Q1. What is the main goal of your project?
A: The main goal is to develop a simple, fast, and accurate machine learning system using CNN to detect brain tumors from MRI images and help improve diagnosis and patient outcomes.

Q2. Why did you choose brain tumor detection as your topic?
A: Because early detection of brain tumors is critical for effective treatment. Using machine learning can enhance diagnostic speed and accuracy, supporting doctors in making timely decisions.

🧠 Technical Concepts

Q3. What is a CNN, and why did you use it?
A: A Convolutional Neural Network (CNN) is a type of deep learning model that is excellent at analyzing images. We used it because it can automatically learn features like edges, shapes, and textures from MRI images for accurate classification.

Q4. What dataset did you use and where did it come from?
A: We used a publicly available dataset from Kaggle. It contains 253 grayscale MRI images—155 with tumors and 98 without.

🛠️ Methodology

Q5. How did you preprocess the data?
A: We resized the images to 224x224 pixels, converted them to RGB format, normalized pixel values, and applied augmentation like flipping to increase dataset diversity.

Q6. Which activation and loss functions did you use?
A: We used the **sigmoid activation function** in the output layer for binary classification and the **binary cross-entropy** loss function for training.

📊 Performance and Results

Q7. What was the accuracy of your model?
A: The CNN model achieved **89% accuracy** and an **F1-score of 0.89**, showing good performance in classifying tumor and non-tumor cases.

Q8. Can you explain what the confusion matrix shows?
A: Yes. Out of all test cases, the model correctly predicted 44 non-tumor and 23 tumor cases. It misclassified 6 tumors as non-tumor and 2 non-tumors as tumors, which means it performed well but still has room for improvement.

🔮 Future Work

Q9. What improvements would you suggest for future versions of your model?
A: We suggest expanding the dataset, especially with different tumor types, and using transfer learning with pre-trained models to improve accuracy and generalization. We also recommend incorporating domain-specific features like tumor size and location.

❓ Conceptual/Why-Type Questions

Q10. Why is early detection so important in brain tumors?
A: Early detection can significantly improve the chances of successful treatment and increase survival rates by allowing intervention before the tumor progresses too far.

🧬 Q1. Why did you choose the DenseNet121 model in your research?

A: We chose DenseNet121 because it's a powerful pre-trained deep learning model that performs well on image classification tasks. It connects each layer to every other layer, which improves feature propagation and reduces the number of parameters. This makes it efficient and accurate, especially with a smaller dataset like ours.

📚 Q2. What is transfer learning, and how did you apply it in your project?

A: Transfer learning is a technique where a model trained on a large dataset is reused on a new but related task. We used DenseNet121, which was pre-trained on ImageNet, and fine-tuned it on our MRI dataset to improve tumor classification without needing a large training set.

🧪 Q3. How did you evaluate the model's performance besides accuracy?

A: Besides accuracy, we used metrics like **precision, recall, F1-score**, and a **confusion matrix**. These give a better understanding of how well the model handles both tumor and non-tumor cases, especially when the dataset is imbalanced.

💻 Q4. What are the main differences between benign and malignant brain tumors?

A: Benign tumors are non-cancerous and grow slowly, often without spreading. Malignant tumors are cancerous, grow quickly, and can spread to other parts of the brain or body. Detecting both types early is crucial for effective treatment.

📦 Q5. What preprocessing steps were necessary before training the model?

A: We resized all images to 224x224 pixels, normalized pixel values to the 0–1 range, converted grayscale to RGB format, and applied augmentation (like flipping) to increase dataset variety and prevent overfitting.