Signature Specimen Matching using ANN

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ABSTRACT
In this work, we used an artificial neural network to do offline specimen signature recognition and achieved 99.47% accuracy given the 940 raw images of signatures of 79 authors from the SigComp 2009 dataset.

1. INTRODUCTION
Writing one's signature is a universally known method when establishing identity in many legal, financial, business, and personal transactions. Each person's signature is unique so as to express acknowledgment, acceptance, or approval. In this work, we looked into the use of artificial neural network (ANN) in matching a signature to its respective author. Research in automatic signature verification and recognition has recently been an active topic because of its potential to provide a secure authentication method in various applications [2]. It must be clear that signature verification tackles a different problem from recognition, the former checks if a signature matches the person whose signature characteristics is known in advance, while the latter searches a signature database to match an identity to the given signature [5]. Also there are two ways of writing a signature, *online* where signatures are written on an electronic capturing device, or *offline* where signatures are written on a piece of paper [4]. This study focuses on offline signature recognition using ANN.

Compared to signature verification, there are only a few studies on offline signature recognition. Having this kind of system can provide an identification tool for security facilities as well as in the analysis of signatures in legal and historical documents [2]. One study was conducted by Frias-Martinez, Sanchez, and Velez [2] wherein they compared the performance of Support Vector Machines (SVM) and Multilayer Perceptrons (MLP) using moment-based characteristics and bitmap feature vectors in offline signature recognition. They were able to achieve 71.2% using SVM and 46.8% accuracy using MLP with bitmap features. Another study was done by Ismail and Gad [3] wherein they tested the performance of a multi-stage classifier using a combination of global and local features from the signatures. They were able achieve 95.00% accuracy using the said method. In the work of Pavlidis, Papanikolopoulos, and Mavuduru [6], they used a revolving active deformable model to approximate the shape of a signature. They were able to achieve 78.89% accuracy using the said method.

In this work, the input features used are the pixel values of the signature images. We used a publicly available dataset from the International Conference on Document Analysis and Recognition (SigComp2009) [1]. The error rate reported in SigComp2009 is 9.15% on offline data. The signature images were preprocessed first before we extracted the gray-scale value of each pixel. This in turn is used to train the ANN and then measured its accuracy in matching a signature to its author.

2. METHODOLOGY
This section discusses the steps done in the study, from preprocessing, feature extraction, model generation, and model evaluation. Figure 1 presents the flowchart of the methodology.

2.1 Preprocessing
The dataset from SigComp 2009[1] is composed of 940 images of various signatures from 79 authors, with each author contributing either 6 or 12 signature images. Each author is identified with an ID number whose value ranges from 1 to 101. These images were preprocessed first to ensure it is ready for feature extraction. The preprocessing techniques include the following:

- *RGB to gray-scale conversion.* The images were first converted from RGB to Gray-scale in order to get the intensity of each pixel of the image in a single value.

[1] `http://tc11.cvc.uab.es/datasets/SigComp2009_1`

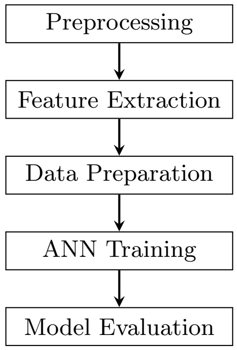

Figure 1: Overall Methodology

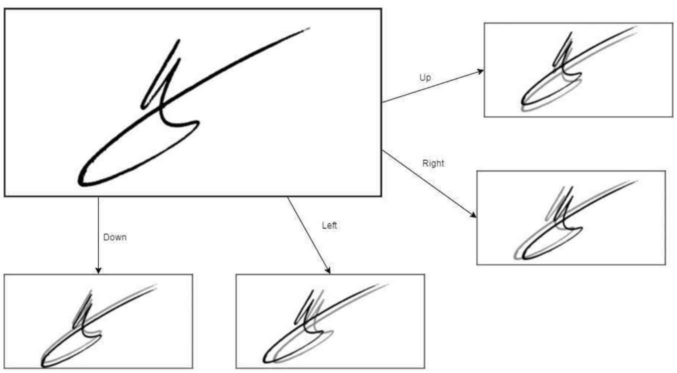

Figure 2: Generating images by shifting pixels

- *Image padding.* Then the height and width of the images were adjusted by padding white pixels on the edges of the image until it reaches an aspect ratio of 2 : 1. It is then re-sized to 1,024 × 512 pixels, which follows the said ratio. This was done to normalize the size of all the images.
- *Histogram equalization.* The intensity of each image was then adjusted to improve its contrast.
- *Image centering.* Since some signatures are shifted to the sides, the signature in the images was then centered by calculating its centroid and using it as the center of the image when shifting all the pixels to the needed direction. Pixels that were emptied after the shifting were replaced with white pixels.

