FINGERPRINT IDENTIFICATION WITH FUSION OF GABOR AND MINUTIAE FEATURES USING BPNN CLASSIFIER

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Contents

Abstract

- Fingerprint identification is a task of personal identification and verification.
- Fingerprint Identification system consists of two modules that are training and testing.
- In this project, The feature vector is formed using combined features obtained from Gabor filtering technique and minutiae technique.
- To address dimensionality concerns, Principal Component Analysis (PCA) is applied.
- The dataset, comprising the fused features and corresponding labels, is then loaded for the final step - classification using a BPNN.

Introduction

- This study focuses on advancing fingerprint identification through the application of Back Propagation Neural Network (BPNN), a prominent deep learning technique.
- Fingerprint identification plays a pivotal role in various domains such as law enforcement, access control, and immigration.
- Traditional methods of fingerprint analysis have relied on manual interpretation and feature extraction, which can be time-consuming and prone to error.
- By employing BPNN, which are capable of learning intricate patterns and

  features directly from raw data, this research seeks to enhance the accuracy and efficiency of fingerprint identification.

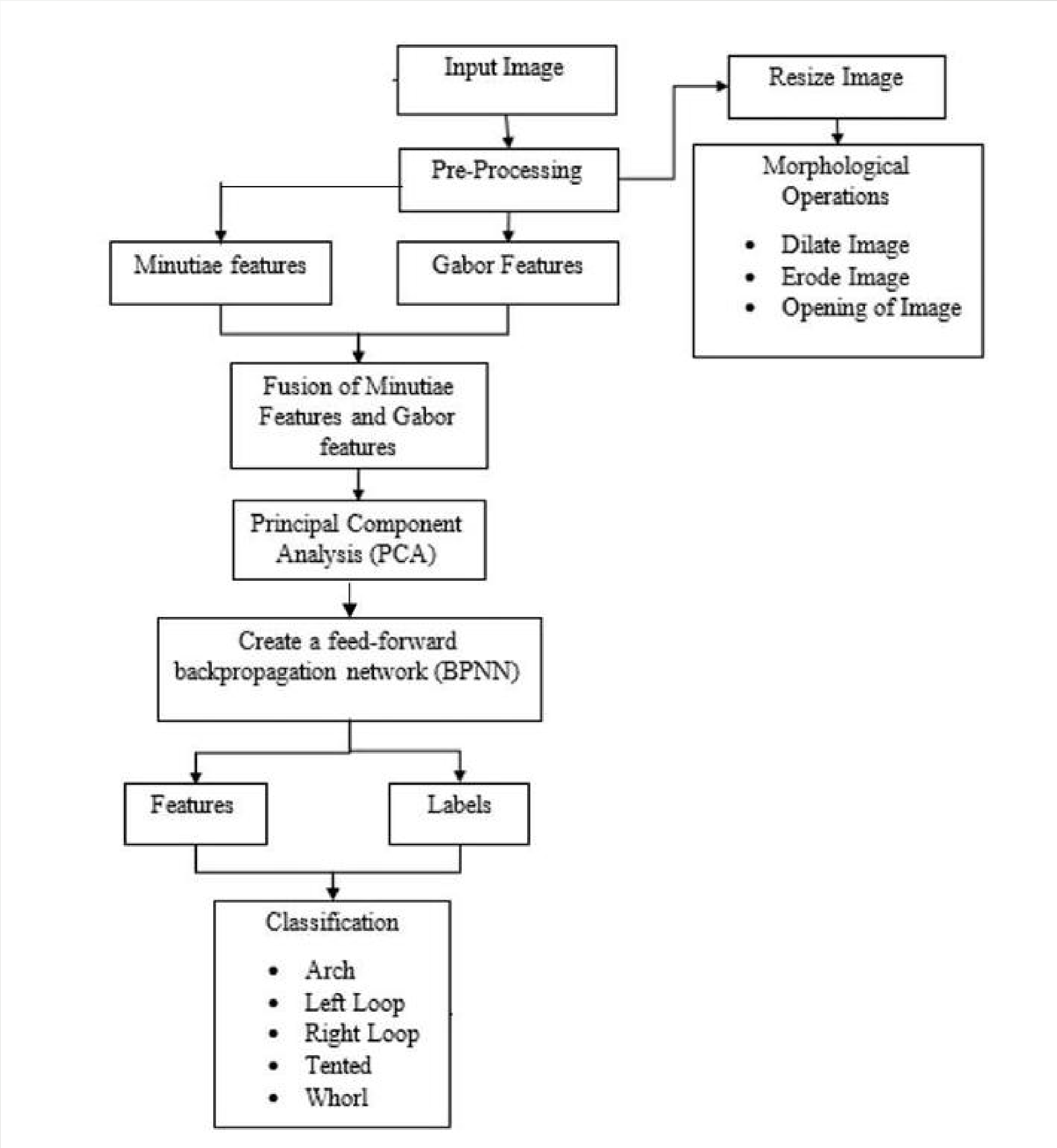
Introduction

- The classification task involves categorizing fingerprints into distinct patterns, including Arch, Left Loop, Right Loop, Tented, and Whorl. BPNN offer significant advantages in handling complex data structures like fingerprint images, making them well-suited for this classification task.
- The utilization of BPNN in fingerprint identification holds promise for improving biometric security systems, streamlining identification processes, and enhancing overall security measures.

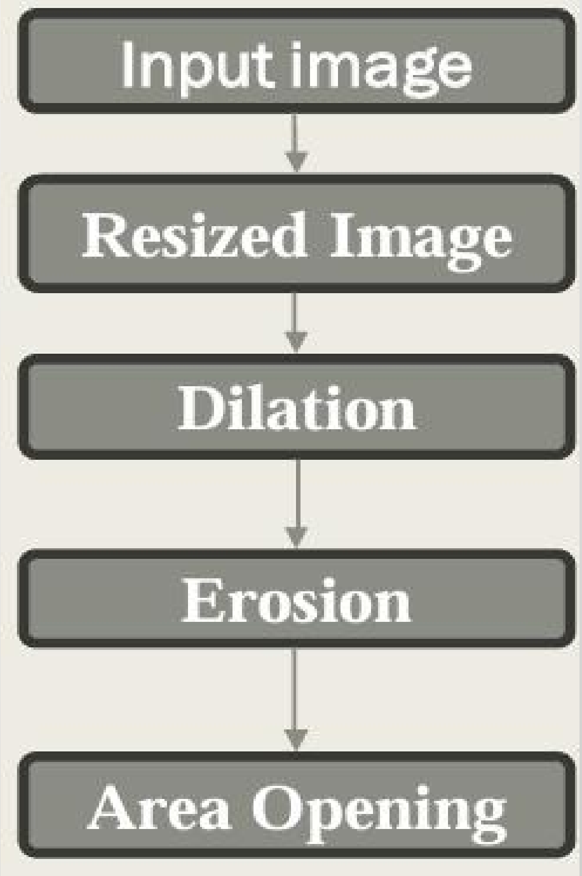
Applications:

- Biometric Security.
- Fingerprint help police catch criminals and track suspects in investigations.
- Fingerprint systems help border control verify travelers and spot fake documents.
- Fingerprint security safeguards banking, blocks unauthorized access to accounts and data.

