Binary Classification of Facial Features using Genetic Algorithm: Are the Individuals in different historic photographs the same Individual

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Abstract. With the development of AI, it is easy to identify an individual when there exist many related photographs; however, it will become difficult when there are only sparse photographs (2-3) of an individual[1]. This report aims to find a method to classify whether the individuals in different photographs are the same individual. The original data is the coordinates of Facial Feature Makers(FFMs) and the lengths of FFM distances. The data was preprocessed by min-max normalization. A simple neural network was implemented as the baseline, the accurcy is 60%. A technique using threshold[3] was implemented to improve the network, the best accurcy is 71%. A genetic algorithm was immplemented to optimize the parameters of the neural network and threshold, the final accurcy is 86%. The future work would focus on implementing more techniques to improve the network.

Keywords: Neural networks, Binary Classification, Facial Feature Makers, Thresholds, Genetic Algorithm

1 Introduction

Photographs are a good tool to record life and history. Thanks to the development of digital image sensors, nowadays people can easily take photos using mobile phones and cameras; However, decades ago, it was not convenient for people to take photos. As time flies, historic photographs are becoming more and more rare and precious. Therefore, identifying individuals from a limited quantity of photos is very meaningful as it can save people's memory.

Related works in face recognition usually use complex and powerful neural networks. For example, Lu, P. et. al.[4] use convolutional neural networks and augmented dataset to deal with this problem; Zhang, J. et. al.[5] also use convolutional neural networks and they implemented a feature fusion method to get better face feature information.

The original data of this report is the coordinates of Facial Feature Makers(FFMs) and the lengths of FFM distances. The aim is to use neural networks, genetic algorithm and technique introduced in the paper written by Milne, L.K. et. al.[3] to process these data in order to classify the individuals in different photographs are the same individual.

2 Method

2.1 Data

The data set for this report are FFMs provided as x,y coordinates and FFM distances provided as lengths. The coordinates shown in figure 1 are mainly used in this report. There are 36 rows and 57 colums in this data. For each row, the colum 1 to colum 28 represent the 14 point coordinates of the marks of a photo, the colum 29 to colum 56 represent the 14 point coordinates of the marks of another photo, and colum 57 represents the comparation outcome.

