

SERS_Raman_Pancreatic_Cancer

June 30, 2024

1 Detection of pancreatic cancer through combination of Raman Spectroscopy and machine learning

We will use spectroscopic data and machine learning methods to detect exosomes, which act as markers for exosomes for pancreatic cancer.

First, let's import some primary packages and look at the files and data.

```
[269]: import os
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

```
[234]: files = os.listdir('Data')
import re
for file in files:
    if bool(re.search('.txt',file)):
        print(file)
```

```
Average spectra.txt
DA.txt
EPC-prediction.txt
HC-prediction.txt
Loading.txt
PCA1.txt
PCA2.txt
PCA3.txt
Raman shift.txt
Raw-CD18.txt
Raw-EPC.txt
Raw-EPC2.txt
Raw-GN.txt
Raw-HC.txt
Raw-HC2.txt
Raw-HPDE.txt
Raw-MiaPaCa.txt
Scaled CD18.txt
```

Scaled GN.txt
 Scaled HPDE.txt
 Scaled MiaPaCa.txt

```
[6]: df_average = pd.read_csv(r'Data\Average spectra.txt',sep='\t',header=[0,1])
```

```
[7]: df_average.head()
```

```
[7]: Unnamed: 0_level_0                                Mean \
      Unnamed: 0_level_1 Statistics On Rows of [Book9]H-HPDE!Col(B):Col(C34)
0          719.421                                1.963618
1          720.629                                1.889719
2          721.838                                1.854428
3          723.046                                1.793777
4          724.253                                1.746564
```

```
                                Standard Deviation \
      Statistics On Rows of [Book9]H-HPDE!Col(B):Col(C34)
0                                1.243561
1                                1.202215
2                                1.155707
3                                1.122544
4                                1.094122
```

```
                                Mean \
      Statistics On Rows of [Book1]H-CD18!Col(B):Col(C32)
0                                2.089354
1                                2.004456
2                                1.955802
3                                1.928820
4                                1.866089
```

```
                                Standard Deviation \
      Statistics On Rows of [Book1]H-CD18!Col(B):Col(C32)
0                                1.986297
1                                1.919989
2                                1.877348
3                                1.853950
4                                1.827821
```

```
                                Mean \
      Statistics On Rows of [Book2]H-MiaPaCa!Col(A1):Col(A31)
0                                1.009154
1                                0.950310
2                                0.902877
3                                0.878549
4                                0.844380
```

```

Standard Deviation \
Statistics On Rows of [Book2]H-MiaPaCa!Col(A1):Col(A31)
0      1.718254
1      1.691151
2      1.648838
3      1.622505
4      1.596352

```

```

Mean \
Statistics On Rows of [Book8]H-GN!Col(B):Col(W)
0      1.569937
1      1.485904
2      1.415847
3      1.323568
4      1.222392

```

```

Standard Deviation
Statistics On Rows of [Book8]H-GN!Col(B):Col(W)
0      1.113830
1      1.096629
2      1.076157
3      1.041825
4      0.991328

```

```
[8]: df_average.shape
```

```
[8]: (1014, 9)
```

```
[9]: columns=[('Raman', 'Frequency'),
               ('Mean', 'HPDE'), ('Standard Deviation', 'HPDE'),
               ('Mean', 'CD'), ('Standard Deviation', 'CD'),
               ('Mean', 'MiaPaCa'), ('Standard Deviation', 'MiaPaCa'),
               ('Mean', 'GN'), ('Standard Deviation', 'GN')]
df_average.columns = pd.MultiIndex.from_tuples(columns)
df_average.head()
```

```
[9]:
```

	Raman	Mean	Standard Deviation	Mean	Standard Deviation \
	Frequency	HPDE	HPDE	CD	CD
0	719.421	1.963618	1.243561	2.089354	1.986297
1	720.629	1.889719	1.202215	2.004456	1.919989
2	721.838	1.854428	1.155707	1.955802	1.877348
3	723.046	1.793777	1.122544	1.928820	1.853950
4	724.253	1.746564	1.094122	1.866089	1.827821

	Mean	Standard Deviation	Mean	Standard Deviation
	MiaPaCa	MiaPaCa	GN	GN

0	1.009154	1.718254	1.569937	1.113830
1	0.950310	1.691151	1.485904	1.096629
2	0.902877	1.648838	1.415847	1.076157
3	0.878549	1.622505	1.323568	1.041825
4	0.844380	1.596352	1.222392	0.991328

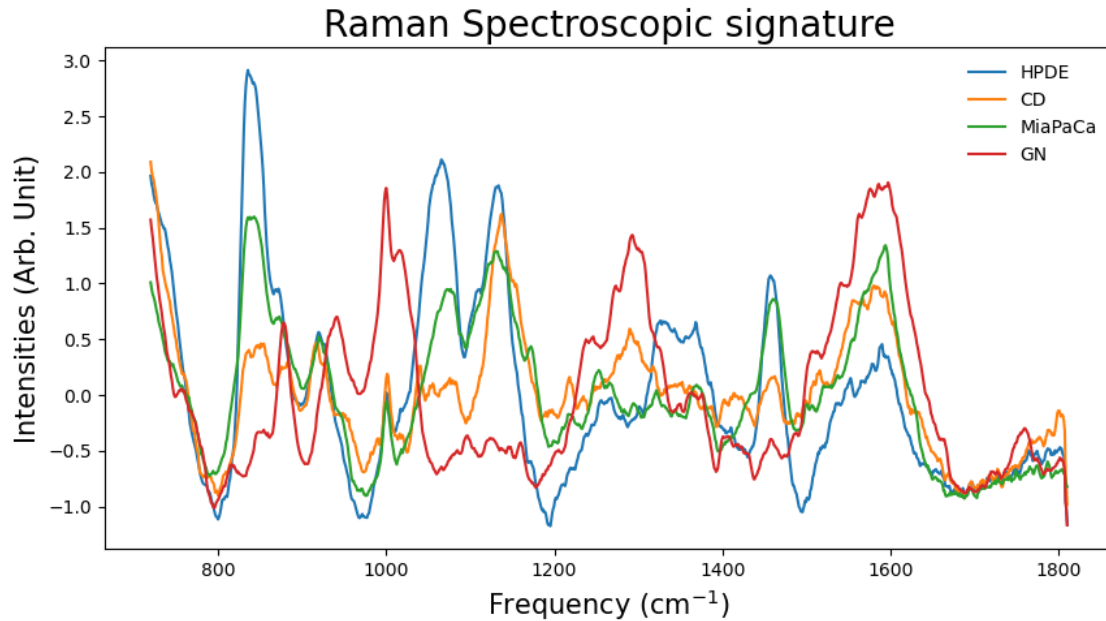
```
[10]: df_average.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1014 entries, 0 to 1013
Data columns (total 9 columns):
#   Column                                Non-Null Count  Dtype
---  -
0   (Raman, Frequency)                   1014 non-null   float64
1   (Mean, HPDE)                        1014 non-null   float64
2   (Standard Deviation, HPDE)          1014 non-null   float64
3   (Mean, CD)                          1014 non-null   float64
4   (Standard Deviation, CD)            1014 non-null   float64
5   (Mean, MiaPaCa)                    1014 non-null   float64
6   (Standard Deviation, MiaPaCa)       1014 non-null   float64
7   (Mean, GN)                         1014 non-null   float64
8   (Standard Deviation, GN)            1014 non-null   float64
dtypes: float64(9)
memory usage: 71.4 KB
```

This is a averaged spectra, which we can use to look at the spectra of exosomes and a control.

Of course, this is spectroscopic data, which means that x-axis will be in frequency (cm^{-1}) and the y-axis will be the intensity.

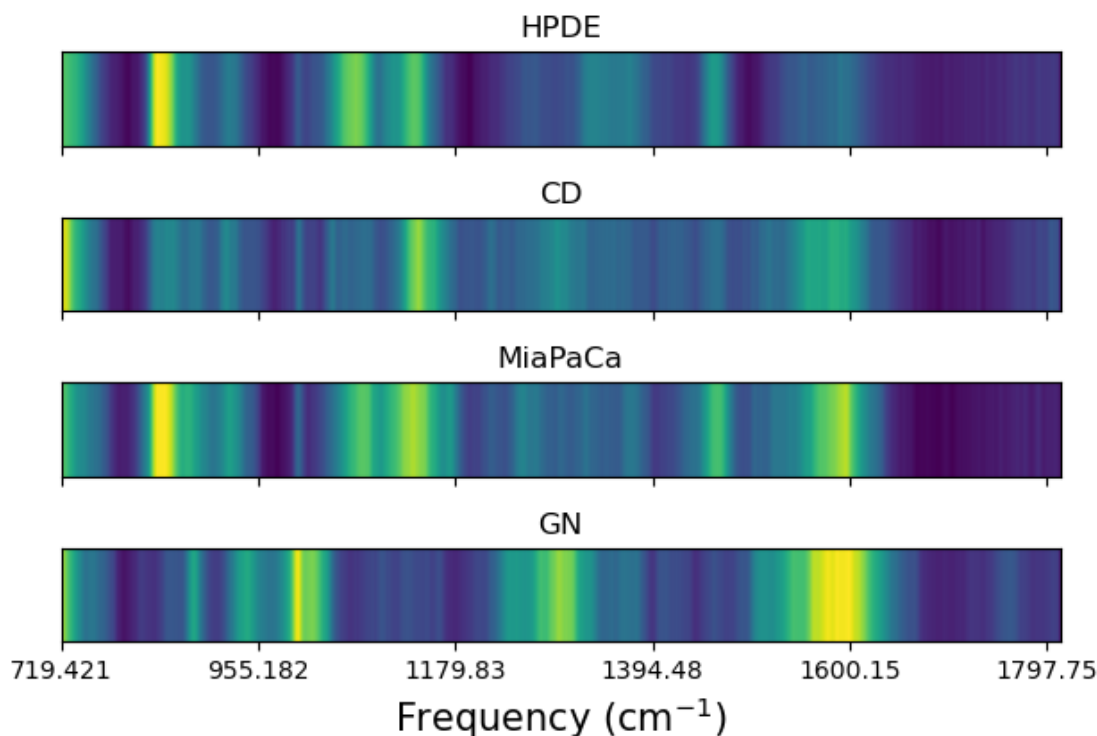
```
[12]: pd.option_context('mode.use_inf_as_na', True)
plt.figure(figsize=(10,5))
plt.title('Raman Spectroscopic signature', fontsize = 20)
plt.plot(df_average.Raman.Frequency,df_average.Mean.HPDE,label='HPDE')
plt.plot(df_average.Raman.Frequency,df_average.Mean.CD,label='CD')
plt.plot(df_average.Raman.Frequency,df_average.Mean.MiaPaCa,label='MiaPaCa')
plt.plot(df_average.Raman.Frequency,df_average.Mean.GN,label='GN')
plt.xlabel(r'Frequency (cm$^{-1}$)',fontsize=15)
plt.ylabel(r'Intensities (Arb. Unit)',fontsize=15)
plt.legend(frameon=False)
plt.show()
```



Another way to visualize the spectroscopic response for each cells.

```
[13]: fig, ax = plt.subplots(4,1,sharex=True,sharey=True)
fig.suptitle('Raman Spectroscopic signature', fontsize = 20)
ax[0].imshow([df_average.Mean.HPDE], aspect="auto")
ax[1].imshow([df_average.Mean.CD], aspect="auto")
ax[2].imshow([df_average.Mean.MiaPaCa], aspect="auto")
ax[3].imshow([df_average.Mean.GN], aspect="auto")
ax[0].set_title('HPDE')
ax[1].set_title('CD')
ax[2].set_title('MiaPaCa')
ax[3].set_title('GN')
plt.yticks([])
plt.xticks(np.arange(0, 1013, 200),df_average.Raman.Frequency[:,200])
plt.xlabel(r'Frequency (cm-1)',fontsize=15)
plt.tight_layout()
'''
for i in range(4):
    ax[i].axvline(x=300, ymin=0.0, ymax=1.0, color='r', linestyle='--', alpha=1)
    ax[i].axvline(x=100, ymin=0.0, ymax=1.0, color='r', linestyle='--', alpha=1)
'''
plt.show()
```

Raman Spectroscopic signature



Now, we can move onto the inspecting the raw data.