Block Diagram



Morphological Operations Flow Chart



Morphological Operations

- Before adopting a fingerprint image into the proposed automatic system, it was preprocessed using a window of size 227×227 pixels.
- Then the morphological operations were performed to augment the ridges of the fingerprint images.
- The ridge width should be decreased so that the ridge end and bifurcates in the fingerprint could be detected easily.
- This procedure was performed using erosion-dilation and area opening techniques of morphological operation

Resized Image

- Resizing an image involves changing its dimensions, either increasing or decreasing its size.
- This process is commonly performed in image processing for various reasons, such as preparing data for a specific algorithm, adjusting display
- sizes, or reducing computational complexity.

Dilated

- It was mainly used to grow an object in size by extracting the outer boundaries of the given fingerprint image.
- Dilation continuously filled the missing pixel of a broken ridge as it added pixels at the boundary of the objects.
- Having applied this operation, the object enlarged its regions, shrank the single hole and reduced the gap between two regions.

Erosion

- This was used as the complement operation of dilation to smooth the fingerprint image after dilation.
- It caused to loss of size by extracting inner boundaries of a fingerprint edge.
- Therefore, it can be used to remove the noisy connections between the two objects.

Area Opening

- In the opening operation, the image was first eroded and then dilation was carried out to smoothen the contour of fingerprint image by clearing the narrow bridge and eliminating the minor extension present in the object.

Extraction of Gabor Features

- The Gabor filter to analyze an image. Gabor filters are commonly used in image processing for texture analysis and feature extraction.

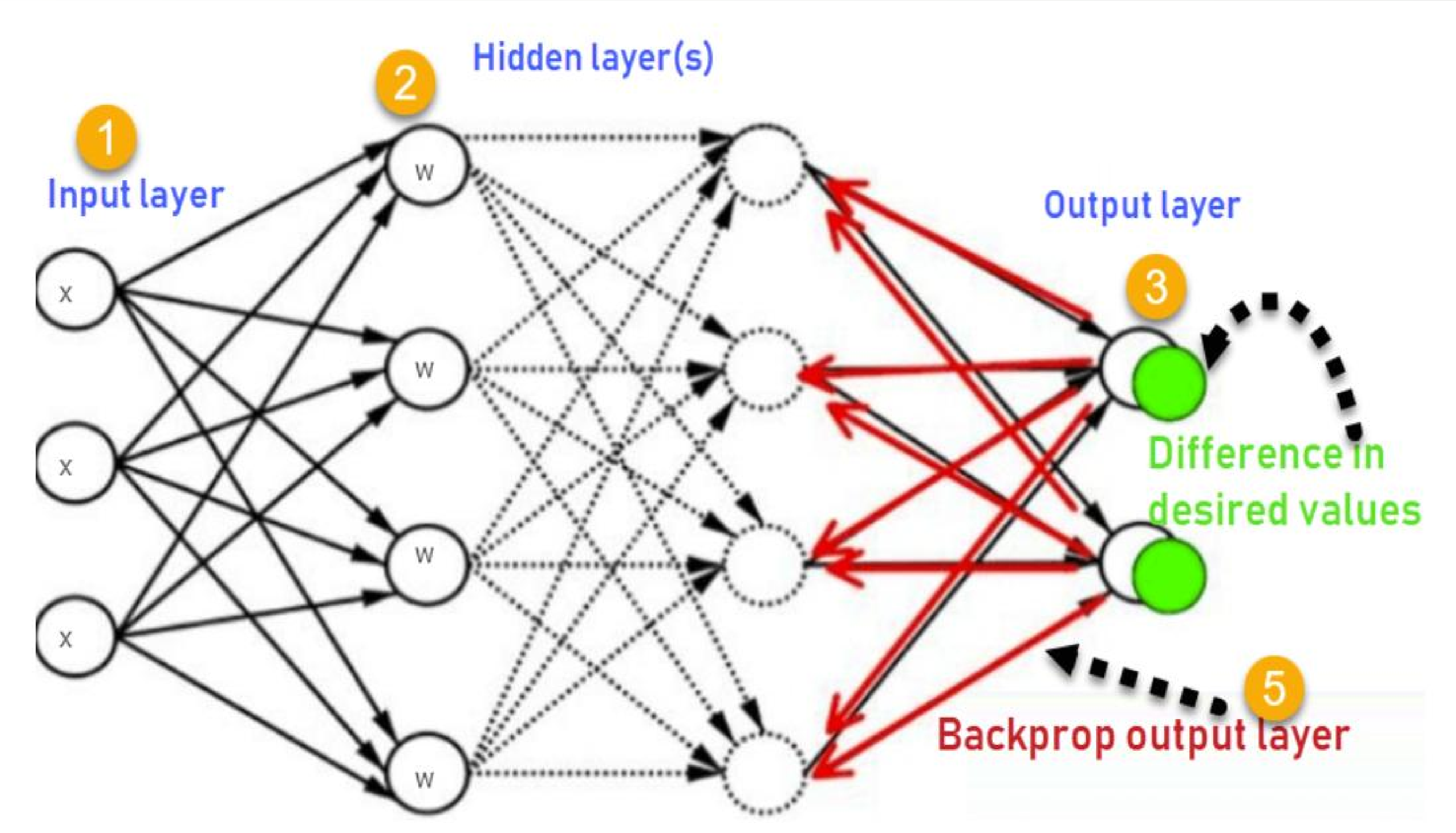
Extraction of Minutiae Features

- The most important step in automatic fingerprint matching is to reliably extract the minutiae from the captured fingerprint images.
- Minutiae points are the major features of a fingerprint image and are used in the matching of fingerprints.
- These minutiae points are used to determine the uniqueness of a fingerprint image.
- A good quality fingerprint image can have 25 to 80 minutiae depending on the fingerprint scanner resolution and the placement of finger on the sensor.

Principal Component Analysis

- The principal component analysis (PCA) is a kind of algorithms in biometrics.
- Principle component analysis is the most popular methods used mainly for dimensionality reduction in recognition problem to extract the region of interest features.
- This is done by the removal of redundant and unwanted data economically.
- PCA is employed to map data from a high dimensional space to a low dimensional space by a mathematical procedure using its linear transformation

Mechanism of BPNN



How Backpropagation Algorithm Works?

- Inputs X, arrive through the preconnected path
- Input is modeled using real weights W. The weights are usually randomly selected.
- Calculate the output for every neuron from the input layer, to the hidden layers, to the output layer.
- Calculate the error in the outputs.

  Error = Actual Output – Desired Output
- Travel back from the output layer to the hidden layer to adjust the weights such that the error is decreased.
- Keep repeating the process until the desired output is achieved

How Backpropagation Algorithm Works?