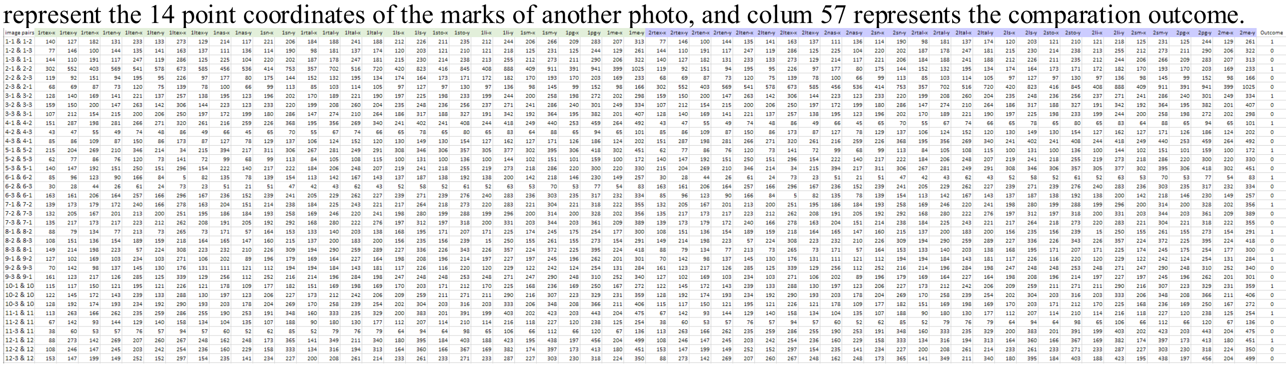

image pairs	1rtex-x	1rtex-y	1rten-x	1rten-y	1lten-x	1lten-y	1ltex-x	1ltex-y	1nas-x	1nas-y	1sn-x	1sn-y	1rtal-x	1rtal-y	1ltal-x	1ltal-y	1ls-x	1ls-y
1-1 & 1-2	140	127	182	131	233	133	273	129	214	117	221	206	184	188	241	188	212	226
1-2 & 1-3	77	146	100	144	135	141	163	137	111	136	114	190	98	181	137	174	120	203
1-3 & 1-1	144	110	191	117	247	119	286	125	225	104	220	202	187	178	247	181	215	230
2-1 & 2-2	302	552	403	569	541	578	673	585	456	536	414	753	357	702	516	720	420	823
2-2 & 2-3	119	92	151	94	195	95	226	97	177	80	175	144	152	132	195	134	174	164
2-3 & 2-1	68	69	87	73	120	75	139	78	100	66	99	113	85	103	114	105	97	127
3-1 & 3-2	128	140	169	141	221	137	257	138	195	123	196	202	170	189	221	190	197	225
3-2 & 3-3	159	150	200	147	263	142	306	144	223	123	233	220	199	208	260	204	235	248
3-3 & 3-1	107	212	154	215	200	206	250	197	172	199	180	286	147	274	210	264	186	317
4-1 & 4-2	151	287	198	281	266	271	320	261	216	259	226	368	195	356	269	340	241	402
4-2 & 4-3	43	47	55	49	74	48	86	49	66	45	65	70	55	67	74	66	65	78
4-3 & 4-1	85	86	109	87	150	86	173	87	127	78	129	137	106	124	152	120	130	149
5-1 & 5-2	215	204	269	210	346	214	34	215	394	217	311	306	267	281	249	291	308	346
5-2 & 5-3	62	77	86	76	120	73	141	72	99	68	99	113	84	105	108	115	100	131
5-3 & 5-1	140	147	192	151	250	151	296	154	222	140	217	222	184	206	248	207	219	241
6-1 & 6-2	85	96	123	90	166	84	5	82	135	78	139	154	113	142	167	143	137	187
6-2 & 6-3	30	28	44	26	61	24	73	23	51	21	51	47	42	43	62	43	52	58
6-3 & 6-1	163	161	206	164	257	166	296	167	236	152	239	241	205	229	262	227	239	271
7-1 & 7-2	139	173	179	172	240	166	278	163	204	151	214	238	184	225	243	221	217	264
7-2 & 7-3	132	205	167	201	213	200	251	195	186	184	193	258	169	246	220	241	198	280
7-3 & 7-1	135	217	173	217	223	212	262	208	191	205	192	292	168	280	222	276	197	312
8-1 & 8-2	88	79	134	77	213	73	265	73	171	57	164	153	133	140	203	138	168	195
8-2 & 8-3	108	151	136	154	189	159	218	164	165	147	160	215	137	200	183	200	156	235
8-3 & 8-1	149	214	198	223	57	224	308	223	232	210	226	309	194	290	259	289	227	336
9-1 & 9-2	127	102	169	103	234	103	271	106	202	89	196	179	169	164	227	164	198	208
9-2 & 9-3	70	142	98	137	145	130	176	131	111	121	112	194	194	184	143	181	117	226
9-3 & 9-1	161	123	217	126	285	125	339	129	256	112	252	216	214	196	284	198	247	248
10-1 & 10	115	117	150	121	195	121	226	121	178	109	177	182	151	169	198	169	170	203
10-2 & 10	122	145	172	143	239	133	288	130	197	123	206	227	173	212	242	206	209	259
10-3 & 10	128	192	174	193	234	192	290	193	203	178	204	269	170	258	239	254	202	304
11-1 & 11	113	263	166	262	235	259	286	255	190	253	191	348	160	333	235	329	200	383
11-2 & 11	67	142	93	144	129	140	158	134	104	135	107	188	90	180	130	177	112	207
11-3 & 11	38	60	53	57	76	57	94	57	60	52	62	85	52	79	76	79	64	94
12-1 & 12	88	273	142	269	207	260	267	248	162	248	173	365	141	349	211	340	180	395
12-2 & 12	108	246	147	245	203	242	254	236	160	229	158	333	134	316	194	313	164	360
12-3 & 12	153	147	199	149	252	152	297	154	235	141	234	227	200	208	261	214	233	261