```
[14]: df_raw_HPDE = pd.read_csv(r'Data\Raw-HPDE.txt', sep='\t', header=None)
```

```
[15]: df_raw_HPDE.head()
```

```
[15]:
```

	0	1	2	3	4	5	\
0	609.927974	516.114881	754.661668	705.967703	656.738695	632.528348	
1	577.079988	499.306887	741.311767	693.952930	651.909844	622.103451	
2	567.509144	494.778295	719.593730	685.773103	620.875998	593.277308	
3	556.111118	489.338721	702.361336	647.813375	603.297393	564.967912	
4	519.609050	484.045332	672.881351	625.759229	563.098662	549.233632	

	6	7	8	9	...	25	\
0	772.015465	422.591102	765.996989	602.369577	...	483.311159	
1	757.722958	412.738901	740.978701	567.555935	...	452.666774	
2	731.967210	411.354746	721.044885	555.519644	...	459.459738	
3	701.938234	408.748626	723.977596	521.221900	...	419.189169	
4	695.287774	406.290715	703.507303	491.233679	...	397.359816	

	26	27	28	29	30	31	\
--	----	----	----	----	----	----	---

0	705.507262	1094.091623	558.716439	629.404883	335.447784	541.850423
1	653.969568	1056.672170	527.188433	625.360328	340.207145	561.789190
2	657.261168	1051.190851	514.644116	630.355072	322.441626	626.401793
3	619.732035	1046.468581	514.961627	614.845027	315.562896	674.224044
4	574.102433	1035.141097	542.418861	596.166903	284.773470	675.428521

	32	33	34
0	648.142592	591.169453	500.048021
1	618.756330	583.428277	470.389714
2	622.671054	590.548488	461.038391
3	604.256185	593.518858	407.134380
4	611.291960	614.497281	404.700299

[5 rows x 35 columns]

```
[16]: df_raw_HPDE.shape
```

```
[16]: (1014, 35)
```

```
[17]: df_raw_CD = pd.read_csv(r'Data\Raw-CD18.txt',sep='\t',header=None)
```

```
[18]: df_raw_CD.head()
```

```
[18]:
```

	0	1	2	3	4	5	\
0	462.250553	-88.956977	12211.075787	138.476666	722.523025	790.705515	
1	436.982475	-84.542468	10383.473577	139.684022	657.891275	779.193184	
2	418.922427	-39.028311	8976.035486	136.195751	628.512955	748.924845	
3	424.457974	-10.446520	6262.718792	146.769691	596.923084	741.777124	
4	422.589851	4.341221	4232.948800	140.303686	578.548094	701.832739	

	6	7	8	9	...	23	\
0	16833.155629	482.846254	924.675995	18.519408	...	682.997381	
1	17778.051350	411.258819	917.786714	-34.277209	...	698.004300	
2	18697.846470	379.465945	924.332020	-40.762669	...	713.090873	
3	20269.935530	367.395086	881.996792	-87.290297	...	710.063955	
4	21081.587106	303.697568	865.527296	-81.014289	...	711.436156	

	24	25	26	27	28	29	\
0	4134.879267	721.836516	570.964342	11876.248771	428.721259	1390.759272	
1	4108.956426	663.477808	565.805419	11187.847228	427.103716	1534.804320	
2	4115.688617	630.933029	558.807819	10571.188859	416.175049	1666.264862	
3	4136.342320	618.125645	552.979513	9670.870581	418.423881	1886.847811	
4	4166.678987	603.947787	533.675528	8967.153636	421.664330	1940.952292	

	30	31	32
0	14686.044405	348.268072	636.765977
1	15007.618378	303.723261	624.358963

```

2  15376.107605  248.493055  598.615002
3  16164.213116  213.520312  576.200426
4  16767.097985  157.238793  551.541815

```

[5 rows x 33 columns]

```
[19]: df_raw_CD.shape
```

```
[19]: (1014, 33)
```

```
[20]: df_frequency = pd.read_csv(r'Data\Raman shift.txt',sep='\t',header=None)
```

```
[21]: df_frequency.head()
```

```

[21]:      0      1
0  719.421 NaN
1  720.629 NaN
2  721.838 NaN
3  723.046 NaN
4  724.253 NaN

```

```
[22]: df_frequency[1].isna().sum()
```

```
[22]: 1014
```

```
[23]: df_frequency.drop(columns=1,axis=1,inplace=True)
```

```
[24]: df_frequency.head()
```

```

[24]:      0
0  719.421
1  720.629
2  721.838
3  723.046
4  724.253

```

```
[25]: df_frequency.column = 'Frequency'
```

```
[26]: df_raw_EPC = pd.read_csv(r'Data\Raw-EPC.txt',sep='\s+',header=None)
```

```
[27]: df_raw_EPC.head()
```

```

[27]:      0      1      2      3      4  \
0  3203.163535  6320.974384  6887.646015 -467.071908  309.968360
1  3103.180691  6321.751083  6161.643276 -653.364664  352.574265
2  2986.780580  6283.240725  5535.486579 -630.492983  392.886723
3  2933.909809  6313.348074  5646.613963 -800.367063  466.192310

```


4	2959.257669	6328.991128	6306.360640	-567.606996	475.672052	
---	-------------	-------------	-------------	-------------	------------	--

	5	6	7	8	9	...	\
0	23964.023828	4914.055589	2071.515841	7798.466443	927.605080	...	
1	23180.087714	4665.178293	2089.593892	7536.362115	1031.550350	...	
2	22482.484591	4311.171479	2064.169876	7288.770278	1110.889652	...	
3	21778.753585	4068.409457	2068.370215	7058.793922	1297.059204	...	
4	21194.492801	3748.711404	2084.700672	6776.520803	1518.303385	...	

	45	46	47	48	49	...	\
0	17106.364263	3213.326052	2235.211800	1647.692268	17618.585039		
1	16108.988438	3196.324199	2227.484274	1640.470158	17481.837070		
2	15021.524728	3191.308086	2219.452056	1628.435502	17402.646657		
3	14279.604815	3162.814938	2218.215596	1642.432518	17757.111924		
4	13523.335750	3248.812738	2205.956784	1703.840559	18033.226992		

	50	51	52	53	54
0	2041.744264	2277.645859	-1456.801366	13727.676672	-1119.050078
1	2059.917444	2196.018035	-1353.687698	14036.332729	-1209.851583
2	2050.200713	2114.993612	-1254.919115	14203.433016	-1466.771130
3	2050.864642	2044.587138	-1162.628716	14727.702996	-1761.390038
4	2093.804655	1969.941371	-977.857172	15065.059637	-1891.941108

[5 rows x 55 columns]

```
[28]: df_raw_EPC.shape
```

```
[28]: (1013, 55)
```

```
[29]: df_raw_EPC2 = pd.read_csv(r'Data\Raw-EPC2.txt', sep='\s+', header=None)
```

```
[30]: df_raw_EPC2.head()
```

```
[30]:
```

	0	1	2	3	4	5	...	\
0	581.899206	-168.985577	-179.710030	-182.049615	2377.232531	1439.513142		
1	613.983272	-110.185162	-116.774939	-166.981462	2326.903225	1456.938548		
2	599.851085	-77.109569	-93.205683	-145.640647	2205.992330	1463.733499		
3	593.456322	-38.334370	-70.958203	-142.017365	2147.541559	1488.171605		
4	594.775348	7.628597	-28.362549	-71.620603	2058.137154	1506.016144		

	6	7	8	9	...	110	...	\
0	56368.903752	-128.628921	8664.769405	1302.905387	...	-1026.891116		
1	54562.986421	-126.600008	8460.275539	1316.941872	...	-979.478719		
2	52244.328672	-138.971015	8157.918141	1280.981950	...	-1005.070031		
3	48137.172235	-195.685023	7783.453295	1277.575975	...	-1024.451703		
4	42947.097344	-263.929965	7364.941814	1266.669817	...	-972.301724		

	111	112	113	114	115	116 \
0	2108.599522	836.056391	2369.803079	-184.149094	-149.793292	977.776456
1	2103.956206	809.058785	2606.446663	-129.519384	-99.907468	967.913236
2	2167.187996	814.162470	2759.642151	-95.634574	-72.685480	981.259543
3	2220.851608	855.599036	3196.568610	-62.872740	-28.588225	991.496365
4	2341.520915	850.865488	3743.599119	-23.792392	17.693773	1031.349264

	117	118	119
0	15002.007838	-5.647692	820.770585
1	13520.234276	25.535020	863.304970
2	12134.442636	60.758067	896.288231
3	10738.174535	273.647065	993.025950
4	9166.361870	379.826107	1087.840792

[5 rows x 120 columns]

```
[31]: df_raw_EPC2.shape
```

```
[31]: (1013, 120)
```

```
[32]: df_raw_GN = pd.read_csv(r'Data\Raw-GN.txt',sep='\s+',header=None)
```

```
[33]: df_raw_GN.head()
```

```
[33]:
```

	0	1	2	3	4 \
0	2160.348717	1314.579420	3218.265846	2351.634956	1718.374803
1	2045.885705	1297.393931	3195.264459	2272.111147	1695.248236
2	1989.764491	1252.535351	3138.935280	2239.438805	1672.247913
3	1951.439372	1232.810425	3011.697036	2220.894062	1628.383404
4	1897.763294	1183.869128	2876.850879	2193.998714	1506.630255

	5	6	7	8	9 ... \
0	1054.734117	1495.768736	1687.681208	838.412255	1455.511128 ...
1	1085.340363	1431.383846	1603.925439	761.849748	1374.513051 ...
2	1093.915553	1406.870278	1557.384257	705.467276	1367.470748 ...
3	1159.616311	1353.378038	1502.961437	649.927359	1267.311728 ...
4	1158.025564	1308.014322	1467.167992	566.581489	1144.444349 ...

	12	13	14	15	16	17 \
0	1189.056338	655.610102	1195.173062	1364.227497	1059.646051	734.268796
1	1061.548439	616.494438	1206.968712	1189.309195	1067.676532	721.596722
2	970.183124	596.253803	1184.270459	1107.595288	1019.047836	680.217221
3	851.921660	573.872773	1131.874819	953.322572	992.805555	646.171478
4	748.880127	592.389565	1055.854998	844.907811	966.076031	634.805981

	18	19	20	21
0	2769.263332	3124.997898	1711.264905	1680.924476

```

1  2642.759384  3006.950948  1668.187469  1613.478943
2  2543.644357  2925.022553  1586.802863  1572.875803
3  2456.899857  2838.141830  1506.328355  1478.687291
4  2336.305663  2731.480400  1497.707680  1394.192856

```

[5 rows x 22 columns]

```
[34]: df_raw_GN.shape
```

```
[34]: (1014, 22)
```

```
[35]: df_raw_HC = pd.read_csv(r'Data\Raw-HC.txt', sep='\s+', header=None)
```

```
[36]: df_raw_HC.head()
```

```

[36]:      0      1      2      3      4      5  \
0  664.066369  891.519617 -55.185891  789.077141  756.648636  575.395903
1  727.637950  938.968041 -20.001006  784.202377  811.105970  620.008865
2  719.349410  943.849373   1.420800  777.689599  789.311420  625.776152
3  771.963997  975.847488  40.013175  826.842720  816.972423  689.352168
4  812.518125 1027.312499  74.733424  810.081306  847.967557  699.872646

      6      7      8      9  ...      50  \
0  812.793173  631.869852  3377.424394 1225.919616  ...  29.214720
1  837.406006  635.436913  3626.686697 1233.630143  ...  67.675125
2  863.507211  649.299885  3937.332330 1242.919809  ...  92.551005
3  876.225500  661.545420  4395.367705 1238.143204  ... 126.703477
4  887.305153  679.512831  4807.660441 1252.448052  ... 154.074688

      51      52      53      54      55  \
0  5741.079109 -4075.177635 -962.449543  46085.982967 16994.411469
1  5845.833450 -2910.158181 -920.334063  44825.210704 16971.574966
2  5930.309376 -2014.917612 -890.593846  43538.695113 16681.662158
3  6084.008584 -462.622593 -903.940795  42375.339802 16546.408443
4  6256.793708  325.072843 -866.324594  41136.213330 15818.275651

      56      57      58      59
0  -52.107264 -1290.924259 -1161.970246  20166.640066
1   36.375592 -1183.832011 -1075.916837  18732.060172
2   77.638293 -1108.209207 -1039.534287  17364.742541
3   79.839218 -818.619517 -908.831754  14780.186982
4  173.226593 -518.478614 -770.107138  12482.214654

```

[5 rows x 60 columns]

```
[37]: df_raw_HC.shape
```

[37]: (1013, 60)

```
[38]: df_raw_HC2 = pd.read_csv(r'Data\Raw-HC2.txt', sep='\s+', header=None)
```