- Most prominent advantages of Backpropagation are:
- Backpropagation is fast, simple and easy to program
- It has no parameters to tune apart from the numbers of input
- It is a flexible method as it does not require prior knowledge about the network.
- It is a standard method that generally works well.
- It does not need any special mention of the features of the function to learned.

Input Image and Resized image

Fig: Input Image

Fig: Resize Image

Input Image Features

374x388 uint8

	169	170	171	172	173	174	175	176	177	178	179	180	181	182
145	162	119	63	12	1	1	1	21	36	52	80	124	182	233
146	234	201	146	82	32	10	1	1	1	1	1	44	121	206
147	243	236	213	175	130	88	47	8	1	1	1	4	79	182
148	185	200	209	207	193	165	117	66	27	8	1	19	93	195
149	77	100	128	153	170	169	150	122	99	86	85	114	176	238
150	1	14	32	52	72	90	103	116	131	147	164	189	221	247
151	1	1	1	1	1	3	20	46	75	106	137	160	176	191
152	5	1	1	1	1	1	1	1	6	29	51	62	70	89
153	82	46	22	6	1	1	1	1	1	1	1	1	1	1
154	182	141	106	78	50	20	1	1	1	1	1	1	1	1
155	247	231	213	189	154	114	77	47	22	7	1	1	1	1
156	254	254	254	250	236	214	185	155	125	93	65	43	21	4
157	221	238	248	254	254	254	248	239	224	202	178	153	125	98
158	128	159	183	201	220	237	249	254	254	254	251	241	224	205
159	25	45	67	90	116	148	181	209	232	249	254	254	254	254
160	1	1	2	13	32	55	79	111	153	201	237	254	254	254
161	33	14	14	22	15	3	2	19	59	113	164	202	230	252

Fig: Input Image Features

Resized Image Features

227x227 uint8

	99	100	101	102	103	104	105	106	107	108	109	110	111	112
113	200	202	125	23	0	0	20	91	160	231	255	218	120	17
114	64	155	207	145	44	6	0	0	23	106	197	242	230	128
115	0	45	186	245	202	145	60	0	0	6	50	134	218	233
116	54	108	199	254	255	254	187	54	0	0	0	13	104	233
117	217	236	238	255	255	255	250	184	85	18	0	0	40	199
118	222	186	154	190	236	254	255	255	226	127	20	0	29	134
119	61	26	11	41	109	172	227	254	255	233	151	60	23	21
120	0	0	0	0	1	27	93	180	237	255	251	206	108	13
121	0	0	0	0	0	0	1	35	114	206	255	255	231	129
122	78	72	61	38	7	0	0	0	7	76	192	254	255	241
123	234	231	221	196	134	66	18	0	0	1	91	215	247	255
124	255	255	255	255	251	224	163	64	5	0	26	76	134	218
125	162	173	173	191	231	254	255	208	130	62	9	0	9	96
126	9	13	13	32	73	145	220	254	250	211	105	8	0	1
127	0	5	4	0	0	14	73	153	221	255	228	131	37	0
128	85	143	127	52	8	0	0	19	95	213	255	246	176	67
129	234	255	248	205	145	73	8	0	7	93	197	249	255	215

Fig: Resized Image Features

Dilated and Eroded Image

Fig: Dilated Image

Fig: Erode Image

Dilated Image Features

227x227 uint8

	08	109	110	111	112	113	114	115	116	117	118	119	120	121
91	255	255	237	158	111	115	152	163	163	178	183	183	183	177
92	255	255	230	230	230	230	162	99	157	178	183	183	183	175
93	229	229	230	230	249	249	249	214	122	120	182	182	192	192
94	170	203	230	230	249	249	249	246	235	188	118	161	192	195
95	173	112	157	227	249	249	249	255	255	255	240	176	192	195
96	255	234	161	113	195	246	246	255	255	255	245	245	184	195
97	255	255	252	208	113	148	224	255	255	255	245	245	232	178
98	255	255	255	255	225	146	123	177	216	245	245	245	232	232
99	255	255	255	255	255	250	208	152	89	179	232	232	232	232
100	244	255	255	255	255	255	255	254	228	147	163	232	232	232
101	143	218	255	255	255	255	255	255	255	247	198	148	205	227
102	211	116	182	237	255	255	255	255	255	255	255	255	212	176
103	254	214	130	127	213	250	255	255	255	255	255	255	249	168
104	255	255	245	207	138	153	210	247	255	255	255	255	249	244
105	255	255	255	255	252	215	139	160	234	252	252	252	249	244
106	255	255	255	255	255	255	248	228	216	182	223	244	244	244
107	255	255	255	255	255	255	255	255	255	255	247	188	232	232

