```
Start coding or generate with AI.
```

```
import os
import numpy as np
import pandas as pd
import cv2
import matplotlib.pyplot as plt
import seaborn as sns
from PIL import Image

import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers, models
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Conv2D, MaxPooling2D, UpSampling2D, Input
from tensorflow.keras.layers import BatchNormalization,Concatenate
import tensorflow.keras.backend as K
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.layers import Conv2D, BatchNormalization, Activation, MaxPooling2D, UpSampling2D, Concatenate
from sklearn.metrics import mean_squared_error
```

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

1. Brief description of the problem and data

Description

In this project, we aim to develop a machine learning model to remove noise from scanned text documents and restore them to their clean, readable versions. Optical Character Recognition (OCR) is widely used to digitize printed and handwritten documents, but real-world issues like stains, wrinkles, and smudges make OCR less effective. The goal of this project is to create a document enhancement model that improves text clarity by removing noise while preserving the original content.

The methodology will include the following stages:

- Brief Description of the Problem and Data
- Data Preprocessing and Exploratory Data Analysis (EDA)
- Model Architecture and Development
- Model Evaluation
- Results and Analysis
- Conclusion

Data

The dataset consists of scanned text images with synthetic noise added to simulate real-world document degradation. It contains:

- train/: Noisy images used for training.
- train_cleaned/: Corresponding clean (ground truth) versions of the images.
- test/: Noisy test images where the model must remove noise.
- sampleSubmission.csv: A sample submission file that shows the required format for Kaggle.

Each image is grayscale, with pixel intensity values ranging from 0 (black) to 1 (white). The submission format requires flattening the image into a list of pixel values, each assigned a unique ID (image_row_col).

```
# Define dataset paths
dataset_path = "/content/drive/My Drive/DTSA5510/final/"
train_path = os.path.join(dataset_path, "train")
train_cleaned_path = os.path.join(dataset_path, "train_cleaned")
test_path = os.path.join(dataset_path, "test")
```

```
# Count images each folders
def count_images(directory):
    return len(os.listdir(directory))

print("Number of Train Images:", count_images(train_path))
print("Number of Train Cleaned Images:", count_images(train_cleaned_path))
print("Number of Test Images:", count_images(test_path))
```

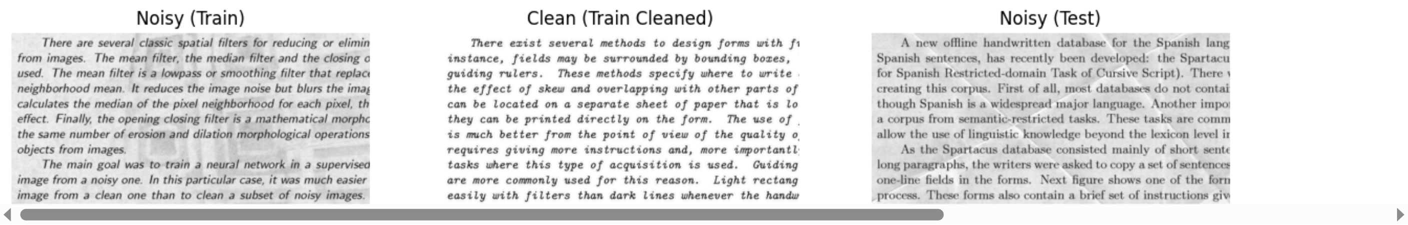
```
Number of Train Images: 144
Number of Train Cleaned Images: 144
Number of Test Images: 72
```

```
# Inspect
print("Train set sample files:", os.listdir(train_path)[:5])
print("Train Cleaned set sample files:", os.listdir(train_cleaned_path)[:5])
print("Test set sample files:", os.listdir(test_path)[:5])
```