```
[39]: df_raw_HC2.head()
```

```
[39]:
```

	0	1	2	3	4	5	\
0	1008.600674	-176.331239	-248.210781	-211.621177	-152.701312	-163.797481	
1	1046.371463	-147.584618	-200.509401	-156.480285	-126.970755	-126.804979	
2	978.631157	-112.422007	-158.221211	-116.235692	-94.430349	-59.928333	
3	814.376885	-63.540342	-94.486609	-60.710620	-87.698196	-7.100967	
4	704.080718	-19.986074	-54.767168	-13.401172	-47.806272	45.427068	

	6	7	8	9	...	100	\
0	114.916213	-26.551247	-204.156848	-922.529271	...	-118.983831	
1	226.510538	48.387896	-145.021424	-887.725883	...	-296.501999	
2	298.777360	88.365984	-111.003317	-883.415887	...	-504.824634	
3	394.487054	146.945886	-61.440373	-836.645116	...	-684.975727	
4	450.609431	182.098345	-8.919438	-776.367364	...	-659.530411	

	101	102	103	104	105	106	\
0	-785.670250	-442.223228	-565.895180	11899.686997	-1466.700795	40.748809	
1	-549.425264	-479.016974	-495.175035	11579.851837	-1202.731401	87.915315	
2	-362.698155	-513.150226	-435.747824	11314.132757	-971.307879	105.810732	
3	-55.706231	-535.935830	-359.469506	11176.782171	-626.442796	155.594252	
4	143.510836	-486.122782	-270.028946	11164.175387	-329.362564	145.734191	

	107	108	109
0	-78.988593	-821.789023	872.508664
1	-60.076447	-941.850909	866.826500
2	-29.435275	-1017.920529	915.228065
3	3.855931	-1183.958936	920.117639
4	53.843324	-1262.201270	872.797323

[5 rows x 110 columns]

```
[40]: df_raw_HC2.shape
```

[40]: (1013, 110)

```
[41]: df_raw_MiaPaCa = pd.read_csv(r'Data\Raw-MiaPaCa.txt', sep='\s+', header=None)
```

```
[42]: df_raw_MiaPaCa.head()
```

```
[42]:
```

	0	1	2	3	4	5	\
0	986.134289	3191.825457	-2.535792	381.293306	-14.670542	222.150897	
1	968.238898	2387.663019	-13.405950	323.864640	-13.062933	221.195522	

	2	940.958141	2042.282002	-4.439658	283.158469	18.430079	212.515654	
	3	931.451280	1140.520027	16.551258	240.507895	72.736326	195.481008	
	4	897.871235	957.922213	8.585703	220.874240	103.296138	186.407781	

		6	7	8	9	...	21	\
0	283.214723	-10.688220	4014.044286	1567.222465	...	28581.246327		
1	274.867820	-6.973148	3329.342639	1497.822661	...	27494.121593		
2	304.850952	0.275607	2779.738368	1405.961540	...	26730.718074		
3	391.133158	26.687282	2049.528623	1295.990866	...	26154.070758		
4	503.418555	37.810452	1464.217353	1168.197266	...	25731.896853		

		22	23	24	25	26	27	\
0	319.677679	755.957734	8008.400770	550.821570	475.220347	424.548050		
1	314.584347	706.747435	7704.657802	543.220942	475.095789	401.035342		
2	306.062605	687.922333	7546.049323	546.734571	457.565767	394.257941		
3	306.240677	665.283137	7362.425379	527.072509	452.180077	386.850138		
4	300.289221	652.321148	7330.103420	524.098047	431.193937	378.305130		

		28	29	30
0	183.399571	49.565123	291.349689	
1	165.500022	55.983494	298.719220	
2	153.319906	51.380073	301.287580	
3	161.356251	29.136447	302.037695	
4	153.314808	42.126248	288.379379	

[5 rows x 31 columns]

```
[43]: df_raw_MiaPaCa.shape
```

```
[43]: (1014, 31)
```

Since the shape is either 1013 or 1014, we can drop one data point to make 1013 data points universal.

```
[44]: df_frequency.drop([0],inplace=True)
```

```
[45]: df_average.drop([0],inplace=True)
```

```
[46]: df_raw_CD.drop([0],inplace=True)
df_raw_HPDE.drop([0],inplace=True)
df_raw_GN.drop([0],inplace=True)
df_raw_MiaPaCa.drop([0],inplace=True)
```

```
[47]: print(df_average.shape)
print(df_raw_CD.shape)
print(df_raw_HPDE.shape)
print(df_raw_GN.shape)
```

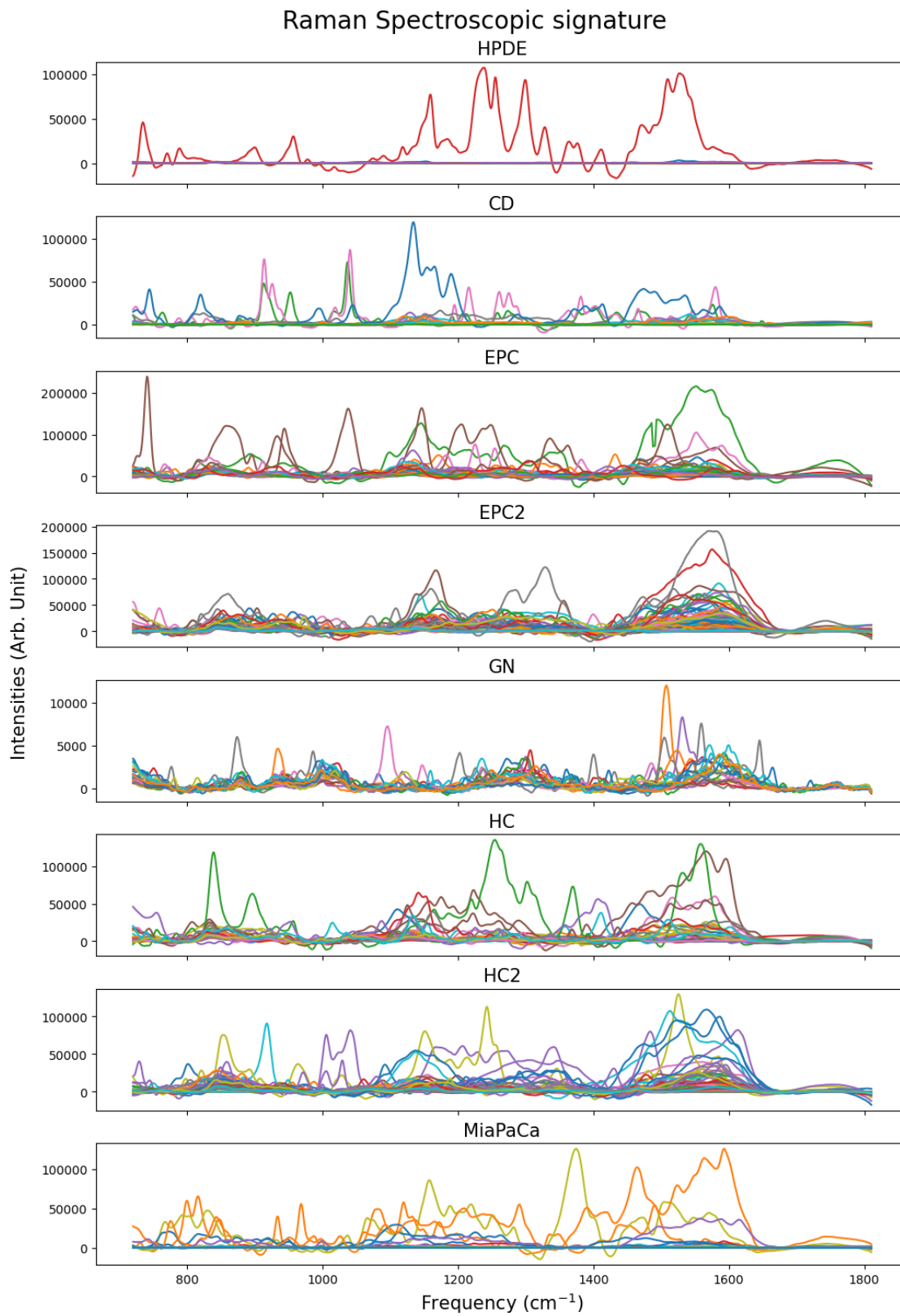
```
print(df_raw_MiaPaCa.shape)
```

```
(1013, 9)
(1013, 33)
(1013, 35)
(1013, 22)
(1013, 31)
```

Now we can visualize the data for each cells

```
[54]: fig, ax = plt.subplots(8,1,sharex=True,sharey=False,layout="constrained")
plt.rcParams['figure.figsize'] = 10, 15
#plt.subplots_adjust(left=0.1, bottom=0.1, right***0.9,top=0.9, wspace=0.
    ↳4,hspace=0.4)
pd.option_context('mode.use_inf_as_na', True)
fig.suptitle('Raman Spectroscopic signature', fontsize = 20)
for i in range(df_raw_HPDE.shape[1]):
    ax[0].plot(df_frequency,df_raw_HPDE.iloc[:,i],label='HPDE')
    ax[0].set_title('HPDE',fontsize=15)
for i in range(df_raw_CD.shape[1]):
    ax[1].plot(df_frequency,df_raw_CD.iloc[:,i],label='CD')
    ax[1].set_title('CD',fontsize=15)
for i in range(df_raw_EPC.shape[1]):
    ax[2].plot(df_frequency,df_raw_EPC.iloc[:,i],label='EPC')
    ax[2].set_title('EPC',fontsize=15)
for i in range(df_raw_EPC2.shape[1]):
    ax[3].plot(df_frequency,df_raw_EPC2.iloc[:,i],label='EPC2')
    ax[3].set_title('EPC2',fontsize=15)
for i in range(df_raw_GN.shape[1]):
    ax[4].plot(df_frequency,df_raw_GN.iloc[:,i],label='GN')
    ax[4].set_title('GN',fontsize=15)
for i in range(df_raw_HC.shape[1]):
    ax[5].plot(df_frequency,df_raw_HC.iloc[:,i],label='HC')
    ax[5].set_title('HC',fontsize=15)
for i in range(df_raw_HC2.shape[1]):
    ax[6].plot(df_frequency,df_raw_HC2.iloc[:,i],label='HC2')
    ax[6].set_title('HC2',fontsize=15)
for i in range(df_raw_MiaPaCa.shape[1]):
    ax[7].plot(df_frequency,df_raw_MiaPaCa.iloc[:,i],label='MiaPaCa')
    ax[7].set_title('MiaPaCa',fontsize=15)

