SESSION // 05
TRANSFER LEARNING

FACULTY OF
SCIENCE AND ENGINEERING
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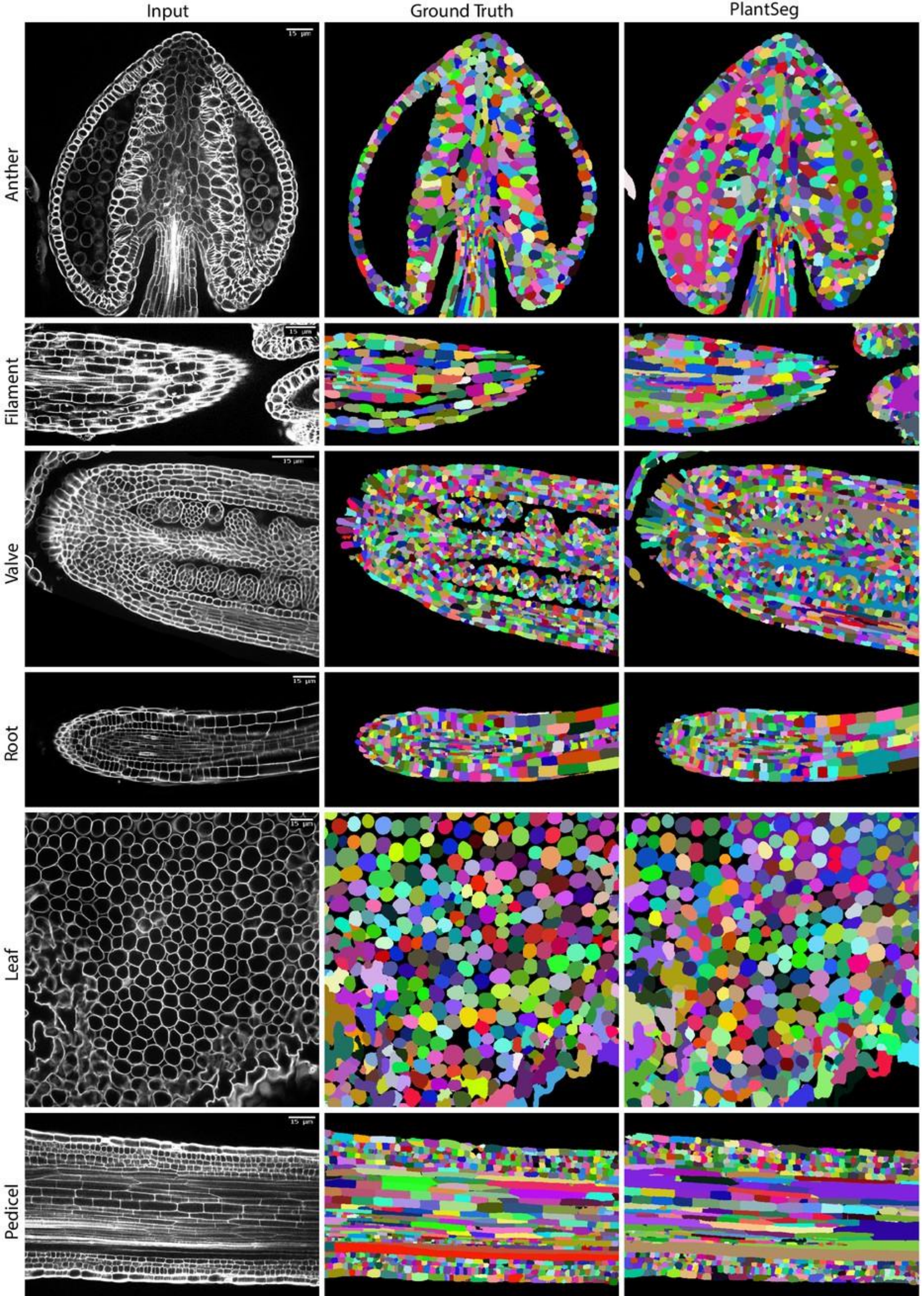


AGENDA

Introduction to Transfer Learning

- Definition and core concepts

Dataset Preparation

- Creating PyTorch dataset classes
- Computing dataset statistics
- Data augmentation for medical images

