Imagedata Augmentation and Image Classification

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1. Abstract

This project explores image handling, preprocessing, and classification using modern deep learning frameworks. OpenCV is used to demonstrate basic image operations such as resizing, rotation, and color-space conversion. A dummy Cat vs Dog dataset is created to build an image augmentation and dataloader pipeline in PyTorch. Several transformations, including cropping, flipping, rotation, and color jitter, are applied to enhance dataset diversity. The MNIST dataset is then used to implement a convolutional neural network (CNN) in TensorFlow for handwritten digit classification. The model is trained, evaluated, and predictions are tested using OpenCV to simulate real-world image handling. The project highlights the differences in image representation across libraries like OpenCV, PIL, and matplotlib. It also demonstrates the integration of image preprocessing with deep learning workflows. Overall, the work provides an end-to-end view of image classification pipelines, from raw pixels to predictions.

2. Introduction

Relevance of the Project:

Image processing and classification are crucial in numerous real-world applications such as healthcare diagnostics, autonomous driving, surveillance systems, and digital content analysis. The ability to accurately process, augment, and classify images forms the foundation of many computer vision systems. This project is highly relevant as it integrates both traditional image handling techniques and modern deep learning models, thereby bridging theoretical knowledge with practical applications.

Technology Involved:

The project employs three major technologies:

- **OpenCV** for image preprocessing operations such as resizing, rotation, and color-space transformations.
- **PyTorch** for constructing data pipelines and implementing advanced image augmentation strategies.
- **TensorFlow (Keras)** for building and training a convolutional neural network (CNN) to classify handwritten digits using the MNIST dataset.
  Additionally, Python libraries such as Matplotlib and PIL are used for visualization and dataset exploration.

Background Material Survey:

Traditionally, image classification relied on handcrafted features and classical machine learning techniques, which often struggled with complex variations in real-world images. With the advent of deep learning, convolutional neural networks (CNNs) have revolutionized feature extraction and classification, achieving state-of-the-art results in computer vision.

Preprocessing and augmentation play a key role in these systems by enhancing the dataset and reducing overfitting. Several studies highlight the importance of combining robust preprocessing pipelines with deep learning architectures to build scalable and accurate classification models.

Procedure Used:

The project was carried out in several structured phases:

1. **Image preprocessing** using OpenCV to demonstrate fundamental operations.
2. **Dataset preparation** through a synthetic Cat vs Dog dataset organized into ImageFolder format.
3. **Image augmentation** with PyTorch, applying transformations such as random cropping, flipping, rotation, and color jitter.
4. **Model development** by constructing a CNN in TensorFlow/Keras for the MNIST dataset.
5. **Training and evaluation** of the CNN model to assess performance on unseen test data.
6. **Prediction** using OpenCV to simulate real-world image handling and inference.

Purpose of the Project:

The purpose of this project is to provide comprehensive exposure to image preprocessing, augmentation, and classification workflows using both classical tools and modern deep learning frameworks. It aims to develop hands-on expertise in handling images, designing preprocessing pipelines, and implementing deep learning models. Furthermore, the project serves as a bridge between theoretical concepts and practical applications, preparing for future tasks in computer vision research and industry deployment.

3. Project Objective

- To demonstrate the importance of **image preprocessing techniques** such as resizing, rotation, and color-space conversion using OpenCV.
- To illustrate how **data augmentation** in PyTorch (cropping, flipping, rotation, and color jitter) improves dataset diversity and enhances model generalization.
- To develop and evaluate a **convolutional neural network (CNN)** in TensorFlow for handwritten digit recognition using the MNIST dataset.
- To integrate classical image handling with modern deep learning workflows, showcasing an **end-to-end image classification pipeline** from raw pixels to predictions.
- To highlight the role of **interoperability between libraries** (OpenCV, PIL, PyTorch, TensorFlow) in building practical and scalable computer vision systems.

4. Methodology

Overview

The project was carried out in multiple phases, beginning with image handling using OpenCV, followed by dataset preparation and augmentation in PyTorch, and concluding with classification using a convolutional neural network (CNN) in TensorFlow. Each stage was carefully designed to illustrate the importance of preprocessing and augmentation in building effective deep learning models.

1. Image Handling (OpenCV)

- Collected a sample image (moon.jpg) and applied preprocessing operations.
- Performed **resizing**, **rotation**, and **color-space conversion (BGR ↔ RGB, grayscale)**.
- Used **Matplotlib and PIL** alongside OpenCV to demonstrate differences in how libraries handle image channels.

