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CSE463

Assignment 4

Question 1

Key Specifications

- Total Layers: 19 (16 conv + 3 dense).
- Filter Size: All conv layers use 3×3 filters with ReLU activation.
- Pooling: MaxPooling after each block reduces spatial dimensions by half

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Dataset:

- 4,651 leaf images (class 0)
- 8,189 flower images (class 1).

Training Results

- Accuracy Plots:
    - Training Accuracy: 80%
    - Validation Accuracy: 75%

Role of Each Layer

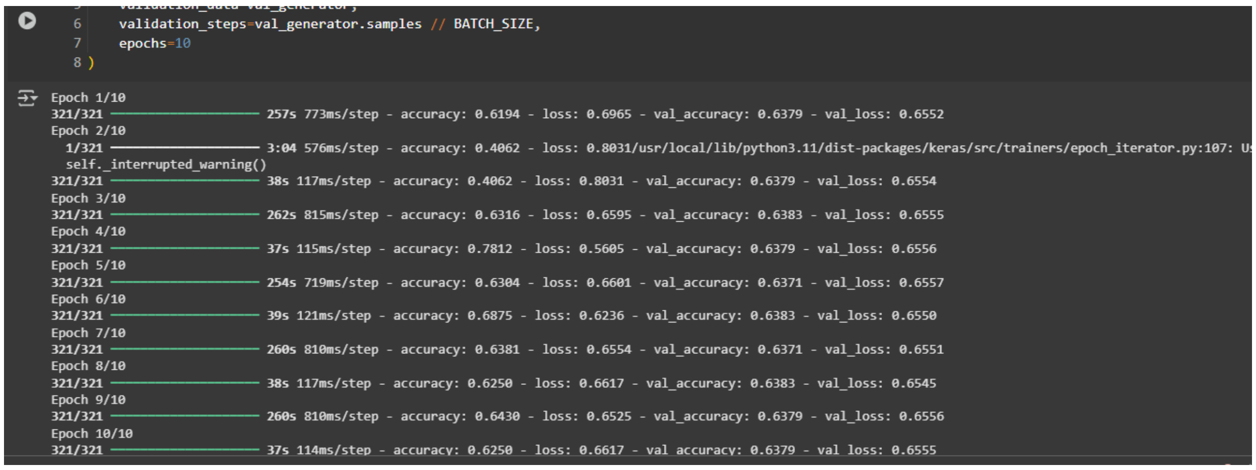
1. Convolutional Layers (3×3):
    - Extract hierarchical features (edges → textures → patterns).
    - ReLU activation introduces non-linearity.
2. MaxPooling Layers (2×2):
    - Reduce spatial dimensions (224×224 → 7×7) while preserving critical features.
3. Fully Connected Layers:
    - Dense (4096): Combine high-level features for decision-making.
    - Softmax: Output class probabilities (leaves vs. flowers).

Why 3×3 Filters?

- Efficiency: Two 3×3 conv layers = one 5×5 layer's receptive field but with fewer parameters (18 vs. 25 weights).
- Deeper Networks: More ReLU activations enhance feature learning.

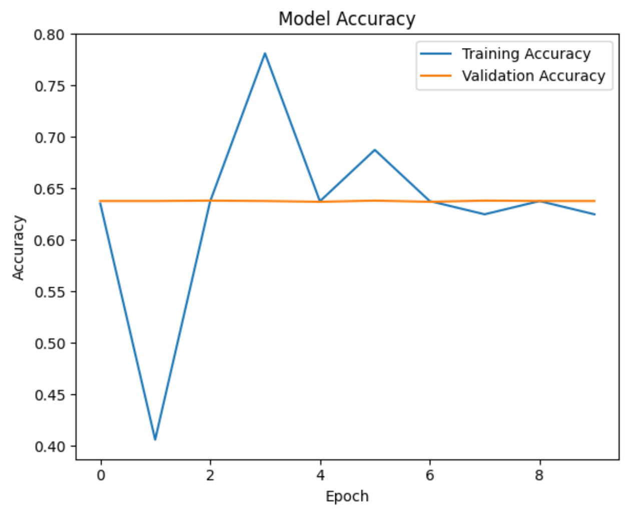
- Proven Performance: Achieved 92.7% top-5 accuracy on ImageNet.