2.1.1 Increasing the number of images

Since each author only has 6 or 12 signatures, we generated additional images to increase the number of images that will be used for training and validation. For each image, the pixels were shifted in each side (top, right, bottom, left) by 5, 10, and 15 pixels to produce additional images. This can be visualized in Figure 2, the top left image shows the original image while the other images portrays the movement of the signature after shifting the pixels.

2.1.2 Image Resolution Reduction

To reduce the memory requirements in training the ANN, the 1,024 × 512 images are resized to lower resolutions. In particular, for each image, we produced images with the following dimensions: 8 × 4, 16 × 8, 32 × 16, and 64 × 32 pixels.

Dimension	Fts.	Shifted Px	No. of Imgs.
8 × 4	32	0	940
8 × 4	32	5	4700
8 × 4	32	10	4700
8 × 4	32	15	4700
16 × 8	128	0	940
16 × 8	128	5	4700
16 × 8	128	10	4700
16 × 8	128	15	4700
32 × 16	512	0	940
32 × 16	512	5	4700
32 × 16	512	10	4700
32 × 16	512	15	4700
64 × 32	2048	0	940
64 × 32	2048	5	4700
64 × 32	2048	10	4700
64 × 32	2048	15	4700

Table 1: Grouped Images

2.2 Feature Extraction

The input features used in the ANN are the pixels of each image. We produced 24 datasets by doing the following in sequence.

2.2.1 Grouping the images

The images were then grouped based on its dimension and pixels shifted. Each group (of a specific dimension) includes the images that were not shifted. For example, the 8 × 4 images with 5 pixel shift and the original 8 × 4 images produces one group. Each group with the additional images is composed of 4,700 images. We also maintained groups (per dimension) composed only of images that were not shifted. These groups only has 940 images.

Table 1 shows the groupings done in this study, wherein each row represents a group and its attributes.

2.2.2 Pixel intensity inversion

The pixel values of the images in each group were then extracted to produce a dataset. These values were inverted by subtracting the pixel value from 255 and saving the resulting value as the new pixel value. Note that in images, 0 is black and 255 is white.

The new pixel values were then divided by 255.0 to convert them to a scale of 0 to 1. These values were then written to the file with its corresponding author ID.

2.2.3 Binary images

For each image, we produced its binary version. In particular, the pixel values of the images was converted to either 0 or 1 only. If the current value is greater than or equal to 32, it is considered as 1, else it is considered 0.

2.3 Data Preparation

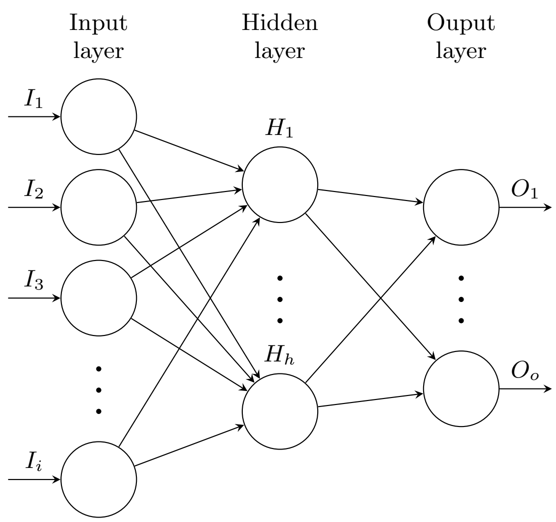

Figure 3: Design of a single layer feedforward ANN

Dimensions	No. of Features	i	h	o
8 × 4	32	32	16	101
16 × 8	128	128	64	101
32 × 16	512	512	256	101
64 × 32	2048	2048	1024	101

Table 2: ANN Design for each Dimension

We produced 64 datasets given the original 940 images of signatures of 79 individuals. Each dataset is split to a training set and a validation set. 60% of the dataset is used for training while the remaining 40% is used for validation.