Fig: Dilated Image Features

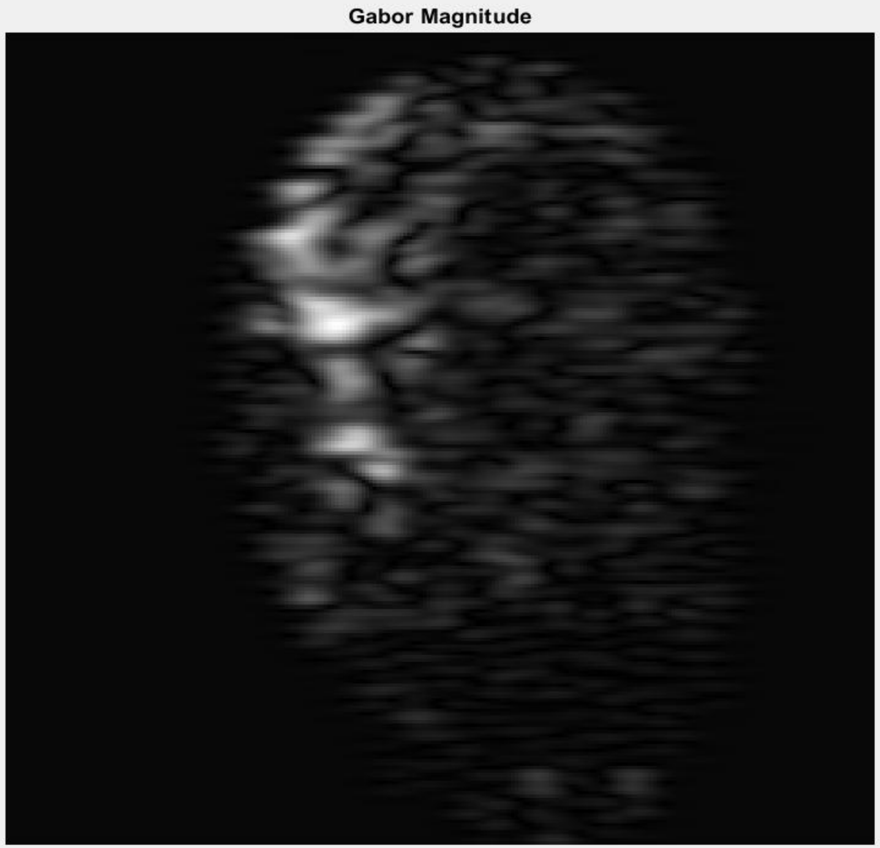
Eroded Image Features

227x227 uint8

	99	100	101	102	103	104	105	106	107	108	109	110	111	112
113	200	202	125	125	125	139	139	145	160	231	255	218	136	136
114	87	155	207	145	139	139	139	106	106	106	197	242	230	179
115	87	155	207	245	202	145	145	106	85	85	85	134	218	233
116	87	155	207	254	255	254	187	106	85	85	85	104	104	233
117	234	236	238	255	255	255	250	184	85	85	85	104	104	199
118	222	190	190	190	236	254	255	255	226	127	104	104	104	161
119	61	41	41	41	109	172	227	254	255	233	151	151	151	129
120	61	41	41	38	38	38	93	180	237	255	251	206	161	129
121	61	41	41	38	38	38	66	66	114	206	255	255	231	129
122	78	72	61	38	38	38	66	66	76	76	192	254	255	241
123	234	231	221	196	134	66	66	66	76	76	130	215	247	255
124	255	255	255	255	251	224	163	76	76	76	130	134	134	218
125	173	173	173	191	231	254	255	208	130	130	130	131	131	131
126	85	143	127	127	127	145	220	254	250	211	134	131	131	84
127	85	143	127	127	127	145	145	153	221	255	228	131	131	84
128	85	143	127	127	127	145	119	119	119	213	255	246	176	84
129	234	255	248	205	145	145	119	119	119	156	197	249	255	215

Fig: Eroded Image Features

Gabor Magnitude and Gabor Phase Images



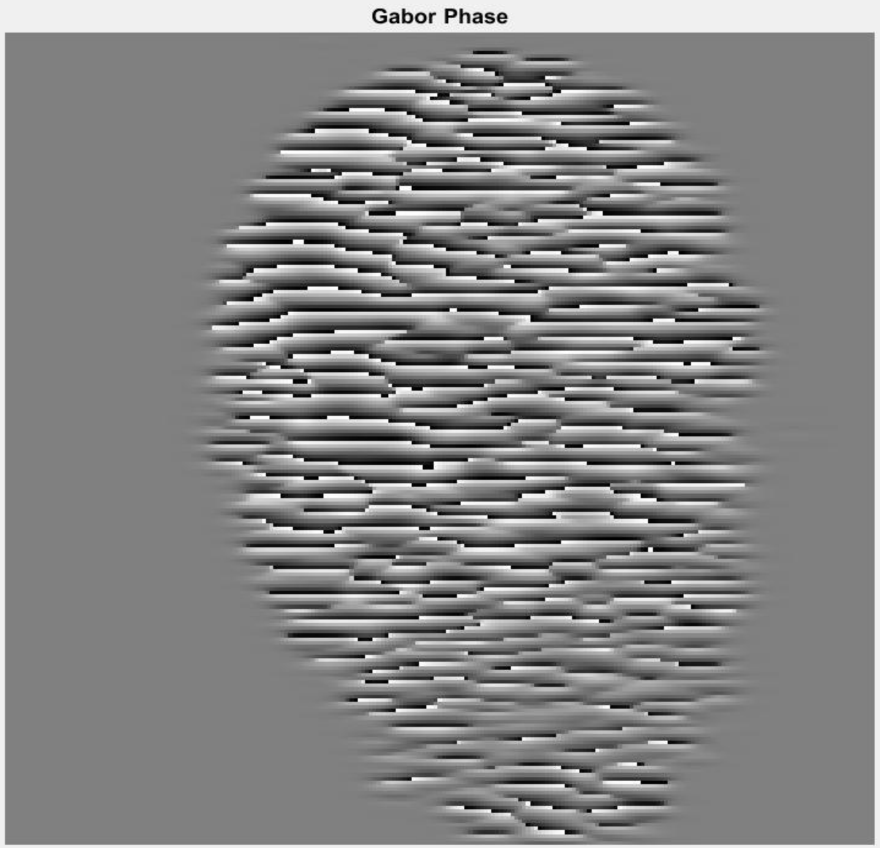


Fig: Gabor Magnitude

Fig: Gabor Phase

Gabor Magnitude Features

227x227 double

	109	110	111	112	113	114	115	116	117	118	119	120	121	122
68	189.8830	166.0567	138.0433	106.5885	74.7904	43.1737	21.9734	19.7949	33.7179	46.4307	55.3430	60.0239	62.9090	65.0598
69	118.2746	109.3439	97.5983	85.4316	75.1940	68.7175	66.6873	68.3950	72.3737	77.2720	82.2083	86.6620	90.2141	92.3484
70	105.8856	116.4046	124.8465	131.2126	135.4381	137.6140	138.1700	137.8850	137.7119	138.5010	140.7260	144.2892	148.4551	151.9396
71	119.5197	146.7454	168.3678	183.6891	192.6605	195.9565	194.9565	191.5525	187.7890	185.4225	185.5196	188.2028	192.6099	197.0849
72	139.0674	168.4137	191.8946	207.2668	214.1620	213.5816	207.5763	198.8350	190.1459	183.8230	181.2363	182.5595	186.7854	192.0034
73	171.2058	187.2395	199.6340	204.9519	202.3791	193.0292	179.3382	164.3875	151.1590	141.8943	137.7370	138.6486	143.4666	150.1301
74	216.2303	217.1117	213.6554	204.1775	189.0402	170.3851	151.4839	135.6441	124.9287	119.5760	118.7558	121.6731	127.6765	135.6960
75	272.2308	259.8786	241.7849	218.4752	192.2344	166.9890	147.4131	136.8592	135.2395	139.6966	147.4532	157.1818	168.3588	180.3256
76	308.0876	284.7126	255.6858	222.7640	189.2562	159.9225	140.0130	132.7470	136.9502	148.6809	164.5779	182.6311	201.3405	219.2099
77	295.0288	262.4911	226.6053	189.5773	154.7416	126.5131	109.6321	106.6498	115.6252	132.3646	153.4682	176.4724	199.1965	219.6611
78	246.3288	205.8268	166.1655	129.4700	98.5078	76.9244	68.4937	73.4998	87.8237	107.5052	130.0755	153.5196	175.8402	195.2014
79	197.7834	152.3420	112.1962	78.9157	54.2281	40.9030	41.2764	52.0378	68.3574	87.8055	108.8726	130.0966	149.9952	167.1662
80	162.1828	118.2862	83.2159	57.3209	39.3841	27.8755	24.2993	31.3873	45.5216	62.5081	80.2321	97.6024	113.9634	128.7730
81	133.6630	103.6892	86.6094	77.8894	71.1268	62.9961	54.1085	47.7282	47.1994	52.4143	60.5127	69.3368	78.2542	87.4119
82	106.1154	107.2889	116.1714	121.8932	119.9811	110.5516	96.2069	80.6074	67.3188	58.6164	54.5679	53.6459	54.5066	56.8420
83	113.9749	149.1324	173.7655	184.5050	181.4910	167.2293	145.6218	120.9678	97.0721	76.6209	60.9281	50.0647	43.2893	39.6185
84	195.2121	231.3926	251.9389	255.9456	245.0147	222.8155	194.2443	164.4075	137.6476	116.7662	102.5784	94.0375	89.0187	85.3084

