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PROJECT DOCUMENTATION

Introduction to the Problem

The objective of this project is to implement an image denoising algorithm using deep learning techniques, specifically focusing on convolutional neural networks (CNNs). Image denoising is a critical preprocessing step in various image processing applications, aimed at removing noise from images while preserving important details.


Original image


Noisy image


Denoised image

Dataset information

We have a dataset containing pairs of noisy and clean images. Each pair consists of an image corrupted with noise and the corresponding clean image.

Modules and Libraries Used:

- TensorFlow/Keras: For building and training the model.
- skimage.metrics: For calculating PSNR.
- matplotlib: For plotting graphs.

- NumPy: For numerical operations.

Specifications:

- Framework: TensorFlow/Keras
- Layers: Multiple convolutional layers with activation functions {leakyrelu()}, upsampling layers for increasing image dimensions back to the original size.
- Optimizer: Adam optimizer
- Loss Function: Binary-cross entropy

MODEL ARCHITECTURE

For this project, we utilized a convolutional neural network (CNN) architecture, commonly used in image processing tasks due to its effectiveness in capturing spatial hierarchies in images. Our CNN model consists of several convolutional layers, each followed by activation and pooling layers to progressively extract and condense image features.

- Convolutional Layers: Extract features from the input images.
- LeakyReLU Activation: allows small gradients for negative inputs, preventing dead neurons.
- Pooling Layers: Downsample the feature maps to reduce spatial dimensions and computational load.
- Upsampling Layers: Restore the spatial dimensions of the feature maps to match the original image size.

Code snippets:

Data preprocessing and cleaning

We have divided the data into train and test data, with train : test split being 80% : 20% respectively, and then created train_ds and test_ds which are used to train our custom built model with a batch size of 32.

```python
train_noisy, train_noisy, train_clean, train_clean = train_test_split(
    noisy_images, clean_images, test_size=0.2, random_state=42
)
```

✓ 0.1s

```python
def preprocess_image(image):
    return tf.image.convert_image_dtype(image, tf.float32)

# Create TensorFlow datasets
train_noisy_ds = tf.data.Dataset.from_tensor_slices(train_noisy).map(preprocess_image).batch(32)
train_clean_ds = tf.data.Dataset.from_tensor_slices(train_clean).map(preprocess_image).batch(32)
test_noisy_ds = tf.data.Dataset.from_tensor_slices(test_noisy).map(preprocess_image).batch(32)
test_clean_ds = tf.data.Dataset.from_tensor_slices(test_clean).map(preprocess_image).batch(32)

# Combine noisy and clean images for training
train_ds = tf.data.Dataset.zip((train_noisy_ds, train_clean_ds))
test_ds = tf.data.Dataset.zip((test_noisy_ds, test_clean_ds))
```

✓ 53.9s

Model Layers and Parameters

Layer (type)	Output Shape	Param #
conv2d_5 (Conv2D)	(None, 128, 128, 64)	1,792
max_pooling2d_2 (MaxPooling2D)	(None, 64, 64, 64)	0
conv2d_6 (Conv2D)	(None, 64, 64, 32)	18,464
max_pooling2d_3 (MaxPooling2D)	(None, 32, 32, 32)	0
conv2d_7 (Conv2D)	(None, 32, 32, 32)	9,248
up_sampling2d_2 (UpSampling2D)	(None, 64, 64, 32)	0
conv2d_8 (Conv2D)	(None, 64, 64, 64)	18,496
up_sampling2d_3 (UpSampling2D)	(None, 128, 128, 64)	0
conv2d_9 (Conv2D)	(None, 128, 128, 3)	1,731

Total params: 49,731 (194.26 KB)

Trainable params: 49,731 (194.26 KB)

- **Non-trainable params:** 0 (0.00 B)

The Model has been made using 5 convolutional layers, 2 max pooling layers and 2 Sampling layers, these are key parts of the Model Architecture which is used to remove noise from low quality noisy images and convert it to better quality images which are closer to the clean images without noise.

