

CS 203: Software Tools & Techniques for AI

IIT Gandhinagar

Sem-II - 2024-25

LAB 05

GROUP : 2

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Task 1: Data Augmentation

- Download the Cat & Dog Dataset

(<https://www.kaggle.com/datasets/samuelcortinhas/cats-and-dogs-image-classification?select=test>) (Only download the test dataset; do not take the training dataset)

Create a train and test set (train-test ratio should be 80:20%).

CODE :

```
# Define paths
dataset_path = "/content/drive/MyDrive/test" # Change if needed
train_path = "/content/drive/MyDrive/test/train"
test_path = "/content/drive/MyDrive/test/test_split"

# Create train and test directories
os.makedirs(train_path, exist_ok=True)
os.makedirs(test_path, exist_ok=True)

# Get all image file paths
cat_images = [os.path.join(dataset_path, "cats", img) for img in os.listdir(os.path.join(dataset_path, "cats"))]
dog_images = [os.path.join(dataset_path, "dogs", img) for img in os.listdir(os.path.join(dataset_path, "dogs"))]

# Split into train (80%) and test (20%)
cat_train, cat_test = train_test_split(cat_images, test_size=0.2, random_state=42)
dog_train, dog_test = train_test_split(dog_images, test_size=0.2, random_state=42)

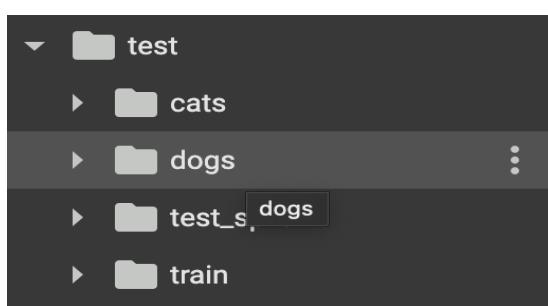
# Create category-specific folders in train and test sets
for folder in ["cats", "dogs"]:
    os.makedirs(os.path.join(train_path, folder), exist_ok=True)
    os.makedirs(os.path.join(test_path, folder), exist_ok=True)

# Function to copy images instead of moving them
def copy_images(file_list, dest_folder):
    for file in file_list:
        shutil.copy(file, os.path.join(dest_folder, os.path.basename(file)))

# Copy images to train and test directories
copy_images(cat_train, os.path.join(train_path, "cats"))
copy_images(dog_train, os.path.join(train_path, "dogs"))
copy_images(cat_test, os.path.join(test_path, "cats"))
copy_images(dog_test, os.path.join(test_path, "dogs"))

print("Dataset successfully split into train and test sets without modifying the original images.")
```

Dataset successfully split into train and test sets without modifying the original images.



test_split → contains the test split (20% of the downloaded dataset)
train → contains the train split (80% of the downloaded dataset, before augmentation)

Create Custom Function using Augly, which will perform multiple random data augmentations according to input. (At least 10 data augmentation needs to be added like rotate, cropping, blur ...)

CODE :

```
def apply_random_augmentations(image_path, num_augmentations=3):
    """
    Apply multiple random augmentations from AugLy to an image.
    Parameters:
    - image_path: Path to the input image
    - num_augmentations: Number of random augmentations to apply (default = 3)
    Returns:
    - Augmented image (PIL.Image object)
    """

    # Load the image
    img = PIL.Image.open(image_path).convert("RGB")

    # Define a list of available functional augmentations
    augmentations = [
        lambda x: imaugs.rotate(x, degrees=random.uniform(-30, 30)), # Rotation
        lambda x: imaugs.crop(x, x1=0.15, y1=0.15, x2=0.85, y2=0.85), # Cropping
        lambda x: imaugs.blur(x, radius=random.uniform(1, 3)), # Blur
        lambda x: imaugs.color_jitter(x, brightness_factor=1.2, contrast_factor=1.2, saturation_factor=1.2),
        lambda x: imaugs.grayscale(x, mode="luminosity"), # Convert to Grayscale
        lambda x: imaugs.brightness(x, factor=random.uniform(0.7, 1.3)), # Brightness
        lambda x: imaugs.shuffle_pixels(x, factor=random.uniform(0.1, 0.5)), # Pixel Shuffle (New)
        lambda x: imaugs.hflip(x), # Horizontal Flip
        lambda x: imaugs.contrast(x, factor=random.uniform(0.5, 1.5)), # Contrast Adjustment
        lambda x: imaugs.change_aspect_ratio(x, ratio=random.uniform(0.8, 1.2)), # Aspect Ratio Change
    ]

    # Randomly choose augmentations to apply
    chosen_augmentations = random.sample(augmentations, num_augmentations)

    # Apply augmentations sequentially
    for aug in chosen_augmentations:
        img = aug(img)

    return img
```