Note that it was divided into a 60:40 ratio for each author rather than the whole dataset itself. This was done so that all authors may be well represented when generating the models.

2.4 ANN training

We trained an ANN using each of the 64 training sets.

2.4.1 *Single layer feedforward ANN*

We used a single hidden layer feedforward ANN in this work.

In Figure 3, the input layer contains i nodes which each represents the value of a certain feature and a bias node. The hidden layer in this design contains h nodes. The output layer contains o nodes. The nodes in one layer are fully connected to the next layer and the bias node is connected to every node in both the hidden and output layer.

For each dimension, the number of nodes of the input and hidden layer is different from one another because of varying number of features. Table 2 shows the number of input (i), hidden (h), and output (o) nodes that were used for each dataset.

Note that for each dimension, there is a corresponding scaled and binary versions of input images.

Training Algorithm	Backpropagation
Learning Rate	0.3
Compute Function	Sigmoid
Initial Weights	Randomized (-0.1 to 0.1)
Number of Epochs	100

Table 3: Backpropagation parameters

The parameters used in the backpropagation algorithm to determine the weights of the network connections are given in Table 3.

After training each extracted dataset, the number of nodes for each layer and weights were saved for the model evaluation.

2.5 Model Evaluation

For each dataset, an ANN model (with the saved weights of directed arcs) is produced and evaluated with respect to validation accuracy, precision, recall, and f-measure using the formulas stated on [7].

The accuracy for signature recognition is computed using the following formula:

$$\text{Accuracy} = \frac{\text{Number of correct matchings}}{\text{Total number of images in validation set}}$$

The precision and recall were computed using:

$$\text{Precision} = \frac{\sum_{i=1}^{n} \frac{tp_i}{tp_i + fp_i}}{\text{n}}$$

$$\text{Recall} = \frac{\sum_{i=1}^{n} \frac{tp_i}{tp_i + fn_i}}{\text{n}}$$

Here tp_i is the number of correct matchings for author i, fp_i is the number of incorrect matches to author i, fn_i is the number of instances of author i that was incorrectly matched as another author, and n is the total number of authors. Note that first computes the precision and recall of each author before averaging it with the total number of authors.

Using the average per-author precision and recall, the f-measure is computed using:

$$\text{F} - \text{measure} = \frac{(\beta^2 + 1) \times Precision \times Recall}{(\beta^2 \times \text{Precision}) + \text{Recall}}$$

wherein $\beta = 1$.

3. RESULTS

This section presents a discussion of the results of this study, which includes the performance measures for each dataset. These measures is presented using accuracy, precision, recall, and f-measure tables. In the Accuracy tables, Co means the number of correct matches, In means the number of incorrect matches, and the Ac means the accuracy. While in the Precision, Recall, and F-measure tables, Pr means the precision, Re means the recall, and Fm means the F-measure.

Dimension	Type	Co	In	Ac
8 × 4	Scaled	5	385	1.28%
16 × 8	Scaled	26	364	6.67%
32 × 16	Scaled	231	159	59.23%
64 × 32	Scaled	331	59	84.87%
8 × 4	Binary	5	385	1.28%
16 × 8	Binary	25	365	6.41%
32 × 16	Binary	249	141	63.85%
64 × 32	Binary	275	115	70.51%

Table 4: Accuracy table for the Original Dataset

Dimension	Type	Pr	Re	Fm
8 × 4	Scaled	0.000	0.013	0.000
16 × 8	Scaled	0.067	0.063	0.066
32 × 16	Scaled	0.618	0.589	0.603
64 × 32	Scaled	0.859	0.846	0.852
8 × 4	Binary	0.000	0.013	0.000
16 × 8	Binary	0.040	0.063	0.049
32 × 16	Binary	0.645	0.636	0.641
64 × 32	Binary	0.764	0.703	0.732

Table 5: Precision, Recall, and F-measure table for the Original Dataset

3.1 Without Pixel Shifting

For our first trial, we tested the accuracy of ANN using the original data set which is composed of 6 or 12 signatures per author. It can be seen in Table 4 that as the dimension increases, the accuracy increases. As with Table 5, the precision, recall, and f-measure also increases as the dimension increases. With this, the 64 × 32 pixel performed best in both the scaled and binarized versions.