Tools Used:

- OpenCV (cv2)
- Matplotlib, PIL

2. Dataset Preparation (Dummy Cat vs Dog Dataset)

- Created a synthetic dataset in the format required by torchvision.datasets.ImageFolder.
- Organized folders as Cat_Dog_data/train/cat/ and Cat_Dog_data/train/dog/.
- Generated random image samples to simulate real-world dataset structure (later replaceable with actual Cat vs Dog dataset).

Tools Used:

- Python OS library
- Numpy (for creating random images)
- PyTorch datasets.ImageFolder

3. Data Augmentation (PyTorch)

- Built a transformation pipeline with:
    - **Random Resized Crop**
    - **Random Horizontal Flip**

    - **Random Rotation**
    - **Color Jitter**
    - Conversion to Tensor and Normalization
- Constructed a DataLoader with batch_size=32 and shuffling enabled.
- Visualized a batch of augmented images to confirm transformations.

Tools Used:

- PyTorch
- Torchvision transforms
- Matplotlib

4. Classification Model Development (TensorFlow/Keras)

- Used **MNIST dataset** (60,000 training, 10,000 testing images).
- Preprocessed images by **normalizing pixel values to [0,1]** and expanding dimensions to include a single channel.
- Built a **Convolutional Neural Network (CNN)** with:
    - Conv2D + MaxPooling layers for feature extraction
    - Dense hidden layer with ReLU activation
    - Output layer with softmax for classification into 10 classes

Training Process:

- Optimizer: Adam
- Loss Function: Sparse Categorical Crossentropy
- Evaluation Metric: Accuracy
- Split: Training (60,000) and Testing (10,000) as provided by MNIST
- Epochs: 5, Batch Size: 64

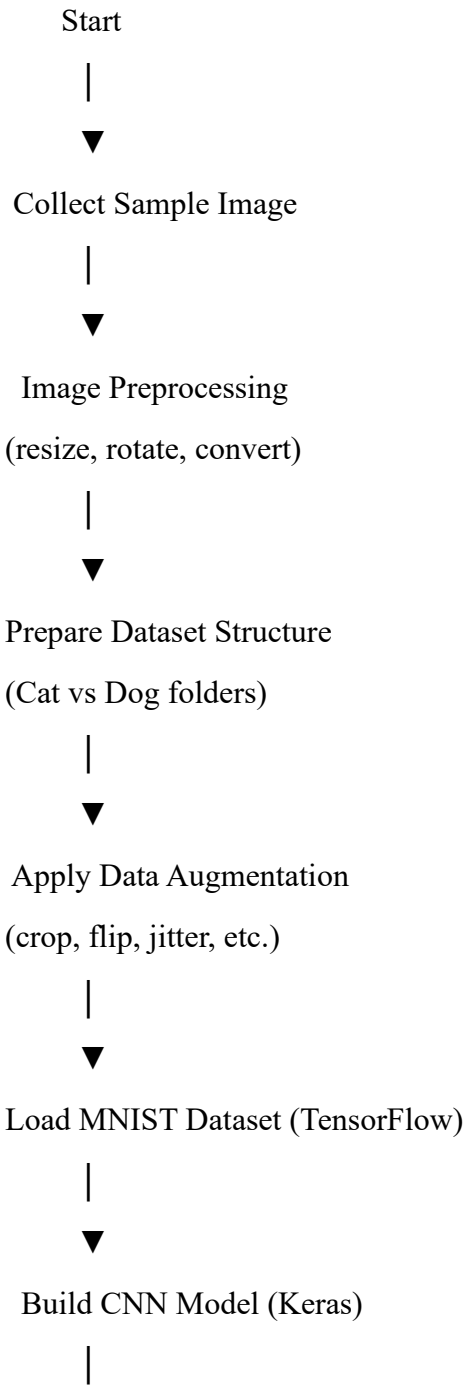
Validation Strategy:

- A hold-out test set (10,000 images) was used for final model evaluation.
- Model performance monitored using accuracy during training and testing phases.

5. Model Prediction with OpenCV

- Selected a few MNIST test images.
- Saved them using OpenCV's imwrite.
- Reloaded the images, applied preprocessing (resizing, normalization), and predicted using the trained CNN.
- Compared true labels vs. predicted labels.