Fig: Gabor Magnitude Features

Gabor Phase Features

227x227 double

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	3.9116e-17	0	-5.7222e-17	-1.2509e-16	-1.8609e-16	-2.2656e-16	-2.4007e-16	-2.0943e-16	-1.2393e-16	2.4012e-17	2.3644e-16	4.8198e-16	7.5909e-16	1.0317e-15
2	7.6180e-16	6.9552e-16	6.0795e-16	4.9074e-16	3.6115e-16	2.2066e-16	8.3654e-17	-4.5845e-17	-1.5259e-16	-2.3789e-16	-2.7769e-16	-2.8059e-16	-2.4825e-16	-1.5492e-16
3	-3.7693e-16	-3.1806e-16	-2.3649e-16	-1.5245e-16	-6.2741e-17	2.2318e-17	7.6877e-17	1.0980e-16	1.1328e-16	7.3198e-17	-5.7125e-18	-1.1696e-16	-2.4031e-16	-3.7838e-16
4	1.1264e-15	1.0799e-15	1.0387e-15	1.0252e-15	1.0231e-15	1.0631e-15	1.0711e-15	1.0751e-15	1.0617e-15	1.0233e-15	9.3501e-16	8.1844e-16	6.6149e-16	5.0987e-16
5	-8.7450e-16	-8.8428e-16	-8.7832e-16	-8.9599e-16	-8.1461e-16	-7.2491e-16	-6.5510e-16	-5.2110e-16	-3.6212e-16	-2.7924e-16	-2.0275e-16	-1.7777e-16	-1.3168e-16	-1.2935e-16
6	-1.3123e-15	-1.3587e-15	-1.4287e-15	-1.4432e-15	-1.5348e-15	-1.5829e-15	-1.7064e-15	-1.6793e-15	-1.7699e-15	-1.7436e-15	-1.8543e-15	-1.7742e-15	-1.8125e-15	-1.8419e-15
7	2.5398e-15	2.5488e-15	2.4812e-15	2.3629e-15	2.3241e-15	2.0418e-15	2.0650e-15	2.0828e-15	1.9543e-15	2.0526e-15	2.0573e-15	2.2680e-15	2.3175e-15	2.5034e-15
8	4.0472e-15	4.0135e-15	3.9442e-15	4.1672e-15	4.3036e-15	4.1641e-15	3.7304e-15	3.9101e-15	3.8543e-15	3.4577e-15	3.7954e-15	3.6467e-15	3.5398e-15	3.5940e-15
9	-1.6870e-15	-1.7134e-15	-1.7939e-15	-1.9333e-15	-1.9024e-15	-1.7474e-15	-1.6483e-15	-1.3137e-15	-1.2641e-15	-1.2703e-15	-1.5739e-15	-1.2765e-15	-1.4748e-15	-1.1774e-15
10	-3.4453e-15	-3.2470e-15	-3.2222e-15	-3.4205e-15	-3.2222e-15	-2.7761e-15	-3.1231e-15	-2.8257e-15	-2.8257e-15	-2.2556e-15	-2.5034e-15	-2.5778e-15	-2.5654e-15	-2.5282e-15
11	-1.5120e-15	-1.1154e-15	-9.1710e-16	-1.0906e-15	-1.0906e-15	-8.4274e-16	-1.0906e-15	-4.4616e-16	-4.4616e-16	-5.4530e-16	-4.9573e-16	-3.4701e-16	-1.4872e-16	-5.2052e-16
12	5.2052e-16	7.9317e-16	8.9231e-16	1.0906e-15	7.9317e-16	1.2889e-15	7.9317e-16	1.1898e-15	1.1898e-15	9.9146e-16	5.9488e-16	6.9402e-16	6.9402e-16	1.4872e-16
13	-3.9658e-16	-2.9744e-16	-8.9231e-16	-3.9658e-16	1.9829e-16	-1.9829e-16	0	3.9658e-16	5.9488e-16	1.9829e-16	0	3.9658e-16	7.9317e-16	9.9146e-17
14	0	-9.9146e-17	-2.9744e-16	0	-9.9146e-17	-3.9658e-16	-3.9658e-16	-3.9658e-16	0	-2.9744e-16	-9.9146e-17	-1.4872e-16	4.9573e-17	1.0906e-15
15	1.0906e-15	1.0906e-15	1.1898e-15	1.9829e-15	1.7846e-15	1.5863e-15	7.9317e-16	7.9317e-16	1.5863e-15	1.1898e-15	7.9317e-16	7.9317e-16	1.1898e-15	6.4445e-16
16	-1.1898e-15	-6.9402e-16	-1.9829e-16	-4.9573e-16	-3.9658e-16	-7.9317e-16	-7.9317e-16	-5.9488e-16	-7.9317e-16	-5.9488e-16	-5.9488e-16	-1.5863e-15	-1.5863e-15	-1.1898e-15
17	-2.5778e-15	-2.5778e-15	-2.5778e-15	-2.6769e-15	-3.6684e-15	-2.3795e-15	-1.9829e-15	-2.1812e-15	-1.9829e-15	-2.2308e-15	-1.9333e-15	-1.7846e-15	-2.9744e-15	-3.1727e-15

