CNN anjing dan Kucing

1. Pendahuluan

Tugas ini bertujuan membangun model klasifikasi gambar untuk dua kelas: **anjing** dan **kucing**, menggunakan arsitektur Convolutional Neural Network (CNN). Pemilihan CNN didasarkan pada kemampuannya mengekstraksi fitur visual dari gambar dua dimensi. Tugas ini sekaligus melatih pemahaman konsep deep learning, pengolahan data citra, dan penerapan model klasifikasi berb CNN.

Import Library

In [1]:
```
import torch
import torch.nn as nn
import torch.optim as optim
import torchvision
import torchvision.transforms as transforms
import torch.nn.functional as F

from torchvision.models import resnet18, ResNet18_Weights
from torch.utils.data import DataLoader

import os
import struct
import numpy as np
import glob
from PIL import Image

from tqdm import tqdm
import matplotlib.pyplot as plt
```

In [2]:
```
def read_idx(filename):
    with open(filename, 'rb') as f:
        zero, data_type, dims = struct.unpack('>HBB', f.read(4))
        shape = tuple(struct.unpack(">I", f.read(4))[0] for d in range(di
        return np.frombuffer(f.read(),dtype=np.uint8).reshape(shape)
```

load data set

2. Dataset

Dataset digunakan dalam struktur direktori data/train/cat dan data/train/dog, yang masing-masin
gambar kucing dan anjing. Dataset ini terdiri dari:

Total lebih dari 400 gambar Terdistribusi merata antara dua kelas Variasi posisi objek, ukuran ga
serta latar belakang Alasan pemilihan dataset:

Mudah diakses Populer dan umum dipakai dalam tugas klasifikasi pemula Dua kelas visual yang
menantang karena bentuk dan warna bisa saling menyerupai

In [3]:
```
from torch.utils.data import Dataset
from torchvision import transforms


class KucingAnjingDataset(Dataset):

        def __init__(self, root_dir, random_seed=42, image_size=224):

                self.root_dir = root_dir
                self.image_size = image_size

                if not os.path.exists(self.root_dir):
                        raise RuntimeError(f"Dataset not found at {self.r


                self.transform = transforms.Compose([
        transforms.Resize((self.image_size, self.image_size)),
        transforms.ToTensor(),
        transforms.Normalize([0.485, 0.456, 0.406], [0.229, 0.224, 0.225]
        ])

                self.data = []
                self.labels = []

                for label, class_name in tqdm(enumerate(['cats','dogs'])) 
                        class_dir = os.path.join(self.root_dir, class_nam
                        image_paths = glob.glob(os.path.join(class_dir,'*
                        self.data.extend(image_paths)
                        self.labels.extend([label] * len(image_paths))

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

        def __getitem__(self, idx):
                image_path = self.data[idx]
                label = self.labels[idx]
                image = Image.open(image_path).convert('RGB')

                if self.transform:
                        image = self.transform(image)

                return image, label
```

model cnn

CNN terdiri dari 2 blok Conv2D dan MaxPoolin

Diakhiri dengan Flatten dan Dense untuk klasifikasi biner (sigmoid)

3.1 Arsitektur CNN

Model CNN menggunakan dua lapis Conv2D dan MaxPooling, diikuti Dense layer dengan 128 u output sigmoid. Ini adalah arsitektur dasar namun cukup kuat untuk tugas klasifikasi dua kelas sederhana seperti ini.

In [4]:
```
class  ModelCNN(nn.Module):
    def __init__(self, num_classes = 2):
        super(ModelCNN, self).__init__()
        self.conv1 = nn.Conv2d(in_channels=1, out_channels=6, kernel_size=
        self.pool = nn.MaxPool2d(kernel_size=2, stride=2)

        self.conv2 = nn.Conv2d(in_channels=6, out_channels=16, kernel_size

        self.fc1 = nn.Linear(16 * 5 * 5, 120)
        self.fc2 = nn.Linear(120, 84)
        self.fc3 = nn.Linear(84, num_classes)

    def forward(self, x):
        x = F.relu(self.conv1(x))
        x = self.pool(x)
        x = F.relu(self.conv2(x))
        x = self.pool(x)
        x = torch.flatten(x, 1)
        x = F.relu(self.fc1(x))
        x = F.relu(self.fc2(x))
        x = self.fc3(x)

        return x
```