Perform data augmentation using the above function, only on the train set. (The number of augmented images should be twice the train set, and images should be augmented thrice example: cropped → rotate→Blur) (Second augmentation should be different)

CODE :

```
# Define original paths
train_dir = "/content/drive/MyDrive/test/train" # Original train folder
test_dir = "/content/drive/MyDrive/test/test_split" # Test folder
aug_train_dir = "/content/drive/MyDrive/test/train_augmented" # Augmented train folder

categories = ["cats", "dogs"]

# Function to copy the train folder
def copy_train_folder(src, dest):
    if os.path.exists(dest):
        shutil.rmtree(dest) # Remove existing copy if any
    shutil.copytree(src, dest)
    print(f"Copied train dataset to {dest}")

# Function to save augmented images
def save_augmented_image(image, save_path, filename, count):
    new_filename = f"{os.path.splitext(filename)[0]}_aug{count}.jpg"
    image.save(os.path.join(save_path, new_filename))

# Copy the train dataset before augmentation
copy_train_folder(train_dir, aug_train_dir)

# Get dataset statistics before augmentation
original_train_counts = {cat: len(os.listdir(os.path.join(aug_train_dir, cat))) for cat in categories}
original_test_counts = {cat: len(os.listdir(os.path.join(test_dir, cat))) for cat in categories}

print(f"Original Train Set Count (Copied): {original_train_counts}")
print(f"Original Test Set Count: {original_test_counts}")

# Augment images in the copied train folder
for category in categories:
    cat_path = os.path.join(aug_train_dir, category)
    images = [img for img in os.listdir(cat_path) if img.lower().endswith(('png', 'jpg', 'jpeg'))]

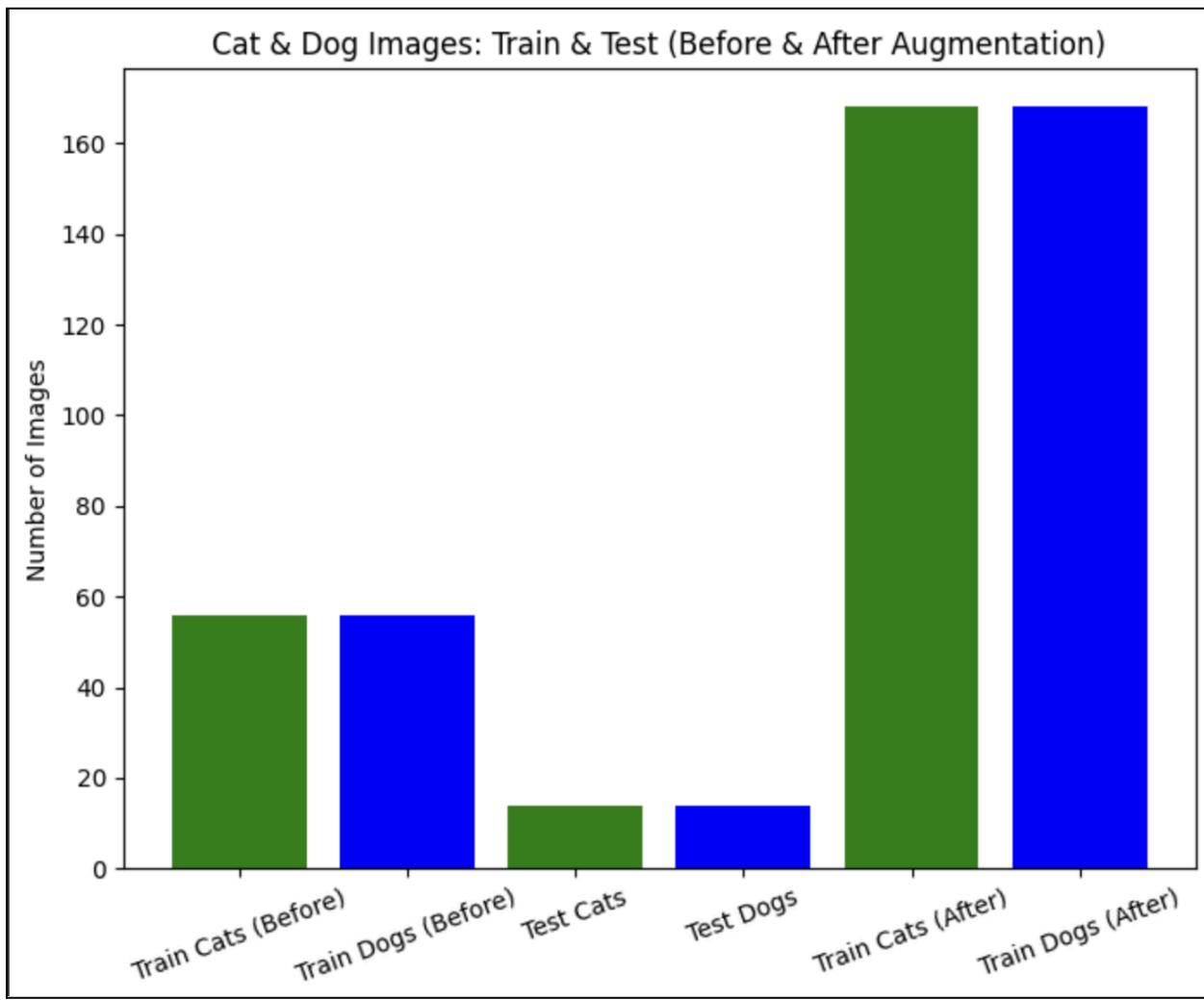
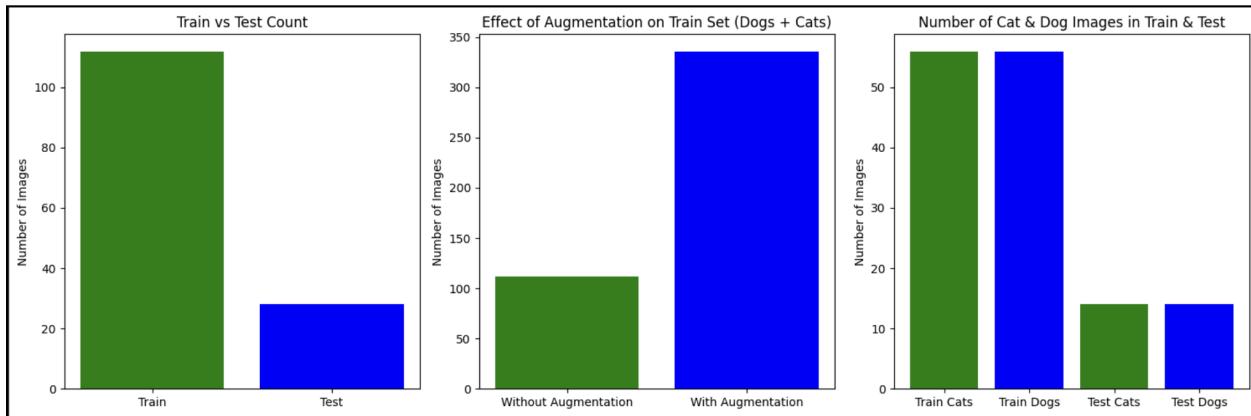
    for image_name in images:
        image_path = os.path.join(cat_path, image_name)

        # Apply augmentation twice with different transformations
        aug_img1 = apply_random_augmentations(image_path, num_augmentations=3)
        aug_img2 = apply_random_augmentations(image_path, num_augmentations=3)

        # Save the augmented images
        save_augmented_image(aug_img1, cat_path, image_name, 1)
        save_augmented_image(aug_img2, cat_path, image_name, 2)

print("Augmentation completed on copied dataset.")
```