Fig: Gabor Phase Features

Minutiae Features

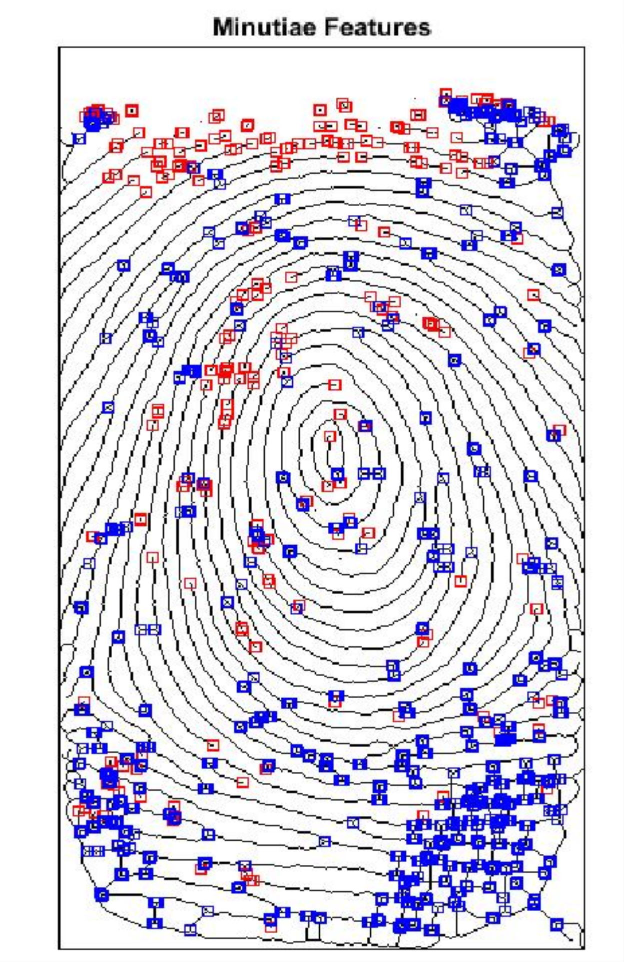


Fig: Minutiae points

376x390x3 double

255	255	255	255	255	255	255	255	255	255	255	255	255	255	255	255	255	255	255	255
255	255	255	255	255	255	255	255	255	255	255	255	255	255	255	255	255	255	255	255
255	255	255	255	255	255	255	255	255	255	255	255	255	255	255	255	255	255	255	255
0	0	0	0	0	255	255	255	255	255	255	255	255	255	255	255	255	255	255	255
0	0	0	0	0	0	255	255	255	255	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	255	255	0	0	255	255	255	255	255	255	255	255	255	255
0	0	0	0	0	0	0	0	255	255	255	255	255	255	255	255	255	255	255	255
255	0	0	0	0	0	255	255	255	255	255	255	255	255	255	255	255	255	255	255
0	255	0	0	0	0	255	255	255	255	255	255	255	255	255	255	255	255	255	255
0	0	0	0	0	0	255	255	255	255	255	255	255	255	255	255	255	255	255	255
0	0	0	0	0	0	255	255	255	255	255	255	255	255	255	255	255	255	255	255
0	0	0	0	255	255	255	255	255	255	255	255	255	255	255	255	255	255	255	255
0	0	0	0	255	255	255	255	255	255	255	255	255	255	255	255	255	255	255	255
255	255	255	255	0	255	255	255	255	255	255	255	255	255	255	255	255	255	255	255
255	255	255	255	255	0	255	255	255	255	255	255	255	255	255	255	255	255	255	255
255	255	255	255	255	255	0	255	255	255	255	255	255	255	255	255	255	255	255	255
255	255	255	255	255	255	255	0	255	255	255	255	255	255	255	255	255	255	255	255
255	255	255	255	255	255	255	255	0	255	255	255	255	255	255	255	255	255	255	255
255	255	255	255	255	255	255	255	255	0	255	255	255	255	255	255	255	255	255	255

Fig: Minutiae Features

Features

5x25 double

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	1.6451	1.6325	1.9798	2.0335	1.4253	1.6969	1.6969	1.3454	1.3331	1.1773	1.8255	1.6562	1.6625	1.5506
2	1.9274	2.0282	2.0282	1.8177	1.8177	1.3158	1.3158	1.3274	1.3274	1.3274	1.7237	1.6181	1.7237	1.4916
3	2.2574	1.8929	2.0011	1.9852	1.8048	2.0144	1.9493	2.5171	1.9798	1.9253	1.8474	2.0732	1.9634	2.3255
4	3.5861	1.2128	1.2069	1.5739	2.1405	1.2923	1.2798	1.6674	1.4340	2.1641	1.9679	1.4948	1.9372	2.0409
5	1.7235	2.1449	2.1449	2.0802	2.0802	2.1703	2.1136	2.0800	1.1661	2.1769	2.3283	1.7235	1.6197	1.6752
6														
7														
8														
9														

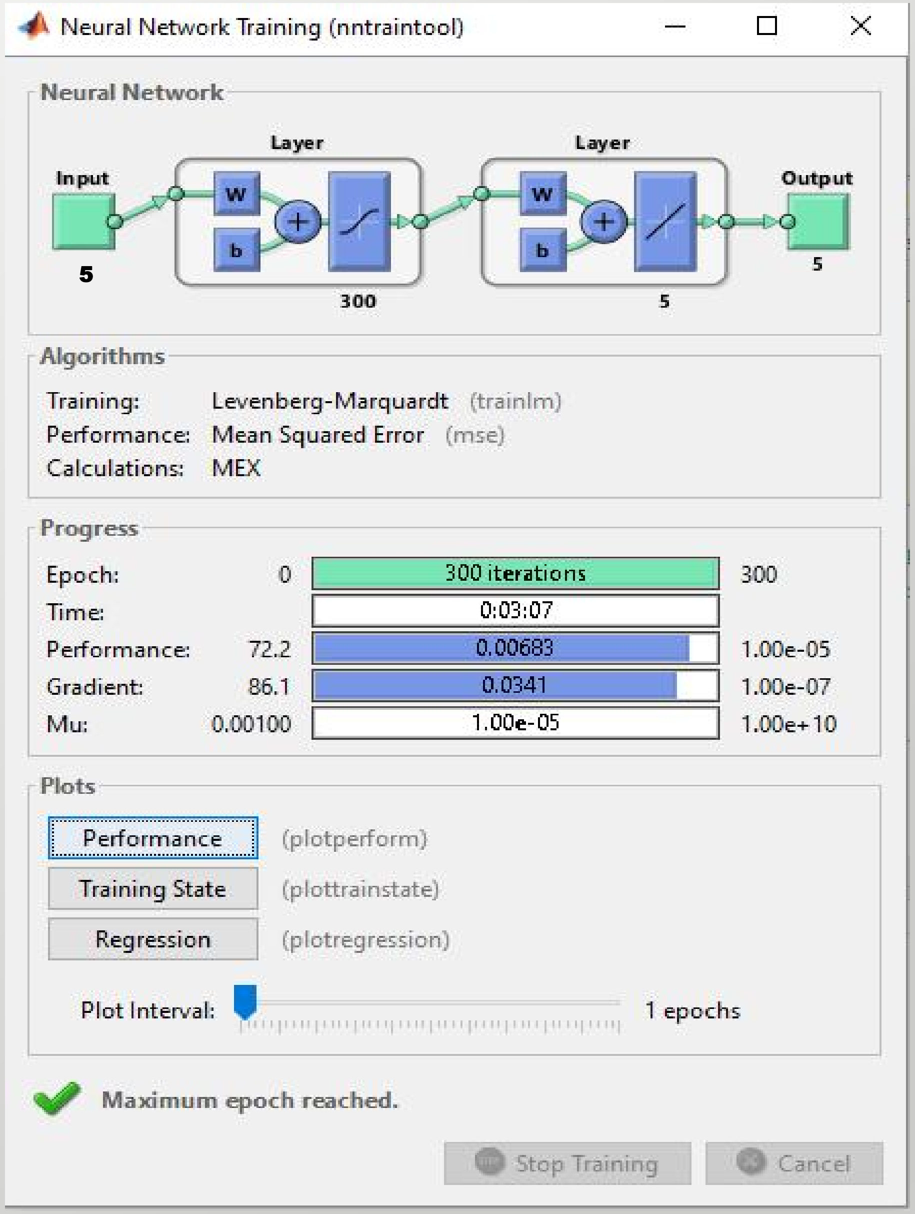
5x25 double

		13	14	15	16	17	18	19	20	21	22	23	24	25	26
1	562	1.6625	1.5506	1.6641	1.8469	1.9428	1.3305	1.6975	1.5835	1.4745	1.5843	1.5888	1.6617	1.5063	
2	181	1.7237	1.4916	1.4916	1.7280	1.7280	1.9274	1.6181	2.2652	2.2652	1.8822	1.8822	2.2087	2.2087	
3	732	1.9634	2.3255	1.5428	1.6641	1.5329	1.4325	1.7913	1.5205	1.5205	2.0766	1.8115	1.8115	2.1115	
4	948	1.9372	2.0409	2.5040	2.5776	1.5959	1.6365	1.4905	1.9439	1.7744	2.3547	2.4730	1.2635	1.2574	
5	235	1.6197	1.6752	1.5669	1.5952	1.4054	1.3820	2.1537	2.1537	2.0259	2.0259	2.0455	2.0455	2.3918	
6															