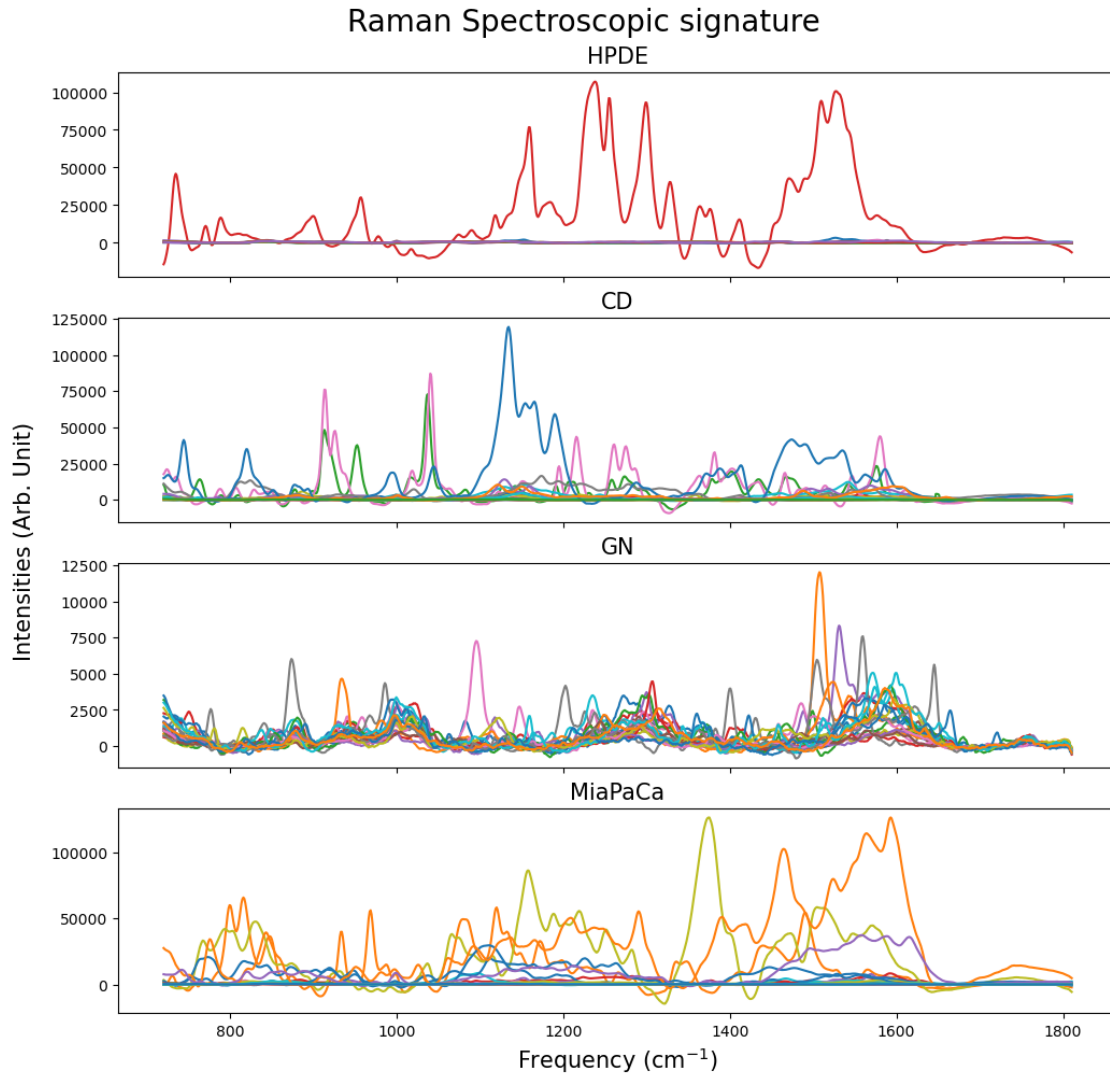
plt.gcf().text(-0.02,0.5, "Intensities (Arb. Unit)", ha="center", va="center",
    ↳rotation=90, fontsize=15)
plt.xlabel(r'Frequency (cm-1)',fontsize=15)
#plt.legend()
#plt.tight_layout()
plt.show()
```



There are HCs and EPCs data (for healthy and sick, respectively), which are out of the scope. So we will reduce it to CD, HPDE, MiaPaCa, and GN.

```
[283]: fig, ax = plt.subplots(4,1,sharex=True,sharey=False,layout="constrained")
#plt.rcParams['figure.figsize'] = 10, 10
#plt.subplots_adjust(left=0.1, bottom=0.1, right***0.9,top=0.9, wspace=0.
    ↪4,hspace=0.4)
pd.option_context('mode.use_inf_as_na', True)
fig.suptitle('Raman Spectroscopic signature', fontsize = 20)
for i in range(df_raw_HPDE.shape[1]):
    ax[0].plot(df_frequency,df_raw_HPDE.iloc[:,i],label='HPDE')
    ax[0].set_title('HPDE',fontsize=15)
for i in range(df_raw_CD.shape[1]):
    ax[1].plot(df_frequency,df_raw_CD.iloc[:,i],label='CD')
    ax[1].set_title('CD',fontsize=15)
for i in range(df_raw_GN.shape[1]):
    ax[2].plot(df_frequency,df_raw_GN.iloc[:,i],label='GN')
    ax[2].set_title('GN',fontsize=15)
for i in range(df_raw_MiaPaCa.shape[1]):
    ax[3].plot(df_frequency,df_raw_MiaPaCa.iloc[:,i],label='MiaPaCa')
    ax[3].set_title('MiaPaCa',fontsize=15)

plt.gcf().text(-0.02,0.5, "Intensities (Arb. Unit)", ha="center", va="center",
    ↪rotation=90, fontsize=15)
plt.xlabel(r'Frequency (cm-1)',fontsize=15)
#plt.legend()
#plt.tight_layout()
plt.show()
```

Note: Here, HPDE, CD, MiaPaCa, and GN are exosomes from different cells, which are identified as a marker for pancreatic cancer cells. HC are the cells from healthy control group and EPC are the early pancreatic cancer cell group.

The author uses Vancouver Raman algorithm to remove fluorescence by fitting the polynomial regression. Also, there are modified Vancouver Raman algorithm to denoise, correct baseline (fitting the fluorescence), and so on. The author also normalizes the spectra as well.

```
[55]: df_scaled_CD = pd.read_csv(r'Data\Scaled CD18.txt', sep='\s+', header=None)
print(df_scaled_CD.shape)
df_scaled_CD.columns = ['CD_scaled_'+str(i) for i in range(df_scaled_CD.
    ↳shape[1])]
df_scaled_CD.head()
```

(1014, 33)

```
[55]:  CD_scaled_0  CD_scaled_1  CD_scaled_2  CD_scaled_3  CD_scaled_4  \
0      0.627240   -0.808440    0.785649   -0.286407    1.117742
1      0.544890   -0.803976    0.580486   -0.284544    0.951922
2      0.486031   -0.757946    0.422489   -0.289928    0.876549
3      0.504072   -0.729041    0.117898   -0.273608    0.795501
4      0.497984   -0.714085   -0.109961   -0.283588    0.748358

      CD_scaled_5  CD_scaled_6  CD_scaled_7  CD_scaled_8  CD_scaled_9  ...  \
0      1.198693    0.783460    0.269363   -0.011685   -0.814099  ...
1      1.171875    0.859946    0.117320   -0.017348   -0.833708  ...
2      1.101364    0.934400    0.049795   -0.011968   -0.836117  ...
3      1.084714    1.061655    0.024158   -0.046767   -0.853397  ...
4      0.991662    1.127355   -0.111128   -0.060305   -0.851067  ...

      CD_scaled_23  CD_scaled_24  CD_scaled_25  CD_scaled_26  CD_scaled_27  \
0      3.614682    0.793426    5.294379    2.974757    2.181770
1      3.721372    0.783691    4.771051    2.938056    1.990713
2      3.828628    0.786220    4.479207    2.888274    1.819568
3      3.807108    0.793976    4.364357    2.846810    1.569697
4      3.816864    0.805368    4.237218    2.709478    1.374390

      CD_scaled_28  CD_scaled_29  CD_scaled_30  CD_scaled_31  CD_scaled_32
0      3.626305    0.989208    0.081365   -0.699944    5.020930
1      3.608480    1.170498    0.098765   -0.718982    4.903327
2      3.488046    1.335950    0.118705   -0.742587    4.659306
3      3.512828    1.613569    0.161349   -0.757534    4.446844
4      3.548538    1.681663    0.193972   -0.781588    4.213111
```

[5 rows x 33 columns]

```
[56]: df_scaled_GN = pd.read_csv(r'Data\Scaled GN.txt',sep='\s+',header=None)
print(df_scaled_GN.shape)
df_scaled_GN.columns = ['GN_scaled_'+str(i) for i in range(df_scaled_GN.
↪shape[1])]
df_scaled_GN.head()
```

(1014, 22)

```
[56]:  GN_scaled_0  GN_scaled_1  GN_scaled_2  GN_scaled_3  GN_scaled_4  \
0      1.605200    0.480491    4.279952    1.537541    0.646067
1      1.478035    0.468102    4.243459    1.456568    0.628288
2      1.415687    0.435763    4.154088    1.423301    0.610606
3      1.373109    0.421543    3.952214    1.404418    0.576885
4      1.313476    0.386261    3.738269    1.377033    0.483284

      GN_scaled_5  GN_scaled_6  GN_scaled_7  GN_scaled_8  GN_scaled_9  ...  \
0      1.565064    0.839120    0.641616    1.293977    0.680262  ...
```

1	1.634938	0.774027	0.578849	1.094202	0.596664	...
2	1.654515	0.749243	0.543971	0.947084	0.589395	...
3	1.804510	0.695163	0.503187	0.802163	0.486022	...
4	1.800878	0.649300	0.476363	0.584689	0.359211	...

	GN_scaled_12	GN_scaled_13	GN_scaled_14	GN_scaled_15	GN_scaled_16	\
0	0.572399	0.810921	3.234632	2.501736	1.417842	
1	0.433070	0.731839	3.273524	2.075808	1.434043	
2	0.333233	0.690918	3.198684	1.876833	1.335939	
3	0.204007	0.645669	3.025929	1.501176	1.282998	
4	0.091412	0.683105	2.775281	1.237185	1.229074	

	GN_scaled_17	GN_scaled_18	GN_scaled_19	GN_scaled_20	GN_scaled_21
0	0.317277	3.007618	2.281700	1.695935	1.377771
1	0.297958	2.835588	2.166988	1.634570	1.294449
2	0.234872	2.700803	2.087374	1.518635	1.244289
3	0.182967	2.582841	2.002947	1.403997	1.127930
4	0.165640	2.418848	1.899299	1.391716	1.023547

[5 rows x 22 columns]

```
[57]: df_scaled_HPDE = pd.read_csv(r'Data\Scaled HPDE.txt',sep='\s+',header=None)
print(df_scaled_HPDE.shape)
df_scaled_HPDE.columns = ['HPDE_scaled_'+str(i) for i in range(df_scaled_HPDE.
↪shape[1])]
df_scaled_HPDE.head()
```

(1014, 35)

```
[57]: HPDE_scaled_0 HPDE_scaled_1 HPDE_scaled_2 HPDE_scaled_3 HPDE_scaled_4 \
0 2.560051 1.970449 3.037619 3.033875 2.412465
1 2.381410 1.883087 2.970336 2.969361 2.388290
2 2.329360 1.859549 2.860879 2.925439 2.232922
3 2.267373 1.831276 2.774029 2.721611 2.144916
4 2.068860 1.803762 2.625452 2.603190 1.943666
```

	HPDE_scaled_5	HPDE_scaled_6	HPDE_scaled_7	HPDE_scaled_8	HPDE_scaled_9	\
0	2.823622	3.452165	1.805597	3.296075	2.898464	
1	2.764960	3.374450	1.744433	3.162275	2.688602	
2	2.602753	3.234404	1.735840	3.055666	2.616045	
3	2.443454	3.071123	1.719661	3.071351	2.409292	
4	2.354916	3.034961	1.704402	2.961873	2.228518	

	HPDE_scaled_25	HPDE_scaled_26	HPDE_scaled_27	HPDE_scaled_28	\
0	0.594899	2.282256	2.820799	1.766969	
1	0.494378	2.040423	2.688267	1.607042	
2	0.516661	2.055868	2.668853	1.543411	

3	...	0.384564	1.879769	2.652128	1.545021
4	...	0.312958	1.665659	2.612008	1.684299

	HPDE_scaled_29	HPDE_scaled_30	HPDE_scaled_31	HPDE_scaled_32	\
0	1.576723	0.498329	1.124748	1.941478	
1	1.559853	0.518802	1.205917	1.810946	
2	1.580687	0.442381	1.468947	1.828335	
3	1.515992	0.412792	1.663626	1.746537	
4	1.438083	0.280347	1.668530	1.777790	

	HPDE_scaled_33	HPDE_scaled_34
0	1.166412	0.235613
1	1.136220	0.147063
2	1.163990	0.119143
3	1.175575	-0.041795
4	1.257393	-0.049063

[5 rows x 35 columns]

```
[58]: df_scaled_MiaPaCa = pd.read_csv(r'Data\Scaled MiaPaCa.
↳txt',sep='\s+',header=None)
print(df_scaled_MiaPaCa.shape)
df_scaled_MiaPaCa.columns = ['MiaPaCa_scaled_'+str(i) for i in_
↳range(df_scaled_MiaPaCa.shape[1])]
df_scaled_MiaPaCa.head()
```

(1014, 31)

```
[58]: MiaPaCa_scaled_0 MiaPaCa_scaled_1 MiaPaCa_scaled_2 MiaPaCa_scaled_3 \
0 2.279001 -0.493665 -0.837637 -0.675826
1 2.224572 -0.546858 -0.902667 -0.705791
2 2.141597 -0.569704 -0.849027 -0.727031
3 2.112681 -0.629354 -0.723450 -0.749285
4 2.010547 -0.641432 -0.771103 -0.759530
```

	MiaPaCa_scaled_4	MiaPaCa_scaled_5	MiaPaCa_scaled_6	MiaPaCa_scaled_7	\
0	-0.654590	0.827089	-0.310579	-0.794842	
1	-0.653416	0.820007	-0.322965	-0.782919	
2	-0.630418	0.755663	-0.278471	-0.759654	
3	-0.590760	0.629385	-0.150431	-0.674885	
4	-0.568444	0.562125	0.016198	-0.639184	

	MiaPaCa_scaled_8	MiaPaCa_scaled_9	...	MiaPaCa_scaled_21	\
0	-0.667363	0.306805	...	0.002890	
1	-0.694757	0.262347	...	-0.034115	
2	-0.716747	0.203500	...	-0.060101	
3	-0.745962	0.133052	...	-0.079730	

4	-0.769380	0.051186	...	-0.094101
---	-----------	----------	-----	-----------

	MiaPaCa_scaled_22	MiaPaCa_scaled_23	MiaPaCa_scaled_24	MiaPaCa_scaled_25	\
0	1.455419	1.612946	-0.048173	3.220945	
1	1.415905	1.455756	-0.078448	3.162044	
2	1.349793	1.395624	-0.094257	3.189273	
3	1.351175	1.323308	-0.112559	3.036901	
4	1.305004	1.281904	-0.115781	3.013851	

	MiaPaCa_scaled_26	MiaPaCa_scaled_27	MiaPaCa_scaled_28	MiaPaCa_scaled_29	\
0	2.680854	2.322535	-0.178839	-0.795637	
1	2.679886	2.129003	-0.261592	-0.769948	
2	2.543733	2.073219	-0.317903	-0.788373	
3	2.501903	2.012246	-0.280749	-0.877399	
4	2.338906	1.941912	-0.317927	-0.825410	

	MiaPaCa_scaled_30
0	1.208965
1	1.266487
2	1.286535
3	1.292390
4	1.185780

[5 rows x 31 columns]

Same with the scaled data. We will need to reduce the dimension from 1014 to 1013.

