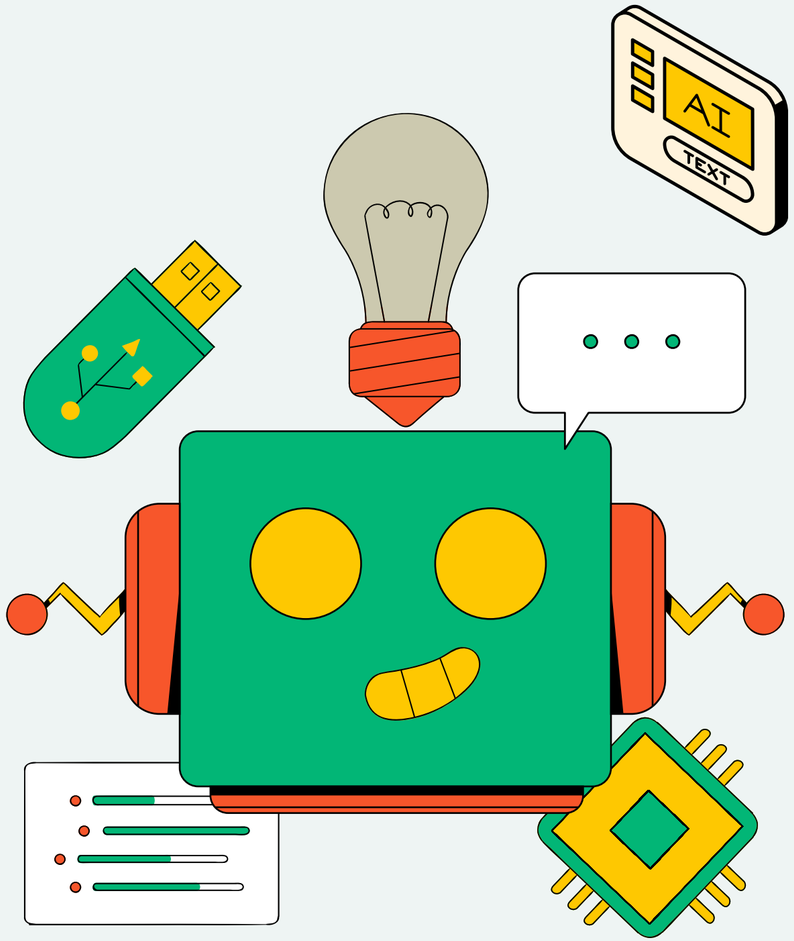
DEEP LEARNING
PROJECT

DENOISING DIRTY DOCUMENT IMAGE USING CAE



PRESENTED BY:

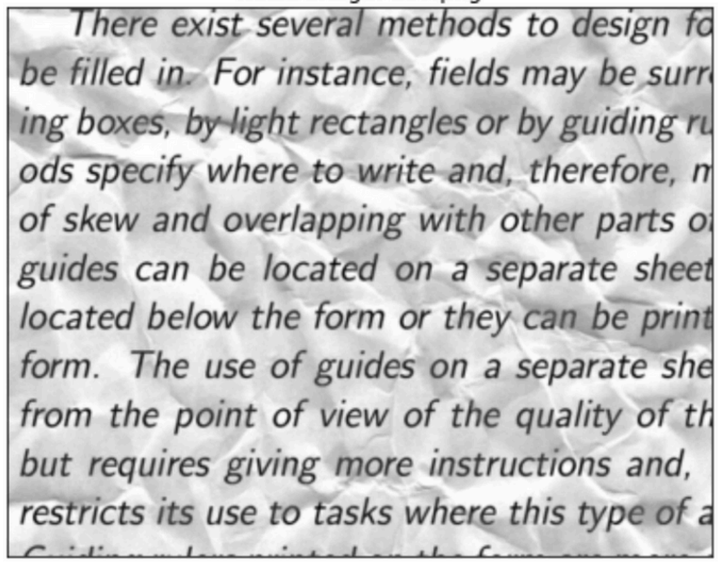
RANJIT N

INTRODUCTION

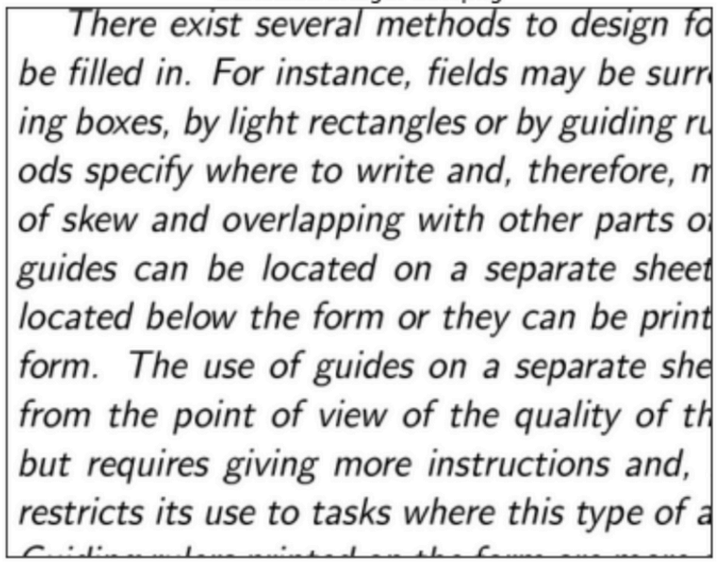
- Objective: To design and implement a model for removing noise from scanned document images using a deep learning-based autoencoder.
- Problem: Scanned documents often contain various types of noise, making them harder to read or process automatically.
- Solution: We built a convolutional autoencoder to clean noisy document images.

TRAINING DATA

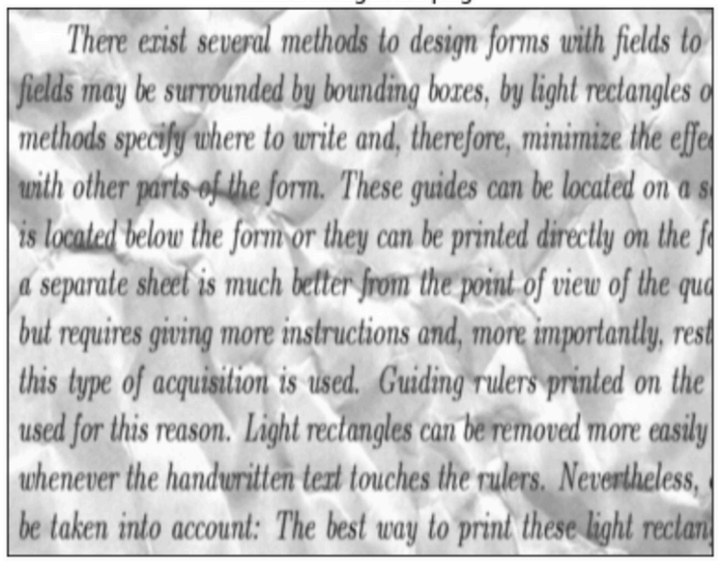
Noise image: 107.png



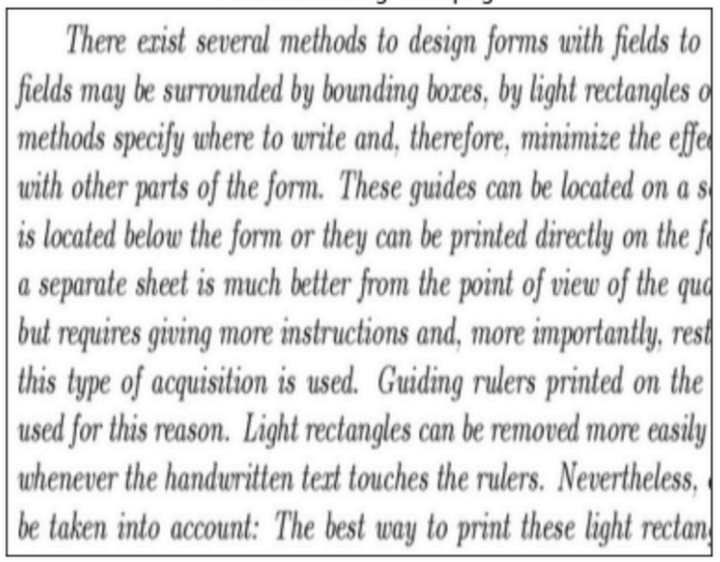
Denoised image: 107.png



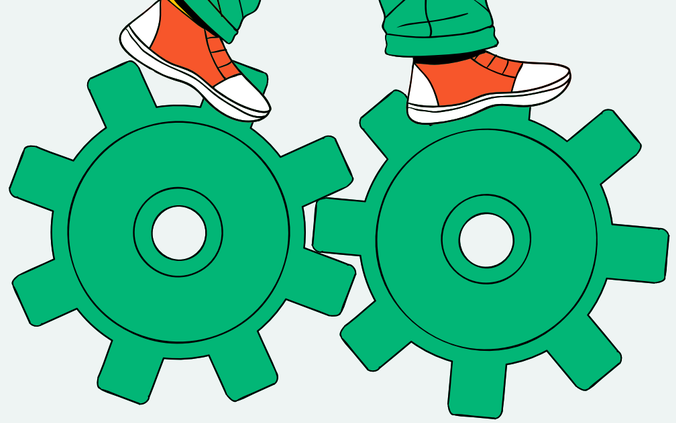
Noise image: 11.png



Denoised image: 11.png



PROJECT WORKFLOW



STEP 1

Data loading and preprocessing.