Fig: Features

Results

Fig: Training Process



Results

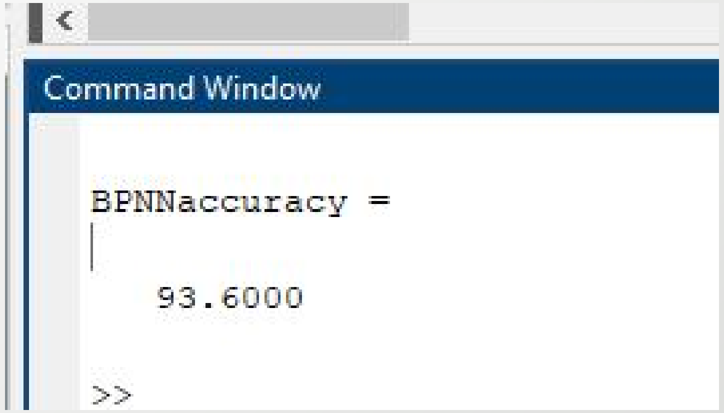


Fig: Accuracy

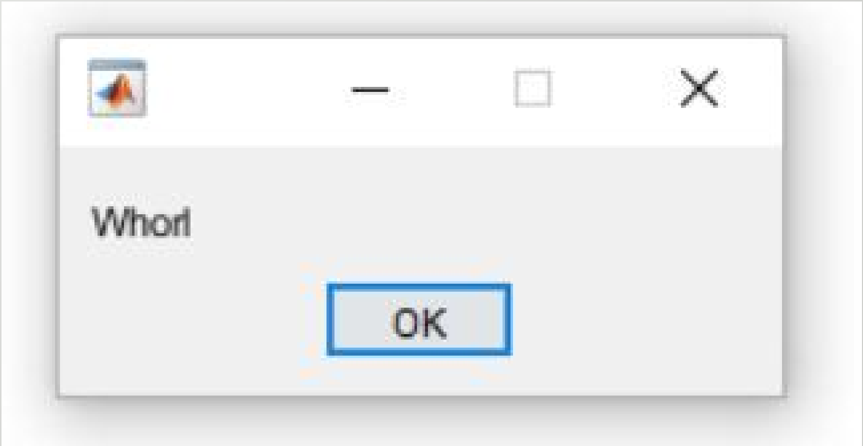


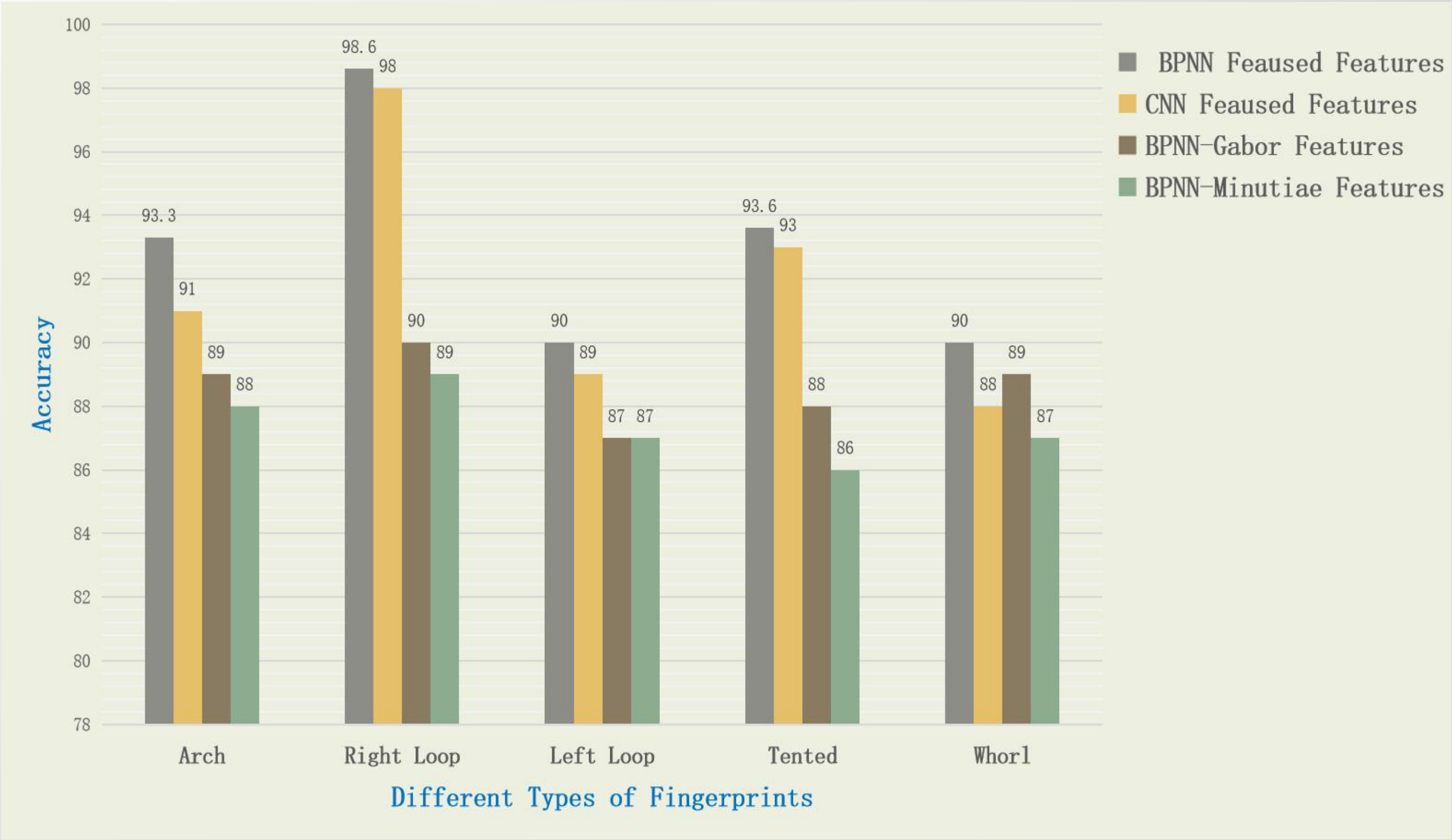
Fig: Final Output

Results

Neural Network Model	Accuracy of Different Models
CNN(Gabor and Minutiae)	98
BPNN(Gabor Features)	90
BPNN(Minutiae Features)	89
BPNN(Gabor and Minutiae)	98.6