```
[59]: df_scaled_CD.drop([0],inplace=True)
df_scaled_GN.drop([0],inplace=True)
df_scaled_HPDE.drop([0],inplace=True)
df_scaled_MiaPaCa.drop([0],inplace=True)
```

```
[60]: print(df_scaled_CD.shape)
print(df_scaled_GN.shape)
print(df_scaled_HPDE.shape)
print(df_scaled_MiaPaCa.shape)
```

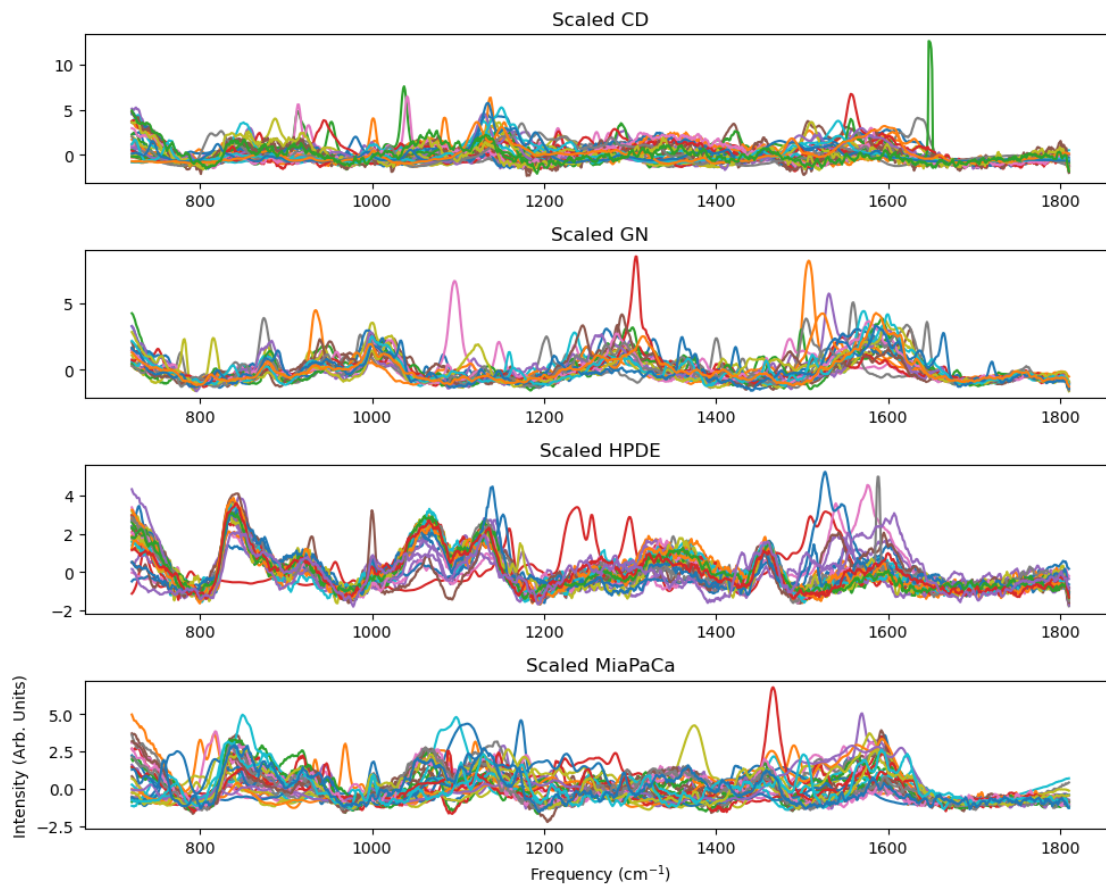
```
(1013, 33)
(1013, 22)
(1013, 35)
(1013, 31)
```

```
[61]: fig, ax = plt.subplots(4,1,figsize=(10,8))
ax[0].plot(df_average.Raman.Frequency, df_scaled_CD[:])
ax[0].set_title('Scaled CD')
ax[1].plot(df_average.Raman.Frequency, df_scaled_GN[:])
ax[1].set_title('Scaled GN')
ax[2].plot(df_average.Raman.Frequency, df_scaled_HPDE[:])
```

```

ax[2].set_title('Scaled HPDE')
ax[3].plot(df_average.Raman.Frequency, df_scaled_MiaPaCa[:])
ax[3].set_title('Scaled MiaPaCa')
plt.ylabel('Intensity (Arb. Units)')
plt.xlabel('Frequency (cm-1)')
plt.tight_layout()
plt.show()

```



It appears that the spectra do not need much cleaning from here. We will use the scaled spectra to move forward and reduce the dimension by applying PCA. However, we might need to create a label and concatenate all of the spectra of different cells.

```

[62]: df = pd.
      ↪concat([df_scaled_CD,df_scaled_GN,df_scaled_HPDE,df_scaled_MiaPaCa],axis=1).
      ↪reset_index()
df.drop('index',axis=1,inplace=True)
print(df.shape)
df.head(200)

```

(1013, 121)

```

[62]:      CD_scaled_0  CD_scaled_1  CD_scaled_2  CD_scaled_3  CD_scaled_4  \
0      0.544890   -0.803976    0.580486   -0.284544    0.951922
1      0.486031   -0.757946    0.422489   -0.289928    0.876549
2      0.504072   -0.729041    0.117898   -0.273608    0.795501
3      0.497984   -0.714085   -0.109961   -0.283588    0.748358
4      0.211190   -0.695870   -0.257283   -0.281549    0.596884
..      ...
195    -0.893031   -0.421444    3.289723   -0.411183   -0.731459
196    -0.801298   -0.385343    3.583743   -0.450027   -0.745795
197    -0.685285   -0.265187    3.652794   -0.456610   -0.811388
198    -0.692354   -0.209580    3.485891   -0.449744   -0.828974
199    -0.638331   -0.161362    3.094565   -0.454888   -0.820842

      CD_scaled_5  CD_scaled_6  CD_scaled_7  CD_scaled_8  CD_scaled_9  ...  \
0      1.171875    0.859946    0.117320   -0.017348   -0.833708  ...
1      1.101364    0.934400    0.049795   -0.011968   -0.836117  ...
2      1.084714    1.061655    0.024158   -0.046767   -0.853397  ...
3      0.991662    1.127355   -0.111128   -0.060305   -0.851067  ...
4      1.057551    1.110658   -0.195160   -0.077421   -0.846064  ...
..      ...
195    -0.291710   -0.487217   -0.201324   -0.602747   -0.189978  ...
196    -0.324891   -0.542334   -0.164296   -0.693464   -0.152620  ...
197    -0.319551   -0.589782   -0.192672   -0.738451   -0.127901  ...
198    -0.311102   -0.623126   -0.175801   -0.779504   -0.124896  ...
199    -0.200330   -0.634639   -0.142212   -0.842001   -0.108719  ...

      MiaPaCa_scaled_21  MiaPaCa_scaled_22  MiaPaCa_scaled_23  \
0      -0.034115         1.415905         1.455756
1      -0.060101         1.349793         1.395624
2      -0.079730         1.351175         1.323308
3      -0.094101         1.305004         1.281904
4      -0.108735         1.188868         1.177508
..      ...
195    -0.520487        -0.090672        -0.583555
196    -0.517873        -0.085111        -0.515748
197    -0.530992         0.058748        -0.427158
198    -0.542873         0.060938        -0.395398
199    -0.560231        -0.166134        -0.471920

      MiaPaCa_scaled_24  MiaPaCa_scaled_25  MiaPaCa_scaled_26  \
0      -0.078448         3.162044         2.679886
1      -0.094257         3.189273         2.543733
2      -0.112559         3.036901         2.501903
3      -0.115781         3.013851         2.338906
4      -0.113850         3.011169         2.202445
..      ...
195    -0.818062        -0.747619        -0.013379

```

196	-0.840648	-0.945677	-0.202091
197	-0.861757	-0.972070	-0.289541
198	-0.893249	-0.867037	-0.316119
199	-0.918029	-0.923572	-0.453956

	MiaPaCa_scaled_27	MiaPaCa_scaled_28	MiaPaCa_scaled_29 \
0	2.129003	-0.261592	-0.769948
1	2.073219	-0.317903	-0.788373
2	2.012246	-0.280749	-0.877399
3	1.941912	-0.317927	-0.825410
4	1.800809	-0.421874	-0.803173
..
195	-0.688681	-0.605225	-0.406731
196	-0.665073	-0.524072	-0.537870
197	-0.645025	-0.452875	-0.648226
198	-0.642546	-0.592518	-0.767308
199	-0.715159	-0.674051	-0.869002

	MiaPaCa_scaled_30
0	1.266487
1	1.286535
2	1.292390
3	1.185780
4	1.083188
..	...
195	-0.300218
196	-0.556224
197	-0.557838
198	-0.511896
199	-0.537066

[200 rows x 121 columns]

Now we can create a label for these concatenated df for classification.

```
[63]: cd_obs = df_scaled_CD.shape[1]
GN_obs = df_scaled_GN.shape[1]
HPDE_obs = df_scaled_HPDE.shape[1]
MiaPaCa_obs = df_scaled_MiaPaCa.shape[1]
y = {}
for i in range(cd_obs):
    name = 'CD_scaled_' + str(i)
    y[name] = 0
for i in range(GN_obs):
    name = 'GN_scaled_' + str(i)
    y[name] = 1
for i in range(HPDE_obs):
```



```

    name = 'HPDE_scaled_' + str(i)
    y[name] = 2
for i in range(MiaPaCa_obs):
    name = 'MiaPaCa_scaled_' + str(i)
    y[name] = 3
y = pd.DataFrame.from_dict(y,orient='index',columns=['Target'])
y.shape

```

[63]: (121, 1)

[64]: y.head()

```

[64]:          Target
CD_scaled_0      0
CD_scaled_1      0
CD_scaled_2      0
CD_scaled_3      0
CD_scaled_4      0

```

Then we can merge this to the main df.

[65]: df_master = pd.concat([df.T,y],axis=1,ignore_index=False)

[66]: df_master

```

[66]:          0          1          2          3          4          5  \
CD_scaled_0    0.544890  0.486031  0.504072  0.497984  0.211190  0.085117
CD_scaled_1   -0.803976 -0.757946 -0.729041 -0.714085 -0.695870 -0.695353
CD_scaled_2    0.580486  0.422489  0.117898 -0.109961 -0.257283 -0.344626
CD_scaled_3   -0.284544 -0.289928 -0.273608 -0.283588 -0.281549 -0.298788
CD_scaled_4    0.951922  0.876549  0.795501  0.748358  0.596884  0.605710
...          ...          ...          ...          ...          ...
MiaPaCa_scaled_26  2.679886  2.543733  2.501903  2.338906  2.202445  2.012167
MiaPaCa_scaled_27  2.129003  2.073219  2.012246  1.941912  1.800809  1.691090
MiaPaCa_scaled_28 -0.261592 -0.317903 -0.280749 -0.317927 -0.421874 -0.358944
MiaPaCa_scaled_29 -0.769948 -0.788373 -0.877399 -0.825410 -0.803173 -0.862064
MiaPaCa_scaled_30  1.266487  1.286535  1.292390  1.185780  1.083188  0.816319