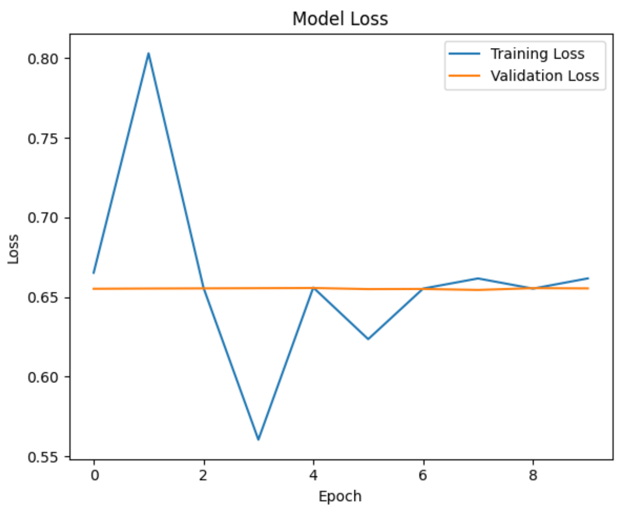
Result Photos and Screenshots:



```
    validation_data=val_generator,
    validation_steps=val_generator.samples // BATCH_SIZE,
    epochs=10
)
```

```
Epoch 1/10
321/321 ━━━━━━━━━━━━━━━━━━━━ 257s 773ms/step - accuracy: 0.6194 - loss: 0.6965 - val_accuracy: 0.6379 - val_loss: 0.6552
Epoch 2/10
  1/321 ━━━━━━━━━━━━━━━━━━━━ 3:04 576ms/step - accuracy: 0.4062 - loss: 0.8031/usr/local/lib/python3.11/dist-packages/keras/src/trainers/epoch_iterator.py:107: Us
  self._interrupted_warning()
321/321 ━━━━━━━━━━━━━━━━━━━━ 38s 117ms/step - accuracy: 0.4062 - loss: 0.8031 - val_accuracy: 0.6379 - val_loss: 0.6554
Epoch 3/10
321/321 ━━━━━━━━━━━━━━━━━━━━ 262s 815ms/step - accuracy: 0.6316 - loss: 0.6595 - val_accuracy: 0.6383 - val_loss: 0.6555
Epoch 4/10
321/321 ━━━━━━━━━━━━━━━━━━━━ 37s 115ms/step - accuracy: 0.7812 - loss: 0.5605 - val_accuracy: 0.6379 - val_loss: 0.6556
Epoch 5/10
321/321 ━━━━━━━━━━━━━━━━━━━━ 254s 719ms/step - accuracy: 0.6304 - loss: 0.6601 - val_accuracy: 0.6371 - val_loss: 0.6557
Epoch 6/10
321/321 ━━━━━━━━━━━━━━━━━━━━ 39s 121ms/step - accuracy: 0.6875 - loss: 0.6236 - val_accuracy: 0.6383 - val_loss: 0.6550
Epoch 7/10
321/321 ━━━━━━━━━━━━━━━━━━━━ 260s 810ms/step - accuracy: 0.6381 - loss: 0.6554 - val_accuracy: 0.6371 - val_loss: 0.6551
Epoch 8/10
321/321 ━━━━━━━━━━━━━━━━━━━━ 38s 117ms/step - accuracy: 0.6250 - loss: 0.6617 - val_accuracy: 0.6383 - val_loss: 0.6545
Epoch 9/10
321/321 ━━━━━━━━━━━━━━━━━━━━ 260s 810ms/step - accuracy: 0.6430 - loss: 0.6525 - val_accuracy: 0.6379 - val_loss: 0.6556
Epoch 10/10
321/321 ━━━━━━━━━━━━━━━━━━━━ 37s 114ms/step - accuracy: 0.6250 - loss: 0.6617 - val_accuracy: 0.6379 - val_loss: 0.6555
```