image pairs	1sto-x	1sto-y	1li-x	1li-y	1sm-x	1sm-y	1pg-x	1pg-y	1me-x	1me-y	2rtex-x	2rtex-y	2rten-x	2rten-y	2lten-x	2lten-y	2ltex-x	2ltex-y	2nas-x	2nas-y
1-1 & 1-2	211	235	212	244	206	266	209	283	207	313	77	146	100	144	135	141	163	137	111	136
1-2 & 1-3	121	210	121	218	125	231	125	244	129	261	144	110	191	117	247	119	286	125	225	104
1-3 & 1-1	214	238	213	255	212	273	211	290	206	322	140	127	182	131	233	133	273	129	214	117
2-1 & 2-2	416	845	408	888	409	911	391	941	399	1025	119	92	151	94	195	95	226	97	177	80
2-2 & 2-3	173	171	172	182	170	193	170	203	169	233	68	69	87	73	120	75	139	78	100	66
2-3 & 2-1	97	130	97	136	98	145	99	152	98	166	302	552	403	569	541	578	673	585	456	536
3-1 & 3-2	198	233	199	244	200	258	198	272	202	298	159	150	200	147	263	142	306	144	223	123
3-2 & 3-3	236	256	237	271	241	286	240	301	249	334	107	212	154	215	200	206	250	197	172	199
3-3 & 3-1	188	327	191	342	192	364	195	382	201	407	128	140	169	141	221	137	257	138	195	123
4-1 & 4-2	241	408	244	418	249	440	253	459	264	492	43	47	55	49	74	48	86	49	66	45
4-2 & 4-3	65	80	65	83	64	88	65	94	65	101	85	86	109	87	150	86	173	87	127	78
4-3 & 4-1	130	154	127	162	127	171	126	186	124	202	151	287	198	281	266	271	320	261	216	259
5-1 & 5-2	306	357	305	377	302	395	306	418	302	451	62	77	86	76	120	73	141	72	99	68
5-2 & 5-3	100	136	100	144	102	151	101	159	100	172	140	147	192	151	250	151	296	154	222	140
5-3 & 5-1	218	255	219	273	218	286	220	300	220	330	215	204	269	210	346	214	34	215	394	217
6-1 & 6-2	138	192	138	200	142	218	146	230	149	257	30	28	44	26	61	24	73	23	51	21
6-2 & 6-3	52	61	52	63	53	70	53	77	54	83	163	161	206	164	257	166	296	167	236	152
6-3 & 6-1	239	276	240	283	236	303	235	317	232	334	85	96	123	90	166	84	5	82	135	78
7-1 & 7-2	218	273	220	283	221	304	221	318	222	355	132	205	167	201	213	200	251	195	186	184
7-2 & 7-3	199	288	199	296	200	314	200	328	202	356	135	217	173	217	223	212	262	208	191	205
7-3 & 7-1	197	318	200	331	203	344	203	361	209	389	139	173	179	172	240	166	278	163	204	151
8-1 & 8-2	171	207	171	225	174	245	175	254	177	300	108	151	136	154	189	159	218	164	165	147
8-2 & 8-3	156	239	15	250	155	261	155	273	154	291	149	214	198	223	57	224	308	223	232	210
8-3 & 8-1	226	343	226	357	224	372	225	395	224	418	88	79	134	77	213	73	265	73	171	57
9-1 & 9-2	196	214	197	227	197	245	196	262	201	301	70	142	98	137	145	130	176	131	111	121
9-2 & 9-3	116	220	120	229	122	242	124	254	131	284	161	123	217	126	285	125	339	129	256	112
9-3 & 9-1	248	253	248	271	247	290	248	310	252	340	127	102	169	103	234	103	271	106	202	89
10-1 & 10	171	212	170	225	168	236	169	250	167	272	122	145	172	143	239	133	288	130	197	123
10-2 & 10	211	271	211	290	216	307	223	329	231	359	128	192	174	193	234	192	290	193	203	178
10-3 & 10	203	316	203	333	206	348	208	366	211	406	115	117	150	121	195	121	226	121	178	109
11-1 & 11	201	391	199	403	202	423	203	443	204	475	67	142	93	144	129	140	158	134	104	135
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11-3 & 11	64	98	65	106	66	112	66	120	67	136	113	263	166	262	235	259	286	255	190	253
12-1 & 12	184	403	188	423	195	438	197	456	204	499	108	246	147	245	203	242	254	236	160	229
12-2 & 12	166	367	169	382	174	397	173	413	180	451	153	147	199	149	252	152	297	154	235	141
12-3 & 12	233	271	233	287	227	303	230	318	224	350	88	273	142	269	207	260	267	248	162	248