STEP 2

Model architecture and training.

STEP 3

Model evaluation using K-fold cross-validation.

STEP 4

Training full dataset using convolution auto encoder.

STEP 5

Performance analysis and optimization.

EFFICIENCY AND OPTIMIZATION

CUSTOM LOSS FUNCTION

- Create a loss function combining MSE and SSIM.

IMPACT

- Improve focus on image reconstruction and perceptual quality.

IMAGE PREPROCESSING

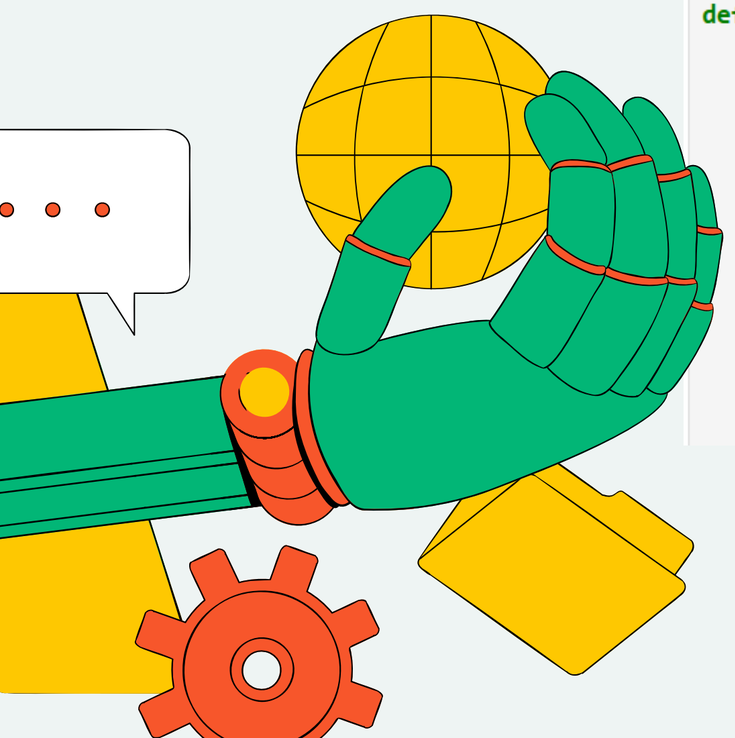
- Implemented efficient techniques like parallel data loading, resizing, and batching.

RESULT

- Faster data handling and reduced training time, boosting productivity.

CODE

```python
def process_image_tensor(image_path, target_size=(270, 350)):
    img = tf.io.read_file(image_path)
    img = tf.image.decode_image(img, channels=1)
    img.set_shape([None, None, 1])
    img = tf.image.resize(img, target_size)
    img = img / 255.0
    return img
```

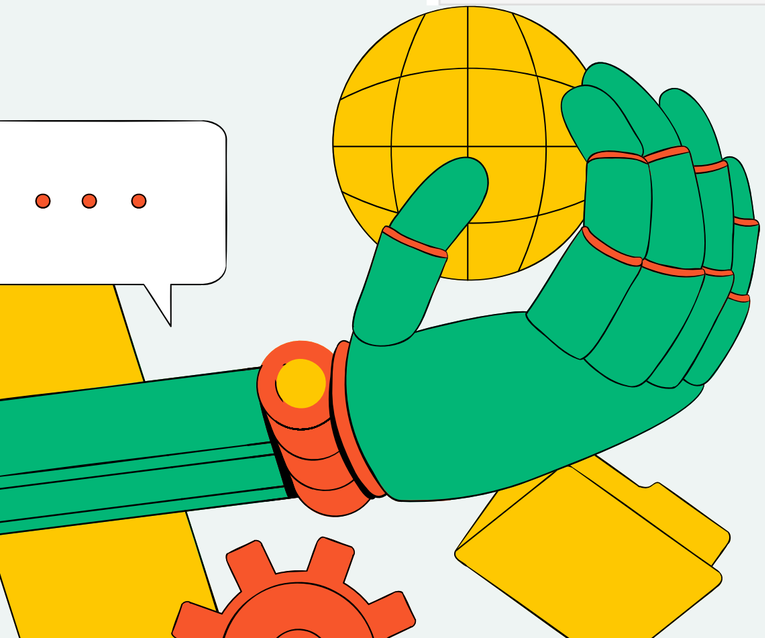


```python
def data_generator_tf(image_paths, clean_paths=None, batch_size=8, target_size=(270, 350)):
    dataset = tf.data.Dataset.from_tensor_slices(image_paths)
    dataset = dataset.map(lambda x: process_image_tensor(x, target_size), num_parallel_calls=tf.data.AUTOTUNE)

    if clean_paths is not None:
        clean_dataset = tf.data.Dataset.from_tensor_slices(clean_paths)
        clean_dataset = clean_dataset.map(lambda x: process_image_tensor(x, target_size), num_parallel_calls=tf.data.AUTOTUNE)
        dataset = tf.data.Dataset.zip((dataset, clean_dataset))

    dataset = dataset.batch(batch_size)
    dataset = dataset.prefetch(buffer_size=tf.data.AUTOTUNE)
    return dataset
```