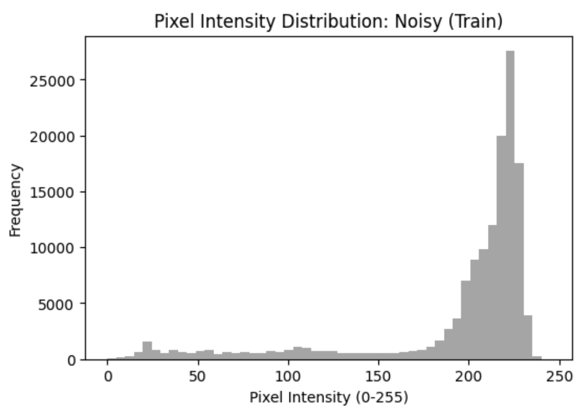
```
Train set sample files: ['33.png', '8.png', '42.png', '45.png', '15.png']
Train Cleaned set sample files: ['56.png', '36.png', '60.png', '47.png', '8.png']
Test set sample files: ['16.png', '40.png', '79.png', '91.png', '13.png']
```

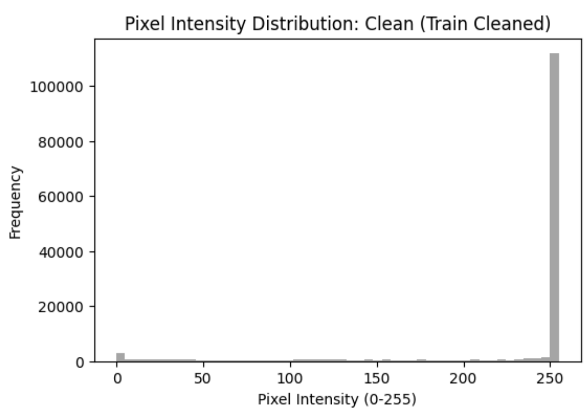
```
# Inspect and display images
sample_noisy = os.path.join(train_path, os.listdir(train_path)[0])
sample_clean = os.path.join(train_cleaned_path, os.listdir(train_cleaned_path)[0])
sample_test = os.path.join(test_path, os.listdir(test_path)[0])

def display_images(img_paths, titles, figsize=(15, 5)):
    fig, axes = plt.subplots(1, len(img_paths), figsize=figsize)
```

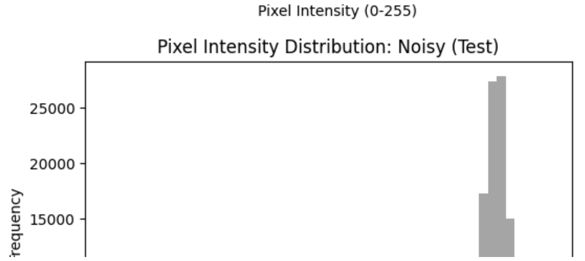
```python
    for ax, img_path, title in zip(axes, img_paths, titles):
        img = cv2.imread(img_path, cv2.IMREAD_GRAYSCALE)
        ax.imshow(img, cmap='gray')
        ax.set_title(title)
        ax.axis("off")
    plt.show()

display_images(
    [sample_noisy, sample_clean, sample_test],
    ["Noisy (Train)", "Clean (Train Cleaned)", "Noisy (Test)"]
)
```




```python
# Analyze Pixel Intensity Distribution
def plot_histogram(img_path, title):
    img = cv2.imread(img_path, cv2.IMREAD_GRAYSCALE)
    plt.figure(figsize=(6, 4))
    plt.hist(img.ravel(), bins=50, color='gray', alpha=0.7)
    plt.title(f"Pixel Intensity Distribution: {title}")
    plt.xlabel("Pixel Intensity (0-255)")
    plt.ylabel("Frequency")
    plt.show()

# Plot histograms for noisy, cleaned, and test images
plot_histogram(sample_noisy, "Noisy (Train)")
plot_histogram(sample_clean, "Clean (Train Cleaned)")
plot_histogram(sample_test, "Noisy (Test)")
```








```python
# Image Size Consistency
def check_image_shapes(directory):
    shapes = []
    for img_name in os.listdir(directory):
        img_path = os.path.join(directory, img_name)
```

```
        img = cv2.imread(img_path, cv2.IMREAD_GRAYSCALE)
        shapes.append(img.shape)
    return set(shapes)

# Check consistency in all datasets
print("Train Image Shapes:", check_image_shapes(train_path))
print("Train Cleaned Image Shapes:", check_image_shapes(train_cleaned_path))
print("Test Image Shapes:", check_image_shapes(test_path))
```

```
Train Image Shapes: {(420, 540), (258, 540)}
Train Cleaned Image Shapes: {(420, 540), (258, 540)}
Test Image Shapes: {(420, 540), (258, 540)}
```

