

Project Analysis: Handwriting Writer Identification

1. Project Objective

This project aims to identify the writer of handwritten text using deep learning techniques. Specifically, it appears to be using two different approaches:

- A ResNet-based classification model to directly identify writers
- A Siamese network to determine if two handwriting samples are from the same writer

2. Datasets Used

The project uses the [IAM Handwriting Dataset](#), specifically a subset containing the top 50 writers. This dataset includes:

- Handwriting samples from various writers
- A mapping of form IDs to writer IDs
- The data is preprocessed to focus on the top 10 writers with the most samples

3. Models Used

ResNet Classification Model

- Base architecture: ResNet50 with pre-trained ImageNet weights
- Transfer learning approach with the base model frozen
- Additional layers:
 - Global Average Pooling
 - Dropout (0.5)
 - Dense layer (128 units)
 - Output layer with softmax activation

Siamese Network

- Custom CNN architecture with:
 - Multiple Conv2D layers (32, 64, 128 filters)
 - BatchNormalization layers
 - MaxPooling layers
 - Dense layer (128 units)
- Uses contrastive loss function to compare image pairs
- Binary output indicating whether two samples are from the same writer

4. Results

ResNet Classification Model

- Training accuracy: ~94.7%
- Validation accuracy: ~95.8%
- Loss decreased steadily from ~1.45 to ~0.18
- Confusion matrix shows strong diagonal values, indicating good classification
- Best results seen after 15 epochs

```
Epoch 1/15
45/45 ----- 362s 8s/step - accuracy: 0.3952 - loss: 2.1408 - val_accuracy: 0.7688 - val_loss: 0.8142 - learning_rate: 0.0010
Epoch 2/15
45/45 ----- 392s 8s/step - accuracy: 0.7314 - loss: 0.8220 - val_accuracy: 0.8552 - val_loss: 0.4476 - learning_rate: 0.0010
Epoch 3/15
45/45 ----- 334s 7s/step - accuracy: 0.7987 - loss: 0.6200 - val_accuracy: 0.8774 - val_loss: 0.3402 - learning_rate: 0.0010
Epoch 4/15
45/45 ----- 391s 8s/step - accuracy: 0.8594 - loss: 0.4267 - val_accuracy: 0.9053 - val_loss: 0.2802 - learning_rate: 0.0010
Epoch 5/15
45/45 ----- 346s 8s/step - accuracy: 0.9003 - loss: 0.3098 - val_accuracy: 0.9109 - val_loss: 0.2670 - learning_rate: 0.0010
Epoch 6/15
45/45 ----- 379s 8s/step - accuracy: 0.9279 - loss: 0.2294 - val_accuracy: 0.9276 - val_loss: 0.2358 - learning_rate: 0.0010
Epoch 7/15
45/45 ----- 409s 8s/step - accuracy: 0.9351 - loss: 0.2161 - val_accuracy: 0.9331 - val_loss: 0.2318 - learning_rate: 0.0010
Epoch 8/15
45/45 ----- 360s 8s/step - accuracy: 0.9202 - loss: 0.2454 - val_accuracy: 0.9164 - val_loss: 0.2411 - learning_rate: 0.0010
Epoch 9/15
45/45 ----- 342s 8s/step - accuracy: 0.9369 - loss: 0.1737 - val_accuracy: 0.9471 - val_loss: 0.2041 - learning_rate: 0.0010
Epoch 10/15
45/45 ----- 383s 8s/step - accuracy: 0.9463 - loss: 0.1589 - val_accuracy: 0.9359 - val_loss: 0.2051 - learning_rate: 0.0010
Epoch 11/15
45/45 ----- 385s 8s/step - accuracy: 0.9591 - loss: 0.1341 - val_accuracy: 0.9387 - val_loss: 0.2019 - learning_rate: 0.0010
Epoch 12/15
45/45 ----- 381s 8s/step - accuracy: 0.9666 - loss: 0.1110 - val_accuracy: 0.9415 - val_loss: 0.2250 - learning_rate: 0.0010
Epoch 13/15
45/45 ----- 363s 7s/step - accuracy: 0.9573 - loss: 0.1346 - val_accuracy: 0.9387 - val_loss: 0.2113 - learning_rate: 0.0010
Epoch 14/15
45/45 ----- 381s 7s/step - accuracy: 0.9602 - loss: 0.1168 - val_accuracy: 0.9415 - val_loss: 0.1998 - learning_rate: 5.0000e-04
Epoch 15/15
45/45 ----- 398s 8s/step - accuracy: 0.9578 - loss: 0.1440 - val_accuracy: 0.9582 - val_loss: 0.1863 - learning_rate: 5.0000e-04
<keras.src.callbacks.history.History at 0x78ef69248c10>
```

Siamese Network

- Training accuracy: ~75.7%
- Validation accuracy: ~73.2%
- Loss decreased steadily from ~1.44 to ~0.15
- Best results seen after 5 epochs

5. Discussion on Results

The ResNet classification model performs very well:

- High accuracy (over 95%) on validation data
- The training curves show a healthy learning pattern with no obvious overfitting
- The confusion matrix shows strong performance across all writer classes
- The model demonstrates ability to correctly identify writers from their handwriting

The training implementation includes several best practices:

- Early stopping and learning rate reduction callbacks
- Data preprocessing including normalization
- Class balancing considerations