          6          7          8          9  ...      1004  \
CD_scaled_0   -0.011104 -0.244996 -0.269232 -0.100159  ...    0.234435
CD_scaled_1   -0.768268 -0.823698 -0.867106 -0.903477  ...   -0.429063
CD_scaled_2   -0.403054 -0.445152 -0.461131 -0.471701  ...   -0.624187
CD_scaled_3   -0.296297 -0.344452 -0.392090 -0.373874  ...    0.202230
CD_scaled_4    0.579334  0.585846  0.485756  0.532293  ...   -0.673613
...          ...          ...          ...          ...
MiaPaCa_scaled_26  2.038291  2.055618  2.057747  2.089668  ...   -1.038924
MiaPaCa_scaled_27  1.653938  1.576651  1.452387  1.455146  ...   -0.815540

```

MiaPaCa_scaled_28	-0.403064	-0.504370	-0.726259	-0.746632	...	-0.429636
MiaPaCa_scaled_29	-0.846209	-0.797101	-0.837419	-0.887668	...	-0.768990
MiaPaCa_scaled_30	0.553298	0.345825	0.371942	0.379366	...	-0.679566

	1005	1006	1007	1008	1009	1010	\
CD_scaled_0	0.293614	0.287794	0.218139	0.202670	0.143649	-0.188851	
CD_scaled_1	-0.413083	-0.404201	-0.431803	-0.452528	-0.496689	-0.571386	
CD_scaled_2	-0.628112	-0.636051	-0.642628	-0.646459	-0.653747	-0.673928	
CD_scaled_3	0.179256	0.182211	0.202127	0.219839	0.230545	0.105348	
CD_scaled_4	-0.711815	-0.719791	-0.655058	-0.607814	-0.677480	-0.896293	
...	
MiaPaCa_scaled_26	-0.871064	-0.831789	-0.792699	-0.814054	-0.847574	-1.017860	
MiaPaCa_scaled_27	-0.797810	-0.699646	-0.699399	-0.792807	-0.673847	-0.840130	
MiaPaCa_scaled_28	-0.443264	-0.500121	-0.559249	-0.489456	-0.431647	-0.500564	
MiaPaCa_scaled_29	-0.643993	-0.655699	-0.694486	-0.677776	-0.715158	-1.061388	
MiaPaCa_scaled_30	-0.804987	-0.846038	-0.911533	-0.948958	-1.035074	-1.189956	

	1011	1012	Target
CD_scaled_0	-0.338167	-0.343832	0
CD_scaled_1	-0.594077	-0.610955	0
CD_scaled_2	-0.681869	-0.695268	0
CD_scaled_3	0.095563	0.021590	0
CD_scaled_4	-0.905580	-1.059267	0
...
MiaPaCa_scaled_26	-1.033726	-1.074580	3
MiaPaCa_scaled_27	-0.843650	-0.801993	3
MiaPaCa_scaled_28	-0.501574	-0.445481	3
MiaPaCa_scaled_29	-1.113616	-1.302723	3
MiaPaCa_scaled_30	-1.290298	-1.297413	3

[121 rows x 1014 columns]

The author uses PCA to reduce the dimension and has reported values of variance and plots that we can compare. Let us see whether we can reproduce their findings.

```
[67]: from sklearn.decomposition import PCA
df_master.columns = df_master.columns.astype(str)
pca_df = PCA().fit(df_master)
#pca_df = PCA().fit(df_master.drop(columns='Target'))
```

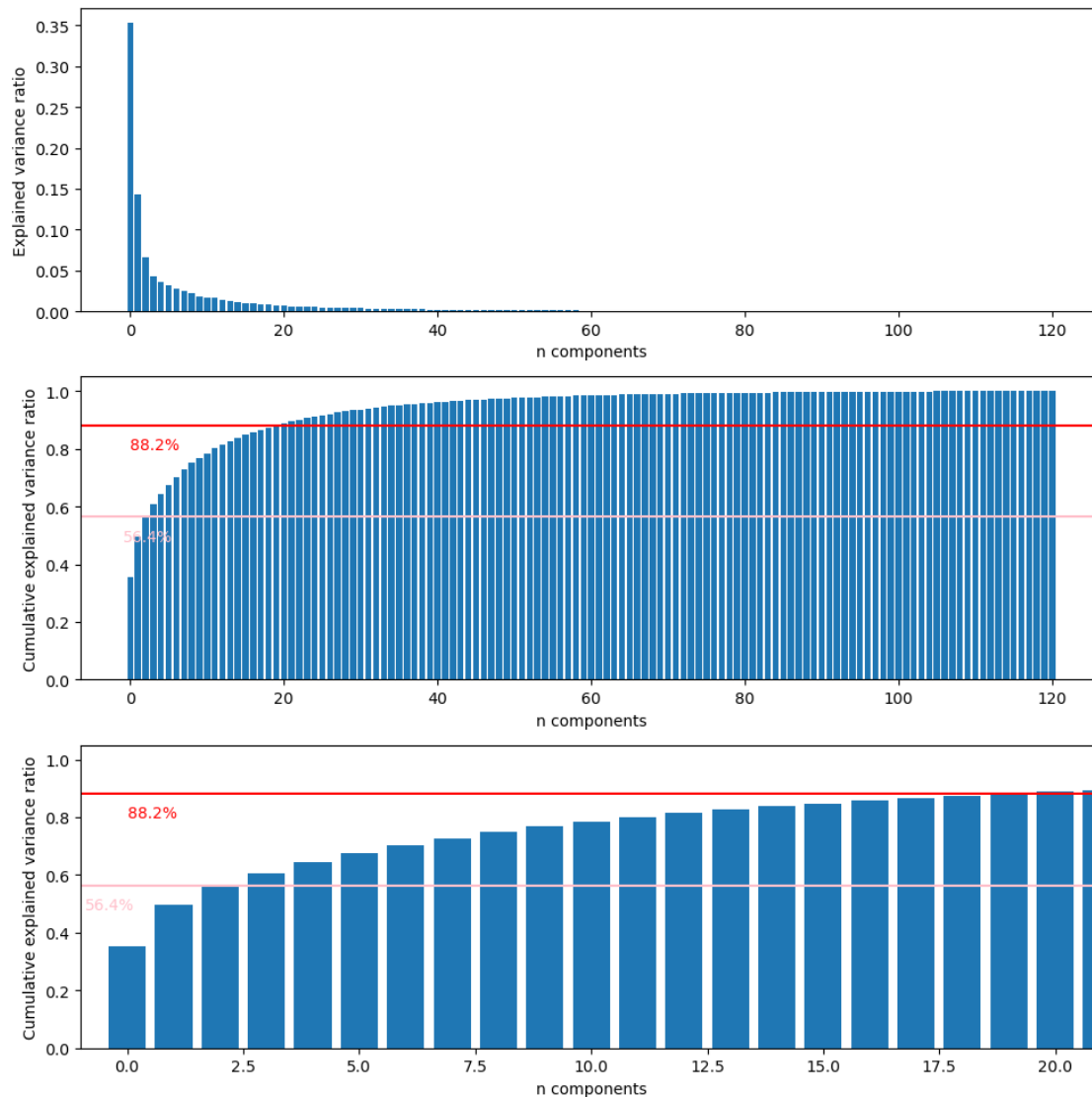
```
[68]: fig, ax = plt.subplots(3,1,figsize=(10,10))
ax[0].bar(range(len(pca_df.explained_variance_ratio_)),pca_df.
    ↪explained_variance_ratio_)
ax[1].bar(range(len(pca_df.explained_variance_ratio_)),pca_df.
    ↪explained_variance_ratio_.cumsum())
ax[0].set_xlabel('n components')
ax[0].set_ylabel('Explained variance ratio')
```

```

ax[1].set_xlabel('n components')
ax[1].set_ylabel('Cumulative explained variance ratio')
ax[1].axhline(0.882,c='r')
ax[1].text(0,0.8,'88.2%',c='r')
ax[1].axhline(0.564,c='pink')
ax[1].text(-0.9,0.48,'56.4%',c='pink')

ax[2].bar(range(len(pca_df.explained_variance_ratio_)),pca_df.
    ↪explained_variance_ratio_.cumsum())
ax[2].set_xlabel('n components')
ax[2].set_ylabel('Cumulative explained variance ratio')
ax[2].axhline(0.882,c='r')
ax[2].text(0,0.8,'88.2%',c='r')
ax[2].axhline(0.564,c='pink')
ax[2].text(-0.9,0.48,'56.4%',c='pink')
ax[2].set_xlim(-1,21)
plt.tight_layout()
plt.show()

```



This PCA fitting and explained variance ratio results verifies the author's results as well. The first three of PC explains 56.4% of the total variance and 20 PCs explains 88.2% of the total variance.

```
[69]: pca_df = PCA(n_components=20).fit(df_master.drop(columns='Target'))
```

```
[70]: X = pca_df.transform(df_master.drop(columns='Target'))
```

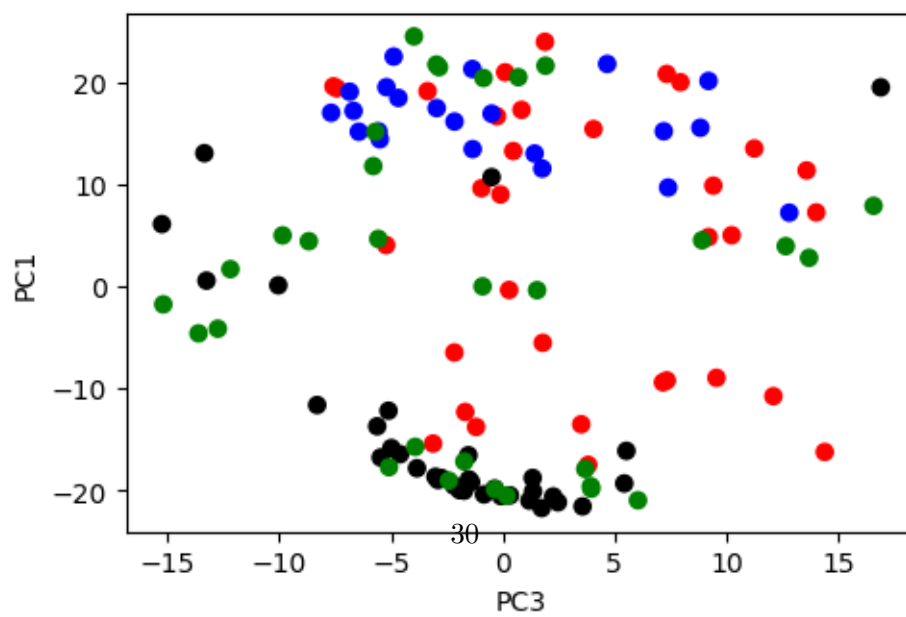
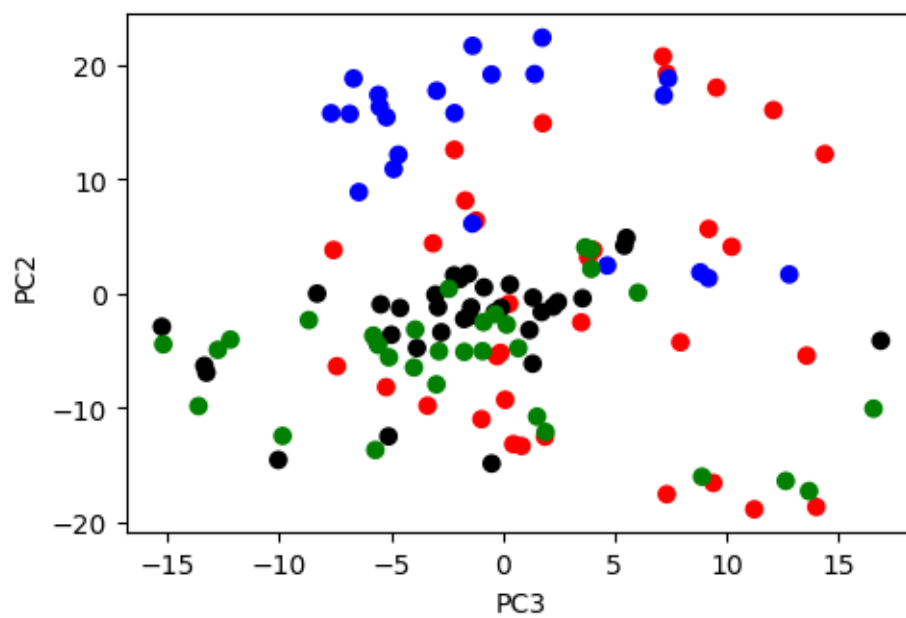
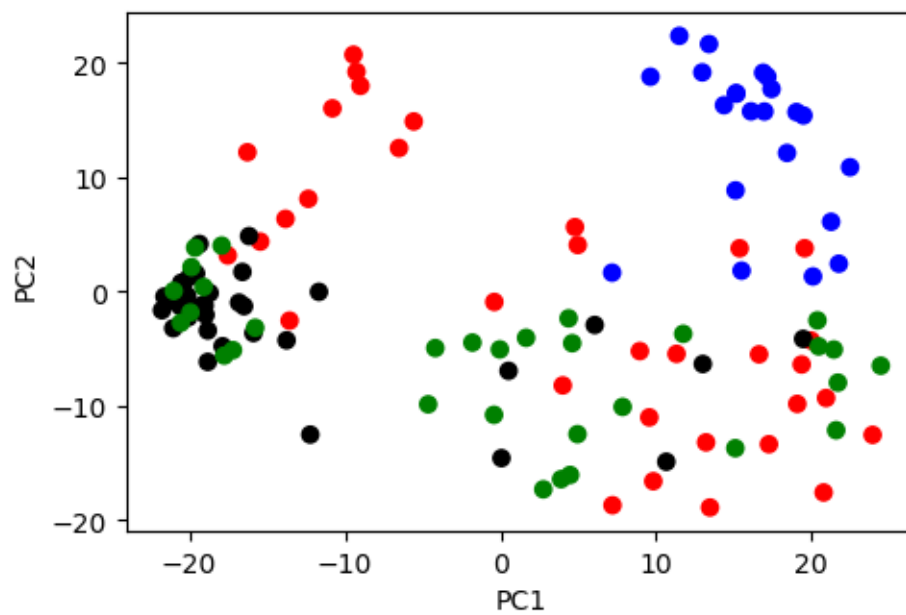
```
[71]: PC1 = X[:,0]
      PC2 = X[:,1]
      PC3 = X[:,2]

