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Neural Networks Project

Mushroom Image Classifier

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All the assets of the project, such as code, dataset and results are also available on my Github repository.

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Dataset and Preprocessing

I made use of this dataset from Kaggle, comprised of 27436 photos of 94 species of mushrooms. I decided to use only 30 species for my classes, as running the training models with 94 classes would have taken quite a significant amount of time and 30 is probably more than sufficient to display how a neural network works.

In preparing the dataset for training, it's essential to ensure uniformity in image dimensions. Convolutional Neural Networks (CNNs) require consistent input sizes to function effectively. Resizing all images to a standard square shape not only simplifies the design of the input layer but also enhances computational efficiency.

However, when resizing images, it's crucial to consider the original resolutions to avoid upscaling, which can introduce artifacts and degrade image quality. Therefore, it's advisable to set the target resize dimensions based on the smallest images in the dataset that meet a minimum acceptable resolution threshold. In this dataset, most images have a resolution of 640x480 pixels, but there are some outliers which have low resolutions such as 180x220 pixels, and quite a handful having resolution around 400x400 pixels therefore, I decided that images with resolutions below 400x400 pixels should be removed with a script.

```
C:\Users\ruse\Desktop\ProjectNN\pythonProject7\.venv\Scripts\python.
Class: Agaricus augustus, Remaining: 329, Deleted: 12
Class: Amanita amerirubescens, Remaining: 316, Deleted: 20
Class: Amanita augusta, Remaining: 319, Deleted: 12
Class: Amanita brunnescens, Remaining: 284, Deleted: 22
Class: Amanita calyptroderma, Remaining: 323, Deleted: 5
Class: Amanita flavoconia, Remaining: 299, Deleted: 22
Class: Amanita muscaria, Remaining: 291, Deleted: 37
Class: Amanita persicina, Remaining: 246, Deleted: 17
Class: Amanita phalloides, Remaining: 313, Deleted: 8
Class: Amanita velosa, Remaining: 273, Deleted: 10
Class: Armillaria mellea, Remaining: 310, Deleted: 18
Class: Armillaria tabescens, Remaining: 310, Deleted: 43
Class: Artomyces pyxidatus, Remaining: 320, Deleted: 32
Class: Bolbitius titubans, Remaining: 300, Deleted: 21
Class: Boletus pallidus, Remaining: 304, Deleted: 16
Class: Boletus rex-veris, Remaining: 297, Deleted: 11
Class: Cantharellus californicus, Remaining: 304, Deleted: 21
Class: Cantharellus cinnabarinus, Remaining: 307, Deleted: 26
Class: Cerioporus squamosus, Remaining: 532, Deleted: 49
Class: Chlorophyllum brunneum, Remaining: 253, Deleted: 24
Class: Chlorophyllum molybdites, Remaining: 212, Deleted: 24
Class: Galerina marginata, Remaining: 223, Deleted: 11
Class: Ganoderma applanatum, Remaining: 228, Deleted: 95
Class: Ganoderma curtisii, Remaining: 207, Deleted: 53
Class: Ganoderma oregonense, Remaining: 244, Deleted: 3
Class: Ganoderma tsugae, Remaining: 261, Deleted: 8
Class: Phaeolus schweinitzii, Remaining: 280, Deleted: 13
Class: Phlebia tremellosa, Remaining: 257, Deleted: 29
Class: Phyllotopsis nidulans, Remaining: 275, Deleted: 22
Class: Pleurotus ostreatus, Remaining: 283, Deleted: 15
------------------------------------------------------------------------


Total images remaining: 8700
Total images deleted: 699

Process finished with exit code 0
```

Fig. 1 Low Resolution Photo Script Remover Output

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In total, 699 low resolution photos were deleted, now remaining 8700 photos across the 30 classes. Each class has currently around 250-300 photos on average, whilst, whilst the lowest one has 207, particularly “Ganoderma Curtisii”, and the highest one being “Cerioporus Squamosus” with 532 photos.

The next step was to divide the dataset into the training, validation and test subsets. I opted for an 80:10:10 split, 80-training, 10-validation, 10-test. For an easier understanding and visualization, I have made histograms for the subsets. On average, it resulted in the train subset having around 250 images per class, and the validation and test having around 30 images per class