CODE

```python
def load_data_as_arrays():
    train_paths = sorted([os.path.join(path, 'train', f) for f in os.listdir(os.path.join(path, 'train'))])
    clean_paths = sorted([os.path.join(path, 'train_cleaned', f) for f in os.listdir(os.path.join(path, 'train_cleaned'))])

    train_X = np.array([process_image_tensor(img_path).numpy() for img_path in train_paths])
    train_y = np.array([process_image_tensor(img_path).numpy() for img_path in clean_paths])

    return train_X, train_y
```

```python
def custom_loss(y_true, y_pred):
    mse = K.mean(K.square(y_true - y_pred))
    ssim_loss = 1 - tf.reduce_mean(tf.image.ssim(y_true, y_pred, max_val=1.0))
    return 0.7 * mse + 0.3 * ssim_loss
```



K-FOLD CROSS-VALIDATION FOR ROBUSTNESS

01

Divide dataset into 5 parts, trained on 4 and validated on 1.

02

Rotate through all splits.

03

Managed memory limitations by tuning batch sizes.

04

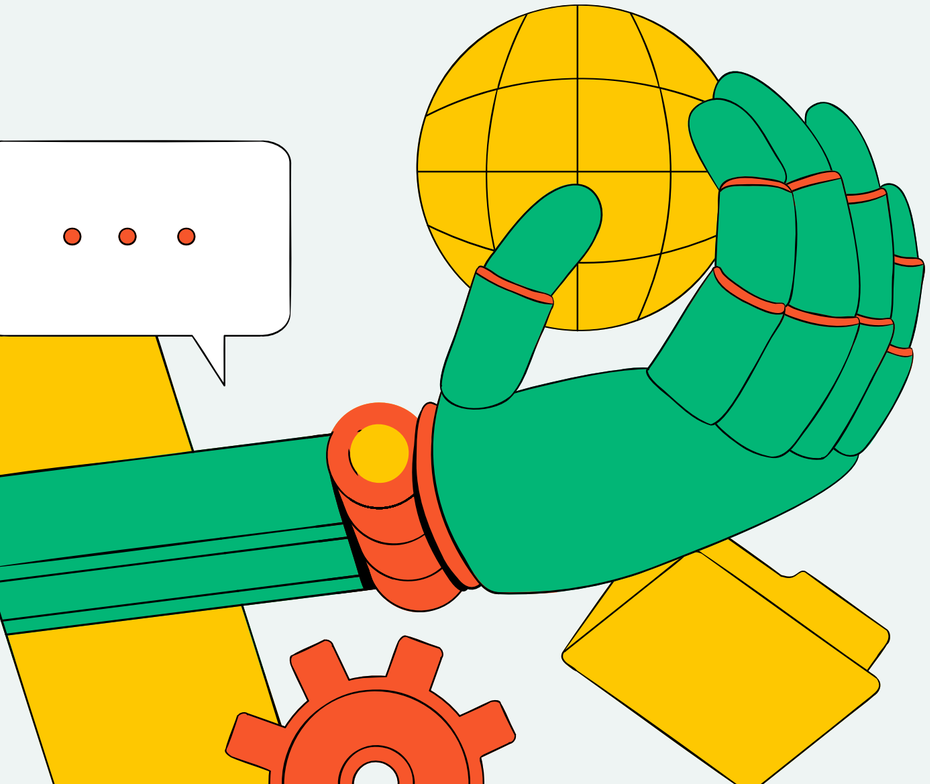
Avoided overfitting through cross-validation.

05

Reliable performance across different data subsets.