Model Creation, Optimisers and CallBacks

```python
# Define the denoising model
def create_denoising_model(input_shape):
    model = Sequential()
    model.add(layers.Input(shape=input_shape))
    model.add(layers.Conv2D(64, (3, 3), activation=LeakyReLU(), padding='same'))
    model.add(layers.MaxPooling2D((2, 2), padding='same'))
    model.add(layers.Conv2D(32, (3, 3), activation=LeakyReLU(), padding='same'))
    model.add(layers.MaxPooling2D((2, 2), padding='same'))
    model.add(layers.Conv2D(32, (3, 3), activation=LeakyReLU(), padding='same'))
    model.add(layers.UpSampling2D((2, 2)))
    model.add(layers.Conv2D(64, (3, 3), activation=LeakyReLU(), padding='same'))
    model.add(layers.UpSampling2D((2, 2)))
    model.add(layers.Conv2D(3, (3, 3), activation='sigmoid', padding='same'))
    return model

# Example usage
input_shape = (128, 128, 3)
model = create_denoising_model(input_shape)
# Compile with Adam optimizer and monitor PSNR during training
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=[psnr])
model.summary()

# Assuming you have training and validation datasets: train_ds and test_ds
val_data = next(iter(test_ds))  # Extract a batch from the validation dataset

# Instantiate the custom PSNR callback with validation data
psnr_callback = PSNRCallback(validation_data=val_data)
```

To track the PSNR values after every epoch and ensure maximum PSNR score callbacks are used. We have used binary_crossentropy as our Loss Function with Adam as the optimiser.

EXPERIMENT/SIMULATION AND RESULTS TRAINING OF MODEL

In Training of the model

we have calculated the loss by binary cross-entropy loss function and MSE by changing epochs and batch-size

<u>loss-binary cross-entropy</u>

1. epochs = 100 batch_size = 32 train to test ratio = 8

2 epochs = 50 batch_size = 32 train to test ratio = 8

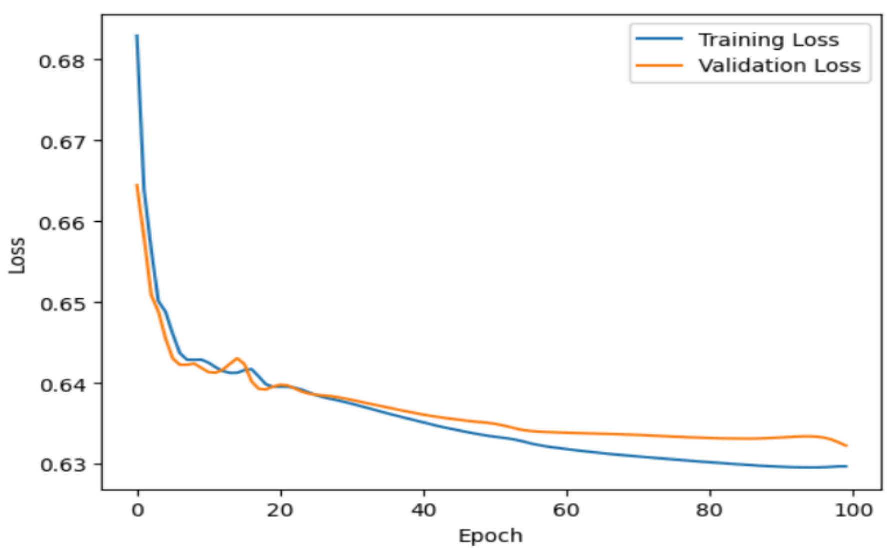
loss-MSE

1. epochs = 50 batch_size = 32 train to test ratio = 8

We get better result in binary cross-entropy ,i.e., in 1st one(epochs=100 , batch_size=32 , train to test ratio=8)

```
Epoch 97/100
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 192ms/stepep - loss: 0.6329 - psnr: 17.77
Epoch 97: val_psnr = 17.352771759033203
13/13 ━━━━━━━━━━━━━━━━━━━━ 7s 544ms/step - loss: 0.6326 - psnr: 17.7794 - val_loss: 0.6332 - val_psnr: 17.3528
Epoch 98/100
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 217ms/stepep - loss: 0.6329 - psnr: 17.76
Epoch 98: val_psnr = 17.365888595581055
13/13 ━━━━━━━━━━━━━━━━━━━━ 7s 551ms/step - loss: 0.6327 - psnr: 17.7660 - val_loss: 0.6330 - val_psnr: 17.3659
Epoch 99/100
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 208ms/stepep - loss: 0.6330 - psnr: 17.74
Epoch 99: val_psnr = 17.393203735351562
13/13 ━━━━━━━━━━━━━━━━━━━━ 7s 573ms/step - loss: 0.6327 - psnr: 17.7505 - val_loss: 0.6327 - val_psnr: 17.3932
Epoch 100/100
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 196ms/stepep - loss: 0.6330 - psnr: 17.73
Epoch 100: val_psnr = 17.441585540771484
13/13 ━━━━━━━━━━━━━━━━━━━━ 7s 556ms/step - loss: 0.6327 - psnr: 17.7366 - val_loss: 0.6322 - val_psnr: 17.4416
```