Fig. 2 Train subset Histogram

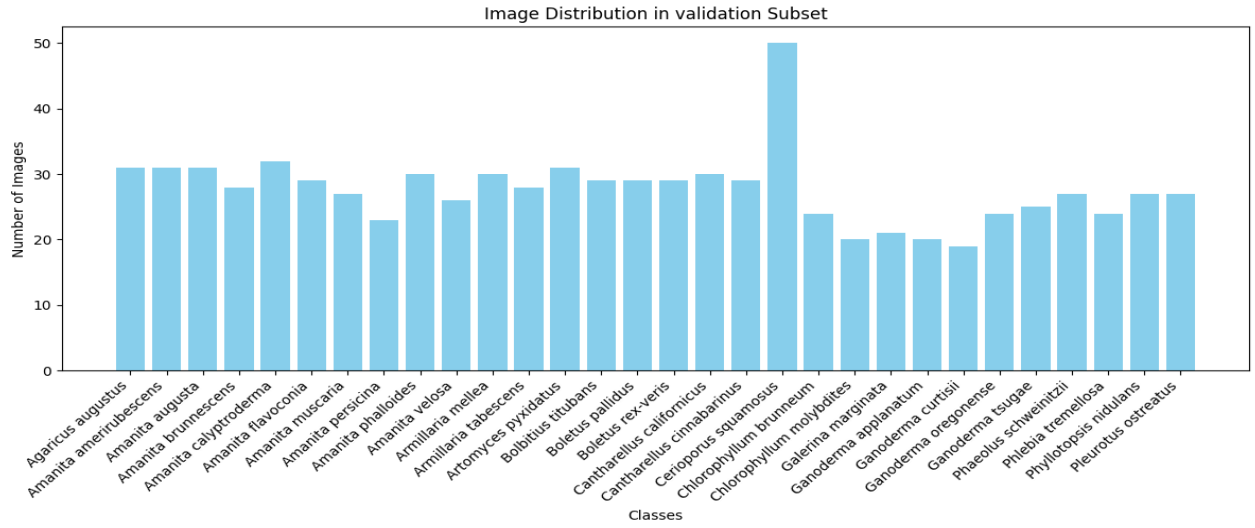

Fig. 3 Validation subset Histogram

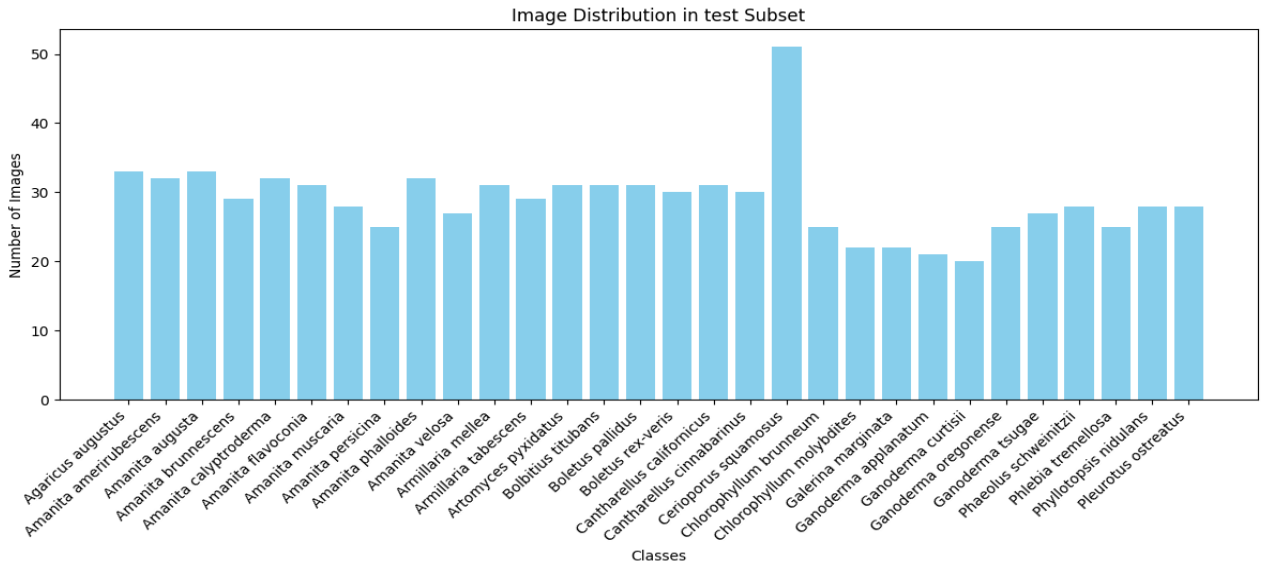

Fig. 4 Test subest Histogram

Environment and Decisions

For this project, I selected **PyTorch** as the primary deep learning framework due to its flexibility, ease of debugging, and compatibility with pre-trained models. PyTorch is widely recognized for its dynamic computation graphs and straightforward integration with GPU acceleration, making it an excellent choice for tasks involving large datasets and complex neural networks.

I utilized a **dedicated GPU** to accelerate training. GPUs are specifically optimized for parallel processing, allowing them to handle the large matrix computations resulting in significantly faster training times.

```
20
21  # Check for GPU availability
22  device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
23  print(f"Using device: {device}")
24  if torch.cuda.is_available():
25      print(f"Number of GPUs: {torch.cuda.device_count()}")
26      for i in range(torch.cuda.device_count()):
27          print(f"GPU {i}: {torch.cuda.get_device_name(i)}")
28
```

Fig. 5 GPU selection for training

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Data Preprocessing

The dataset comprises images from multiple classes, which were processed to ensure consistency and enhance model generalization. The following preprocessing steps were applied:

1. **Uniform Image Dimensions**: Images were resized to **400x400 pixels** to standardize input dimensions across the dataset
2. **Augmentation**: Techniques such as random horizontal flipping and rotation were employed to artificially increase data variability (for training only), improving model robustness.
3. **Normalization**: Pixel values were normalized to match the expectations of pre-trained models we are going to use:

```
# Define data transformations
data_transforms = {
    'train': transforms.Compose([
        transforms.Resize((img_height, img_width)),
        transforms.RandomHorizontalFlip(),
        transforms.RandomRotation(20),
        transforms.ToTensor(),
        transforms.Normalize( mean: [0.485, 0.456, 0.406], std: [0.229, 0.224, 0.225])
    ]),
    'test': transforms.Compose([
        transforms.Resize((img_height, img_width)),
        transforms.ToTensor(),
        transforms.Normalize( mean: [0.485, 0.456, 0.406], std: [0.229, 0.224, 0.225])
    ])
}
```

Fig. 6 Data Preprocessing

Model Selection

In this project, we utilized two pre-trained convolutional neural networks from PyTorch, each with distinct architectural features and design philosophies:

MobileNetV2:

- MobileNetV2 is built for computational efficiency. It uses techniques like depthwise separable convolutions to significantly reduce the number of calculations needed while still achieving good accuracy.
- This model is more balanced, it supposedly does not have the same level of depth and complexity, but it is an agreeable enough option for the amount of processing power it requires

ResNet18:

- **Residual Connections**: ResNet18 employs skip connections, allowing the output of a layer to bypass one or more layers and directly contribute to subsequent layers. This design mitigates the vanishing gradient problem, enabling the training of deeper networks.
- **Standard Convolutional Layers**: ResNet18 uses traditional convolutional layers organized into blocks, each followed by batch normalization and ReLU activation. This straightforward structure enables effective feature extraction.
- **Deeper Architecture**: With 18 layers, this model is designed to extract more complex and nuanced features, making it better suited for datasets with higher variance and complexity.

I decided to select these 2 particular models as from the research I've done it appears that MobileNetV2 is a more simplistic model, made for low resource device(ie mobiles, that's where the Mobile comes from), whilst ResNet18 is more advanced, thus I think it might be interesting to see if at the end of training there is a substantial difference between the two models in terms of accuracy of predicting correctly the classes.

Training Methodology

The training process focused on optimizing model performance while minimizing overfitting. Key aspects of the methodology include:

1. **Early Stopping:** Inspired by TensorFlow's implementation, early stopping was incorporated to monitor validation loss. If validation loss failed to improve over 5 consecutive epochs, training was halted. This approach prevents overfitting and conserves computational resources:

```
111
112         if val_loss < best_val_loss:
113             best_val_loss = val_loss
114             best_epoch = epoch + 1
115             torch.save(model.state_dict(), model_name)
116             print(f"Model saved as {model_name}")
117             early_stop_counter = 0
118         else:
119             early_stop_counter += 1
120
121         if early_stop_counter >= patience:
122             print("Early stopping triggered.")
123             break
124
```

Fig. 7. Early Stopping Code Implementation

2. **Optimizer and Loss Function:** The Adam optimizer was chosen for its adaptive learning rate capabilities, ensuring efficient convergence. Cross-entropy loss was used as the objective function, aligning with the multi-class classification nature of the task.