CODE

```
Average scores across folds:
Loss: 0.08332
MAE: 0.06193
```

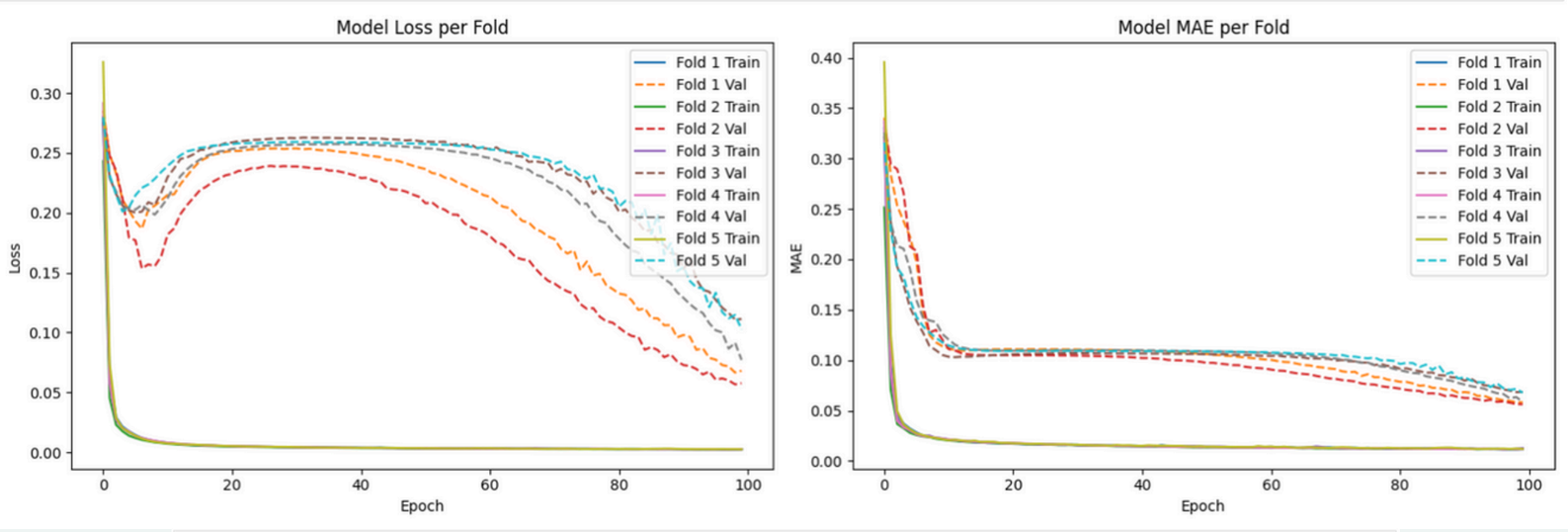


```python
def train_k_fold(model_builder, X, y, k=5, batch_size=32, epochs=100):
    histories = []
    kf = KFold(n_splits=k, shuffle=True, random_state=42)
    fold_no = 1
    mae_per_fold = []
    loss_per_fold = []

    for train_index, val_index in kf.split(X):
        print(f"\nTraining Fold {fold_no} / {k}")

        X_train, X_val = X[train_index], X[val_index]
        y_train, y_val = y[train_index], y[val_index]

        X_train_resized = tf.image.resize(X_train, [270, 350])
        X_val_resized = tf.image.resize(X_val, [270, 350])

        model = model_builder()

        history = model.fit(X_train_resized, y_train,
                            validation_data=(X_val_resized, y_val),
                            batch_size=batch_size, epochs=epochs, verbose=1)
        histories.append(history.history)
        mae_per_fold.append(history.history['val_mae'][-1])
        loss_per_fold.append(history.history['val_loss'][-1])

        fold_no += 1

    print("\nAverage scores across folds:")
    print(f"Loss: {np.mean(loss_per_fold):.5f}")
    print(f"MAE: {np.mean(mae_per_fold):.5f}")

    return model, histories
```

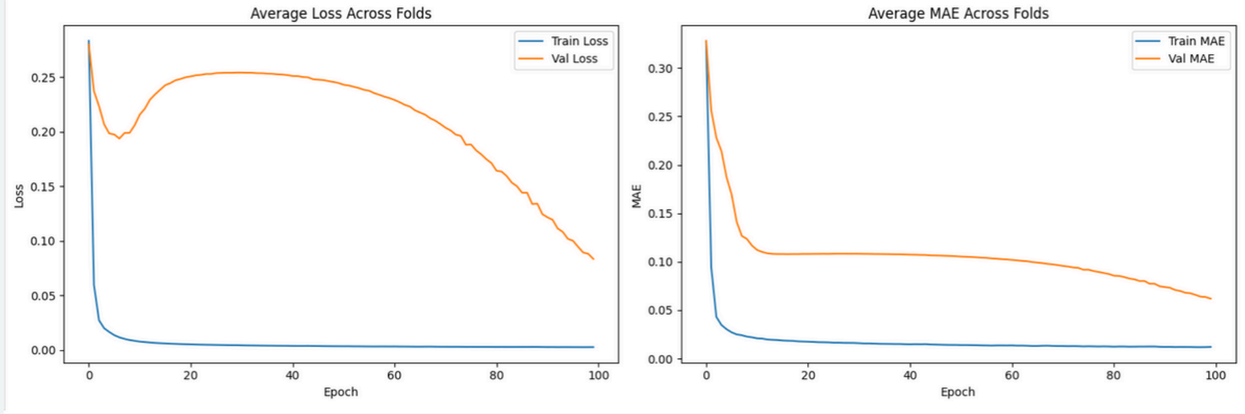
```python
print("Loading data for K-Fold...")
X, y = load_data_as_arrays()

print("Training model with K-Fold Cross-Validation...")
trained_model, histories = train_k_fold(build_model, X, y, k=5, batch_size=32, epochs=100)
```