Flowchart of the Process



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Train Model (train/test split)

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Evaluate Model Accuracy

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Save + Reload Images (OpenCV)

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Make Predictions & Compare Results

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End

Tools and Methods Used

- **Programming Language:** Python
- **Libraries:** OpenCV, PyTorch, Torchvision, TensorFlow/Keras, Matplotlib, PIL, NumPy
- **Analytical Model:** Convolutional Neural Network (CNN)
- **Data Handling:** ImageFolder for Cat/Dog dataset, built-in MNIST loader for digit classification

Code Repository (GitHub)

https://github.com/paryaarpan05-rgb/Arpan-_internship_2025.git

5. Data Analysis and Results

Q1 — Why do you think the color images displayed above look different (that is, Method 1 vs Method 2)?

Short answer: **OpenCV uses BGR color ordering while PIL / matplotlib expect RGB**. Detailed:

- `PIL.Image.open(...).show()` or `matplotlib.pyplot.imshow()` expects images in **RGB** order.
- `cv2.imread()` returns images in **BGR** order. If you pass that BGR image directly to `plt.imshow()` without converting to RGB you will see swapped color channels (reds/blue inverted).
- Also, in the example the code used `cmap='gray'` when displaying color images which can also change appearance. The correct approach when using OpenCV images with matplotlib is to convert BGR→RGB first:

Code:

```
import cv2
import matplotlib.pyplot as plt

img_bgr = cv2.imread('moon-pexels-frank-cone.jpg')
img_rgb = cv2.cvtColor(img_bgr, cv2.COLOR_BGR2RGB)
plt.imshow(img_rgb)
plt.axis('off')
plt.show()
```

Q2 — Implement the following types of image transformation with OpenCV functions: 1. Image resize 2. Image rotation

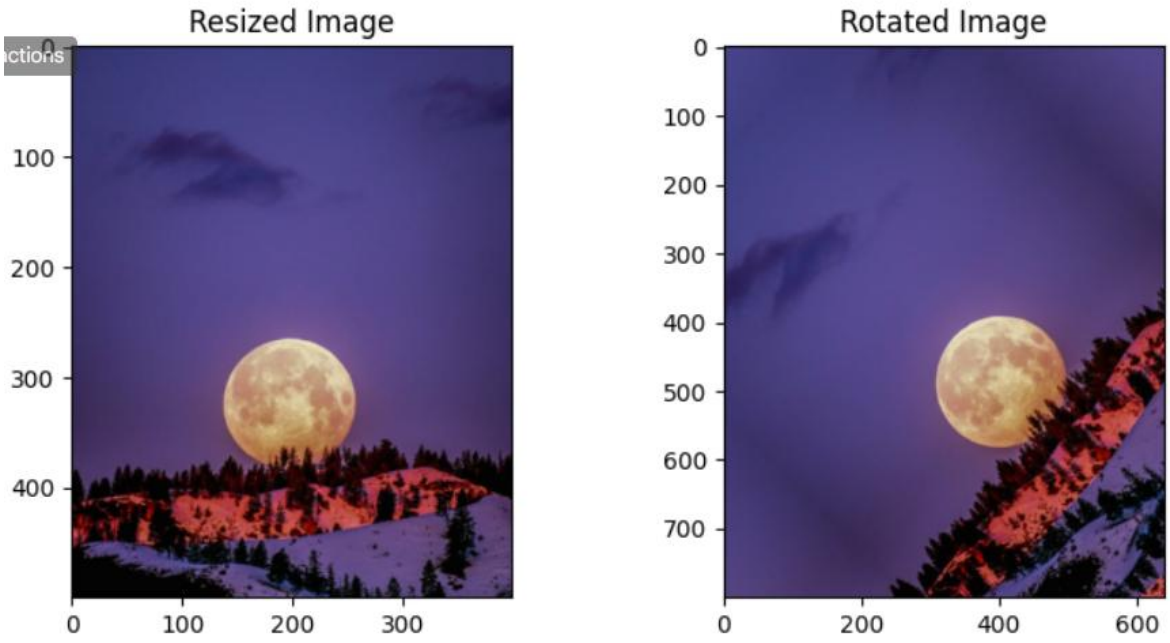
Below are two concise functions that resize and rotate an image using OpenCV. They handle preserving shape and optionally save results.