image pairs	2sn-x	2sn-y	2rtal-x	2rtal-y	2ltal-x	2ltal-y	2ls-x	2ls-y	2sto-x	2sto-y	2li-x	2li-y	2sm-x	2sm-y	2pg-x	2pg-y	2me-x	2me-y	Outcome
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9-3 & 9-1	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
10-1 & 10	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
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10-3 & 10	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
11-1 & 11	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
11-2 & 11	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
11-3 & 11	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
12-1 & 12	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
12-2 & 12	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
12-3 & 12	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

Figure 1. Facial Feature Makers

The data is normalized to between 0 and 1 using min-max normalization:

$$x_{scaled} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{1}$$

The data will randomly split approximate 80% into the training set and approximate 20% into the testing set. This was confirmed by cross validation.

2.2 Neural Network

This report implements two simple binary classification networks.

The first one is a simple neural network with two output neurons, it contains one input layer, one hidden layer and one output layer. For FFMs, the number of input neurons is equal to the number of inputs. The number of neurons in the hidden layer is close to two-thirds of the number of input neurons in this case it is 40. The output layer contains two output neurons. The hidden layer uses a sigmoid activation function. The loss function is Cross-Entropy Loss and the optimiser is Adam. The maximum output of the two output neurons is the final output.

The second one is similar to the first one but it has only one output neuron. For FFMs, the number of input neurons is equal to the number of inputs. The number of neurons in the hidden layer is close to two-thirds of the number of input neurons in this case it is 40. The hidden layer uses a sigmoid activation function. The network also uses sigmoid to make sure the output is between 0 and 1. The loss function is Binary Cross-Entropy Loss and the optimiser is Adam. As the output is between 0 and 1, based on the paper of Milne, L.K. et. al.[3], a pre-defined threshold is applied to do the classification, which means the samples in output that large than the threshold equal to 1, other samples equal to 0.

2.3 Genetic Algorithm

In neural net work, the number of hidden neurons, the learning rate and the threshold was selected by experience, in order to find the most suitable parameters, genetic algrathim was implemented.

Genetic algorithm is a common type of evolutionary algorithm, it is usually used in optimize problems. In this paper, the learning rate, the number of hidden neurons and the threshold build the populations. The learning rate is randomly selected from 0.001 and 0.0001, the number of hidden neurons is selected between 10 and 80, the threshold is selected between 0.20 to 0.80. For the fitness function, the threshold neural network is implemented and the loss of its output is used to evaluate the fitness. The population is sorted by the fitness from the lowest loss to the highest loss and the top 20% called parents will be used in next generation. The elements of new population is build with parents, children generate by crossover 2 parents with cross rate 0.8, children after mutating with mutate rate 0.001. The first element of the final output is the best result.

2.4 Evaluation

To evaluate how well the network performs, the loss of the network, the accuracy of the network and the confusion should be considered. The standard confusion matrix is shown in Table 1[2].

Table 1. The standard confusion matrix

	Predicted Positive	Predicted Negative
Actual Positive	True Positives (TP)	False Negatives (FN)
Actual Negative	False Positives (FP)	True Negatives (TN)

True Positives and True Negatives are the correct predictions; False Negatives and False Positives are the incorrect predictions[2]. Based on the confusion matrix, the recall scores, precision scores and accuracy could be calculated.