VISUALIZATION

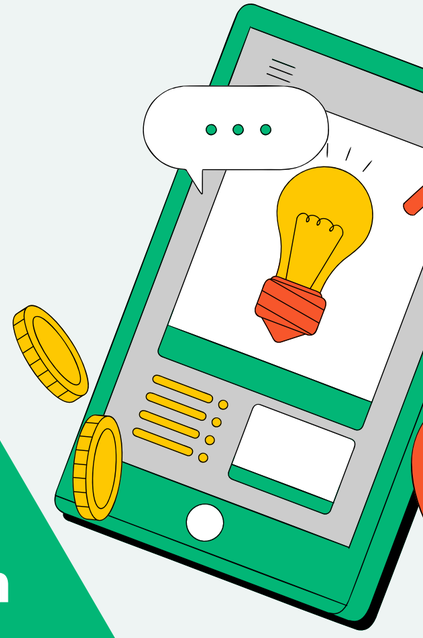
```
plot_comparative_folds(histories)
```




```
plot_average_metrics(histories)
```



MODEL ARCHITECTURE



Model Layers

Encoder with Conv2D and MaxPooling

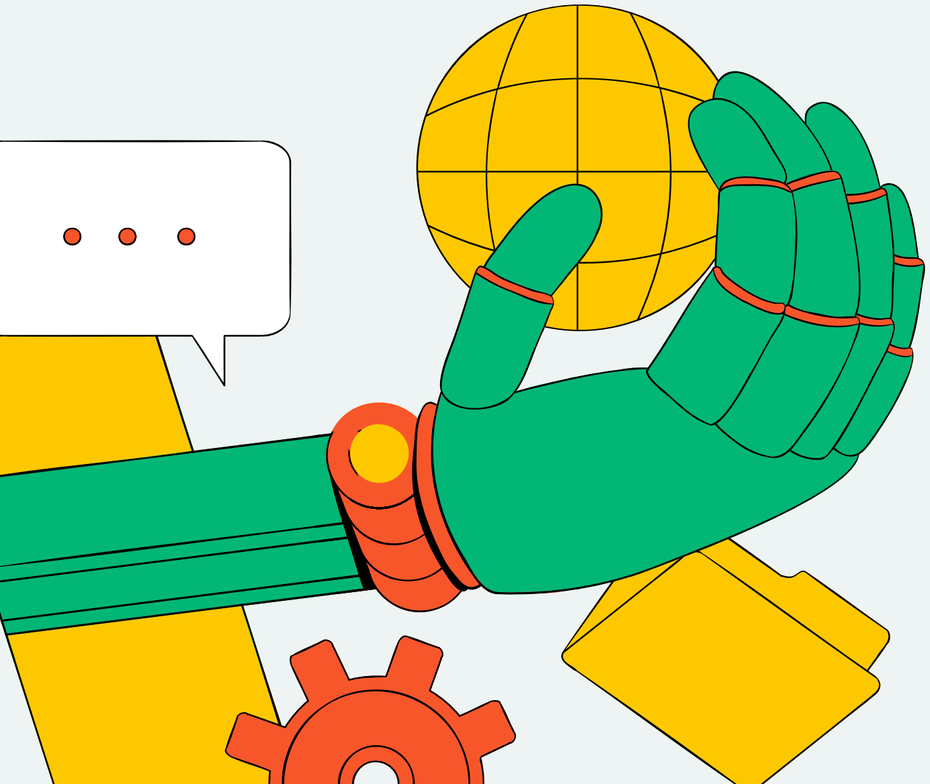
Decoder with Conv2D and UpSampling

Batch Normalization for stable training

Dropout for regularization

Mixed Precision Training: Optimized memory usage on GPUs

CODE



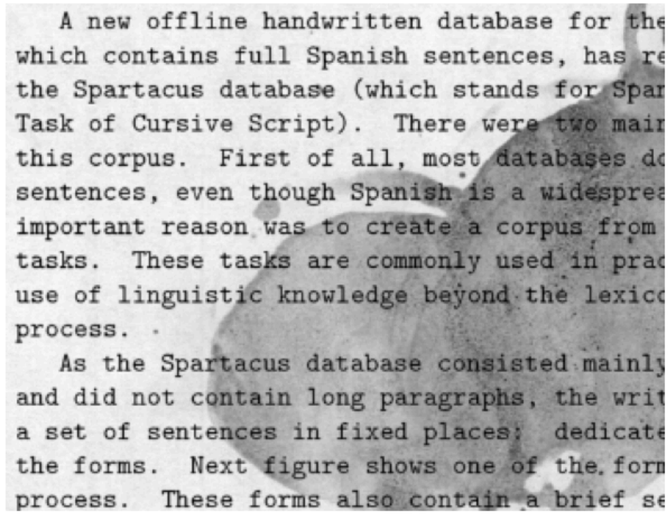
```python
def prepare_data(batch_size=32):
    train_paths = sorted([os.path.join(path, 'train', f) for f in os.listdir(os.path.join(path, 'train'))])
    clean_paths = sorted([os.path.join(path, 'train_cleaned', f) for f in os.listdir(os.path.join(path, 'train_cleaned'))])
    train_generator = data_generator_tf(train_paths, clean_paths, batch_size=batch_size)
    return train_generator, len(train_paths)
```

```python
def build_model(input_shape=(270, 350, 1)):
    input_layer = Input(shape=input_shape)

    # Encoder
    x = Conv2D(32, (3, 3), activation='relu', padding='same')(input_layer)
    skip1 = x
    x = Conv2D(64, (3, 3), activation='relu', padding='same')(x)
