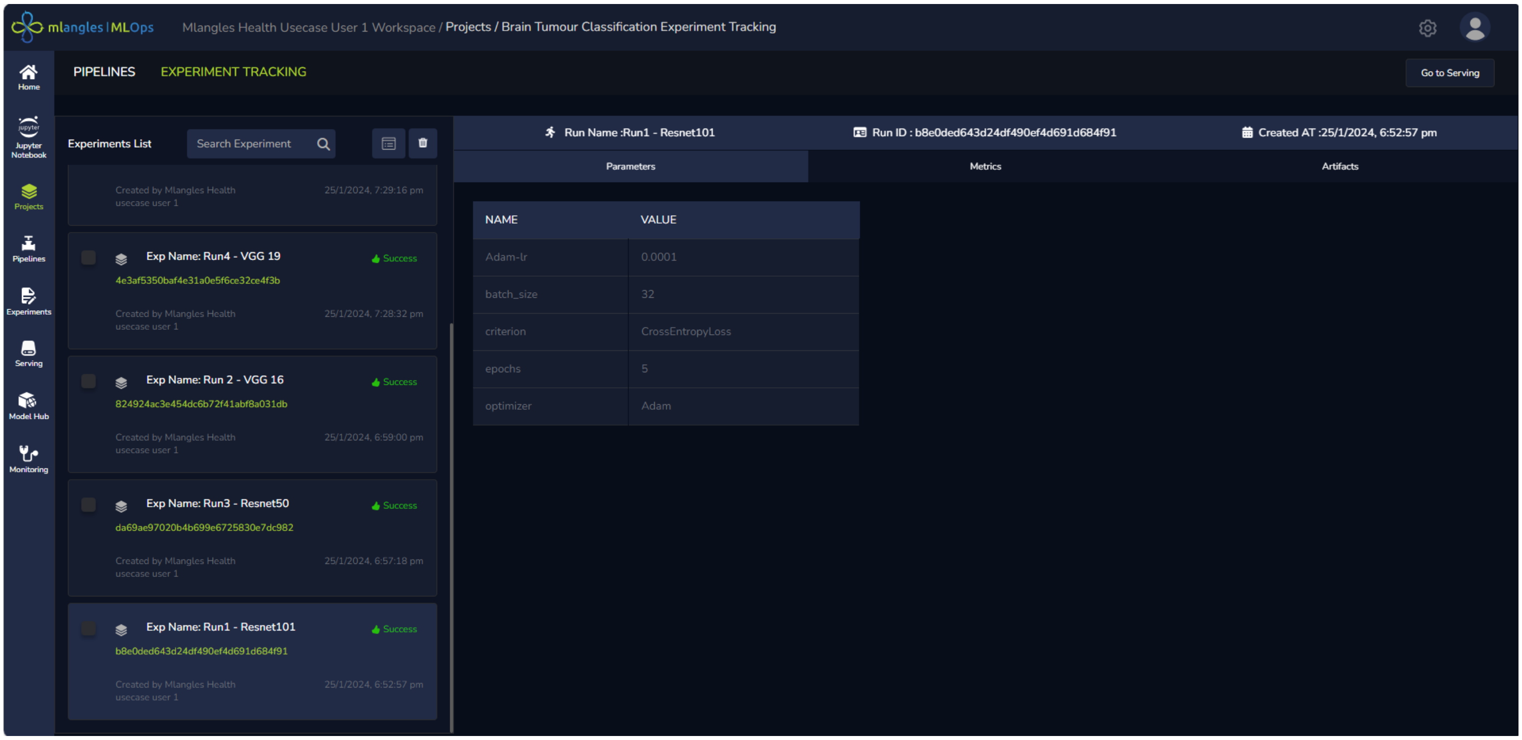
meningioma_tumor
no_tumor
pituitary_tumor