Here is the full code for the training file, with comment explainations

```python
base_dir = "mushrooms"  # Base directory containing the dataset
train_dir = os.path.join(base_dir, "train")  # Directory for training data
val_dir = os.path.join(base_dir, "validation")  # Directory for validation data
test_dir = os.path.join(base_dir, "test")  # Directory for test data

# Set parameters
img_height, img_width = 400, 400  # Standard size to which all images will be resized
batch_size = 32  # Number of samples per batch during training and validation

# Check for GPU availability
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")  # Use GPU if available
print(f"Using device: {device}")
if torch.cuda.is_available():
    print(f"Number of GPUs: {torch.cuda.device_count()}")
    for i in range(torch.cuda.device_count()):
        print(f"GPU {i}: {torch.cuda.get_device_name(i)}")

# Define data transformations for preprocessing
data_transforms = {
    'train': transforms.Compose([
        transforms.Resize((img_height, img_width)),  # Resize images to standard dimensions
        transforms.RandomHorizontalFlip(),  # Randomly flip images horizontally (augmentation)
        transforms.RandomRotation(20),  # Randomly rotate images up to 20 degrees (augmentation)
        transforms.ToTensor(),
        transforms.Normalize( mean: [0.485, 0.456, 0.406], std: [0.229, 0.224, 0.225])  # Normalize using ImageNet statistics
    ]),
    'test': transforms.Compose([
        transforms.Resize((img_height, img_width)),  # Resize images to standard dimensions
        transforms.ToTensor(),  # Convert images to PyTorch tensors
        transforms.Normalize( mean: [0.485, 0.456, 0.406], std: [0.229, 0.224, 0.225])  # Normalize using ImageNet statistics
    ])
}

# Load datasets into PyTorch DataLoader objects
data_loaders = {
    'train': DataLoader(datasets.ImageFolder(train_dir, transform=data_transforms['train']), batch_size=batch_size, shuffle=True),
    'validation': DataLoader(datasets.ImageFolder(val_dir, transform=data_transforms['test']), batch_size=batch_size, shuffle=False),
    'test': DataLoader(datasets.ImageFolder(test_dir, transform=data_transforms['test']), batch_size=batch_size, shuffle=False)
}

# Determine the number of classes in the dataset
num_classes = len(datasets.ImageFolder(train_dir).classes)

# Define pre-trained models
# Model 1: MobileNetV2
model1 = models.mobilenet_v2(pretrained=True)  # Load pre-trained MobileNetV2
model1.classifier[1] = nn.Linear(model1.last_channel, num_classes)  # Modify the classifier to match the dataset classes
model1 = model1.to(device)  # Move the model to the selected device

# Model 2: ResNet18
model2 = models.resnet18(pretrained=True)  # Load pre-trained ResNet18
model2.fc = nn.Linear(model2.fc.in_features, num_classes)  # Modify the fully connected layer to match the dataset classes
model2 = model2.to(device)  # Move the model to the selected device

# Define loss function and optimizers
criterion = nn.CrossEntropyLoss()  # Loss function for multi-class classification
optimizer1 = optim.Adam(model1.parameters(), lr=0.001)  # Optimizer for MobileNetV2
optimizer2 = optim.Adam(model2.parameters(), lr=0.001)  # Optimizer for ResNet18
```

Fig. 8 Before Training Preparation Code

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```python
# Training function
2 usages  RuseCristian *
def train_model(model, optimizer, criterion, train_loader, val_loader, num_epochs=40, patience=5, model_name="model.pth"):
    """
    Parameters:
    - model: PyTorch model to be trained
    - optimizer: Optimizer for updating model weights
    - criterion: Loss function
    - train_loader: DataLoader for training data
    - val_loader: DataLoader for validation data
    - num_epochs: Maximum number of training epochs
    - patience: Number of epochs to wait for improvement before stopping
    - model_name: File name to save the best model

    Returns:
    - Training and validation metrics for each epoch
    """
    best_val_loss = float('inf')  # Initialize the best validation loss
    early_stop_counter = 0  # Counter for early stopping
    train_acc, val_acc, train_losses, val_losses = [], [], [], []  # Lists to store metrics
    best_epoch = 0  # Epoch with the best validation loss

    for epoch in range(num_epochs):
        print(f"Epoch {epoch+1}/{num_epochs}")
        model.train()  # Set the model to training mode
        running_loss, correct = 0.0, 0

        # Training loop
        for inputs, labels in tqdm(train_loader, desc="Training", leave=False):
            inputs, labels = inputs.to(device), labels.to(device)
            optimizer.zero_grad()  # Reset gradients
            outputs = model(inputs)  # Forward pass
            loss = criterion(outputs, labels)  # Compute loss
            loss.backward()  # Backward pass
            optimizer.step()  # Update weights

            running_loss += loss.item() * inputs.size(0)
            correct += (outputs.argmax(1) == labels).sum().item()

        train_loss = running_loss / len(train_loader.dataset)
        train_acc.append(correct / len(train_loader.dataset))
        train_losses.append(train_loss)

        # Validation loop
        model.eval()  # Set the model to evaluation mode
        running_loss, correct = 0.0, 0
        with torch.no_grad():
            for inputs, labels in tqdm(val_loader, desc="Validation", leave=False):
                inputs, labels = inputs.to(device), labels.to(device)
                outputs = model(inputs)
                loss = criterion(outputs, labels)

                running_loss += loss.item() * inputs.size(0)
                correct += (outputs.argmax(1) == labels).sum().item()

        val_loss = running_loss / len(val_loader.dataset)
        val_acc.append(correct / len(val_loader.dataset))
```

Fig. 9 Training function code part 1

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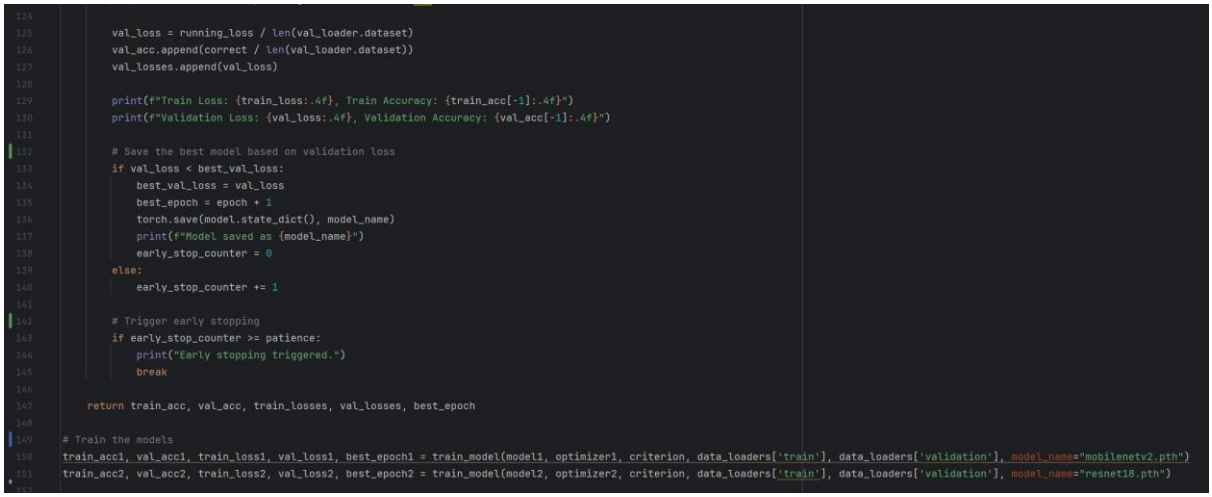