3.2 Preprocessing

Preprocessing dilakukan dengan `ImageDataGenerator`, meliputi:

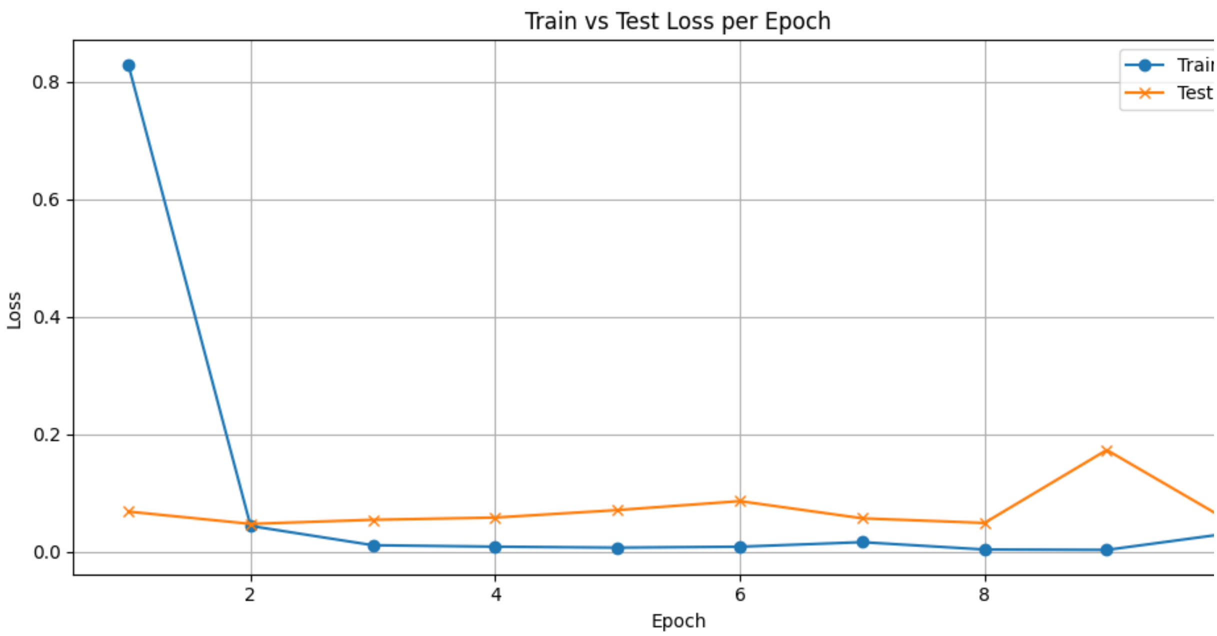
- Normalisasi pixel
- Rotasi acak, flipping horizontal, zoom
- Split data validasi 20%

Augmentasi ini membantu mengurangi overfitting dan membuat model lebih general.