Step 2: Experiment Tracking - Modelling



Once the dataset is created from the pipelines, it is then used to finetune any of the various pretrained models such as ResNet, VGG, Efficient Net. The idea of using pretrained models involves utilizing knowledge gained from training a model on one task to improve performance on a different but related task. In the context of using pretrained models for predicting tumors, transfer learning entails taking a model that has been pre-trained on a large dataset (such as ResNet, pretrained on ImageNet), and fine-tuning it on a smaller dataset containing images of brain scans with four classes: glioma, pituitary, meningioma, and no tumor. By leveraging the features learned during the initial training on ImageNet, the model can quickly adapt to the new.

task of tumor classification, potentially achieving higher accuracy and efficiency compared to training from scratch. This approach reduces the need for extensive labeled data and computational resources, making it a powerful technique for medical image analysis tasks. Once the model is fine-tuned, the parameters used to finetune, the results of fine-tuning are displayed in the form of parameters, metrics and artifacts respectively.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Search Experiment
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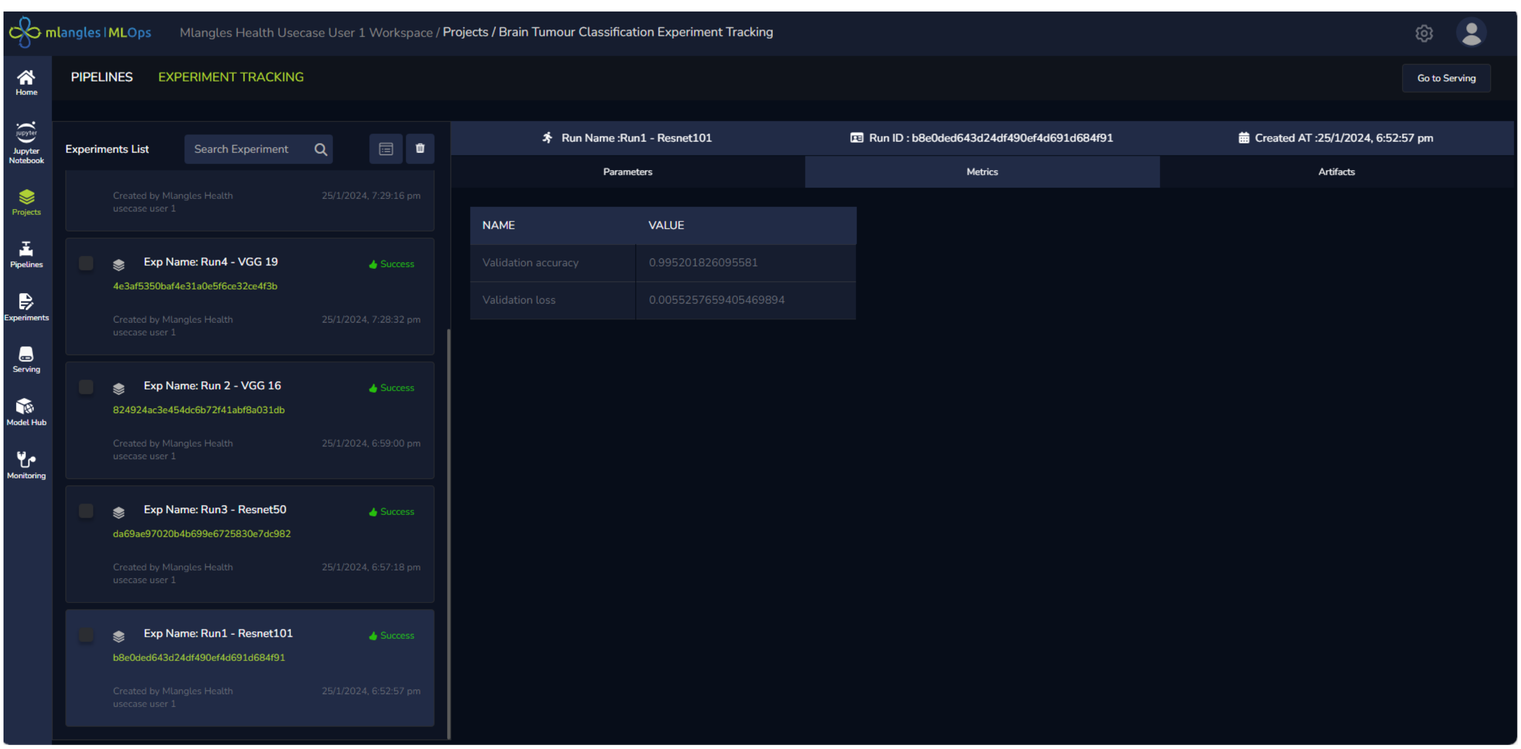
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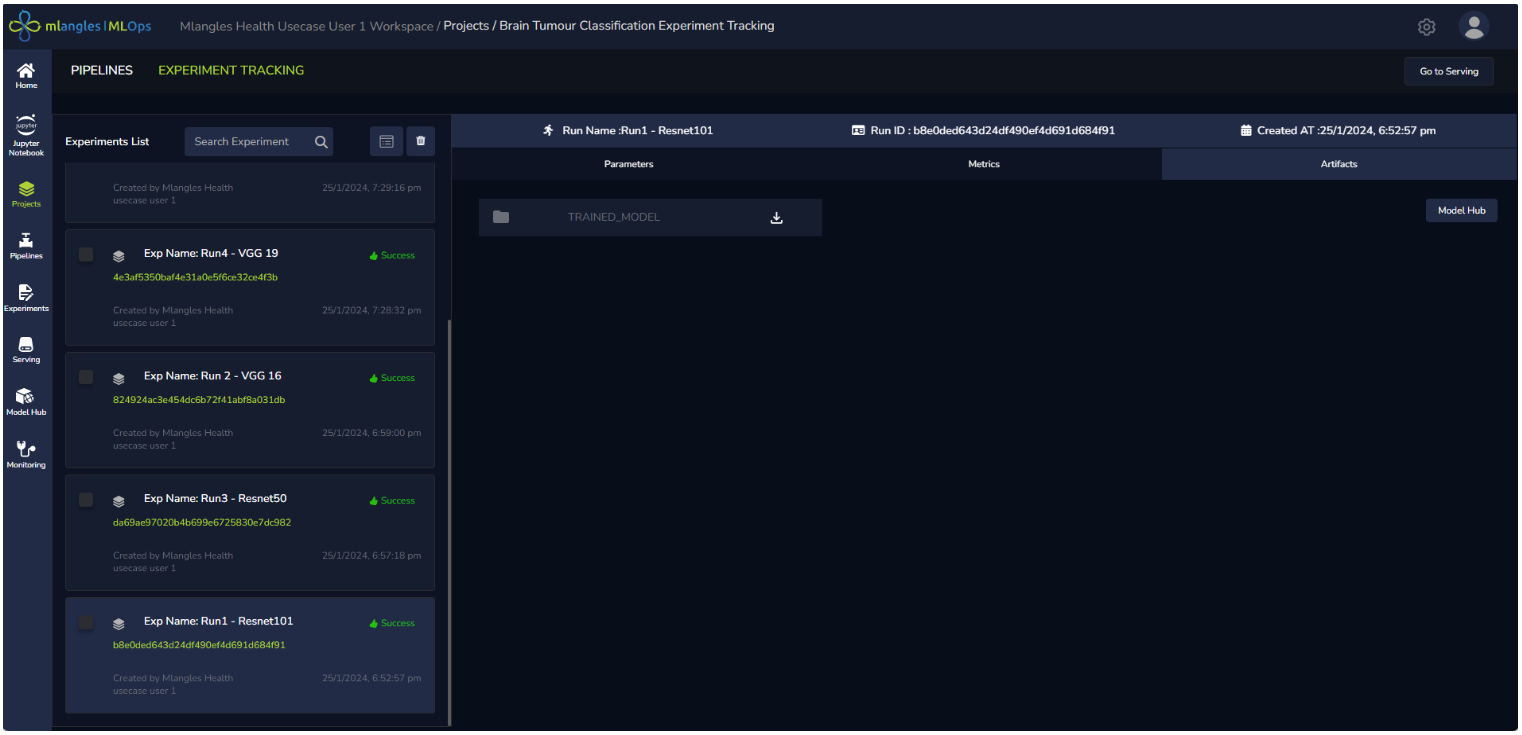
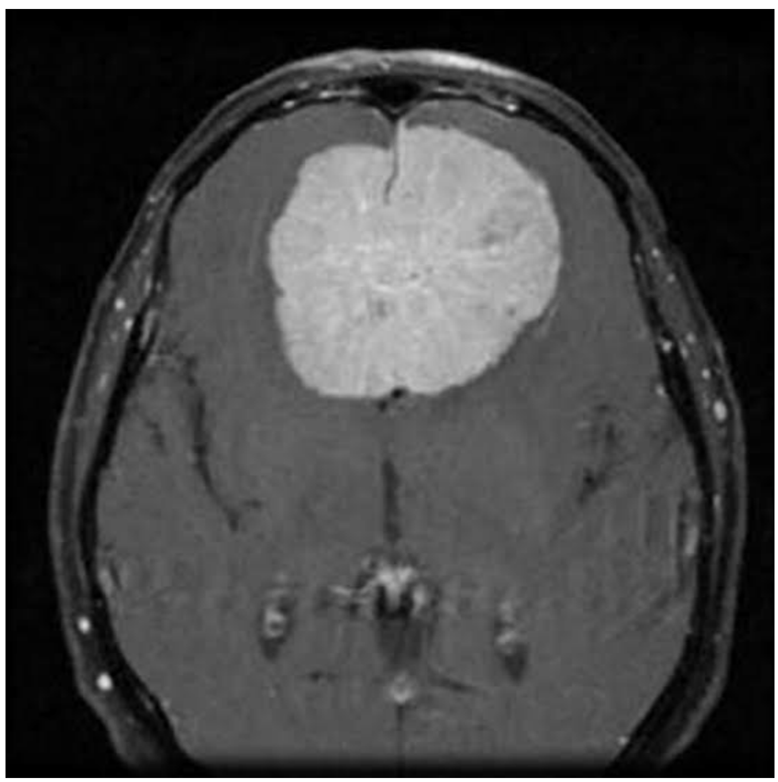
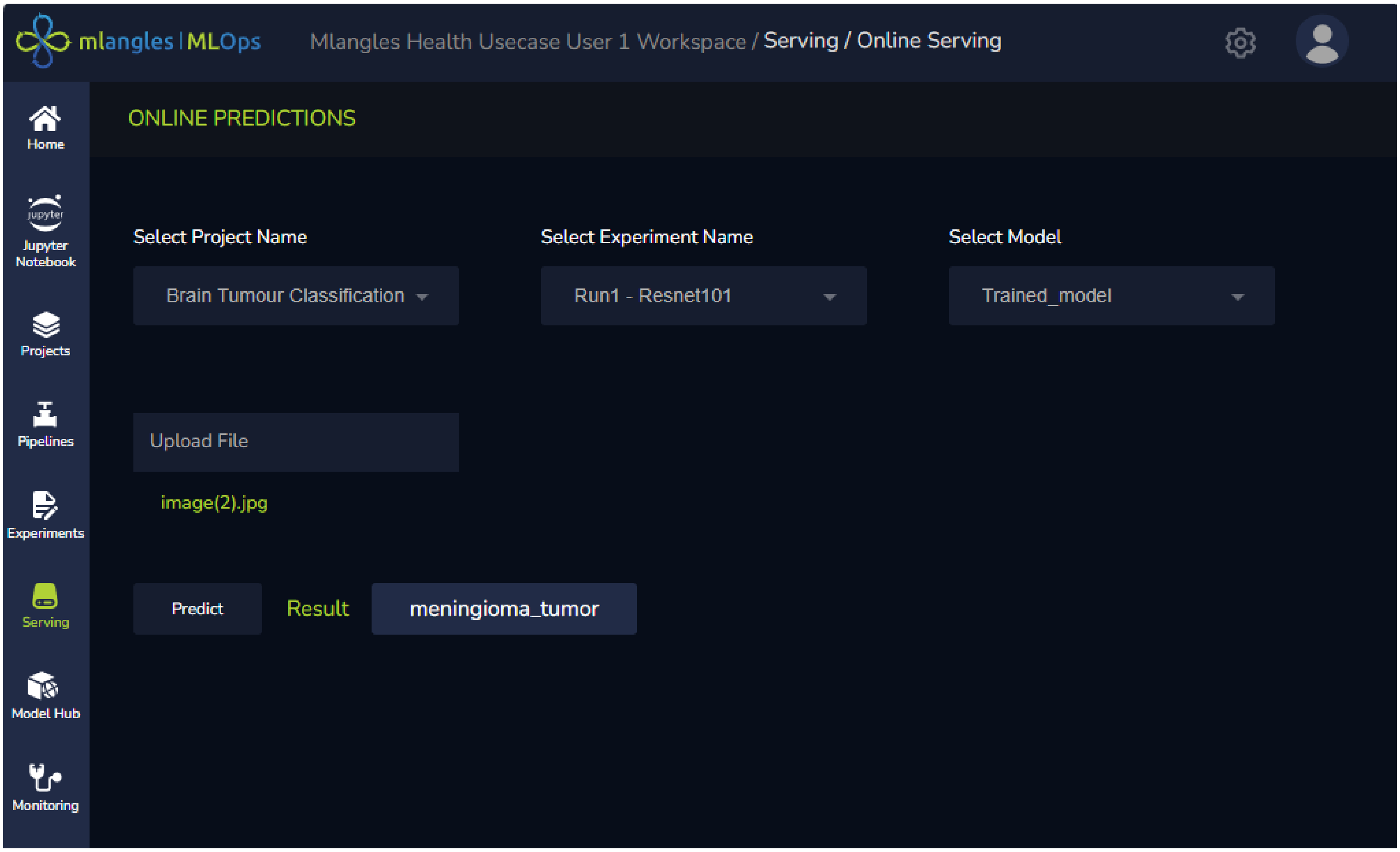