Baseline Architecture

- U-Net architecture overview
- Implementation of encoder-decoder structure

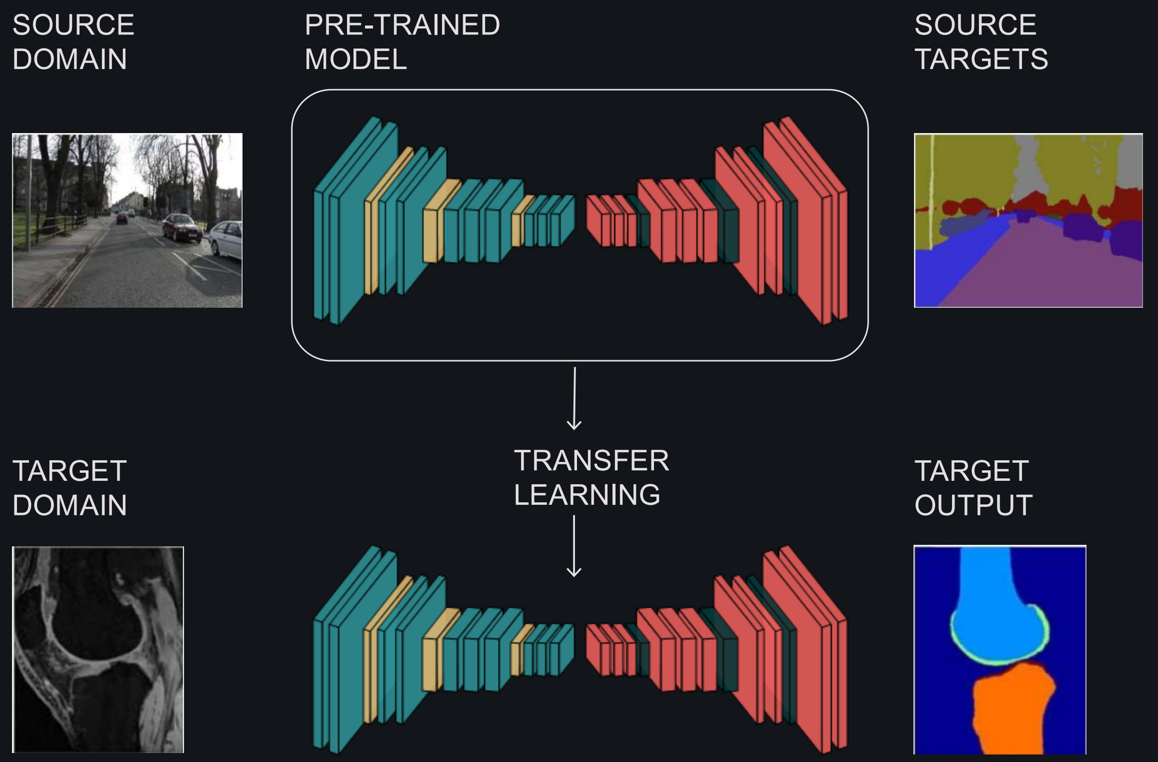
Loss Functions for Segmentation

- Dice Loss implementation

Transfer Learning with Pre-trained Models

- Introducing EfficientNet architecture
- Adapting pre-trained models for segmentation

Advantages of transfer learning approach



WHAT IS TRANSFER LEARNING?

A technique where a model developed for one task is reused as a starting point for a model on a second task. It leverages knowledge from pre-trained models instead of starting from scratch

It is particularly effective for deep learning models that require massive datasets and computational resources

WHEN SHOULD YOU USE TRANSFER LEARNING?