```
        val_loss = running_loss / len(val_loader.dataset)
        val_acc.append(correct / len(val_loader.dataset))
        val_losses.append(val_loss)

        print(f"Train Loss: {train_loss:.4f}, Train Accuracy: {train_acc[-1]:.4f}")
        print(f"Validation Loss: {val_loss:.4f}, Validation Accuracy: {val_acc[-1]:.4f}")

        # Save the best model based on validation loss
        if val_loss < best_val_loss:
            best_val_loss = val_loss
            best_epoch = epoch + 1
            torch.save(model.state_dict(), model_name)
            print(f"Model saved as {model_name}")
            early_stop_counter = 0
        else:
            early_stop_counter += 1

        # Trigger early stopping
        if early_stop_counter >= patience:
            print("Early stopping triggered.")
            break

    return train_acc, val_acc, train_losses, val_losses, best_epoch

# Train the models
train_acc1, val_acc1, train_loss1, val_loss1, best_epoch1 = train_model(model1, optimizer1, criterion, data_loaders['train'], data_loaders['validation'], model_name="mobilenetv2.pth")
train_acc2, val_acc2, train_loss2, val_loss2, best_epoch2 = train_model(model2, optimizer2, criterion, data_loaders['train'], data_loaders['validation'], model_name="resnet18.pth")
```

Fig. 10 Training function code part 2

```
# MobileNetV2 Plots
plt.figure(figsize=(10, 6))
plt.plot( *args: train_acc1, label='Train Accuracy (MobileNetV2)')
plt.plot( *args: val_acc1, label='Validation Accuracy (MobileNetV2)')
plt.axvline(best_epoch1 - 1, color='red', linestyle='--', label='Early Stopping Trigger (MobileNetV2)')
plt.title('MobileNetV2 Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.grid()
plt.savefig("mobilenetv2_accuracy.png")
plt.show()

plt.figure(figsize=(10, 6))
plt.plot( *args: train_loss1, label='Train Loss (MobileNetV2)')
plt.plot( *args: val_loss1, label='Validation Loss (MobileNetV2)')
plt.axvline(best_epoch1 - 1, color='red', linestyle='--', label='Early Stopping Trigger (MobileNetV2)')
plt.title('MobileNetV2 Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.grid()
plt.savefig("mobilenetv2_loss.png")
plt.show()

# ResNet18 Plots
plt.figure(figsize=(10, 6))
plt.plot( *args: train_acc2, label='Train Accuracy (ResNet18)')
plt.plot( *args: val_acc2, label='Validation Accuracy (ResNet18)')
plt.axvline(best_epoch2 - 1, color='red', linestyle='--', label='Early Stopping Trigger (ResNet18)')
plt.title('ResNet18 Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.grid()
plt.savefig("resnet18_accuracy.png")
plt.show()

plt.figure(figsize=(10, 6))
plt.plot( *args: train_loss2, label='Train Loss (ResNet18)')
plt.plot( *args: val_loss2, label='Validation Loss (ResNet18)')
plt.axvline(best_epoch2 - 1, color='red', linestyle='--', label='Early Stopping Trigger (ResNet18)')
plt.title('ResNet18 Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.grid()
plt.savefig("resnet18_loss.png")
plt.show()
```

Fig. 11 Code for Making the Loss Accuracy Plots

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```python
2 usages  RuseCristian
def evaluate_model(model, test_loader, model_name):
    model.load_state_dict(torch.load(model_name))
    model.eval()
    y_true, y_pred = [], []
    with torch.no_grad():
        for inputs, labels in tqdm(test_loader, desc="Testing", leave=False):
            inputs, labels = inputs.to(device), labels.to(device)
            outputs = model(inputs)
            y_true.extend(labels.cpu().numpy())
            y_pred.extend(outputs.argmax(1).cpu().numpy())

    print(classification_report(y_true, y_pred, target_names=datasets.ImageFolder(test_dir).classes))


evaluate_model(model1, data_loaders['test'], model_name: "mobilenetv2.pth")
evaluate_model(model2, data_loaders['test'], model_name: "resnet18.pth")
```

Fig. 11 Code for generating the classification reports

Results and Observations

Tracking Metrics

Throughout the training process, I kept track of two key metrics: **accuracy** and **loss** for both training and validation datasets. These helped me evaluate how well the models were learning and generalizing. By monitoring these trends, I could spot overfitting and decided when to stop training using early stopping.

MobileNetV2

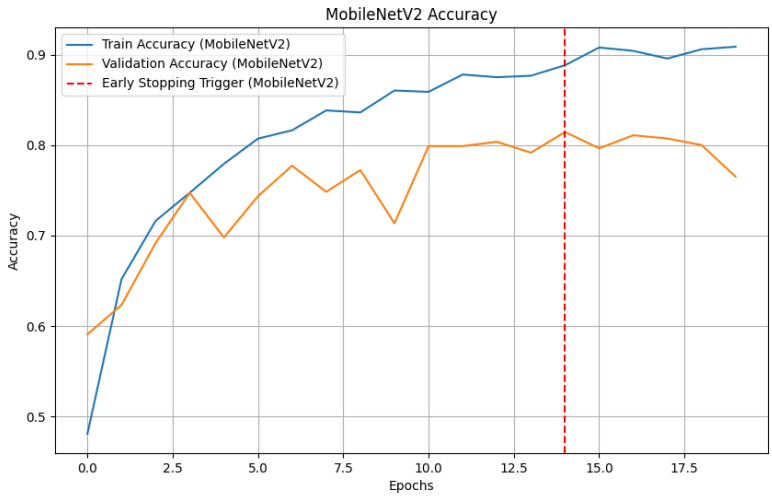

Fig. 12 MobileNetV2 Accuracy Graph

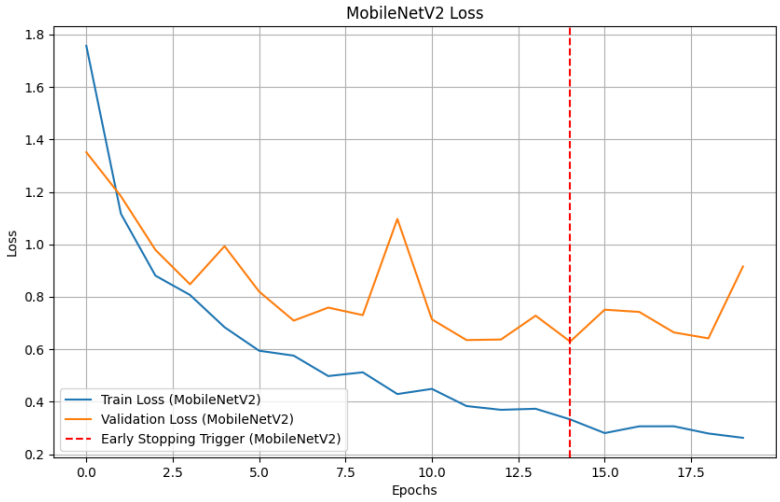

Fig. 13 MobileNetV2 Loss Graph

Accuracy:

- Training accuracy increased steadily, eventually reaching **90%**. This shows the model's ability to fit well to the training data.
- Validation accuracy, on the other hand, plateaued at **80%**, with occasional fluctuations. The gap between training and validation accuracy hinted at overfitting, but the model still managed to improve overall performance until at epoch 14. It continued to run up until epoch 18 where the early stopping decided to stop training as there were 5 continuous epochs were the validation loss did not improve.