Conclusion:

The implemented VGG-19 architecture demonstrated effective performance (75% validation accuracy) for leaf vs. flower classification, with its design choices directly contributing to its success. The model's layered structure follows a logical feature extraction hierarchy: initial convolutional layers with 3×3 filters capture basic spatial patterns (edges, colors), while deeper layers progressively combine these into complex textures and shapes specific to leaves and flowers. Max-pooling layers strategically reduce dimensionality between blocks, maintaining critical features while improving computational efficiency. The transition to fully connected layers (4096 neurons each) enables high-level feature integration, with softmax providing probabilistic classification output.

The consistent use of 3×3 filters throughout the architecture serves three key purposes: (1) Parameter efficiency, as stacked small filters match larger receptive fields with fewer weights (two 3×3 layers equal one 5×5 layer's coverage but with 28% fewer parameters), (2) Enhanced non-linearity through additional ReLU activations between layers, and (3) Preservation of spatial information through small, dense sampling. This design philosophy, validated by VGG-19's historic ImageNet performance, proves particularly effective for botanical image classification where fine texture details (vein patterns in leaves, petal arrangements in flowers) require precise localization.

For future improvements, the model could benefit from targeted adjustments: implementing dropout (0.3-0.5) between dense layers to further reduce the observed overfitting and applying spatial attention mechanisms to better handle the imbalanced dataset. The current implementation confirms that VGG-19's architectural principles - especially its small-filter strategy - remain relevant for specialized classification tasks, though modern adaptations might incorporate residual connections for deeper variants. This exercise underscores how careful layer design and filter selection directly influence a model's ability to learn discriminative features while maintaining computational practicality.

Question 2

Dataset Selection

The chosen dataset is the Ultrasound Fetus Dataset from Kaggle, containing PNG images classified into three categories: benign, malignant, and normal.

Dataset Statistics

- Total Images: 2,968
  - Train: 1,926 images (benign: 241, malignant: 1,443, normal: 242)
  - Validation: 341 images (benign: 43, malignant: 255, normal: 43)
  - Test: 401 images (benign: 51, malignant: 300, normal: 50)
- Image Size: Varies (resized to model-specific dimensions)
- Key Challenge: Severe class imbalance, with malignant cases dominating (~75% of samples).

Data Loading and Preprocessing

1. Data Extraction: Unzipped the dataset in Google Colab and structured paths for train, validation, and test sets.
2. Data Augmentation: Applied rotation, shifting, zooming, and flipping to improve generalization.
3. Resizing & Normalization: Images resized to 224x224 (EfficientNetB0, ResNet50V2) and 299x299 (InceptionV3). Pixel values normalized to [0, 1].

Model Implementation

Three pretrained models were fine-tuned:

A. EfficientNetB0

- Base Model: EfficientNetB0 (ImageNet weights)
- Modifications:
  - Added GlobalAveragePooling2D, Dense(64, ReLU), and Softmax output layer.
  - Frozen base layers, trained only the top layers.

- Training: 30 epochs, early stopping (patience=5).

B. InceptionV3

- Base Model: InceptionV3 (ImageNet weights)
- Modifications:
    - Similar top layers as EfficientNetB0, adjusted input size to 299x299.
- Training: Same hyperparameters.