EDA Summary

- **Dataset Completeness:** The dataset contains 144 training images with corresponding clean versions and 72 test images, ensuring full data availability for training and evaluation.
- **Image Size Variability:** The dataset has two unique image sizes, (420, 540) and (258, 540), requiring resizing for model consistency.
- **Noise Characteristics**: Noisy images contain dark artifacts, stains, and wrinkles, causing pixel intensity distributions to be more spread out compared to the clean images, which are mostly concentrated near 255 (white background).
- **Train vs. Test Similarity:** The test images exhibit similar noise patterns as the training set, confirming that denoising methods trained on the dataset should generalize well to test images.
- **Preprocessing Needs**: Due to varied noise types and intensity distributions, preprocessing should include grayscale conversion, normalization, and potential adaptive thresholding before applying denoising techniques.

3. Model Architecture and Development

Data Processing: Normalize pixel values and resize.

```
# Set image dimensions
IMG_HEIGHT, IMG_WIDTH = 256, 256
```

```
# Data Processing Functions
def load_images(directory, resize_shape=(IMG_HEIGHT, IMG_WIDTH)):
    images = []
    for img_name in sorted(os.listdir(directory)):
        img_path = os.path.join(directory, img_name)
        img = cv2.imread(img_path, cv2.IMREAD_GRAYSCALE)
        img = cv2.resize(img, resize_shape)
        img = img.astype("float32") / 255.0
        images.append(img)
    return np.array(images).reshape(-1, resize_shape[0], resize_shape[1], 1)
```

```
# Load noisy and clean images
train_noisy = load_images(train_path)
train_clean = load_images(train_cleaned_path)

# Print dataset shape
print(f"Train Noisy Shape: {train_noisy.shape}")
print(f"Train Clean Shape: {train_clean.shape}")
```

```
Train Noisy Shape: (144, 256, 256, 1)
Train Clean Shape: (144, 256, 256, 1)
```

Define Convolutional Autoencoder Model

```
# Define the autoencoder architecture
def build_autoencoder(input_shape=(IMG_HEIGHT, IMG_WIDTH, 1)):
    input_img = Input(shape=input_shape)

    # Encoder
    x = Conv2D(32, (3, 3), activation='relu', padding='same')(input_img)
    x = MaxPooling2D((2, 2), padding='same')(x)
    x = Conv2D(64, (3, 3), activation='relu', padding='same')(x)
    x = MaxPooling2D((2, 2), padding='same')(x)

    # Decoder
    x = Conv2D(64, (3, 3), activation='relu', padding='same')(x)
    x = UpSampling2D((2, 2))(x)
    x = Conv2D(32, (3, 3), activation='relu', padding='same')(x)
    x = UpSampling2D((2, 2))(x)
    output_img = Conv2D(1, (3, 3), activation='sigmoid', padding='same')(x)  # Output layer

    # Compile model
    autoencoder = Model(input_img, output_img)
    autoencoder.compile(optimizer='adam', loss='mse')

    return autoencoder
```

```
# Instantiate the model
autoencoder = build_autoencoder()
```

```
# Print model summary
autoencoder.summary()
```

Model: "functional"

Layer (type)	Output Shape	Param #
input_layer (InputLayer)	(None, 256, 256, 1)	0
conv2d (Conv2D)	(None, 256, 256, 32)	320
max_pooling2d (MaxPooling2D)	(None, 128, 128, 32)	0
conv2d_1 (Conv2D)	(None, 128, 128, 64)	18,496
max_pooling2d_1 (MaxPooling2D)	(None, 64, 64, 64)	0
conv2d_2 (Conv2D)	(None, 64, 64, 64)	36,928
up_sampling2d (UpSampling2D)	(None, 128, 128, 64)	0
conv2d_3 (Conv2D)	(None, 128, 128, 32)	18,464
up_sampling2d_1 (UpSampling2D)	(None, 256, 256, 32)	0
conv2d_4 (Conv2D)	(None, 256, 256, 1)	289