Loss:

- Training loss consistently dropped below **0.4**, showing how well the model fit the training data.
- However, validation loss oscillated around **0.8–1.0**, creating a widening gap between training and validation losses as epochs progressed. This gap is an early indicator of overfitting, as the model becomes increasingly focused on the training data while struggling to generalize to unseen data.
- Despite the widening loss gap, the model's validation accuracy remained stable, indicating that MobileNetV2 was still improving before overfitting fully set in. Early stopping prevented further overfitting while preserving the model's performance at epoch 14.

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ResNet18

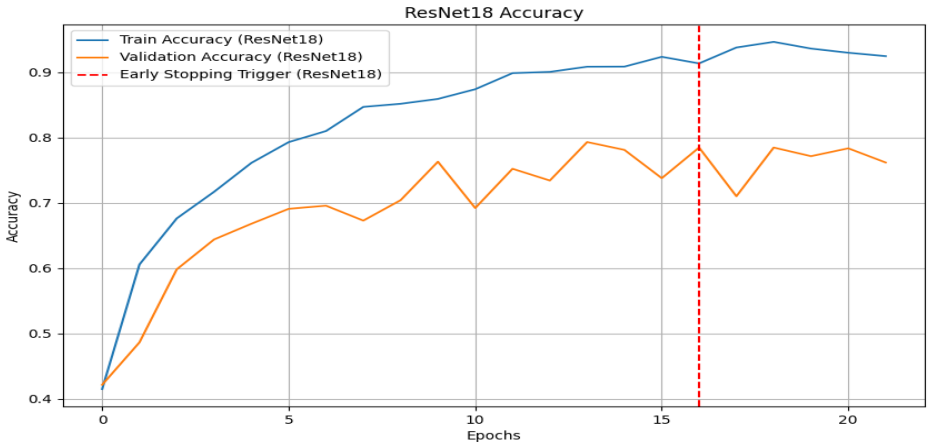

Fig. 14 ResNet18 Accuracy Graph

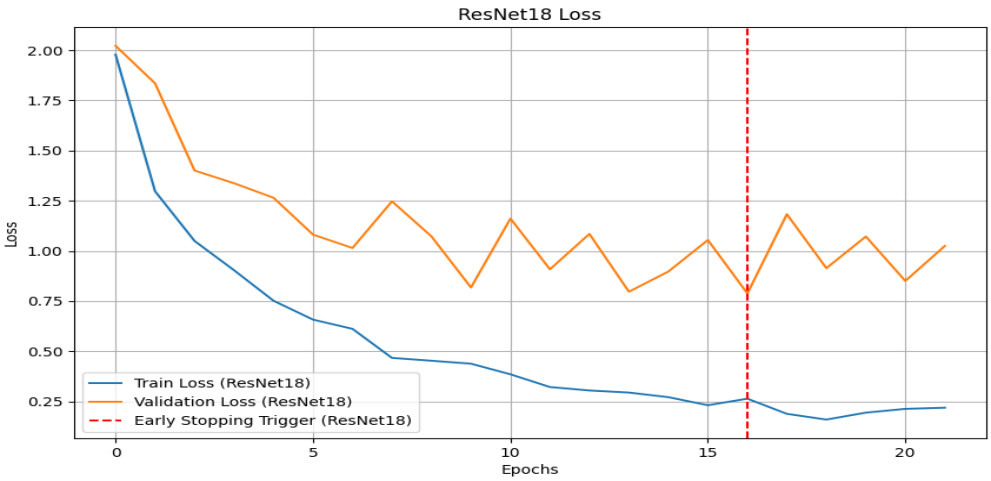

Fig. 15 ResNet18 Loss Graph

Accuracy:

- Training accuracy climbed higher than MobileNetV2, reaching **95%**, demonstrating the strength of ResNet18's deeper architecture and residual connections in capturing complex patterns.
- Validation accuracy remained steady just slightly below **80%** but showed more variability compared to MobileNetV2. The fluctuations reflected the model's attempt to generalize, with occasional signs of overfitting as the gap between training and validation accuracy grew.

Loss:

- Training loss dropped significantly to **0.25**, indicating the model's high confidence in its predictions on the training data.
- Validation loss decreased but fluctuated between **0.7–1.0**, like MobileNetV2. The growing gap between training and validation losses highlighted overfitting tendencies. However, ResNet18 continued improving its validation accuracy until reaching its best results at epoch 16. Similarly, 5 epochs later, at epoch 21, the early stopping saw no improvement to the loss value compared to the best value, found at epoch 16, and decided to stop the training process.
- The model's deeper architecture allowed it to perform better on the training data, but this also made it more prone to overfitting, as we can see the validation loss over the later epochs zig-zags up and downs and does not really improves, whilst the training loss improves consistently, thus it was a good idea to stop at epoch 16 due to definitely overfitting if continuing.

Both models showed clear signs of overfitting as training progressed, highlighted by the widening gap between training and validation losses. However, the early stopping mechanism ensured that the models retained their best validation performance.

- **MobileNetV2** demonstrated efficiency and robustness for a lightweight model, with validation accuracy stabilizing around **80%**.
- **ResNet18** achieved higher training accuracy, but its fluctuations in validation accuracy and loss revealed its sensitivity to overfitting due to its more complex architecture.

Model Performance Results

The classification reports for the MobileNetV2 and ResNet18 models on the test dataset are presented below. These reports include precision, recall, F1-score, and support for each class.