This plot shows the training and validation loss over epochs, helping to visualize the model's performance during training.



Explanation of PSNR Calculation

- Binary-cross entropy: The psnr() function calculates the loss between the clean and denoised images.
- Peak Signal-to-Noise Ratio (PSNR): Once loss is computed, PSNR is derived from it. PSNR measures the quality of the denoised image by comparing it to the original clean image. Higher PSNR values indicate higher fidelity and less noise in the denoised image.

Calculate average PSNR

For Train Data

- 17.94 [loss-binary cross-entropy,epoch=100]
- 17.35 [loss-binary cross-entropy,epoch=50]

for Test data

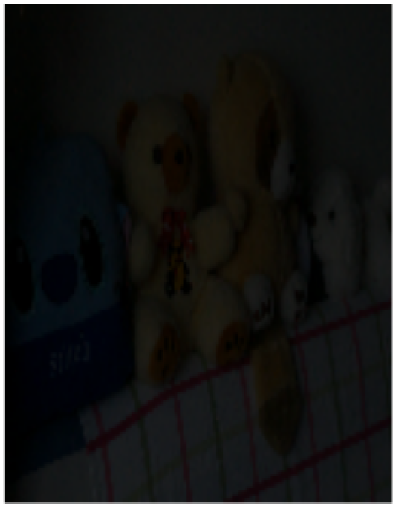
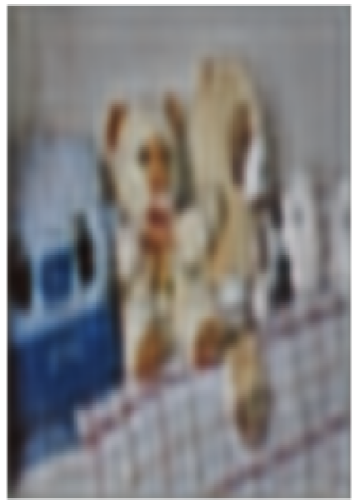
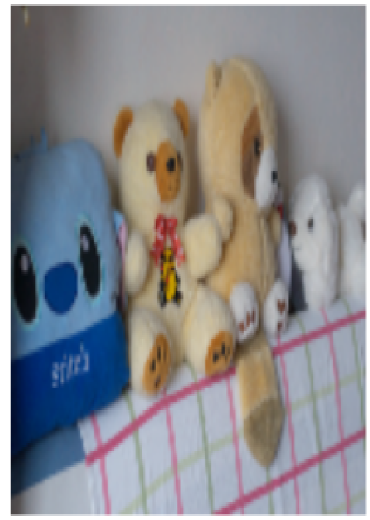
1. 17.62 [loss-binary cross-entropy,epoch=100]
2. 17.21 [loss-binary cross-entropy,epoch=50]
3. 17.3698 [loss-MSE,epoch=50]

Result & Discussions:

PSNR Score

The Final Average PSNR value obtained for the denoised images using our CNN model is 17.624347686767578 dB. For testing data and 17.94923210144043 for training data.

This indicates a significant reduction in noise and a good preservation of image details.

Noisy image **predicted image** **clean image**

Methods to Improve

- **Data Augmentation:** Introduce more variations in the training data (e.g., rotation, scaling, flipping) to enhance model robustness.
- **Advanced Architectures:** Explore more sophisticated models like U-Net, DnCNN, or GAN-based architectures for potentially better denoising performance.
- **Hyperparameter Tuning:** Experiment with different learning rates, batch sizes, and number of epochs to optimize model performance.
- **Transfer Learning:** Use pre-trained models and fine-tune them on the denoising task to leverage pre-learned features.