The **effectiveness** depends on similarity between source and target domains

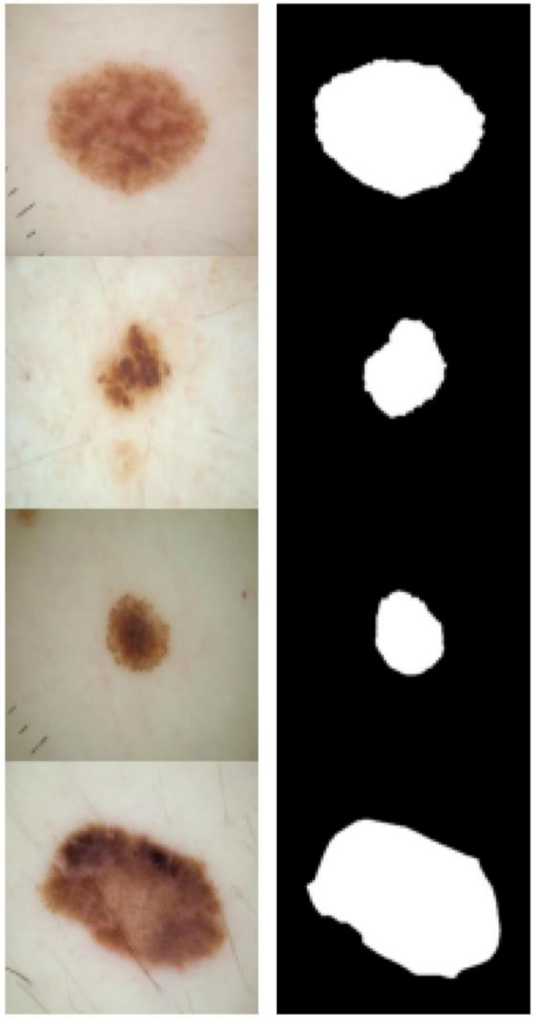
SCENARIO	EXAMPLE	BENEFIT
Limited training data	Medical imaging with few samples	Pre-trained features compensate for data scarcity
Similar domains	From natural images to satellite imagery	Underlying features (edges, textures) transfer well
Time constraints	Rapid prototyping needs	Accelerates model development cycle
Hardware limitations	Training with limited GPU access	Reduces computational requirements
Preventing overfitting	Small dataset applications	Regularization effect from pre-trained weights

ISIC 2016 SKIN LESION DATASET

Medical datasets like ISIC are typically smaller than general computer vision datasets, making transfer learning particularly valuable

- Contains dermoscopic images of skin lesions with expert-annotated segmentation masks
- 900 training images and 379 test images with corresponding binary masks
- Critical for developing automated diagnostic tools for early melanoma detection
- Challenging due to varying lesion sizes, shapes, colours, and skin types

IMAGE MASK



PYTORCH DATASET

```
from torch.utils.data import Dataset, DataLoader

class ISICDataset(Dataset):
    def __init__(self, image_dir, mask_dir, img_transform=None, mask_transform=None):
        self.image_dir = Path(image_dir)
        self.mask_dir = Path(mask_dir)
        self.img_transform = img_transform
        self.mask_transform = mask_transform
        self.images = sorted(self.image_dir.glob("*.jpg"))

    def __len__(self):
        return len(self.images)

    def __getitem__(self, idx):
        # Load image and mask
        img_name = self.images[idx]
        image = Image.open(self.image_dir / img_name).convert("RGB")
        mask = Image.open(self.mask_dir / f"{img_name.stem}_segmentation.png").convert("L")

        # Apply transformations if provided
        if self.img_transform:
            image = self.img_transform(image)
        if self.mask_transform:
            mask = self.mask_transform(mask)

        return image, mask
```

PyTorch's Dataset class is the foundation for data loading

Three key methods:

- __init__
- __len__
- __getitem__

Enables efficient data handling and batch processing

DATA AUGMENTATION FOR SEGMENTATION

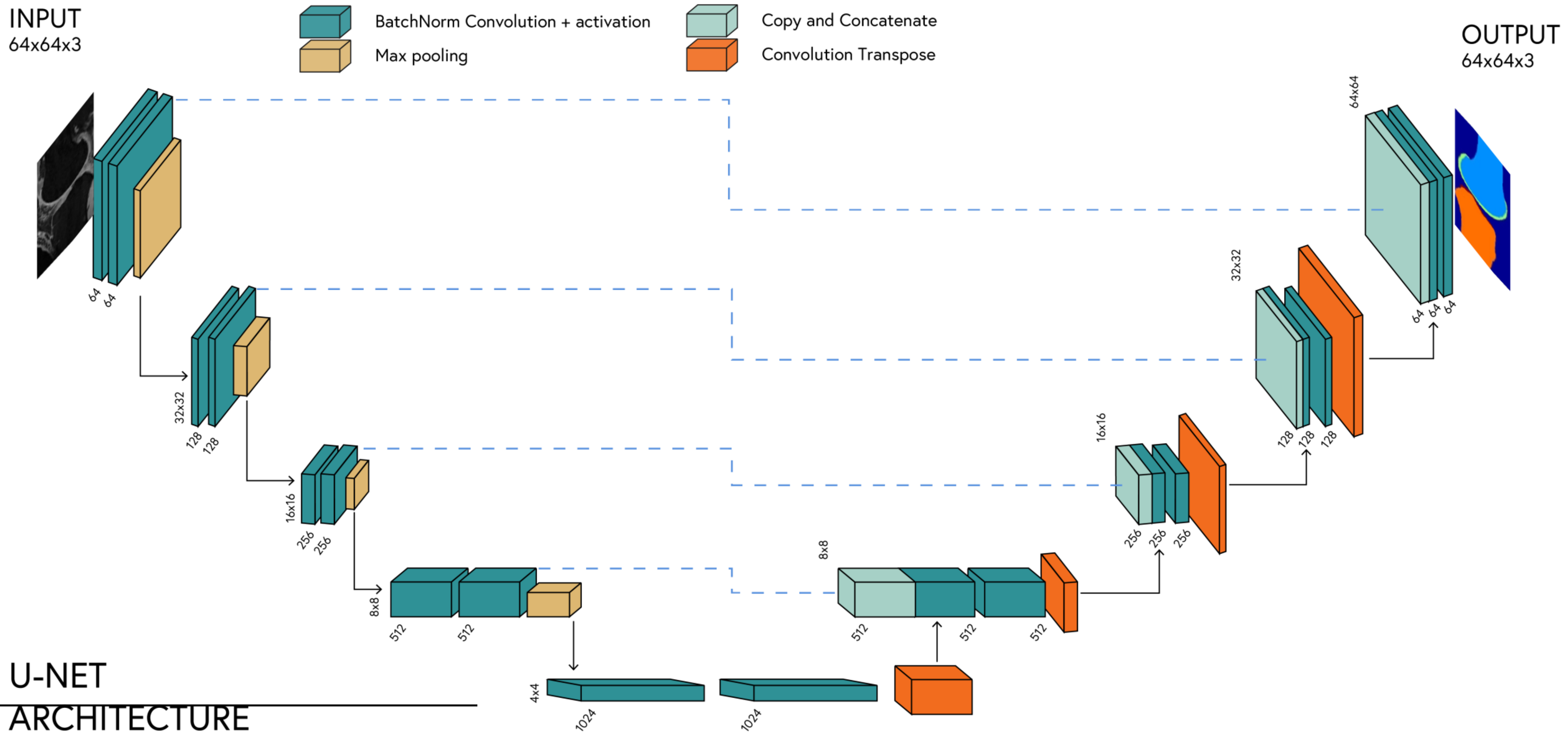
- **Synchronized** augmentation for images and masks
- **Careful selection** of transformations to preserve diagnostic features
- **Geometric transforms:** rotation, flipping, resizing
- **Color adjustments:** brightness, contrast

```python
import albumentations as A
from albumentations.pytorch import ToTensorV2

train_img_ts = A.Compose([
    A.Resize(64, 64),
    A.HorizontalFlip(p=0.5),
    A.VerticalFlip(p=0.5),
    A.Rotate(limit=10, p=0.5),
    A.ColorJitter(brightness=0.2, contrast=0.2, saturation=0.2, hue=0.1, p=0.5),
    A.Normalize(mean=mean, std=std, p=1.0),
    ToTensorV2()
])
```

U-NET

- **Encoder-decoder** architecture with skip connections
- Captures both **context and localisation** information
- Widely used for biomedical **image segmentation**