MobileNetV2 Classification Report

Class	Precision	Recall	F1-Score	Support
Agaricus augustus	0.84	0.82	0.83	33
Amanita amerirubescens	0.76	0.69	0.72	32
Amanita augusta	0.90	0.85	0.88	33

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Class	Precision	Recall	F1-Score	Support
Amanita brunnescens	0.62	0.90	0.73	29
Amanita calyptroderma	0.74	0.78	0.76	32
Amanita flavoconia	0.88	0.94	0.91	31
Amanita muscaria	0.81	0.93	0.87	28
Amanita persicina	0.79	0.44	0.56	25
Amanita phalloides	0.83	0.75	0.79	32
Amanita velosa	0.88	0.85	0.87	27
Armillaria mellea	0.72	0.74	0.73	31
Armillaria tabescens	0.80	0.83	0.81	29
Artomyces pyxidatus	0.97	1.00	0.98	31
Bolbitius titubans	0.82	0.87	0.84	31
Boletus pallidus	0.90	0.87	0.89	31
Boletus rex-veris	0.88	0.73	0.80	30
Cantharellus californicus	0.88	0.97	0.92	31
Cantharellus cinnabarinus	1.00	0.93	0.97	30
Cerioporus squamosus	0.87	0.90	0.88	51
Chlorophyllum brunneum	0.64	0.92	0.75	25
Chlorophyllum molybdites	0.67	0.55	0.60	22
Galerina marginata	0.95	0.82	0.88	22
Ganoderma applanatum	0.89	0.81	0.85	21
Ganoderma curtisii	0.75	0.60	0.67	20
Ganoderma oregonense	0.53	0.76	0.62	25
Ganoderma tsugae	0.82	0.52	0.64	27
Phaeolus schweinitzii	0.79	0.96	0.87	28

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Class	Precision	Recall	F1-Score	Support
Phlebia tremellosa	0.95	0.76	0.84	25
Phyllotopsis nidulans	0.89	0.89	0.89	28
Pleurotus ostreatus	0.85	0.79	0.81	28
Overall Accuracy			**0.81**	868
Macro Average	0.82	0.81	0.81	
Weighted Average	0.82	0.81	0.81	

ResNet18 Classification Report

Class	Precision	Recall	F1-Score	Support
Agaricus augustus	0.81	0.64	0.71	33
Amanita amerirubescens	0.75	0.66	0.70	32
Amanita augusta	0.75	0.64	0.69	33
Amanita brunnescens	0.75	0.72	0.74	29
Amanita calyptroderma	0.71	0.69	0.70	32
Amanita flavoconia	0.86	0.81	0.83	31
Amanita muscaria	0.81	0.93	0.87	28
Amanita persicina	0.92	0.48	0.63	25
Amanita phalloides	0.58	0.81	0.68	32
Amanita velosa	0.77	0.85	0.81	27
Armillaria mellea	0.58	0.68	0.63	31
Armillaria tabescens	0.65	0.59	0.62	29
Artomyces pyxidatus	1.00	0.94	0.97	31
Bolbitius titubans	0.79	0.84	0.81	31
Boletus pallidus	0.68	0.97	0.80	31

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Class	**Precision**	**Recall**	**F1-Score**	**Support**
Boletus rex-veris	0.89	0.80	0.84	30
Cantharellus californicus	1.00	0.71	0.83	31
Cantharellus cinnabarinus	0.83	1.00	0.91	30
Cerioporus squamosus	0.94	0.88	0.91	51
Chlorophyllum brunneum	0.85	0.68	0.76	25
Chlorophyllum molybdites	0.68	0.68	0.68	22
Galerina marginata	1.00	0.50	0.67	22
Ganoderma applanatum	0.80	0.95	0.87	21
Ganoderma curtisii	0.49	0.90	0.63	20
Ganoderma oregonense	0.71	0.60	0.65	25
Ganoderma tsugae	0.84	0.59	0.70	27
Phaeolus schweinitzii	0.92	0.86	0.89	28
Phlebia tremellosa	0.77	0.96	0.86	25
Phyllotopsis nidulans	0.90	0.96	0.93	28
Pleurotus ostreatus	0.63	0.79	0.70	28
Overall Accuracy			**0.77**	868
Macro Average	0.79	0.77	0.77	
Weighted Average	0.79	0.77	0.77	

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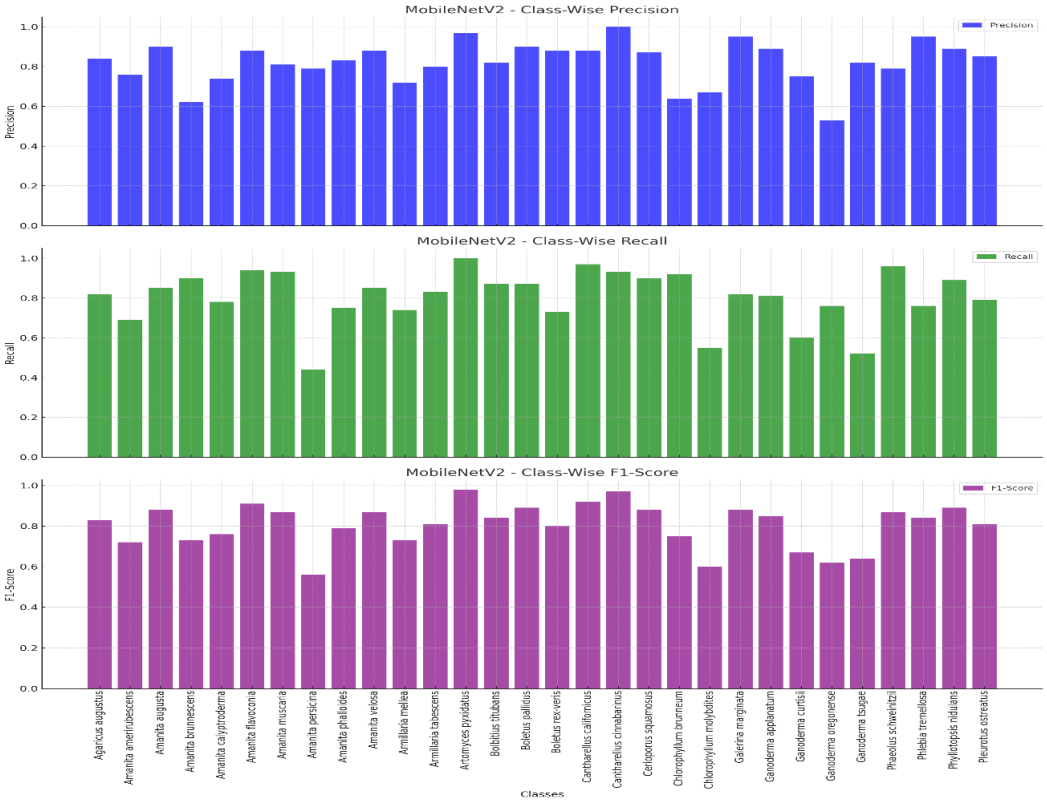