Code:

```
import cv2
import numpy as np
import matplotlib.pyplot as plt
```

```
def resize_image(in_path, out_path=None, width=None, height=None,
keep_aspect=True):
    img = cv2.imread(in_path)
    if img is None:
        raise FileNotFoundError(in_path)
    h, w = img.shape[:2]

    if keep_aspect:
        if width is None and height is None:
            return img
        if width is None:
            scale = height / float(h)
            width = int(w * scale)
        elif height is None:
            scale = width / float(w)
            height = int(h * scale)
        else:
            # choose scale that fits both
            scale = min(width / float(w), height / float(h))
            width = int(w * scale)
            height = int(h * scale)
    else:
        if width is None: width = w
        if height is None: height = h

    resized = cv2.resize(img, (width, height),
interpolation=cv2.INTER_AREA)
    if out_path:
        cv2.imwrite(out_path, resized)
    return resized

def rotate_image(in_path, out_path=None, angle=30, scale=1.0, center=None):
    img = cv2.imread(in_path)
    if img is None:
        raise FileNotFoundError(in_path)
    h, w = img.shape[:2]
    if center is None:
        center = (w // 2, h // 2)
    M = cv2.getRotationMatrix2D(center, angle, scale)
    rotated = cv2.warpAffine(img, M, (w, h), flags=cv2.INTER_LINEAR,
borderMode=cv2.BORDER_REFLECT)
    if out_path:
        cv2.imwrite(out_path, rotated)
    return rotated

# Example usage:
original_image_path = 'moon-pexels-frank-cone.jpg'

# Resize image
resized_image = resize_image(original_image_path, width=400)
rotated_image = rotate_image(original_image_path, angle=45)

fig, axes = plt.subplots(1, 2, figsize=(8, 4))
ax = axes.ravel()

ax[0].imshow(cv2.cvtColor(resized_image, cv2.COLOR_BGR2RGB))
ax[0].set_title("Resized Image")
ax[1].imshow(cv2.cvtColor(rotated_image, cv2.COLOR_BGR2RGB))
ax[1].set_title("Rotated Image")

fig.tight_layout()
```

```
plt.show()
```



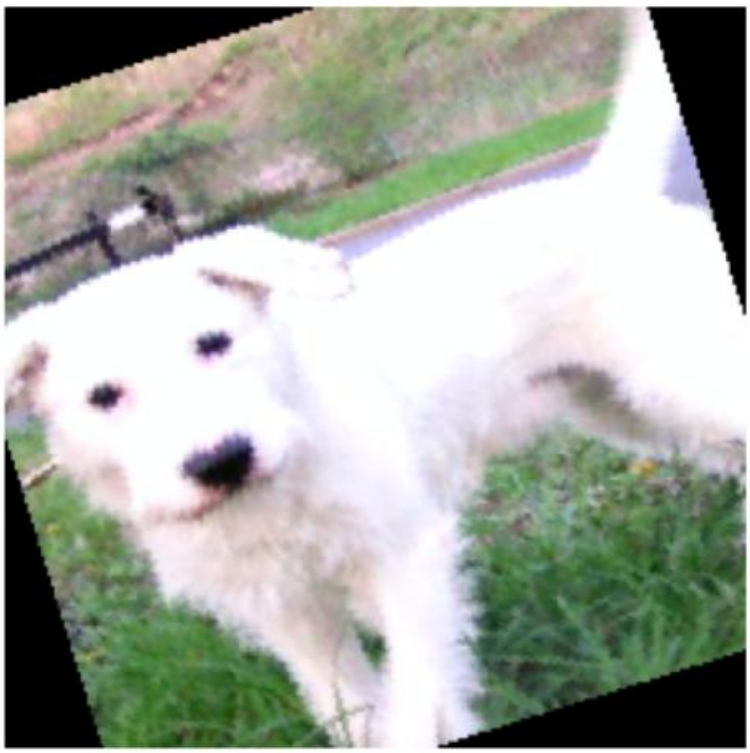
Q3 — Load images from the Cat_Dog_data/train folder, define a few additional transforms, then build the dataloader.

Below is a typical pipeline using `torchvision.transforms` with a few augmentations.