    x = BatchNormalization()(x)
    skip2 = x
    x = MaxPooling2D((2, 2), padding='same')(x)
    x = Dropout(0.5)(x)

    # Bridge
    x = Conv2D(128, (3, 3), activation='relu', padding='same')(x)

    # Decoder
    x = Conv2D(64, (3, 3), activation='relu', padding='same')(x)
    x = BatchNormalization()(x)
    x = UpSampling2D((2, 2))(x)
    x = Concatenate()([x, skip2])
    x = Conv2D(32, (3, 3), activation='relu', padding='same')(x)
    x = Concatenate()([x, skip1])

    output_layer = Conv2D(1, (3, 3), activation='sigmoid', padding='same')(x)

    model = Model(inputs=[input_layer], outputs=[output_layer])

    optimizer = tf.keras.optimizers.Adam(learning_rate=0.001)
    model.compile(optimizer=optimizer, loss=custom_loss, metrics=['mae'])

    return model
```

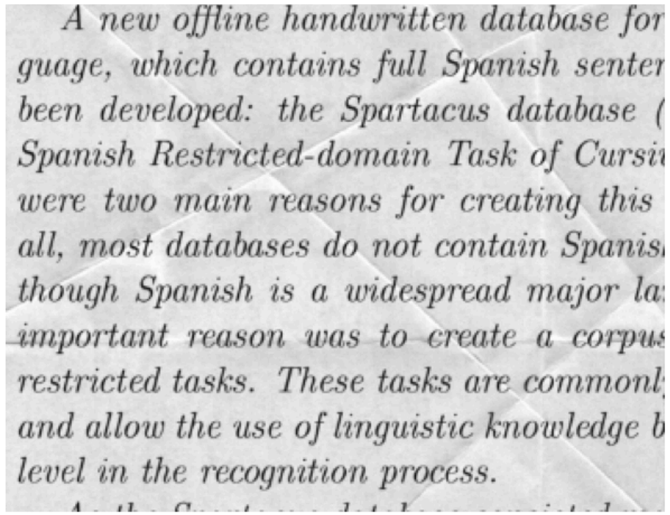
```python
print("\nTraining final model on the full dataset...")
train_generator, num_train_samples = prepare_data(batch_size=32)
final_model = build_model()

history = final_model.fit(train_generator, epochs=300, verbose=1)
final_model.save('final_model.keras')
```