      fig, ax = plt.subplots(3,1,figsize=(5,10))
```

```

ax[0].scatter(PC1,PC2,c=df_master.iloc[:,-1].apply(lambda x: 'red' if x==0 else
↳'blue' if x==1 else 'black' if x==2 else 'green'))
ax[0].set_xlabel('PC1')
ax[0].set_ylabel('PC2')
ax[1].scatter(PC3,PC2,c=df_master.iloc[:,-1].apply(lambda x: 'red' if x==0 else
↳'blue' if x==1 else 'black' if x==2 else 'green'))
ax[1].set_xlabel('PC3')
ax[1].set_ylabel('PC2')
ax[2].scatter(PC3,PC1,c=df_master.iloc[:,-1].apply(lambda x: 'red' if x==0 else
↳'blue' if x==1 else 'black' if x==2 else 'green'))
ax[2].set_xlabel('PC3')
ax[2].set_ylabel('PC1')
plt.tight_layout()
plt.show()

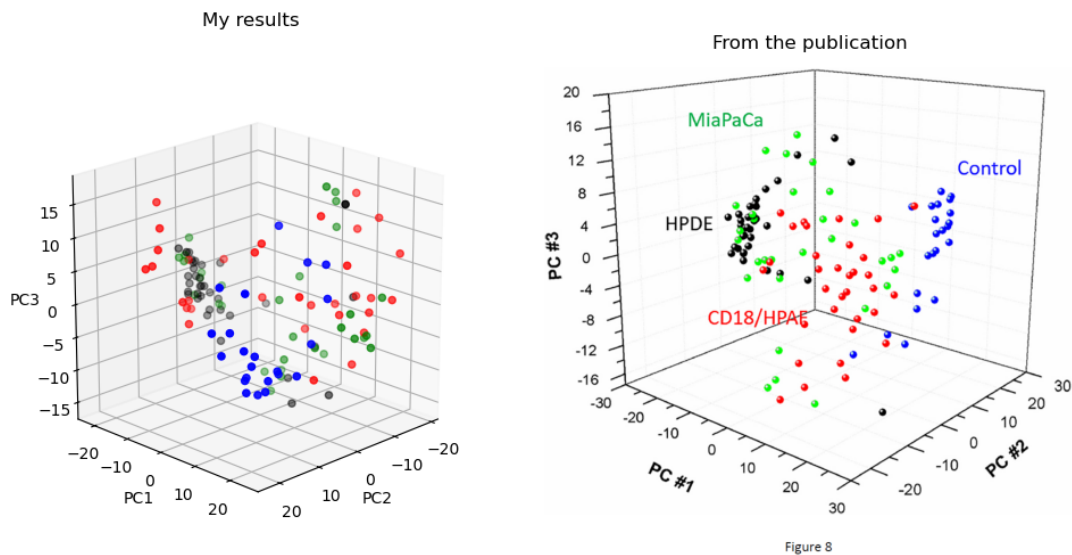
```



```
[72]: from PIL import Image

PC_fig = Image.open('Data\PC_fig.PNG')
fig = plt.figure(figsize=(10,10))
ax = fig.add_subplot(1,2,1,projection='3d')
ax.scatter(PC2,PC1,PC3,c=df_master.iloc[:,-1].apply(lambda x: 'red' if x==0_
    ↪else 'blue' if x==1 else 'black' if x==2 else 'green'))
ax.set(xlabel=('PC2'), ylabel=('PC1'), zlabel=('PC3'))
plt.tight_layout()
ax.set_box_aspect(aspect=(4,4,4), zoom=0.8)
ax.view_init(elev=20, azim=45)
ax.set_title('My results')

ax1 = fig.add_subplot(1,2,2)
ax1.imshow(PC_fig)
ax1.axis(False)
ax1.set_title('From the publication')
plt.show()
```



These plots do not seem to agree with the results in the paper. However, the explained variance ratio is perfectly matched, evidenced by their statistical variance description of PC#1, 2, and 3 corresponding to my results.

Now we can try LDA approach to compare the PC-DFA predictive results from the paper.

```
[73]: from sklearn.model_selection import train_test_split
#X_train, X_test, y_train, y_test = train_test_split(df_master.
↳ drop('Target',axis=1),df_master.Target,test_size=0.3,stratify=df_master.
↳ Target)
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.
↳ 3,stratify=y)
```

```
[74]: from sklearn.discriminant_analysis import LinearDiscriminantAnalysis

lda = LinearDiscriminantAnalysis()
lda_model = lda.fit(X_train,y_train.to_numpy().ravel())
score = lda_model.score(X_test,y_test.to_numpy().ravel())
print(score)
```

0.972972972972973

This accuracy is way better than the reported accuracy value. The author uses cross validation, which we will also do and will give more consistent and accurate picture.

```
[75]: from sklearn.model_selection import cross_val_score
from sklearn import metrics
from sklearn.model_selection import cross_val_predict
from sklearn.metrics import confusion_matrix
from sklearn.metrics import precision_recall_fscore_support

split = 24
scores = cross_val_score(lda, X, y.to_numpy().ravel(), cv=split)
print('cross-validation scores: ', scores)
print('mean cross-validation score: ', scores.mean())

y_pred = cross_val_predict(lda, X, y.to_numpy().ravel(), cv=split)
conf_mat = confusion_matrix(y, y_pred,labels=[0,1,2,3])

res = []
for l in [0,1,2,3]:
    prec,recall,_,_ = precision_recall_fscore_support(y.to_numpy().ravel()==l,
                                                    y_pred==l)
    res.append([l,recall[0],recall[1]])

statistics_df = pd.DataFrame(res,columns =_
↳ ['class','specificity','sensitivity'])
statistics_df['label'] = statistics_df['class'].apply(lambda x: 'CD' if x==0_
↳ else 'GN' if x==1 else 'HPDE' if x==2 else 'MiaPaCa')

print('Specificity: \n', statistics_df[['label','specificity']])
```



```

print('Sensitivity: \n', statistics_df[['label','sensitivity']])
print('Overall Specificity: \n', statistics_df[['specificity']].mean())
print('Overall Sensitivity: \n', statistics_df[['sensitivity']].mean())

cm_display = metrics.ConfusionMatrixDisplay(confusion_matrix = conf_mat,
display_labels = statistics_df['label'].to_list())
cm_display.plot()
plt.show()

```

C:\Users\brian\Anaconda3\Lib\site-packages\sklearn\model_selection_split.py:737: UserWarning: The least populated class in y has only 22 members, which is less than n_splits=24.

warnings.warn(

C:\Users\brian\Anaconda3\Lib\site-packages\sklearn\model_selection_split.py:737: UserWarning: The least populated class in y has only 22 members, which is less than n_splits=24.

warnings.warn(

cross-validation scores: [1. 1. 0.6 1. 1. 1. 0.8 1. 0.8 0.8 0.8 1. 1. 0.8 1. 1. 0.8 1.

0.8 0.8 1. 0.8 0.8 1.]

mean cross-validation score: 0.9

Specificity:

	label	specificity
0	CD	0.954545
1	GN	1.000000
2	HPDE	0.930233
3	MiaPaCa	0.977778

Sensitivity:

	label	sensitivity
0	CD	0.939394
1	GN	1.000000
2	HPDE	0.971429
3	MiaPaCa	0.709677

Overall Specificity:

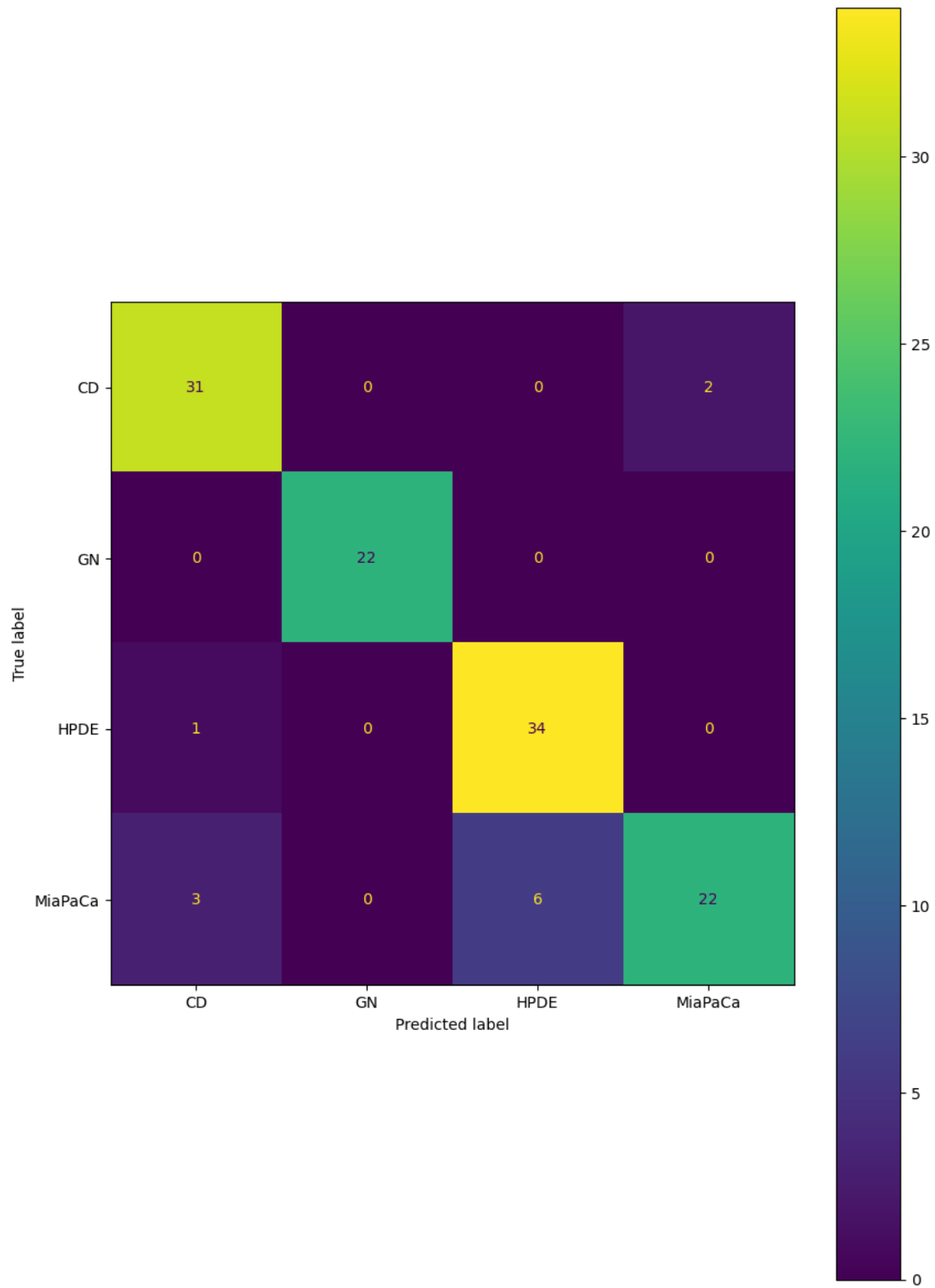
specificity	0.965639
-------------	----------

dtype: float64

Overall Sensitivity:

sensitivity	0.905125
-------------	----------

dtype: float64



It looks good. It reproduces the values for overall accuracy, specificity, and sensitivity. We can plot

the axis to compare.