U-NET ARCHITECTURE

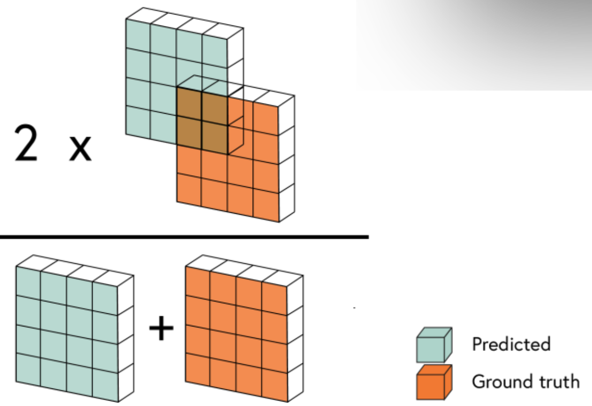
DICE LOSS

- Measures **overlap** between predicted and ground truth masks
- Handles **class imbalance** better than binary cross-entropy

```python
class DiceLoss(torch.nn.Module):
    def __init__(self, smooth=1.0):
        super().__init__()
        self.smooth = smooth

    def forward(self, y_pred, y_true):
        y_pred = y_pred.view(-1)
        y_true = y_true.view(-1).float()
        intersection = (y_pred * y_true).sum()
        union = y_pred.sum() + y_true.sum()
        dice = (2. * intersection + self.smooth) / (union + self.smooth)
        return torch.clamp(1 - dice, 0.0, 1.0)
```

$$\text{DICE} = \frac{2 \times \text{OVERLAP}}{\text{TOTAL AREA}} =$$

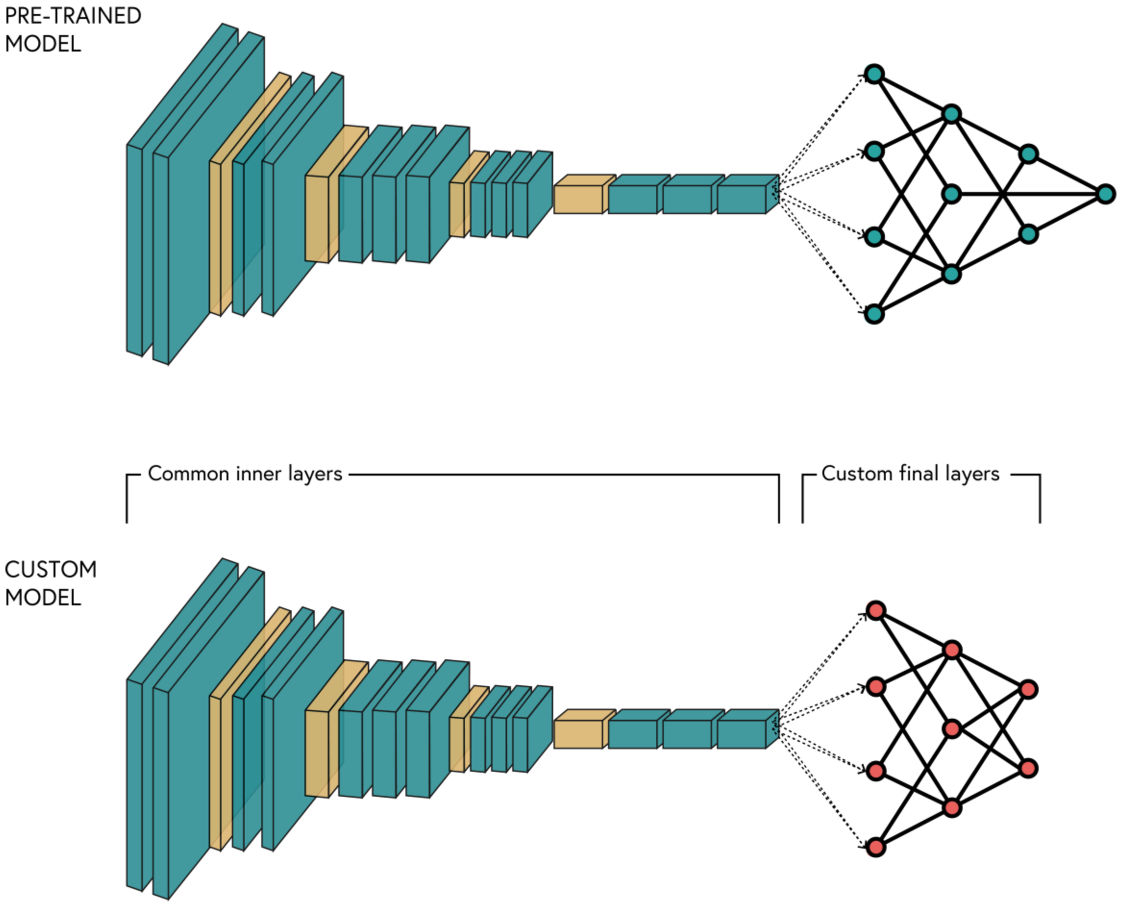


$$\text{DiceLoss} = 1 - \frac{2|X \cap Y|}{|X| + |Y|}$$

TRANSFER LEARNING STEPS

Steps:

1. Select source model
2. Feature extraction
3. Fine-tuning
4. Model adaptation



PRE-TRAINED MODELS

- ResNet (11.7M-60M parameters)
- VGG (138M-144M parameters)
- Inception (6.8M-54M parameters)
- EfficientNet (5.3M-66M parameters)
- MobileNet (4.2M-6.9M parameters)

EFFICIENT-NET
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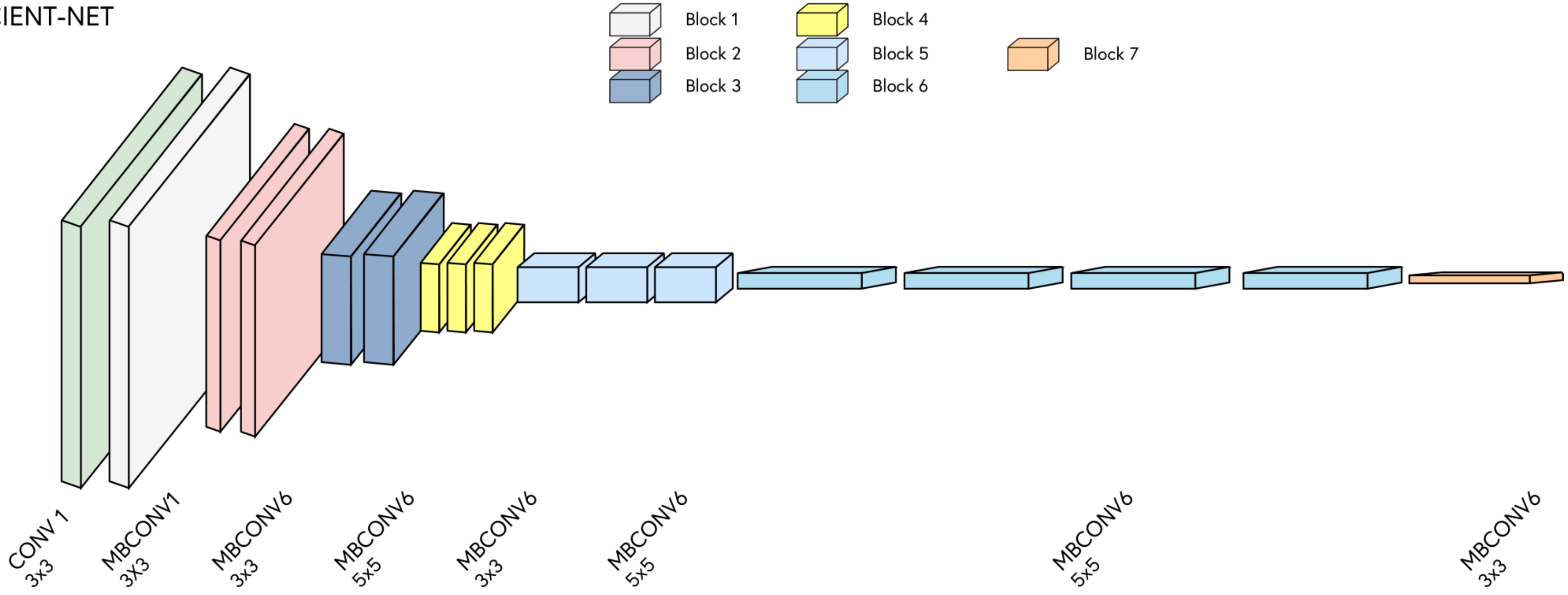