3.2 With Pixel Shifting

The performance of ANN can be further increased if there is more data for it to use for training. To prove this, we generated additional data sets by producing a shifted version of each signature image. For each trial, there are 30 or 60 signatures per author, with a total 4,700 signature images.

We first tested using the 5 pixel shift. The highest accuracy in this trial reached a 99.47% using 64 × 32 scaled images, matching 1870 out of 1880 instances (Table 6). The highest accuracy for 10 pixel shift was 96.12% using 64 × 32 binary images, matching 1807 out of 1880 instances (Table 8). While the 15 pixel shift produced the highest accuracy of 92.20% using 64 × 32 binary images, matching 1730 out of 1880 instances (Table 10).

The overall highest accuracy was produced by the 5 pixel shift, with a 99.47% accuracy. As the shift went higher, the accuracy decreased. With this, it can be said that a high shift values would make the accuracy of the ANN lower.

As for the precision, recall, and f-measure, the highest was also attained using 64 × 32 images with 5 pixel shift.

It can be seen that there is no difference if whether the data is scaled or binary (See figures 4 and 5). This is probably because the positioning of the signature pixels mattered more

Dimension	Type	Co	In	Ac
8 × 4	Scaled	103	1777	5.48%
16 × 8	Scaled	953	927	50.69%
32 × 16	Scaled	1395	485	74.20%
64 × 32	Scaled	1870	10	99.47%
8 × 4	Binary	107	1773	5.69%
16 × 8	Binary	1060	820	56.38%
32 × 16	Binary	1462	418	77.77%
64 × 32	Binary	1861	19	98.99%

Table 6: Accuracy table for 5 pixel shift

Dimension	Type	Pr	Re	Fm
8 × 4	Scaled	0.105	0.054	0.072
16 × 8	Scaled	0.597	0.504	0.547
32 × 16	Scaled	0.758	0.589	0.748
64 × 32	Scaled	0.995	0.995	0.995
8 × 4	Binary	0.047	0.056	0.052
16 × 8	Binary	0.592	0.560	0.576
32 × 16	Binary	0.782	0.776	0.779
64 × 32	Binary	0.990	0.988	0.989

Table 7: Precision, Recall, and F-measure table for 5 pixel shift

Dimension	Type	Co	In	Ac
8 × 4	Scaled	82	1798	4.36%
16 × 8	Scaled	732	1148	38.94%
32 × 16	Scaled	1190	690	63.30%
64 × 32	Scaled	1793	87	95.37%
8 × 4	Binary	85	1795	4.52%
16 × 8	Binary	733	1147	38.99%
32 × 16	Binary	1191	689	63.35%
64 × 32	Binary	1807	73	96.12%

Table 8: Accuracy table for 10 pixel shift

Dimension	Type	Pr	Re	Fm
8 × 4	Scaled	0.044	0.043	0.043
16 × 8	Scaled	0.462	0.387	0.421
32 × 16	Scaled	0.641	0.632	0.636
64 × 32	Scaled	0.954	0.951	0.953
8 × 4	Binary	0.045	0.045	0.045
16 × 8	Binary	0.427	0.388	0.407
32 × 16	Binary	0.637	0.631	0.634
64 × 32	Binary	0.962	0.959	0.960

Table 9: Precision, Recall, and F-measure table for 10 pixel shift

Dimension	Type	Co	In	Ac
8 × 4	Scaled	62	1818	3.30%
16 × 8	Scaled	624	1256	33.19%
32 × 16	Scaled	1003	877	53.35%
64 × 32	Scaled	1707	173	90.80%
8 × 4	Binary	73	1807	3.88%
16 × 8	Binary	608	1272	32.34%
32 × 16	Binary	1118	762	59.47%
64 × 32	Binary	1730	150	92.02%

Table 10: Accuracy table for 15 pixel shift

Dimension	Type	Pr	Re	Fm
8 × 4	Scaled	0.014	0.033	0.020
16 × 8	Scaled	0.390	0.330	0.357
32 × 16	Scaled	0.565	0.531	0.547
64 × 32	Scaled	0.912	0.905	0.908
8 × 4	Binary	0.035	0.039	0.036
16 × 8	Binary	0.371	0.322	0.345
32 × 16	Binary	0.601	0.592	0.596
64 × 32	Binary	0.925	0.917	0.921