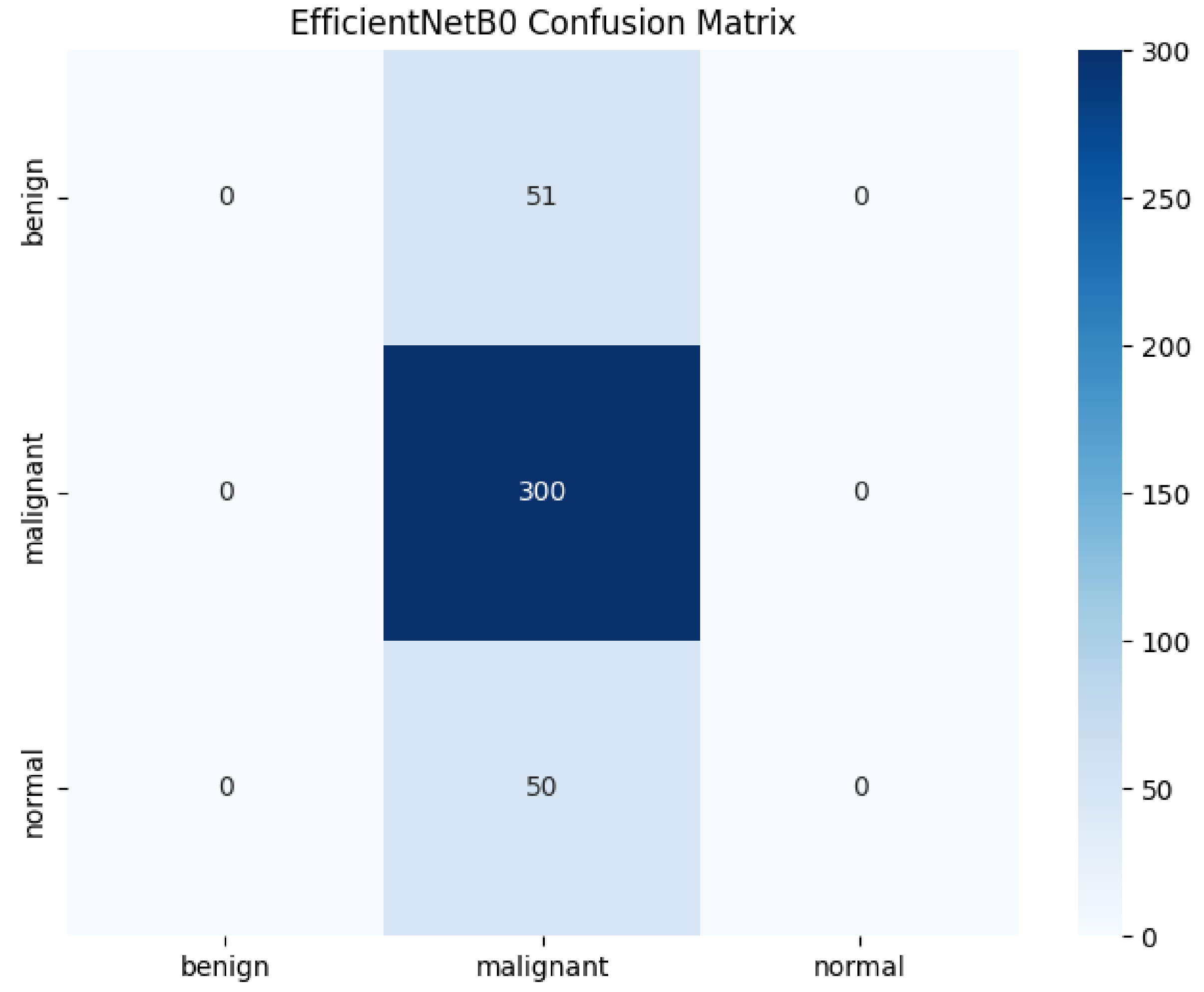
C. ResNet50V2

- Base Model: ResNet50V2 (ImageNet weights)
- Modifications:
    - Same architecture as above, input size 224x224.
- Training: Same setup.