Fig: Comparision of Accuracy for Different Models

Bar Graph



100
98
96
94
92
90
88
86
84
82
80
78
Accuracy
98.6
98
93.3
91
89
88
90
89
90
89
87
87
93.6
93
88
86
90
88
89
87
Arch
Right Loop
Left Loop
Tented
Whorl
Different Types of Fingerprints
BPNN Feaused Features
CNN Feaused Features
BPNN-Gabor Features
BPNN-Minutiae Features

Performance Metrics

- Accuracy is a degree of closeness between a measurement and its true value

$$\text{Accuracy} = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}}$$

Accuracy = TP+TN/(TP+TN+FP+FN)

Confusion Matrix

- A confusion matrix is a table that is used to evaluate the performance of a classification model by comparing the predicted and actual class labels of a set of test data. The matrix shows the number of true positives, true negatives, false positives, and false negatives, arranged in a tabular form.
- In a binary classification problem, a confusion matrix typically has two rows and two columns. The rows represent the predicted class labels (positive or negative), while the columns represent the actual class labels.

Confusion Matrix

- The four entries of the matrix are defined as follows:
  - **True positives (TP):** the number of positive examples that were correctly classified as positive
  - **True negatives (TN):** the number of negative examples that were correctly classified as negative
  - **False positives (FP):** the number of negative examples that were incorrectly classified as positive
  - **False negatives (FN)**: the number of positive examples that were incorrectly classified as negative

Confusion Matrix

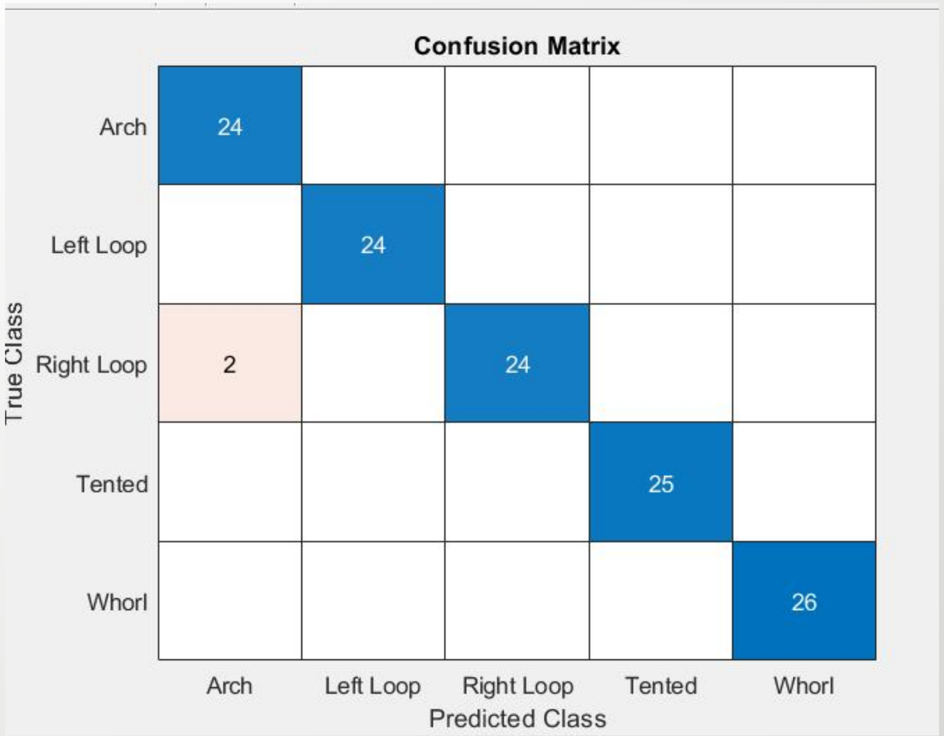


Fig: Confusion Matrix BPNN-(Fused Features of both gabour and Minutiae)

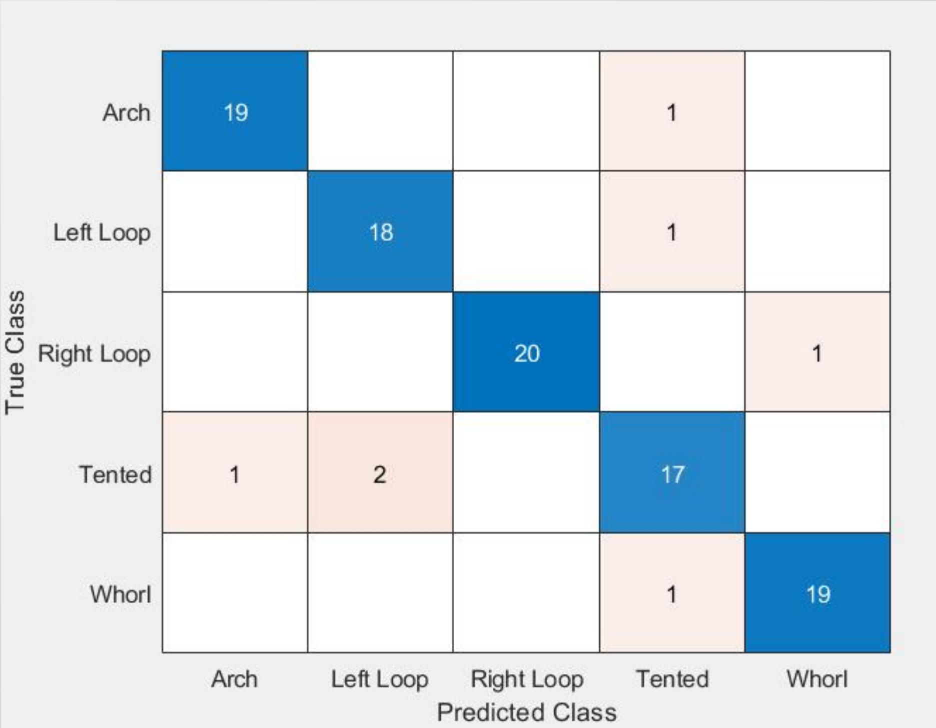


Fig: Confusion Matrix CNN-(fused Features of both gabour and minutiae)

Conclusion

- The fusion of Gabor and Minutiae features coupled with a BPNN classifier presents a robust approach to fingerprint identification.
- Through the systematic process involving preprocessing, feature extraction, fusion, dimensionality reduction, and classification, the system achieves accurate recognition of various fingerprint patterns including arches, loops, tented arches, and whorls.
- The application of morphological operations, PCA for dimensionality reduction, and the utilization of a BPNN classifier contribute to the system's reliability and efficiency.

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THANK YOU