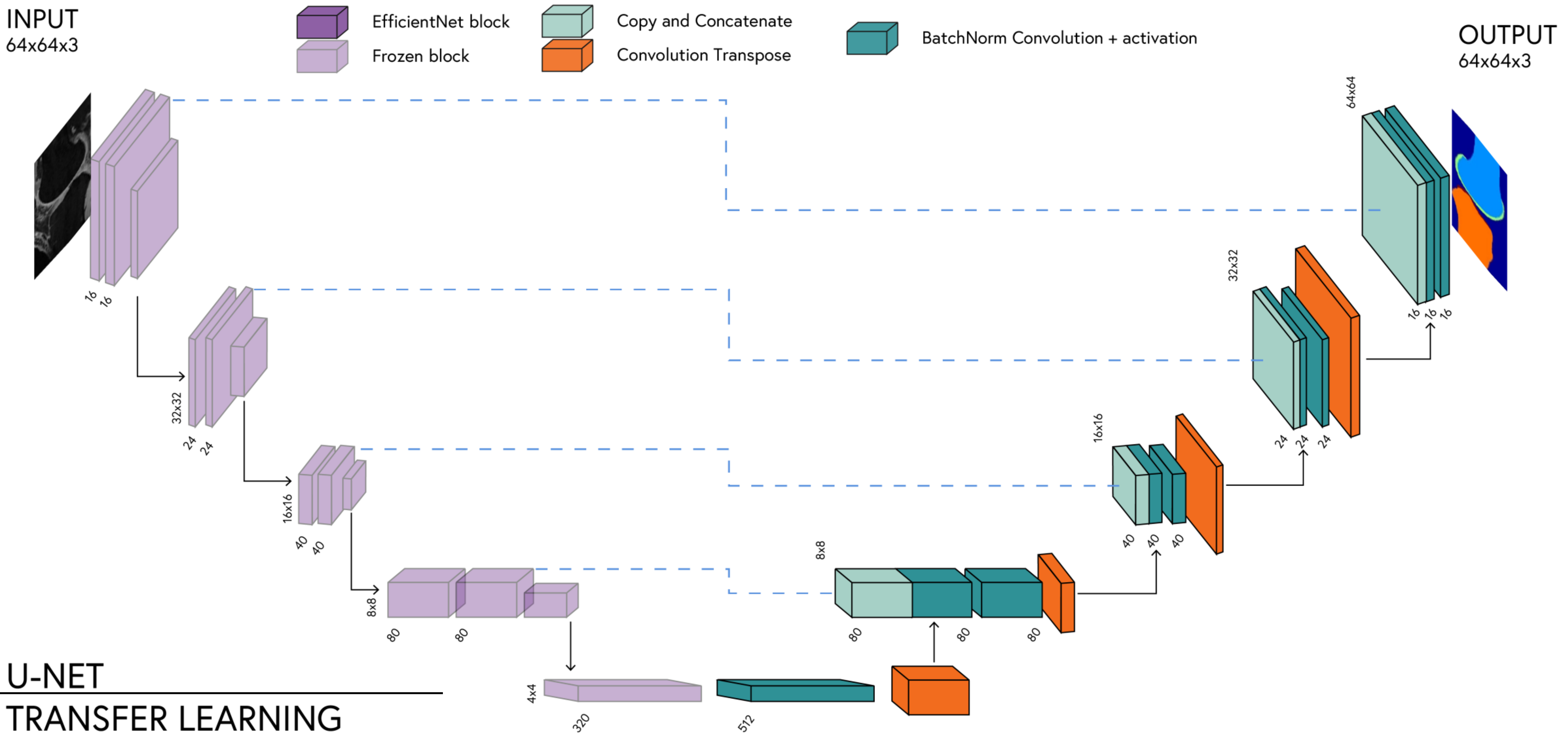
LOADING PRE-TRAINED MODELS

- **Torchvision** provides easy access to state-of-the-art pre-trained models
- Models include weights trained on **ImageNet** (1.2M+ images, 1000 classes)
- Simple API for loading models **with or without** pre-trained weights
- Supports **many architectures**: ResNet, EfficientNet, VGG, MobileNet, etc.

```python
import torchvision.models as models

# Load with pre-trained weights (default)
resnet50 = models.resnet50(weights='IMAGENET1K_V1')

# Load with latest weights
efficientnet = models.efficientnet_b0(weights='IMAGENET1K_V2')

# Load without pre-trained weights
vgg16 = models.vgg16(weights=None)

# Access only feature extractor portion
features = efficientnet.features

# See available architectures
print(dir(models))

# Access weights info
print(models.EfficientNet_B0_Weights.IMAGENET1K_V1.meta)
```