Show the statistics of the newly created dataset. (Old dataset count and new dataset count)



Task 2: Model Training

Choose (microsoft/resnet-50)model from the huging face and initialize its new weights :

ResNet-50 is a **deep convolutional neural network (CNN)** that introduced **residual learning** to solve the vanishing gradient problem in very deep networks. It consists of **50 layers**.

Initial Layers:

- **7×7 Convolution** (64 filters, stride 2) → **BatchNorm + ReLU**
- **3×3 Max Pooling** (stride 2)

Residual Blocks (Bottleneck Architecture):

- **Stage 1:** 3 residual blocks
- **Stage 2:** 4 residual blocks
- **Stage 3:** 6 residual blocks
- **Stage 4:** 3 residual blocks

(Each block consists of three convolutions: 1×1, 3×3, 1×1)

Final Layers:

- **Global Average Pooling**
- **Fully Connected Layer** (1000 classes for ImageNet)

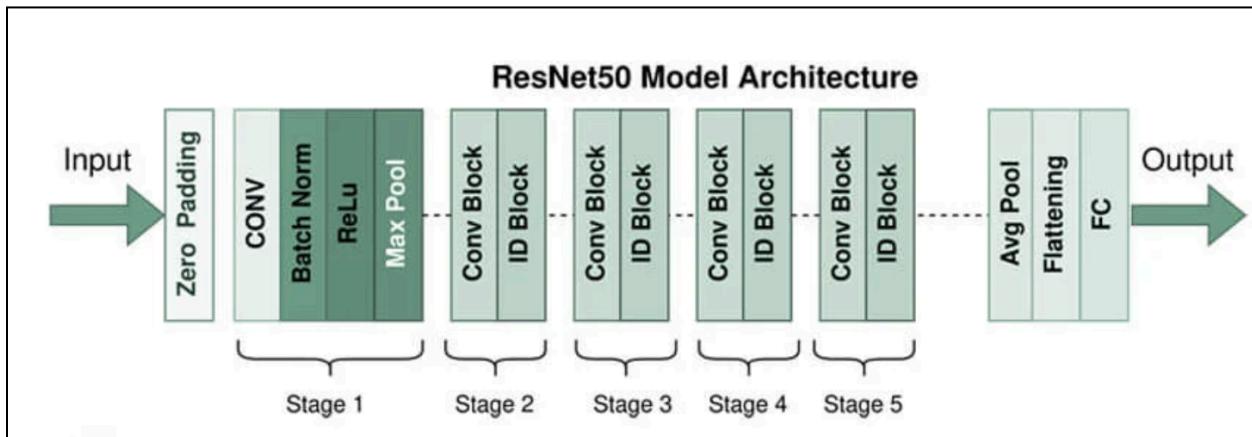


Image source : <https://www.educba.com/keras-resnet50/>

```
# Set device
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")

# Load model with new random weights
model_name = "microsoft/resnet-50"
feature_extractor = AutoFeatureExtractor.from_pretrained(model_name)
model = AutoModelForImageClassification.from_pretrained(model_name, num_labels=2, ignore_mismatched_sizes=True)

# Save initial model weights for consistency
initial_state_dict = model.state_dict()
```


TRAINING CODE :

```
# Training function
def train_model(model, train_loader, epochs=5, lr=1e-4):
    model.to(device)
    criterion = nn.CrossEntropyLoss()
    optimizer = optim.Adam(model.parameters(), lr=lr)

    model.train()
    for epoch in range(epochs):
        running_loss = 0.0
        for images, labels in train_loader:
            images, labels = images.to(device), labels.to(device)

            optimizer.zero_grad()
            outputs = model(images).logits
            loss = criterion(outputs, labels)
            loss.backward()
            optimizer.step()

            running_loss += loss.item()

        print(f"Epoch {epoch+1}, Loss: {running_loss/len(train_loader)}")

    return model
```

Train model(created in the above point) on a downloaded dataset, without augmentation.

```
Training on dataset without augmentation...
Epoch 1, Loss: 0.6802100794655936
Epoch 2, Loss: 0.6520122374807086
Epoch 3, Loss: 0.6242221934454781
```

Train model(created in the first point) on a downloaded dataset with augmentation.

```
Training on dataset with augmentation...
Epoch 1, Loss: 0.613908344791049
Epoch 2, Loss: 0.5475856023175376
Epoch 3, Loss: 0.45314411180359976
```

EVALUATION

Get the precision, recall, F1 score, and accuracy of both the models on the test set.

Performance on Test Set

Model Trained Without Augmentation:

Accuracy: 0.8571, Precision: 0.8646, Recall: 0.8571, F1 Score: 0.8564

Model Trained With Augmentation:

Accuracy: 0.9286, Precision: 0.9375, Recall: 0.9286, F1 Score: 0.9282

The model trained on augmented data performed better because augmentation introduced greater data diversity, making it more robust to real-world variations. By exposing the model to transformations like rotation, cropping, and brightness changes, it learned to focus on essential object features rather than memorizing specific patterns, thereby reducing overfitting. This improved generalization enabled the model to recognize test images more accurately, even if they had slight differences from the training set. Additionally, augmentation ensured that minor distortions did not mislead the model, leading to stronger representation learning. As a result, the model adapted better to unseen data, ultimately improving its accuracy and overall performance.