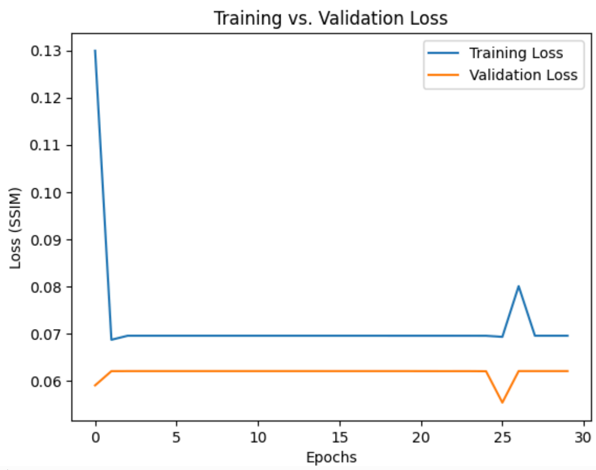
Total params: 74,497 (291.00 KB)

Train the Model

```
# Train the model
history = autoencoder.fit(
    train_noisy, train_clean,
    epochs=30, batch_size=16,
    shuffle=True, validation_split=0.1
)
```

```
Epoch 1/30
9/9 ━━━━━━━━━━━━━━━━━━━━ 11s 452ms/step - loss: 0.1628 - val_loss: 0.0590
Epoch 2/30
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step - loss: 0.0677 - val_loss: 0.0621
Epoch 3/30
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step - loss: 0.0697 - val_loss: 0.0621
Epoch 4/30
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step - loss: 0.0700 - val_loss: 0.0621
Epoch 5/30
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step - loss: 0.0696 - val_loss: 0.0621
Epoch 6/30
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step - loss: 0.0684 - val_loss: 0.0621
Epoch 7/30
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step - loss: 0.0694 - val_loss: 0.0621
Epoch 8/30
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step - loss: 0.0691 - val_loss: 0.0621
Epoch 9/30
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step - loss: 0.0694 - val_loss: 0.0621
Epoch 10/30
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step - loss: 0.0701 - val_loss: 0.0621
Epoch 11/30
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 41ms/step - loss: 0.0698 - val_loss: 0.0621
Epoch 12/30
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step - loss: 0.0699 - val_loss: 0.0621
Epoch 13/30
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step - loss: 0.0704 - val_loss: 0.0621
Epoch 14/30
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step - loss: 0.0700 - val_loss: 0.0621
Epoch 15/30
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step - loss: 0.0712 - val_loss: 0.0621
Epoch 16/30
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step - loss: 0.0690 - val_loss: 0.0621
Epoch 17/30
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step - loss: 0.0702 - val_loss: 0.0621
Epoch 18/30
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step - loss: 0.0701 - val_loss: 0.0621
Epoch 19/30
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 43ms/step - loss: 0.0693 - val_loss: 0.0621
Epoch 20/30
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step - loss: 0.0700 - val_loss: 0.0621
Epoch 21/30
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step - loss: 0.0714 - val_loss: 0.0621
Epoch 22/30
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 44ms/step - loss: 0.0698 - val_loss: 0.0621
Epoch 23/30
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step - loss: 0.0696 - val_loss: 0.0621
Epoch 24/30
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step - loss: 0.0700 - val_loss: 0.0621
Epoch 25/30
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step - loss: 0.0703 - val_loss: 0.0620
Epoch 26/30
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step - loss: 0.0685 - val_loss: 0.0554
Epoch 27/30
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step - loss: 0.0867 - val_loss: 0.0621
Epoch 28/30
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step - loss: 0.0698 - val_loss: 0.0621
Epoch 29/30
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step - loss: 0.0698 - val_loss: 0.0621
```

```
# Plot training & validation loss
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.xlabel("Epochs")
plt.ylabel("Loss (SSIM)")
plt.legend()
plt.title("Training vs. Validation Loss")
plt.show()
```