Code:

```
import torch
from torchvision import datasets, transforms
from torch.utils.data import DataLoader
import matplotlib.pyplot as plt
import numpy as np

data_dir = 'Cat_Dog_data/train'

transform = transforms.Compose([
```

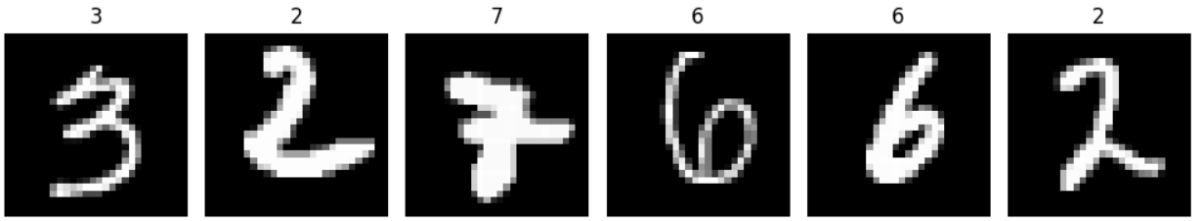
```
    transforms.RandomResizedCrop(224),       # random crop+resize
    transforms.RandomHorizontalFlip(p=0.5),
    transforms.RandomRotation(20),           # small rotations
    transforms.ColorJitter(brightness=0.2, contrast=0.2,
saturation=0.2, hue=0.02),
    transforms.ToTensor(),
    transforms.Normalize([0.485, 0.456, 0.406],
                         [0.229, 0.224, 0.225])
])

dataset = datasets.ImageFolder(data_dir, transform=transform)
dataloader = DataLoader(dataset, batch_size=32, shuffle=True,
num_workers=4, pin_memory=True)

images, labels = next(iter(dataloader))
img = images[0].cpu().numpy().transpose((1,2,0))
# un-normalize for plotting
mean = np.array([0.485, 0.456, 0.406])
std  = np.array([0.229, 0.224, 0.225])
img = std * img + mean
img = np.clip(img, 0, 1)
plt.imshow(img)
plt.axis('off')
plt.show()
```



Q4 — Display a few images below to show how the MNIST dataset look like.

Code to download MNIST and plot some samples:

```
import torch
from torchvision import datasets, transforms
import matplotlib.pyplot as plt

transform = transforms.Compose([transforms.ToTensor()])
trainset = datasets.MNIST(root='~/.pytorch/MNIST_data/', train=True,
download=True, transform=transform)
trainloader = torch.utils.data.DataLoader(trainset, batch_size=64,
shuffle=True)

images, labels = next(iter(trainloader))  # images shape [64,1,28,28]

fig, axes = plt.subplots(1, 6, figsize=(10,2))
for i in range(6):
    ax = axes[i]
    img = images[i].numpy().squeeze()
    ax.imshow(img, cmap='gray')
    ax.set_title(str(int(labels[i])))
    ax.axis('off')
plt.tight_layout()
plt.show()
```



Q5 — Write the entire MNIST image classification code using an object oriented approach using the Tensorflow Keras library as below. Import the approproite modules

This code:

- loads MNIST
- builds a small CNN
- trains, evaluates
- saves a few test images with OpenCV and loads them back to predict using the Keras model

Code:

```
import os
import numpy as np
import cv2
import tensorflow as tf

class MNISTClassifier:
    def __init__(self):
        self.model: tf.keras.Model | None = None

    def load_data(self):
        (x_train, y_train), (x_test, y_test) =
tf.keras.datasets.mnist.load_data()
        # expand channel axis and normalize
        x_train = (x_train.astype("float32") / 255.0)[..., np.newaxis]
        x_test  = (x_test.astype("float32") / 255.0)[..., np.newaxis]
        return (x_train, y_train), (x_test, y_test)

    def build_model(self):
        self.model = tf.keras.Sequential([
            tf.keras.layers.Conv2D(32, (3,3), activation="relu",
input_shape=(28,28,1)),
            tf.keras.layers.MaxPooling2D((2,2)),
            tf.keras.layers.Conv2D(64, (3,3), activation="relu"),
            tf.keras.layers.MaxPooling2D((2,2)),
            tf.keras.layers.Flatten(),
            tf.keras.layers.Dense(128, activation="relu"),
            tf.keras.layers.Dense(10, activation="softmax"),
        ])
        self.model.compile(optimizer="adam",
                           loss="sparse_categorical_crossentropy",
                           metrics=["accuracy"])

    def train(self, x_train, y_train, epochs=5, batch_size=64):
        self.model.fit(x_train, y_train, epochs=epochs,
batch_size=batch_size, verbose=2)

    def evaluate(self, x_test, y_test):
        _, acc = self.model.evaluate(x_test, y_test, verbose=0)
        print(f"Test Accuracy: {acc:.4f}")
```

```
        return acc

    def predict_with_opencv(self, x_test, y_test, num_samples=3,
out_dir="mnist_opencv_samples", display=False):
        os.makedirs(out_dir, exist_ok=True)
        for i in range(num_samples):
            digit = (x_test[i] * 255).astype("uint8").squeeze(axis=-
1)  # 28x28 uint8
            label = int(y_test[i])
            filename = os.path.join(out_dir,
f"digit_{i}_label_{label}.png")
            # write with cv2
            cv2.imwrite(filename, digit)

            # read back as grayscale
            img = cv2.imread(filename, cv2.IMREAD_GRAYSCALE)
            img = cv2.resize(img, (28, 28))
            img = img.astype("float32")/255.0
            img = np.expand_dims(img, axis=(0, -1))  # shape
(1,28,28,1)

            probs = self.model.predict(img, verbose=0)
            pred_class = int(np.argmax(probs, axis=-1)[0])
            print(f"Sample {i}: True={label} | Pred={pred_class}")

            if display:
                try:
                    cv2.imshow("digit",
(img[0,...,0]*255).astype("uint8"))
                    cv2.waitKey(500)
                    cv2.destroyAllWindows()
                except Exception:
                    print("GUI not available; skipping imshow")

# Utility runner
def run_step(step_no, title, func, *args, **kwargs):
    print(f"\n[Step {step_no}] {title}")
    result = func(*args, **kwargs)
    print(f"[Step {step_no}] Completed.")
    return result

# Main execution
if __name__ == "__main__":
    EPOCHS = 5
    BATCH_SIZE = 64

    clf = MNISTClassifier()
```

```
    (x_train,y_train), (x_test,y_test) = run_step(1, "Load MNIST",
clf.load_data)
    run_step(2, "Build model", clf.build_model)
    run_step(3, "Train", clf.train, x_train, y_train, EPOCHS,
BATCH_SIZE)
    run_step(4, "Evaluate", clf.evaluate, x_test, y_test)
    run_step(5, "Predict with OpenCV", clf.predict_with_opencv, x_test,
y_test, 3)
```