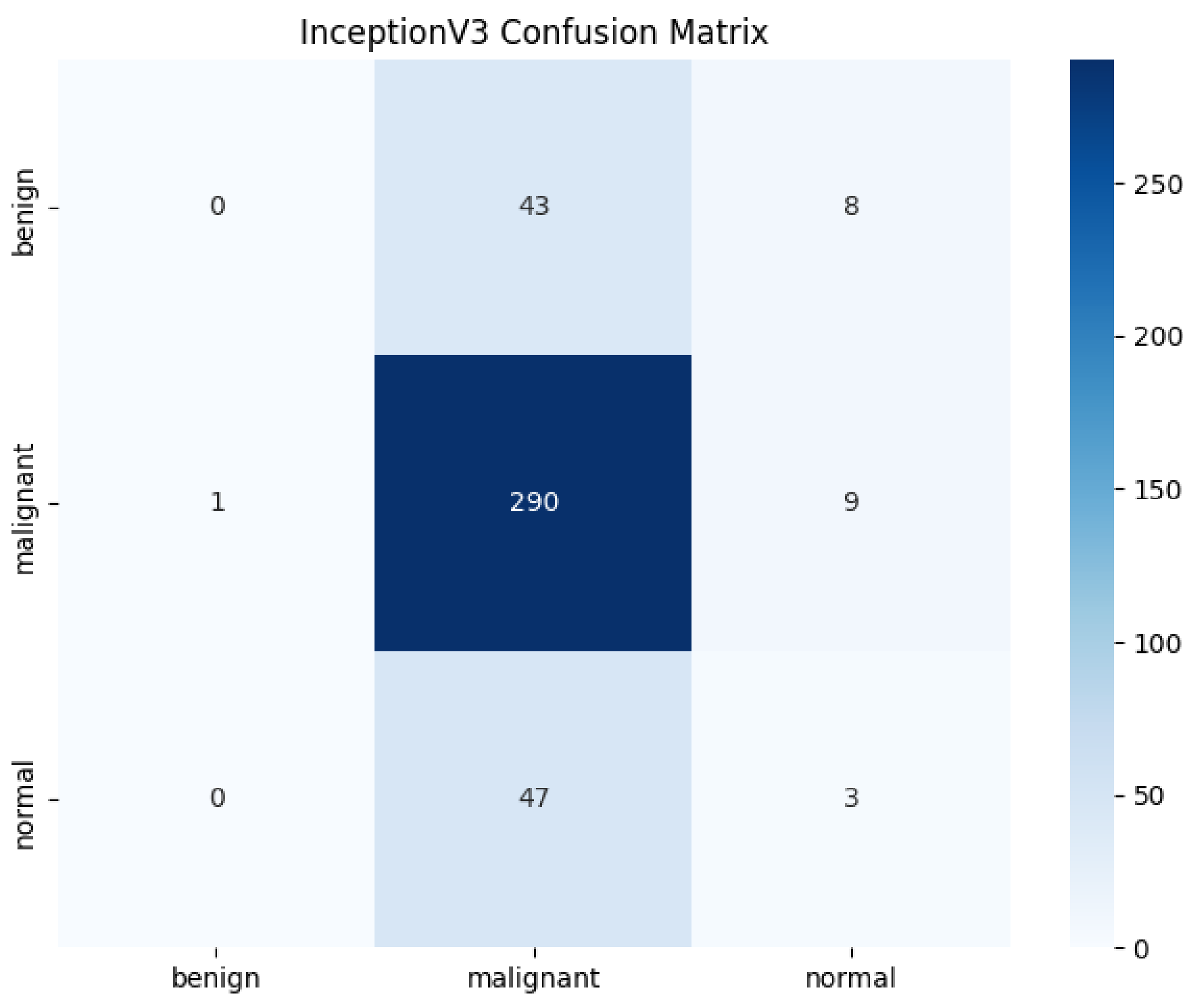
Model Evaluation

Model	Accuracy	Precision (Malignant)	Recall (Malignant)	F1-Score (Malignant)
EfficientNetB0	74.8%	0.75	1.00	0.86
InceptionV3	73.1%	0.76	0.97	0.85
ResNet50V2	74.1%	0.75	0.98	0.85