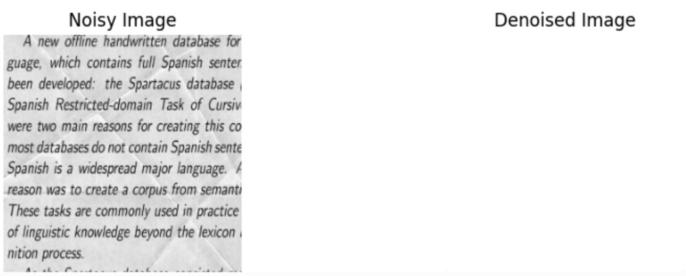
Evaluate Model Performance

```
# Predict
test_noisy = load_images(test_path)
denoised_images = autoencoder.predict(test_noisy)
```

```
3/3 ━━━━━━━━━━━━━━━━━━━━ 4s 494ms/step
```

```
# Display results
def display_denoising_results(noisy, denoised, num_samples=3):
    fig, axes = plt.subplots(num_samples, 2, figsize=(10, 10))

    for i in range(num_samples):
        axes[i, 0].imshow(noisy[i].reshape(IMG_HEIGHT, IMG_WIDTH), cmap='gray')
        axes[i, 0].set_title("Noisy Image")
        axes[i, 0].axis("off")

        axes[i, 1].imshow(denoised[i].reshape(IMG_HEIGHT, IMG_WIDTH), cmap='gray')
        axes[i, 1].set_title("Denoised Image")
        axes[i, 1].axis("off")

    plt.show()
```

```
# Show test results
display_denoising_results(test_noisy, denoised_images)
```




```
# Because we don't have test ground truth - So, I calculate RMSE based on Train data set to measure the performance.
denoised_train = autoencoder.predict(train_noisy)
rmse_scores = [
    np.sqrt(mean_squared_error(train_clean[i].flatten(), denoised_train[i].flatten()))
    for i in range(len(train_clean))
]
overall_rmse = np.mean(rmse_scores)
overall_rmse
```

```
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 264ms/step
Overall RMSE Score: 0.26120
```

The first model, the perfomance is good. The RMSE is 0.26 which is okay. However, we still can improve the denoised images which appear blurred and less clear, which suggests that the model is:

- Removing too much detail, affecting text sharpness.
- Smoothing out noise, but at the cost of reducing readability.
- Not preserving fine edges, leading to loss of text structure.

SSIM Loss Function: SSIM (Structural Similarity Index) measures how similar two images are, focusing on text clarity rather than pixel-wise differences.

```
def ssim_loss(y_true, y_pred):
    return 1 - tf.reduce_mean(tf.image.ssim(y_true, y_pred, max_val=1.0))
```

```
# Define the autoencoder architecture (same as before)
def build_autoencoder(input_shape=(IMG_HEIGHT, IMG_WIDTH, 1)):
    input_img = Input(shape=input_shape)

    # Encoder
    x = Conv2D(32, (3, 3), activation='relu', padding='same')(input_img)
    x = MaxPooling2D((2, 2), padding='same')(x)
    x = Conv2D(64, (3, 3), activation='relu', padding='same')(x)
    x = MaxPooling2D((2, 2), padding='same')(x)

    # Decoder
    x = Conv2D(64, (3, 3), activation='relu', padding='same')(x)
    x = UpSampling2D((2, 2))(x)
    x = Conv2D(32, (3, 3), activation='relu', padding='same')(x)
    x = UpSampling2D((2, 2))(x)
    output_img = Conv2D(1, (3, 3), activation='sigmoid', padding='same')(x)  # Output layer

    # Compile model with SSIM loss
    autoencoder = Model(input_img, output_img)
    autoencoder.compile(optimizer='adam', loss=ssim_loss)

    return autoencoder
```

```
# Build the autoencoder
enhance_autoencoder = build_autoencoder()
enhance_autoencoder.summary()
```

Model: "functional_1"