EFFICIENT U-NET

- **Replace** standard encoder with pre-trained EfficientNet
- **Freeze** pre-trained weights to preserve learned features
- Train **only decoder** layers initially

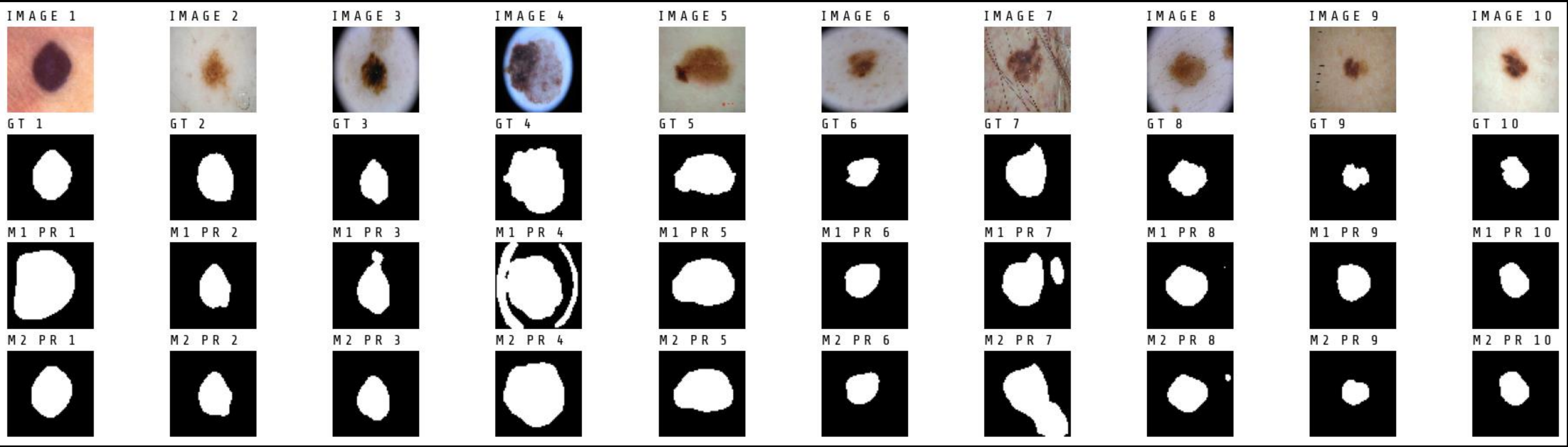


U-NET
TRANSFER LEARNING

SMART UP BLOCK

- Handles feature map size mismatches between encoder and decoder
- Employs bilinear interpolation to resolve size discrepancies when needed
- Bilinear interpolation creates smoother transitions between pixels compared to nearest-neighbour
- Allows flexibility when working with arbitrary encoder architectures

```python
class SmartUp(torch.nn.Module):
    def __init__(self, in_channels, skip_channels, out_channels):
        super().__init__()
        self.up = torch.nn.ConvTranspose2d(in_channels,
                                           skip_channels,
                                           kernel_size=2, stride=2)
        self.conv = DoubleConv(skip_channels * 2, out_channels)

    def forward(self, x1, x2):
        x1 = self.up(x1)  # Initial upsampling via transposed convolution

        # Handle size mismatches with interpolation
        if x1.size()[2:] != x2.size()[2:]:
            # Bilinear interpolation - weighted average of 4 nearest pixels
            # align_corners=False prevents edge artifacts
            x1 = torch.nn.functional.interpolate(
                x1,
                size=x2.size()[2:],  # Match skip connection dimensions
                mode='bilinear',     # Smoother than nearest neighbor
                align_corners=False  # Consistent behavior with odd dimensions
            )

        # Concatenate skip connection along channel dimension
        x = torch.cat([x2, x1], dim=1)
        return self.conv(x)  # Apply convolution to fused features
```



ADVANTAGES OF T-LEARNING

- Reduced training time (5-10x faster)
- Works with limited medical imaging data
- Better performance with challenging cases
- Faster convergence
- Lower computational cost
- Knowledge retention from source domain