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{4}$$

3 Results and Discussion

3.1 Testing

The data will randomly split approximate 80% into the training set and approximate 20% into the testing set, which is confirmed by cross-validation. For the neural network with two output neurons, it can simply output its results. For the neural network with one output neurons with a threshold, the threshold will be tested from 0.3 to 0.8 to find the best threshold.

3.2 Results

Results of the neural network with two output neurons:
Loss:

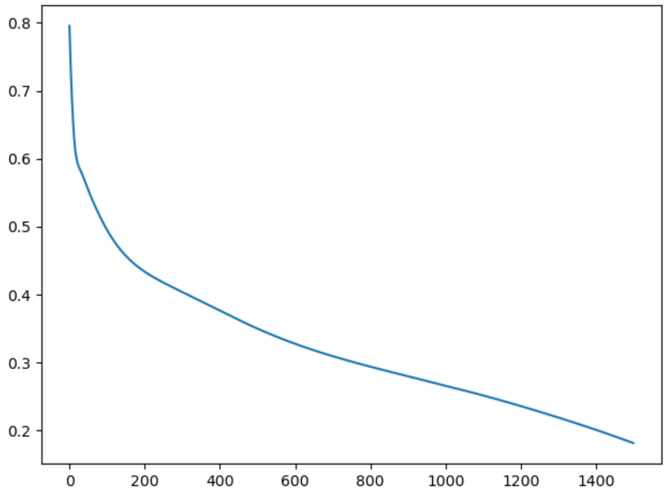

Figure 2. Loss when training; x label: number of the epoch; y label: loss

Table 2. Results of the neural network with two output neurons

Train		
Recall	Precision	Accuracy
0.76	0.95	96%
Testing		
0.67	0.57	60%

Results of the neural network with one output neurons using threshold technique:

Table 2. Results of the neural network with one output neurons using threshold technique:

Threshold	Recall		Precision		Accuracy		Last loss
	Training	Testing	Training	testing	training	testing	
0.2	0.59	0.67	0.93	0.67	76%	43%	0.2576
0.3	0.70	0.67	0.90	0.67	93%	43%	0.2443
0.4	0.70	0.67	0.90	0.67	93%	43%	0.2613
0.5	0.70	0.75	0.90	0.75	93%	57%	0.2437
0.6	0.70	0.75	0.90	0.75	93%	57%	0.2328
0.7	0.70	0.75	0.90	0.75	93%	57%	0.2328
0.8	0.70	0.80	0.90	0.80	93%	71%	0.2547

The result of the genetic algorithm is:
Learning rate: 0.001
Number of hidden neurons: 75
Threshold: 0.79

Using these parameters in the threshold method neural network, the results are:

Table 2. Results of the threshold method neural network optimized by genetic algorithm:

Train		
Recall	Precision	Accuracy
0.70	0.90	93%
Testing		
0.83	0.83	86%

3.2 Disscussion

For the neural network with one out put neurons using threshold technique, when threshold = 0.8, we get the best result, the testing accuracy is 71%. Comparing with the basic neural network with two output neurons, similar as the paper of Milne, L.K. et. al.[3], the threshold technique can improve the neural network. This technique increases the accuracy by 11%.

For the network optimized by genetic algorithm, the result is much better, it increases the accuracy from 71% to 86%, which shows that the genetic algorithm is useful on optimizing the parameters of the network.

4 Conclusion and future work

This project is using neural networks, genetic algorithm and threshold technique introduced in the paper written by Milne, L.K. et. al.[3] to process FFM data in order to classify the individuals in different photographs are the same individual. The results is quite good, the accuary increased 11% when using threshold technique and 26% when optimize by genetic algorithm. During experiment, we found that the result is not very stable. Different split data may lead to different result. That is because the training data and the testing data are both too less. But on the whole, the threshold technique bring better results than the basic neural network, and the genetic algorithm opitmizes the threshold network better. The future work will focus on implementing more techniques to improve the network. Expanding the dataset is important, and we can also add more FFMs. Improving the genetic algorithm is another possible way to get a better result.

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