Step 3: Prediction/ Serving

The side image is an MRI image of brain having meningioma tumor and is provided to the trained model. It accurately identifies the presence and type of the tumor and the result is displayed on the screen.

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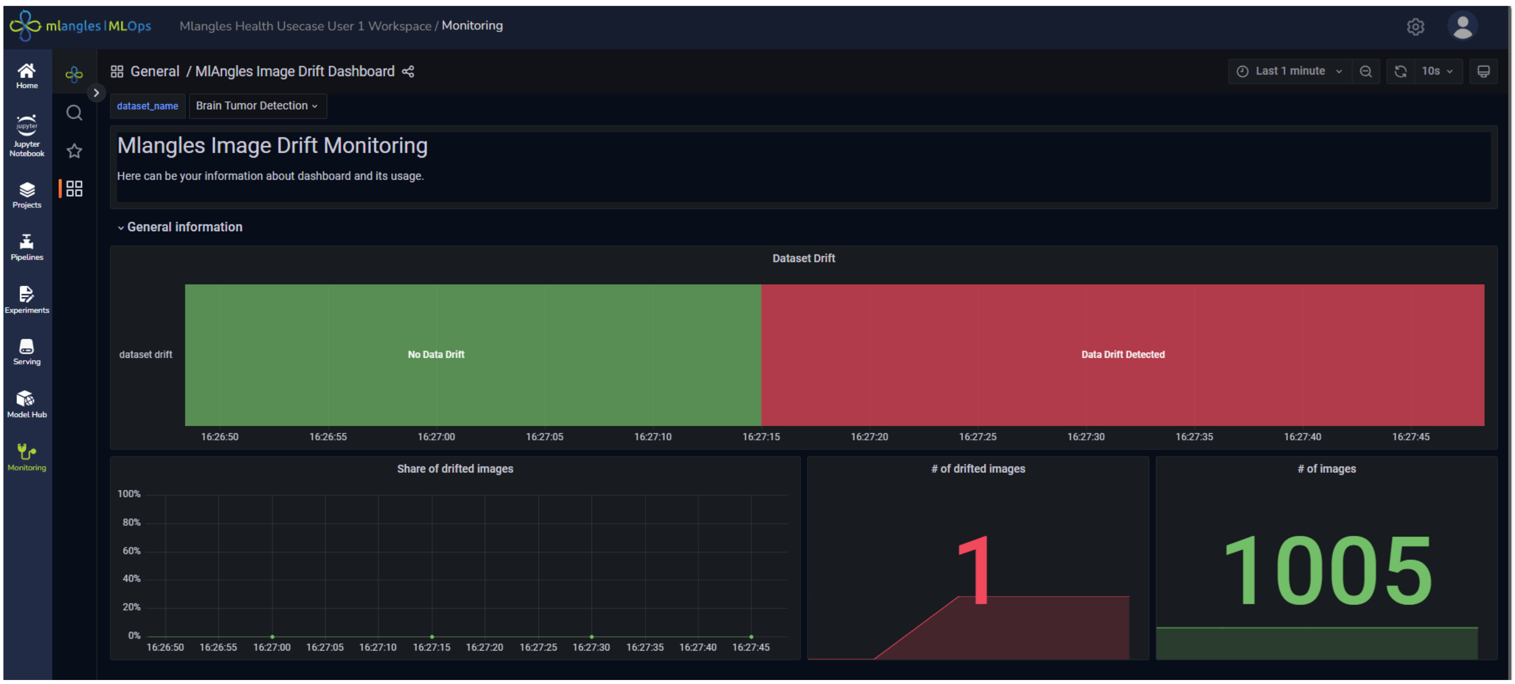
Select Project Name
Brain Tumour Classification
Select Experiment Name
Run1 - Resnet101
Select Model
Trained_model
Upload File
image(2).jpg
Predict
Result
meningioma_tumor


Brain Wiring Centre
Analyzing all data from the database...

Step 4: Monitoring

Image drift refers to the phenomenon where the statistical properties of images in a dataset change over time, potentially leading to a decrease in the performance of machine learning models trained on that dataset. This change can occur due to various factors such as changes in imaging equipment, variations in lighting conditions, differences in image acquisition techniques, or shifts in the characteristics of the target population being imaged.

In medical imaging, for example, image drift can occur if there are updates or variations in imaging protocols, changes in patient demographics, or alterations in the hardware or software of the imaging devices. If a model is trained on data that doesn't adequately represent the current distribution of images, it may exhibit degraded performance when applied to new data, as it may not generalize well to the shifted distribution.



Conclusion

In conclusion, leveraging pretrained models like ResNet for fine-tuning against our dataset has yielded promising results in predicting four distinct types of tumors: glioma, pituitary, meningioma, and identifying cases with no tumor. Through this project, we've demonstrated the effectiveness of transfer learning in medical image analysis, showcasing its potential for accurate and efficient diagnosis. Our findings underscore the significance of integrating advanced machine learning techniques into healthcare practices, paving the way for enhanced diagnostic capabilities and improved patient outcomes in neuroimaging.