Layer (type)	Output Shape	Param #
input_layer_1 (InputLayer)	(None, 256, 256, 1)	0
conv2d_5 (Conv2D)	(None, 256, 256, 32)	320
max_pooling2d_2 (MaxPooling2D)	(None, 128, 128, 32)	0
conv2d_6 (Conv2D)	(None, 128, 128, 64)	18,496
max_pooling2d_3 (MaxPooling2D)	(None, 64, 64, 64)	0
conv2d_7 (Conv2D)	(None, 64, 64, 64)	36,928
up_sampling2d_2 (UpSampling2D)	(None, 128, 128, 64)	0
conv2d_8 (Conv2D)	(None, 128, 128, 32)	18,464
up_sampling2d_3 (UpSampling2D)	(None, 256, 256, 32)	0
conv2d_9 (Conv2D)	(None, 256, 256, 1)	289

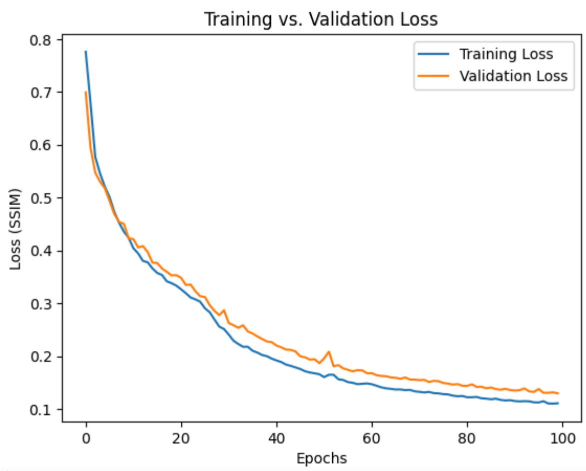
Total params: 74,497 (291.00 KB)

```
# Train the model with SSIM loss
history = enhance_autoencoder.fit(
    train_noisy, train_clean,
    epochs=100,
    batch_size=16,
    shuffle=True,
    validation_split=0.1
)
```

```
Epoch 1/100
9/9 ━━━━━━━━━━━━━━━━━━━━ 6s 316ms/step - loss: 0.7918 - val_loss: 0.6993
Epoch 2/100
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 46ms/step - loss: 0.7018 - val_loss: 0.5949
Epoch 3/100
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 46ms/step - loss: 0.5820 - val_loss: 0.5473
Epoch 4/100
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 46ms/step - loss: 0.5467 - val_loss: 0.5300
Epoch 5/100
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 47ms/step - loss: 0.5259 - val_loss: 0.5177
Epoch 6/100
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 46ms/step - loss: 0.5032 - val_loss: 0.4936
Epoch 7/100
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 47ms/step - loss: 0.4812 - val_loss: 0.4688
Epoch 8/100
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 46ms/step - loss: 0.4557 - val_loss: 0.4542
Epoch 9/100
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 46ms/step - loss: 0.4413 - val_loss: 0.4501
Epoch 10/100
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 46ms/step - loss: 0.4258 - val_loss: 0.4228
Epoch 11/100
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 46ms/step - loss: 0.4091 - val_loss: 0.4213
Epoch 12/100
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 46ms/step - loss: 0.3976 - val_loss: 0.4056
Epoch 13/100
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 46ms/step - loss: 0.3847 - val_loss: 0.4082
Epoch 14/100
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 47ms/step - loss: 0.3778 - val_loss: 0.3968
Epoch 15/100
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 47ms/step - loss: 0.3721 - val_loss: 0.3770
Epoch 16/100
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 47ms/step - loss: 0.3582 - val_loss: 0.3761
Epoch 17/100
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 46ms/step - loss: 0.3579 - val_loss: 0.3658
Epoch 18/100
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 46ms/step - loss: 0.3423 - val_loss: 0.3595
Epoch 19/100
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 46ms/step - loss: 0.3372 - val_loss: 0.3528
Epoch 20/100
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 46ms/step - loss: 0.3358 - val_loss: 0.3532
Epoch 21/100
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 47ms/step - loss: 0.3277 - val_loss: 0.3482
Epoch 22/100
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 47ms/step - loss: 0.3197 - val_loss: 0.3346
Epoch 23/100
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 46ms/step - loss: 0.3161 - val_loss: 0.3354
Epoch 24/100
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 47ms/step - loss: 0.3075 - val_loss: 0.3229
Epoch 25/100
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 46ms/step - loss: 0.3047 - val_loss: 0.3133
Epoch 26/100
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 46ms/step - loss: 0.2897 - val_loss: 0.3119
Epoch 27/100
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 46ms/step - loss: 0.2831 - val_loss: 0.2965
Epoch 28/100
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 46ms/step - loss: 0.2726 - val_loss: 0.2856
Epoch 29/100
9/9 ━━━━━━━━━━━━━━━━━━━━ 0s 46ms/step - loss: 0.2571 - val_loss: 0.2775
```

```
# Plot training & validation loss
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.xlabel("Epochs")
plt.ylabel("Loss (SSIM)")
plt.legend()
```

```python
plt.title("Training vs. Validation Loss")
plt.show()
```