Fig. 16 Histogram for MobileNetv2

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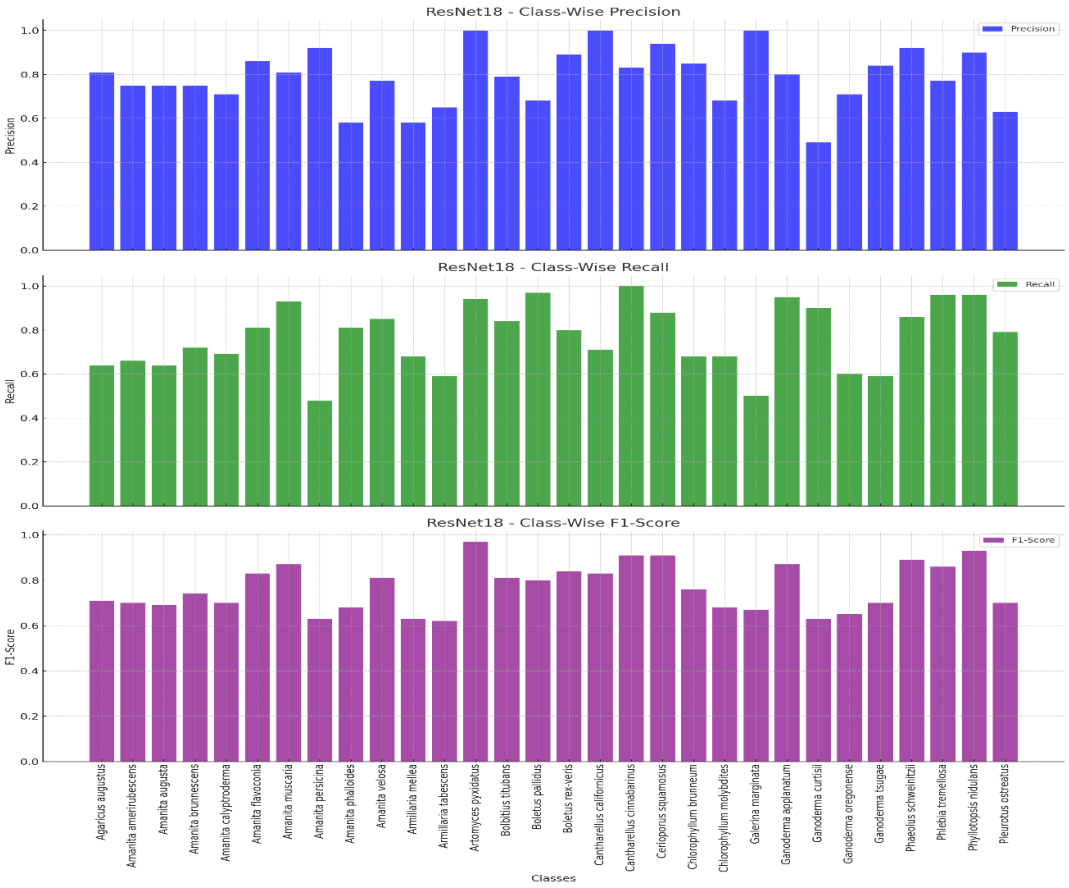

Fig. 17 Histogram for ResNet18

What each parameter represents:

Precision = True Positives / (True Positives + False Positives)

Recall = True Positives / (True Positives + False Negatives)

F1-Score = 2 * (Precision * Recall) / (Precision + Recall)

Support = Number of true instances for each class in the dataset.

Accuracy = Correct Predictions / Total Predictions

Observations

- **MobileNetV2** achieved an overall accuracy of **81%**, with notable performance in classes such as *Artomyces pyxidatus* (F1-Score: 0.98) and *Cantharellus cinnabarinus* (F1-Score: 0.97). However, it struggled with some classes like *Amanita persicina* (F1-Score: 0.56) due to lower recall.
- **ResNet18** attained an overall accuracy of **77%**, slightly lower than MobileNetV2. While its performance was comparable for certain classes, such as *Artomyces pyxidatus* (F1-Score: 0.97), it showed weaknesses in classes like *Galerina marginata* (F1-Score: 0.67) due to lower recall and precision.

- Both models demonstrated strong performance in highly distinguishable classes, but more complex or visually similar classes presented challenges.

Confusion Matrices

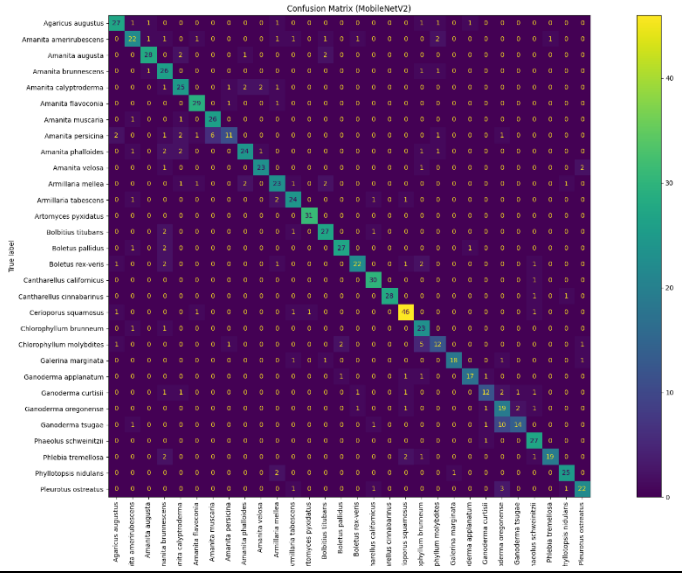

Fig. 18 MobileNetv2 Confusion Matrix

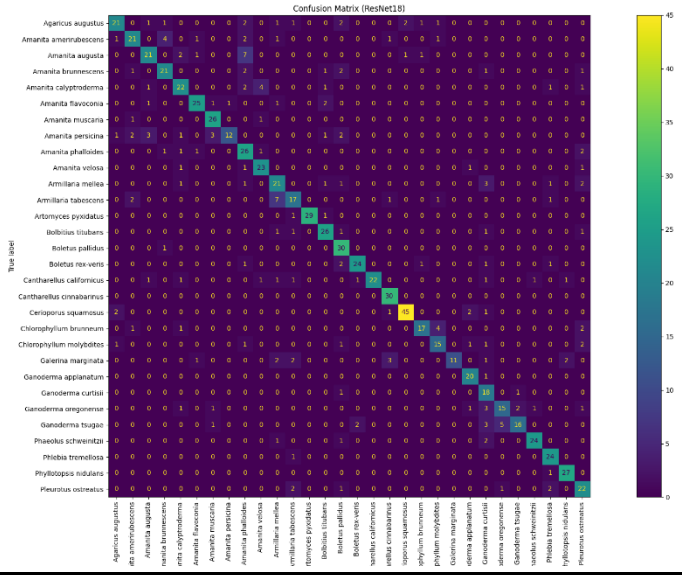

Fig. 19 ResNet18 Confusion Matrix

The confusion matrices provide a clear view of how well each model classified the test data.