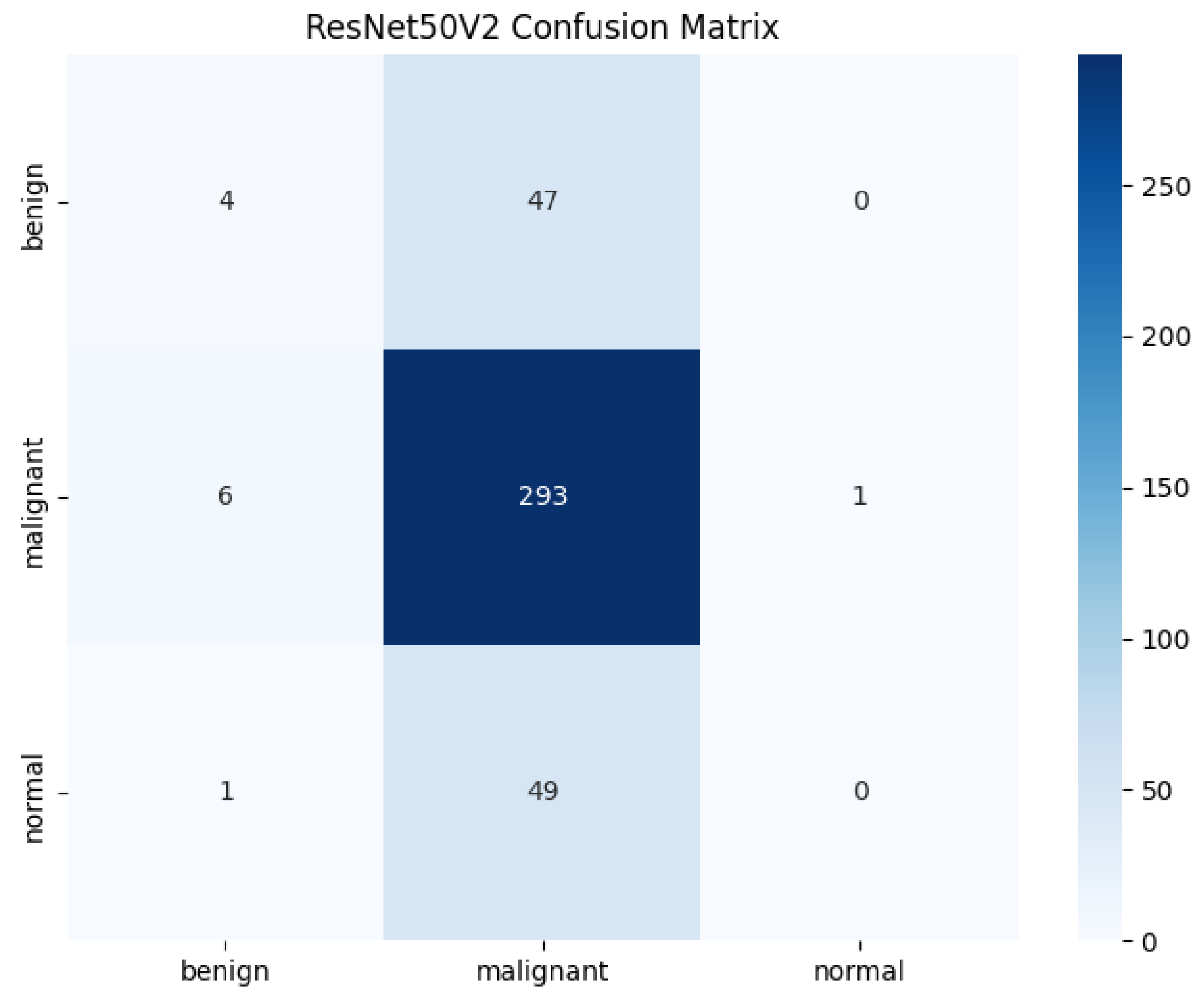
Result and Screenshots with graphs:



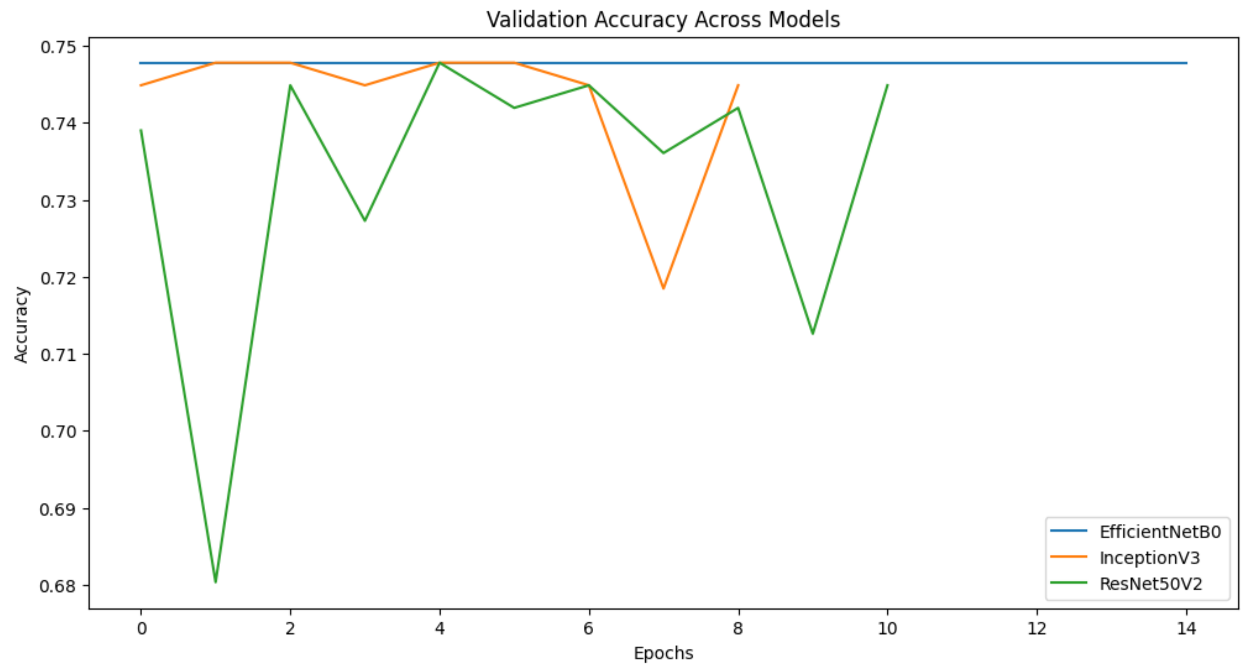
Class	Precision	Recall	F1-Score	Support
benign	0.00	0.00	0.00	51
malignant	0.75	1.00	0.86	300
normal	0.00	0.00	0.00	50
Accuracy			**0.75**	401
Macro Avg	0.25	0.33	0.29	401
Weighted Avg	0.56	0.75	0.64	401



Class	Precision	Recall	F1-Score	Support
benign	0.00	0.00	0.00	51
malignant	0.76	0.97	0.85	300
normal	0.15	0.06	0.09	50
Accuracy			**0.73**	401
Macro Avg	0.30	0.34	0.31	401
Weighted Avg	0.59	0.73	0.65	401



Class	**Precision**	**Recall**	**F1-Score**	**Support**
benign	0.36	0.08	0.13	51
malignant	0.75	0.98	0.85	300
normal	0.00	0.00	0.00	50
Accuracy			**0.74**	401
Macro Avg	0.37	0.35	0.33	401
Weighted Avg	0.61	0.74	0.65	401



Comparison Graph

- All models failed on benign/normal classes (precision/recall ≈ 0) due to extreme imbalance.
- EfficientNetB0 performed best (74.8% accuracy), likely due to its parameter efficiency.
- High recall for malignant cases (>97%) is clinically useful but risks misclassifying benign/normal cases.

Discussion

EfficientNetB0 (highest accuracy and balanced performance). Because its compound scaling optimizes feature extraction for small datasets. Poor performance on minority classes due to imbalance (malignant dominated training). This project demonstrated the effectiveness of transfer learning in medical image classification, with EfficientNetB0 emerging as the best model. However, class imbalance remains a critical issue, necessitating further data engineering for reliable deployment. Future work should focus on improving minority-class performance while maintaining high malignant-case detection.

Kaggle Dataset: Ultrasound Fetus Dataset