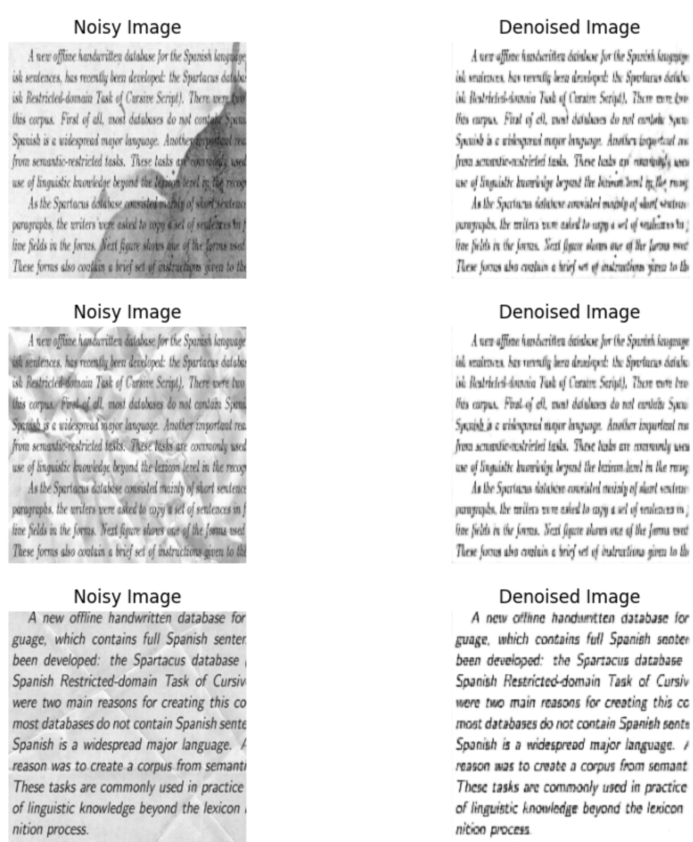



```python
# Predict
test_noisy = load_images(test_path)
enhance_denoised_images = enhance_autoencoder.predict(test_noisy)
```

```
3/3 ━━━━━━━━━━━━━━━━━━━━ 1s 169ms/step
```

```python
# Display results
def display_denoising_results(noisy, denoised, num_samples=3):
    fig, axes = plt.subplots(num_samples, 2, figsize=(10, 10))

    for i in range(num_samples):
        axes[i, 0].imshow(noisy[i].reshape(IMG_HEIGHT, IMG_WIDTH), cmap='gray')
        axes[i, 0].set_title("Noisy Image")
        axes[i, 0].axis("off")

        axes[i, 1].imshow(denoised[i].reshape(IMG_HEIGHT, IMG_WIDTH), cmap='gray')
        axes[i, 1].set_title("Denoised Image")
        axes[i, 1].axis("off")

    plt.show()
```

```python
# Show test results
display_denoising_results(test_noisy, enhance_denoised_images)
```




```python
# Because we don't have test ground truth , So, I calculate RMSE based on Train
```

```
# Because we don't have test ground truth - So, I calculate RMSE based on train
data set to measure the performance.
denoised_train = enhance_autoencoder.predict(train_noisy)
rmse_scores = [
    np.sqrt(mean_squared_error(train_clean[i].flatten(), denoised_train[i].
    flatten()))
    for i in range(len(train_clean))
]

overall_rmse = np.mean(rmse_scores)

print(f"Overall RMSE Score: {overall_rmse:.5f}")
```