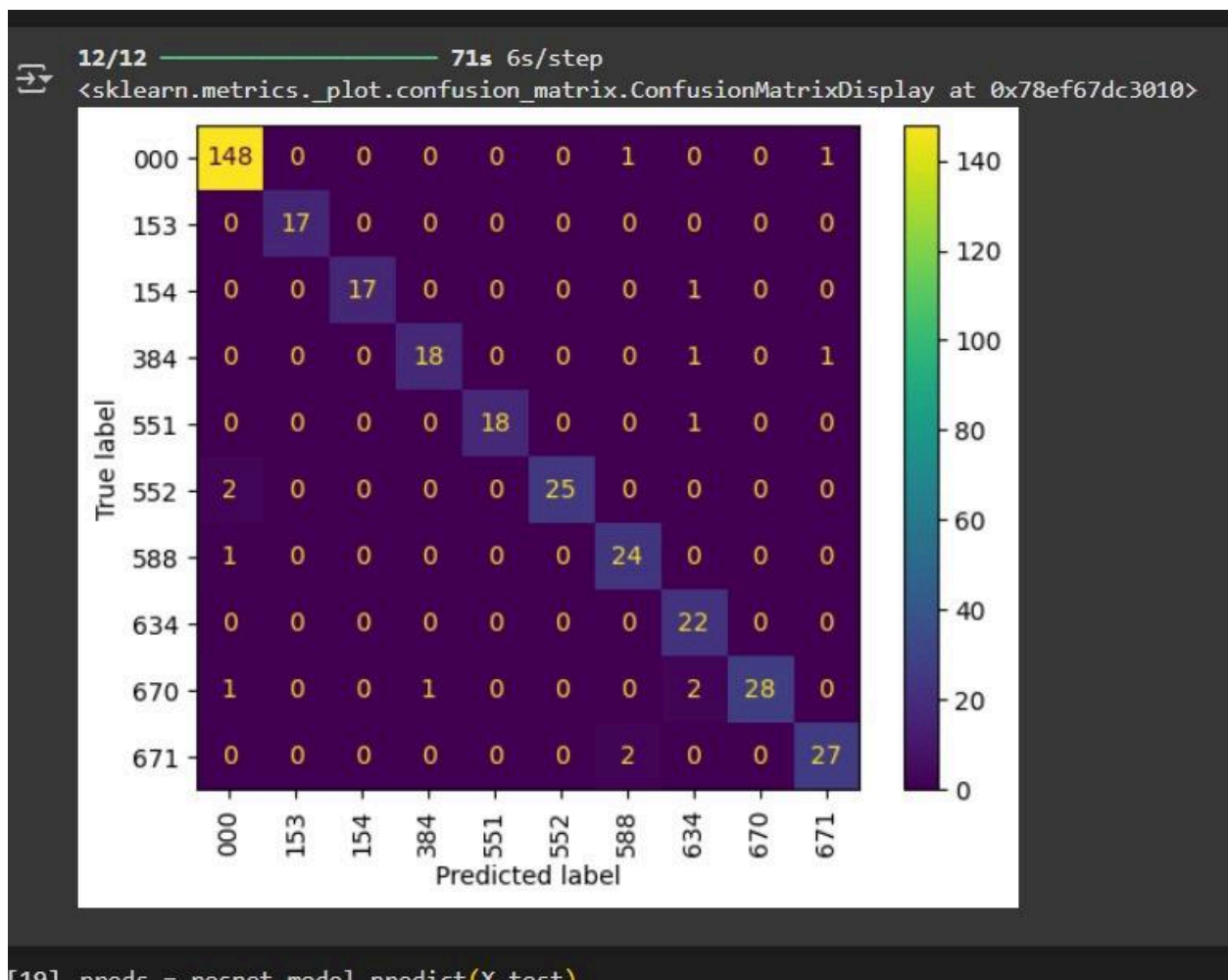
- Visualization of training progress

The Siamese network provides a complementary approach that focuses on similarity between handwriting samples rather than direct classification. This is particularly useful when:

- New writers are introduced to the system
- Limited examples per writer are available
- A verification system is needed

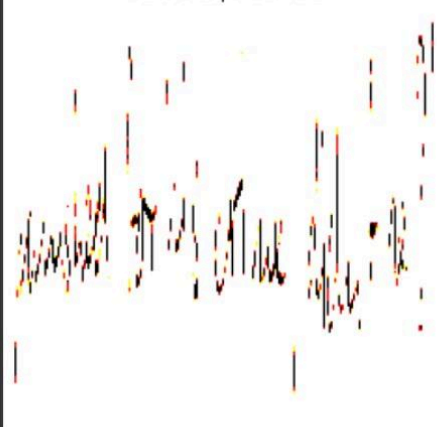
The confusion matrix shows exceptionally strong performance on writer identification, with most classes achieving perfect or near-perfect classification. The model appears particularly effective at distinguishing between different handwriting styles.

The example predictions show successful classification of test samples where the predicted label matches the true label.



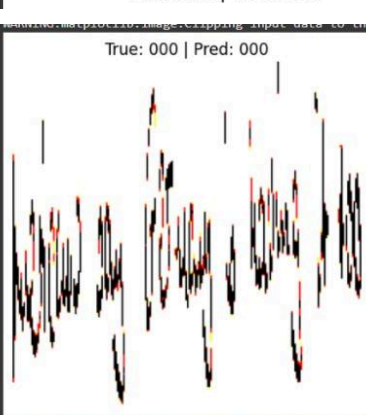
WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers). Got range

True: 671 | Pred: 671



WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers). Got range

True: 000 | Pred: 000



WARNING:matplotlib.image:Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers). Got range [-73.68..151.061].

True: 671 | Pred: 671

