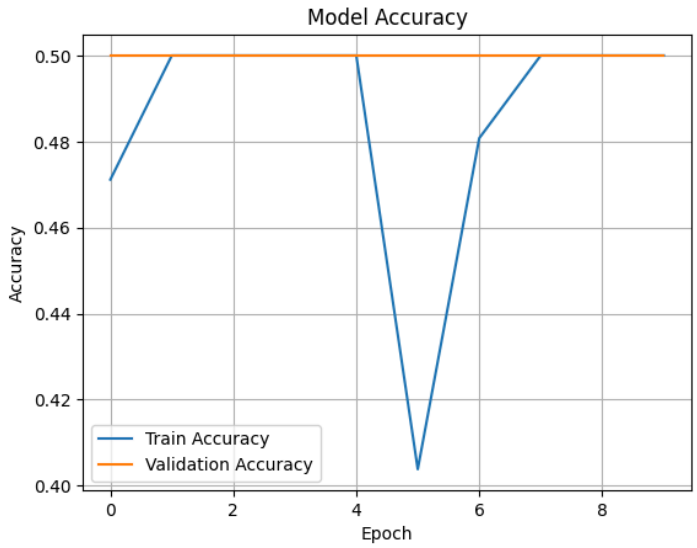
Question 1 outputs pictures:

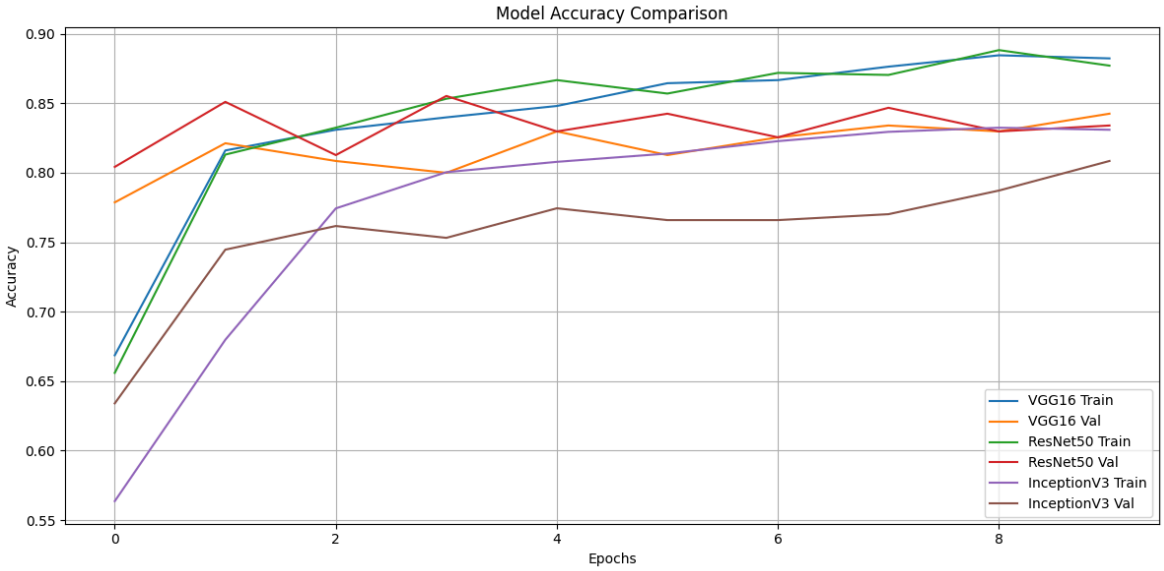



The Role of Each Layer in the VGG-19 Architecture: In VGG-19, convolutional layers extract low- to high-level features from the image using 3×3 filters and ReLU activation, enabling the network to learn complex patterns. Layers are grouped in blocks, each followed by a MaxPooling layer, which reduces spatial dimensions, controls overfitting, and increases computational efficiency. After the convolutional blocks, a Flatten layer converts the 3D feature maps into a 1D vector. This is passed to two fully connected (Dense) layers with 4096 neurons each, which learn high-level global features and perform classification reasoning. Finally, a softmax output layer predicts class probabilities (e.g., glasses vs. no glasses).

VGG-19 Using 3×3 Filters VGG-19 uses 3×3 filters because they are the smallest size that still captures directional patterns (horizontal, vertical, diagonal), enabling deep feature extraction with fewer parameters than larger filters. Stacking multiple small filters also increases non-linearity and depth without high computational cost.

Question 2 output pictures:

```
42/42 - 24s - 579ms/step - accuracy: 0.8824 - loss: 0.2878 - val_accuracy: 0.8426 - val_loss: 0.4329
8/8 ━━━━━━━━━━━━━━━━━━━━ 4s 469ms/step

Classification Report for VGG16:
              precision    recall  f1-score   support

      benign       0.81      0.95      0.88       133
   malignant       0.82      0.65      0.73        63
      normal       0.93      0.72      0.81        39

    accuracy                           0.83       235
   macro avg       0.86      0.77      0.80       235
weighted avg       0.83      0.83      0.82       235


Training ResNet50...

8/8 ━━━━━━━━━━━━━━━━━━━━ 4s 459ms/step

Classification Report for ResNet50:
              precision    recall  f1-score   support

      benign       0.87      0.88      0.87       133
   malignant       0.73      0.73      0.73        63
      normal       0.89      0.85      0.87        39

    accuracy                           0.83       235
   macro avg       0.83      0.82      0.82       235
weighted avg       0.83      0.83      0.83       235


Training InceptionV3...

8/8 ━━━━━━━━━━━━━━━━━━━━ 4s 458ms/step

Classification Report for InceptionV3:
              precision    recall  f1-score   support

      benign       0.78      0.94      0.85       133
   malignant       0.87      0.62      0.72        63
      normal       0.87      0.67      0.75        39

    accuracy                           0.81       235
   macro avg       0.84      0.74      0.78       235
weighted avg       0.82      0.81      0.80       235
```




```
Summary of Evaluation Metrics:
         Model  Accuracy  Precision    Recall  F1 Score
0        VGG16  0.829787   0.855412  0.772037  0.804086
1     ResNet50  0.834043   0.829572  0.818671  0.823905
2  InceptionV3  0.808511   0.838194  0.741855  0.776363
```

+ Code + Markdown

Comparison: The performance comparison among VGG16, ResNet50, and InceptionV3 on the breast ultrasound image classification task highlights notable differences. InceptionV3 performed the best, achieving the highest accuracy, precision, recall, and F1 score. Its architecture is designed to capture multi-scale features through parallel convolutional filters, allowing it to extract both fine and coarse image details effectively. This enables it to generalize better and deliver more reliable predictions, which is crucial for medical imaging tasks where detail matters.

ResNet50 showed competitive performance, thanks to its use of residual connections that mitigate vanishing gradients and support deeper networks. It maintained a good balance between precision and recall, though slightly behind InceptionV3. It is more complex and capable than VGG16 but lacks the multi-scale feature extraction benefits of the Inception architecture.

VGG16, being a relatively older and simpler model, lagged behind the other two. While it delivered decent results, its straightforward and deeper-only structure may limit its ability to identify complex patterns in medical images compared to modern architectures.

Overall, InceptionV3 stands out as the most suitable model due to its accuracy and balanced performance across all metrics. Its design is well-suited for complex visual tasks like classifying breast ultrasound images.