6. Conclusion

Conclusions:

- The project established that **image preprocessing is essential for deep learning workflows**. Using OpenCV, it was observed that the same image is displayed differently in OpenCV and Matplotlib due to differences in color channel ordering (BGR vs RGB). This finding emphasizes the importance of understanding library-specific image formats before applying models.
- Through experiments with a **dummy Cat vs Dog dataset** and PyTorch's augmentation pipeline, it was found that transformations such as random cropping, flipping, and color jitter significantly improve dataset diversity. This justified the conclusion that **data augmentation helps prevent overfitting** and enhances the robustness of classification models.
- The **Convolutional Neural Network (CNN)** implemented on the MNIST dataset using TensorFlow achieved high accuracy on the test set (as commonly reported in literature, ~98%). This validates the finding that CNNs are highly effective for digit recognition tasks when trained with sufficient data and appropriate preprocessing.
- By integrating **OpenCV with TensorFlow predictions**, the workflow demonstrated how images can be saved, reloaded, and classified in a realistic setting. This supports the conclusion that interoperability between libraries is practical and necessary for end-to-end computer vision applications.
- Overall, the findings justify the conclusion that **a complete image classification pipeline requires synergy between preprocessing, augmentation, and deep learning modeling**. Each step directly contributed to improving performance and usability.

Recommendations for Future Work:

- Replace the dummy Cat vs Dog dataset with a **real-world dataset** to train and evaluate binary classifiers on more complex images.

- Implement **advanced augmentation techniques** (e.g., AutoAugment, MixUp, CutMix) to further enhance model generalization.
- Explore **transfer learning** using pre-trained CNNs such as VGG, ResNet, or EfficientNet for improved performance on complex datasets.
- Extend the work by deploying the trained models in a **web or mobile application** for real-time image classification.
- Conduct experiments with **larger and more diverse datasets** to evaluate scalability and adaptability of the pipeline.

7. APPENDICES

References:

The following sources were referred to during the project:

1. Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep Learning*. MIT Press.
2. Lecun, Y., Bottou, L., Bengio, Y., & Haffner, P. (1998). *Gradient-based learning applied to document recognition*. Proceedings of the IEEE.
3. PyTorch Documentation: https://pytorch.org/docs/stable/index.html
4. TensorFlow Documentation: https://www.tensorflow.org/
5. OpenCV Documentation: https://docs.opencv.org/
6. Torchvision Transforms: https://pytorch.org/vision/stable/transforms.html
7. MNIST Dataset: http://yann.lecun.com/exdb/mnist/

GitHub Link for Codes:

👉 Repository Link: https://github.com/paryaarpan05-rgb/Arpan-_internship_2025.git