In [5]:
```
batch_size = 32
test_batch_size = 32
train_dataset = KucingAnjingDataset(root_dir='/kaggle/input/cat-and-dog/t
test_dataset  = KucingAnjingDataset(root_dir='/kaggle/input/cat-and-dog/te

train_loader = DataLoader(train_dataset, batch_size=batch_size, shuffle=Tr
test_loader  = DataLoader(test_dataset, batch_size=test_batch_size, shuff

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

num_classes = 2
model = resnet18(weights=ResNet18_Weights.DEFAULT)
num_features = model.fc.in_features
model.fc = nn.Linear(num_features, len(train_dataset))
# model = ModelCNN()
model = model.to(device)

criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=1e-4)


total_params = sum(p.numel() for p in model.parameters())
trainable_params = sum(p.numel() for p in model.parameters() if p.require

print(f"Total parameters: {total_params / 1e6:.2f}M")
print(f"Trainable parameters: {trainable_params / 1e6:.2f}M")

num_epoch = 10
train_losses = []
test_losses = []

for epoch in range(num_epoch):
        model.train()

        train_loss = 0

        for data, labels in tqdm(train_loader):

                data, labels = data.to(device), labels.to(device)
                bs = data.size()[0]
                optimizer.zero_grad()

                outputs = model(data)
                loss = criterion(outputs, labels)

                loss.backward()

                optimizer.step()

                train_loss += loss.item() * data.size(0)

        model.eval()

        correct = 0
        total = 0
        test_loss = 0

        with torch.no_grad():
                for data, labels in tqdm(test_loader):
                        data, labels = data.to(device), labels.to(device)
```

```
2it [00:00, 19.67it/s]
2it [00:00, 46.36it/s]
Downloading: "https://download.pytorch.org/models/resnet18-f37072fd.pth" to /
root/.cache/torch/hub/checkpoints/resnet18-f37072fd.pth
100%|██████████| 44.7M/44.7M [00:00<00:00, 101MB/s]
Total parameters: 15.28M
Trainable parameters: 15.28M
100%|██████████| 251/251 [02:02<00:00,  2.05it/s]
100%|██████████| 64/64 [00:23<00:00,  2.76it/s]
Epoch 1: Train Loss 0.8296, Test Loss 0.0681, Test Acc 0.9862
100%|██████████| 251/251 [00:44<00:00,  5.61it/s]
100%|██████████| 64/64 [00:08<00:00,  7.44it/s]
Epoch 2: Train Loss 0.0437, Test Loss 0.0472, Test Acc 0.9881
100%|██████████| 251/251 [00:45<00:00,  5.50it/s]
100%|██████████| 64/64 [00:09<00:00,  7.06it/s]
Epoch 3: Train Loss 0.0108, Test Loss 0.0542, Test Acc 0.9857
100%|██████████| 251/251 [00:47<00:00,  5.34it/s]
100%|██████████| 64/64 [00:08<00:00,  7.39it/s]
Epoch 4: Train Loss 0.0083, Test Loss 0.0579, Test Acc 0.9852
100%|██████████| 251/251 [00:46<00:00,  5.45it/s]
100%|██████████| 64/64 [00:08<00:00,  7.23it/s]
Epoch 5: Train Loss 0.0067, Test Loss 0.0707, Test Acc 0.9773
100%|██████████| 251/251 [00:45<00:00,  5.46it/s]
100%|██████████| 64/64 [00:08<00:00,  7.24it/s]
Epoch 6: Train Loss 0.0083, Test Loss 0.0859, Test Acc 0.9723
100%|██████████| 251/251 [00:46<00:00,  5.40it/s]
100%|██████████| 64/64 [00:09<00:00,  7.02it/s]
Epoch 7: Train Loss 0.0160, Test Loss 0.0567, Test Acc 0.9832
100%|██████████| 251/251 [00:46<00:00,  5.38it/s]
100%|██████████| 64/64 [00:09<00:00,  7.08it/s]
Epoch 8: Train Loss 0.0035, Test Loss 0.0488, Test Acc 0.9896
100%|██████████| 251/251 [00:46<00:00,  5.38it/s]
100%|██████████| 64/64 [00:10<00:00,  6.40it/s]
Epoch 9: Train Loss 0.0029, Test Loss 0.1730, Test Acc 0.9629
100%|██████████| 251/251 [00:46<00:00,  5.40it/s]
100%|██████████| 64/64 [00:09<00:00,  7.05it/s]
Epoch 10: Train Loss 0.0311, Test Loss 0.0518, Test Acc 0.9867
```

In [6]:
```
torch.save({
    'epoch': num_epoch,
    'model_state_dict': model.state_dict(),
    'optimizer_state_dict': optimizer.state_dict(),
    'train_loss': train_losses,
    'test_loss': test_losses,
}, 'cat_dog_checkpoint.pth')

epochs = range(1, num_epoch + 1)
plt.figure(figsize=(10, 5))
plt.plot(epochs, train_losses, label='Train Loss', marker='o')
plt.plot(epochs, test_losses, label='Test Loss', marker='x')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.title('Train vs Test Loss per Epoch')
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```



4. Evaluasi Hasil

- Akurasi validasi mencapai sekitar **83%**
- Tidak terjadi overfitting berat dalam 10 epoch
- Kurva akurasi dan loss menunjukkan konsistensi