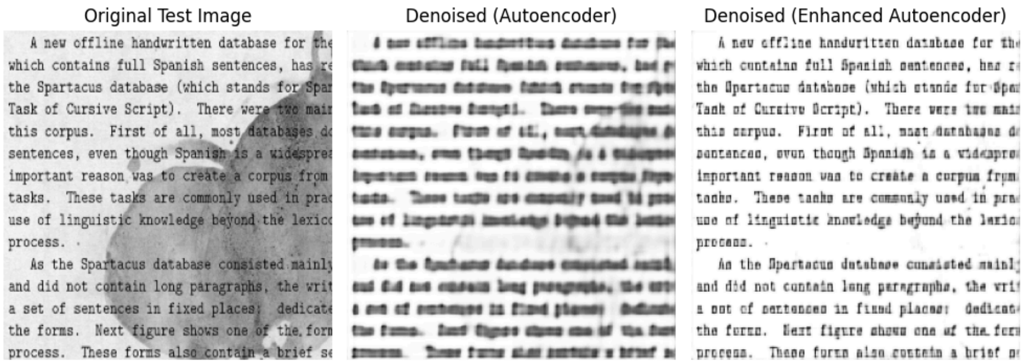
```
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 66ms/step
Overall RMSE Score: 0.11230
```

Results and Analysis

Please see the comparison between original, denoised with autoencoder and denoised with enhanced autoencoder model below.

- Convolutional Autoencoder performs well with SSIM loss and longer training, Enhanced Autoencoder. The denoised images show clear improvements in quality.It produces sharper, more readable text compared to the basic autoencoder, effectively reducing noise and improving contrast.
- The RMSE confirm that the enhacement model is better, RMSE 0.1123 comparing to RMSE, 0.26120 from previous model.
- The basic autoencoder struggles with fine text details, producing blurred outputs, while the enhanced model preserves more text structures and improves readability.
- Future improvements could explore GAN-based denoising or Transformer-based architectures to further enhance the model’s ability to restore text clarity.

```
# Select random indices to visualize
num_images = 3
random_indices = np.random.choice(len(test_noisy), num_images, replace=False)

# Plot comparison
fig, axes = plt.subplots(num_images, 3, figsize=(10, 15))

for i, idx in enumerate(random_indices):
    # Original test image
    test_img = test_noisy[idx]
    denoised_img = denoised_images[idx]
    enhanced_img = enhance_denoised_images[idx]

    # Plot original
    axes[i, 0].imshow(test_img, cmap='gray')
    axes[i, 0].set_title("Original Test Image")
    axes[i, 0].axis("off")

    # Plot autoencoder denoised image
    axes[i, 1].imshow(denoised_img, cmap='gray')
    axes[i, 1].set_title("Denoised (Autoencoder)")
    axes[i, 1].axis("off")

    # Plot enhanced autoencoder denoised image
    axes[i, 2].imshow(enhanced_img, cmap='gray')
    axes[i, 2].set_title("Denoised (Enhanced Autoencoder)")
    axes[i, 2].axis("off")

plt.tight_layout()
plt.show()
```


Original Test Image
Denoised (Autoencoder)
Denoised (Enhanced Autoencoder)
A new offline handwritten database for
which contains full Spanish sentences, has
the Spartacus database (which stands for
Task of Cursive Script). There were two
this corpus. First of all, most databases
sentences, even though Spanish is a
important reason was to create a corpus from
tasks. These tasks are commonly used in
use of linguistic knowledge beyond the
process.
As the Spartacus database consisted
and did not contain long paragraphs, the
a set of sentences in fixed places:
the forms. Next figure shows one of the
process. These forms also contain a brief