Table 11: Precision, Recall, and F-measure table for 15 pixel shift

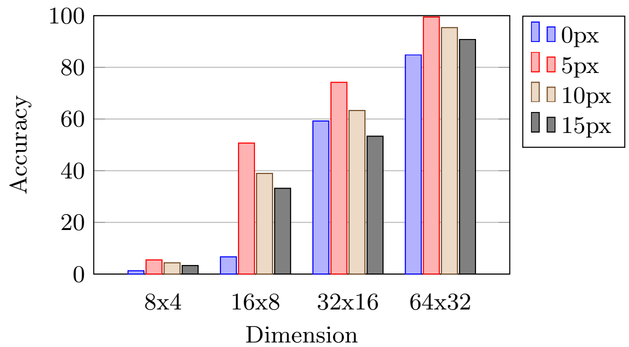

Figure 4: Accuracy when using scaled images

than its intensity.

3.2.1 Sample mismatched signatures

Figure 6 shows examples of signature mismatched. The first record shows a signature of author with ID 16 is matched with the signature of author with ID 46. In this record, author with ID 46 has 3 examples of his/her signature. Note that visually, the signature of author 69 being matched with the signature of author 1, is plausible. The same goes with author 88 with author 45 and author 88 with author 58. One factor that could possibly be attributed to the mismatches is the similarity of where the pixel values are distributed in the image.

3.2.2 Signature Verification

In addition to signature recognition, the best performing model was tested for signature verification. For signature verification, a model must determine if the given instance is genuine or forged. In this study, the model generated by ANN using 64 × 32 scaled images with 5 pixel shift was used. The 624 forged signatures from the SigComp2009 dataset was used to validate this model. It is composed of 19 authors each having 24 or 36 forged signatures. Table 12 shows the matches when using the forged instances. The Author ID is the identification of the author in the genuine dataset who's signature was forged, the Matched with Target is the number of forgeries of that was determined as genuine, while the Matched with Others is the number of forgeries that was determined as forgery.

The false acceptance rate (FAR) of the model is 28.36%, which means that 177 out of 624 instances was matched as a genuine signature of an author.

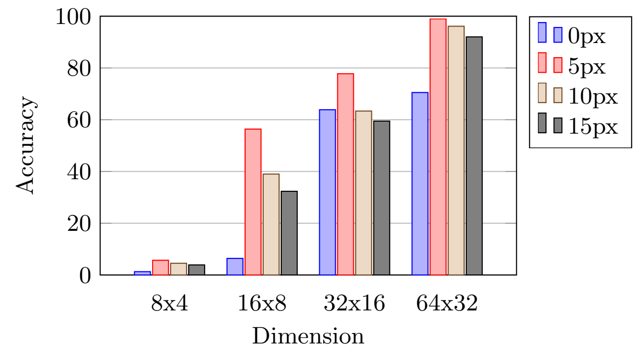

Figure 5: Accuracy when using binary images

Author ID	Matched w/ Target	Matched w/ Other
2	18	6
8	5	31
16	3	27
18	0	24
24	2	34
33	9	27
35	6	18
44	25	11
46	6	18
63	10	26
70	7	29
71	9	21
77	17	19
84	4	32
85	12	24
86	3	33
89	25	11
92	9	27
93	7	29

Table 12: Matches of forged signatures

4. CONCLUSION

Using 64 × 32 pixel scaled images, with an additional 5 pixel shifted images, the single hidden layer ANN was able to achieve a 99.47% accuracy. This accuracy is better than what is reported in [2] [3] [6] for offline data. The difficulty in offline signature recognition is that there is no standard corpus to use. Each study must either obtain signatures through manual data gathering or use a publicly available dataset like the SigComp2009 signature dataset.

As for the other findings in this work, we observed that as the image dimension increases, the accuracy, precision, recall, and f-measure also increases. This is probably because the images with lower dimensions would have a limited amount of detail about a signature.

We note that the accuracy when the non-binary version are used is not far from the binary version of the images. Also, having a large shift value lowers the accuracy of the ANN. This means too much shift of the image from the centroid is not good.

Figure 6: Ten incorrect signature recognition

5. REFERENCES

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