IMAGE DENOISING

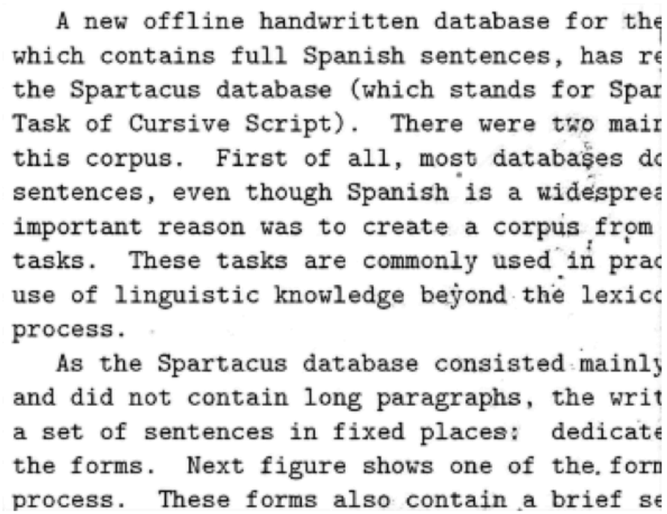
Original Image 40



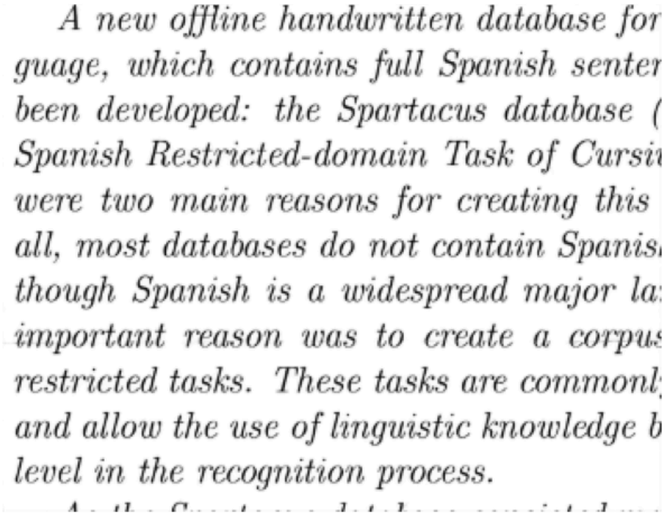
Original Image 64



Denoised Prediction 40



Denoised Prediction 64

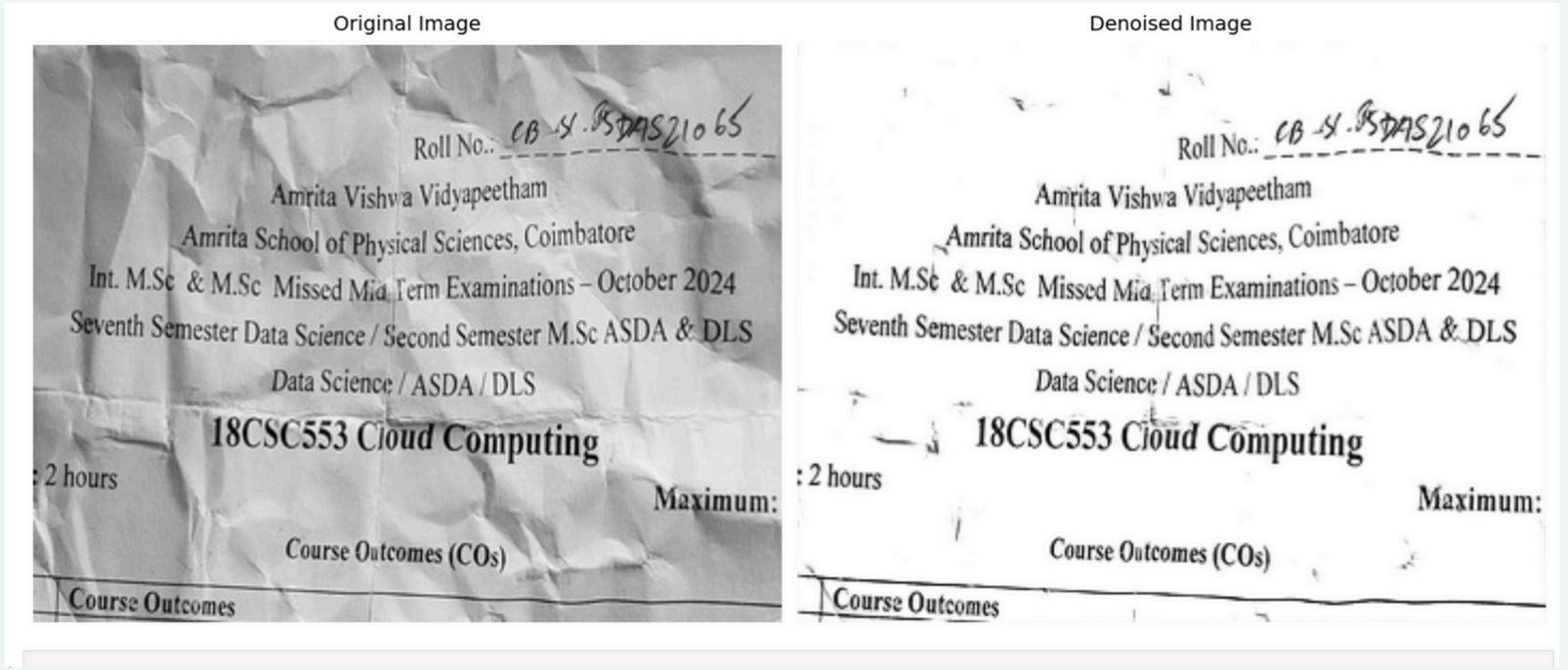


CONCLUSION & FUTURE WORK

Summary: Developed an efficient model for document denoising using a convolutional autoencoder.

- Used techniques like custom loss functions, skip connections, and K-fold cross-validation.
- Future Work: Improve the model to handle more complex noise types. Experiment with additional architectures like UNet

SAMPLE INPUT IMAGE TO THE MODEL



THANK YOU