- **MobileNetV2**: This model shows strong overall performance, with many classes like *Artomyces pyxidatus* and *Pleurotus ostreatus* being classified almost perfectly. However, it struggles with visually similar classes, such as *Amanita flavoconia* and *Bolbitius titubans*.
- **ResNet18**: ResNet18 performs well on complex classes like *Cerioporus squamosus*, leveraging its deeper architecture. However, it also misclassifies certain challenging classes, showing that its complexity can lead to overfitting in some cases.

Predictions

Both models were tested on 15 images from the test subset, therefore none of the images it was asked to predict were used in its training. This will show more of a real-world example of their performances.

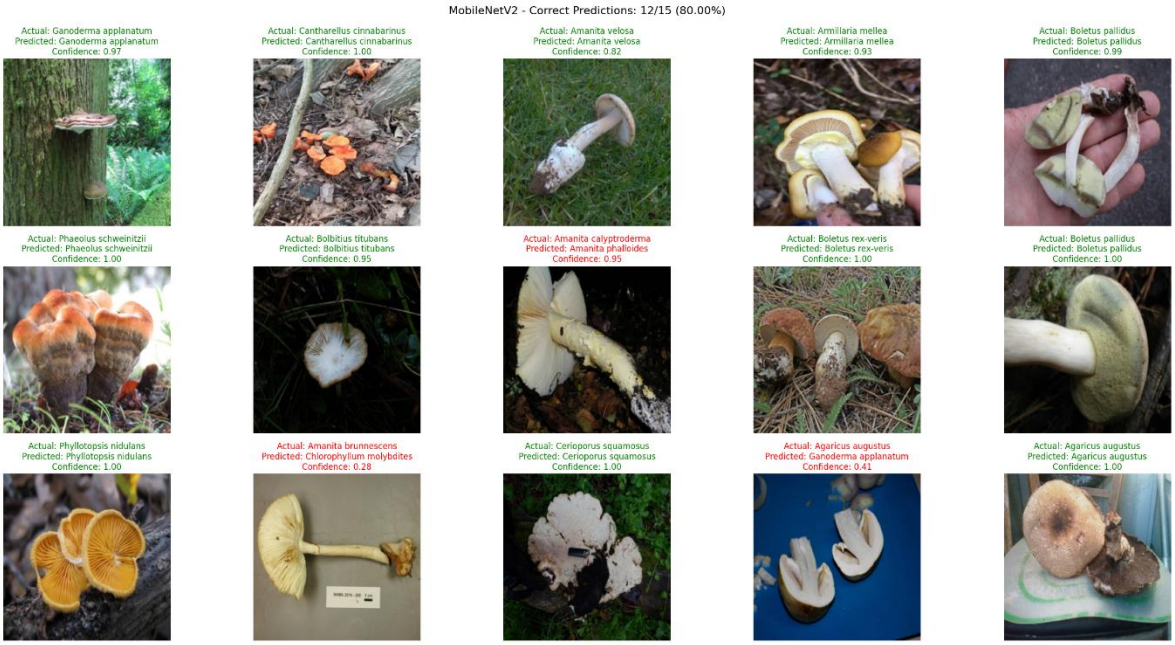

Fig. 20 MobileNetV2 Predictions

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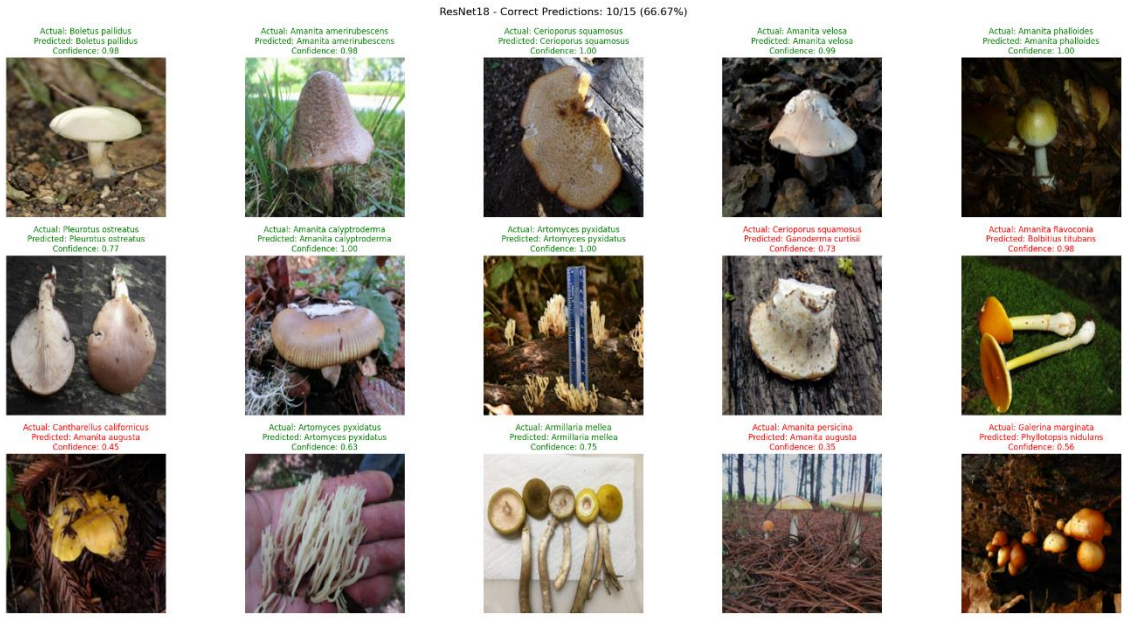

Fig. 21 ResNet18 Predictions

- **MobileNetV2**: Correctly predicted 12/15 images (80% accuracy). It handled simpler classes effectively but misclassified ambiguous images like *Amanita calyptroderma*. Misclassified predictions had noticeably lower confidence scores, which showcase that even though it misclassified 3 of the images, it was quite unsure of them to begin with.
- **ResNet18**: Correctly predicted 10/15 images (66.67% accuracy). While it performed well on complex features, it struggled with certain ambiguous classes, resulting in slightly more misclassifications than MobileNetV2, which is in accordance with the previous results as ResNet18 performed slightly worse in the accuracy metrics.

Conclusion

The results highlight a distinction in the performance of MobileNetV2 and ResNet18. MobileNetV2 demonstrated stronger accuracy and reliability, particularly for simpler classifications, with fewer errors and lower confidence in its misclassifications. This suggests that MobileNetV2 might be a better choice for tasks requiring efficiency and consistent performance, especially when working with smaller datasets. While I did not test these models on larger datasets, the lightweight design of MobileNetV2 could make it more suitable for such scenarios. ResNet18, on the other hand, excelled at capturing complex features but showed slightly higher misclassification rates, indicating that it may be more appropriate for datasets with greater complexity or diversity, but that also would probably require bigger training datasets to make sure that the misclassifications do not occur so often.