```
[76]: X_lda = lda.fit_transform(X,y.to_numpy().ravel())

[77]: DA12_pubfig = Image.open('Data\DA12.PNG')
DA23_pubfig = Image.open('Data\DA23.PNG')
DA13_pubfig = Image.open('Data\DA13.PNG')

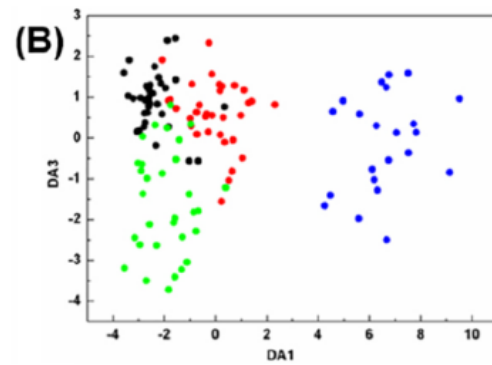
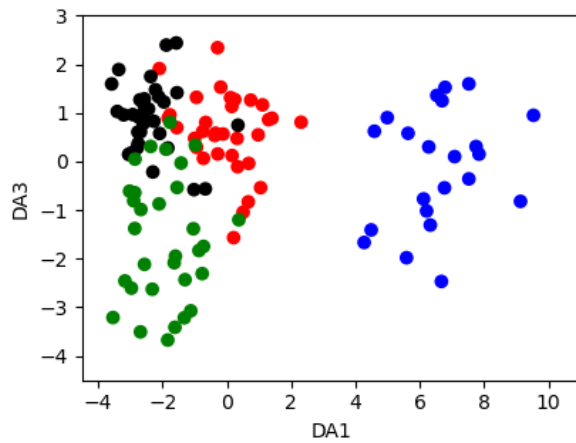
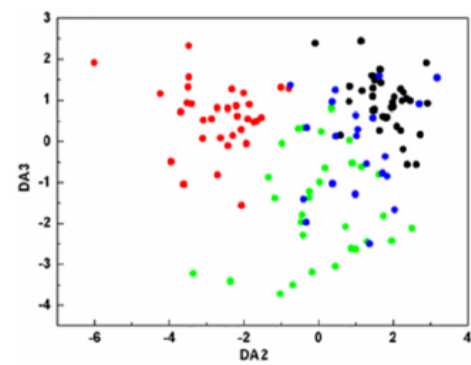
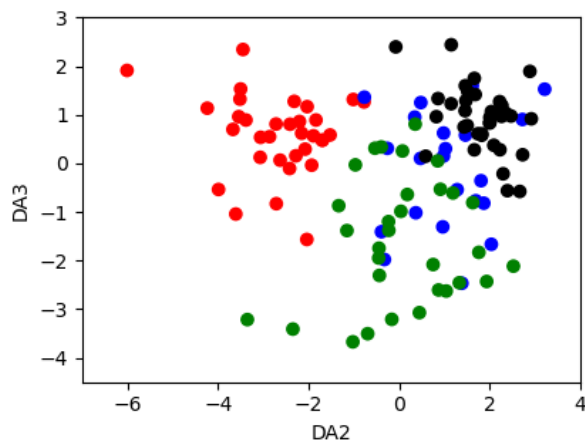
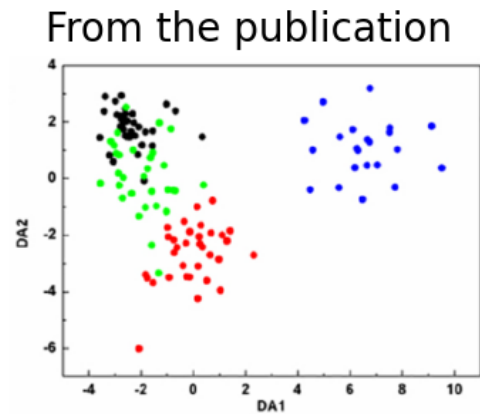
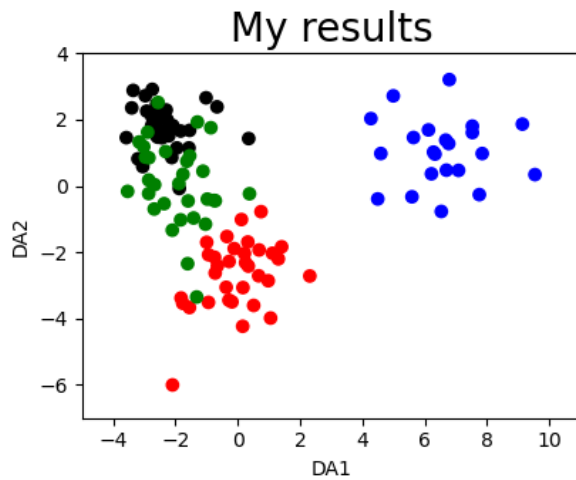
# multiplied by -1 just to reproduce and match their findings.
DA1 = X_lda[:,0]*-1
DA2 = X_lda[:,1]
DA3 = X_lda[:,2]

fig, ax = plt.subplots(3,2,figsize=(8,10))
ax[0,0].set_title('My results',fontsize=20)
ax[0,1].set_title('From the publication',fontsize=20)
ax[0,0].scatter(DA1,DA2,c=df_master.iloc[:,-1].apply(lambda x: 'red' if x==0_
↳else 'blue' if x==1 else 'black' if x==2 else 'green'))
ax[0,0].set_xlabel('DA1')
ax[0,0].set_ylabel('DA2')
ax[0,0].set_xlim(-5,11)
ax[0,0].set_ylim(-7,4)
ax[0,1].imshow(DA12_pubfig)
ax[0,1].axis('off')

ax[1,0].scatter(DA2,DA3,c=df_master.iloc[:,-1].apply(lambda x: 'red' if x==0_
↳else 'blue' if x==1 else 'black' if x==2 else 'green'))
ax[1,0].set_xlabel('DA2')
ax[1,0].set_ylabel('DA3')
ax[1,0].set_xlim(-7,4)
ax[1,0].set_ylim(-4.5,3)
ax[1,1].imshow(DA23_pubfig)
ax[1,1].axis('off')

ax[2,0].scatter(DA1,DA3,c=df_master.iloc[:,-1].apply(lambda x: 'red' if x==0_
↳else 'blue' if x==1 else 'black' if x==2 else 'green'))
ax[2,0].set_xlabel('DA1')
ax[2,0].set_ylabel('DA3')
ax[2,0].set_xlim(-4.5,11)
ax[2,0].set_ylim(-4.5,3)
ax[2,1].imshow(DA13_pubfig)
ax[2,1].axis('off')

plt.tight_layout()
plt.show()
```



```
[78]: DA123_pubfig = Image.open('Data\DA123.PNG')

fig = plt.figure(figsize=(10,10))
ax = fig.add_subplot(1,2,1,projection='3d')
```

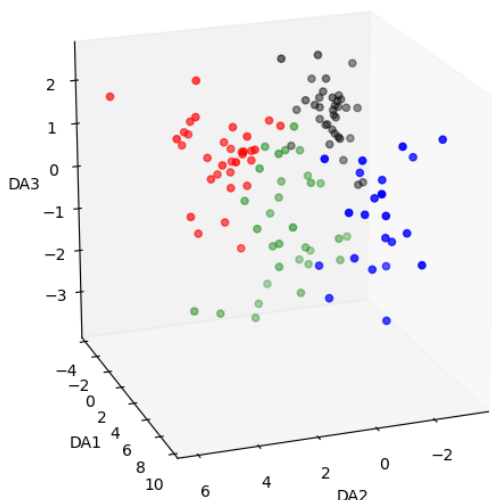
```

ax.scatter(DA2*-1,DA1,DA3,c=df_master.iloc[:, -1].apply(lambda x: 'red' if x==0
↳else 'blue' if x==1 else 'black' if x==2 else 'green'))
# multiplied by -1 just to reproduce and match their findings.
ax.set(xlabel=('DA2'), ylabel=('DA1'), zlabel=('DA3'))
plt.tight_layout()
ax.set_box_aspect(aspect=(4,4,4), zoom=1)
ax.view_init(elev=20, azim=70)
ax.grid(False)
ax.set_title('My results',fontsize=20)

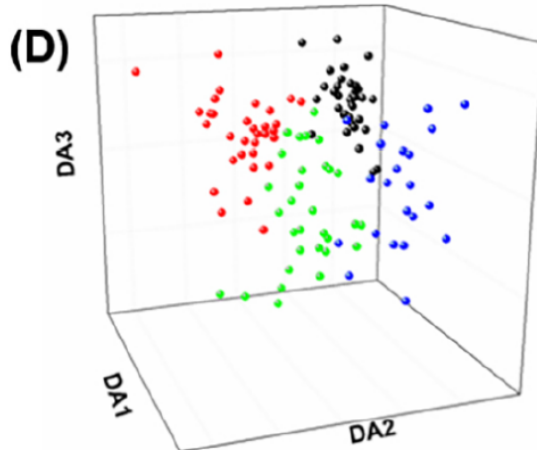
ax1 = fig.add_subplot(1,2,2)
ax1.imshow(DA123_pubfig)
ax1.axis(False)
ax1.set_title('From the publication',fontsize=20)
plt.show()

```

My results



From the publication



It looks like we can reproduce their results really well. It is bang on. Perfect.

I wonder what would LDA results give without using PCA since LDA also reduces dimension as well. We can find out.

```

[79]: X_train_noPCA, X_test_noPCA, y_train_noPCA, y_test_noPCA =
↳train_test_split(df_master.drop(columns=['Target']),y,test_size=0.3)

lda = LinearDiscriminantAnalysis()
lda_noPCA_model = lda.fit(X_train_noPCA,y_train_noPCA.to_numpy().ravel())
score = lda_noPCA_model.score(X_test_noPCA,y_test_noPCA.to_numpy().ravel())
print(score)

```

```
X_lda_noPCA = lda_noPCA_model.transform(df_master.drop(columns=['Target']))
```

0.8108108108108109

The accuracy is worse than the PCA-reduced one.

```
[80]: split=24

scores = cross_val_score(lda, df_master.drop(columns=['Target']), y.to_numpy().
    ↪ravel(), cv=split)
print('cross-validation scores: ', scores)
print('mean cross-validation score: ', scores.mean())

y_pred = cross_val_predict(lda, df_master.drop(columns=['Target']), y.
    ↪to_numpy().ravel(), cv=split)
conf_mat = confusion_matrix(y, y_pred)

res = []
for l in [0,1,2,3]:
    prec,recall,_,_ = precision_recall_fscore_support(y.to_numpy().ravel()==l,
    ↪y_pred==l)
    res.append([l,recall[0],recall[1]])

statistics_df = pd.DataFrame(res,columns =_
    ↪['class','specificity','sensitivity'])
statistics_df['label'] = statistics_df['class'].apply(lambda x: 'CD' if x==0_
    ↪else 'GN' if x==1 else 'HPDE' if x==2 else 'MiaPaCa')

print('Specificity: \n', statistics_df[['label','specificity']])
print('Sensitivity: \n', statistics_df[['label','sensitivity']])
print('Overall Specificity: \n', statistics_df[['specificity']].mean())
print('Overall Sensitivity: \n', statistics_df[['sensitivity']].mean())

cm_display = metrics.ConfusionMatrixDisplay(confusion_matrix = conf_mat,_
    ↪display_labels = statistics_df['label'].to_list())
cm_display.plot()
plt.show()
```

C:\Users\brian\Anaconda3\Lib\site-

packages\sklearn\model_selection_split.py:737: UserWarning: The least populated class in y has only 22 members, which is less than n_splits=24.

warnings.warn(

cross-validation scores: [0.83333333 0.6 1. 1. 1.
1.

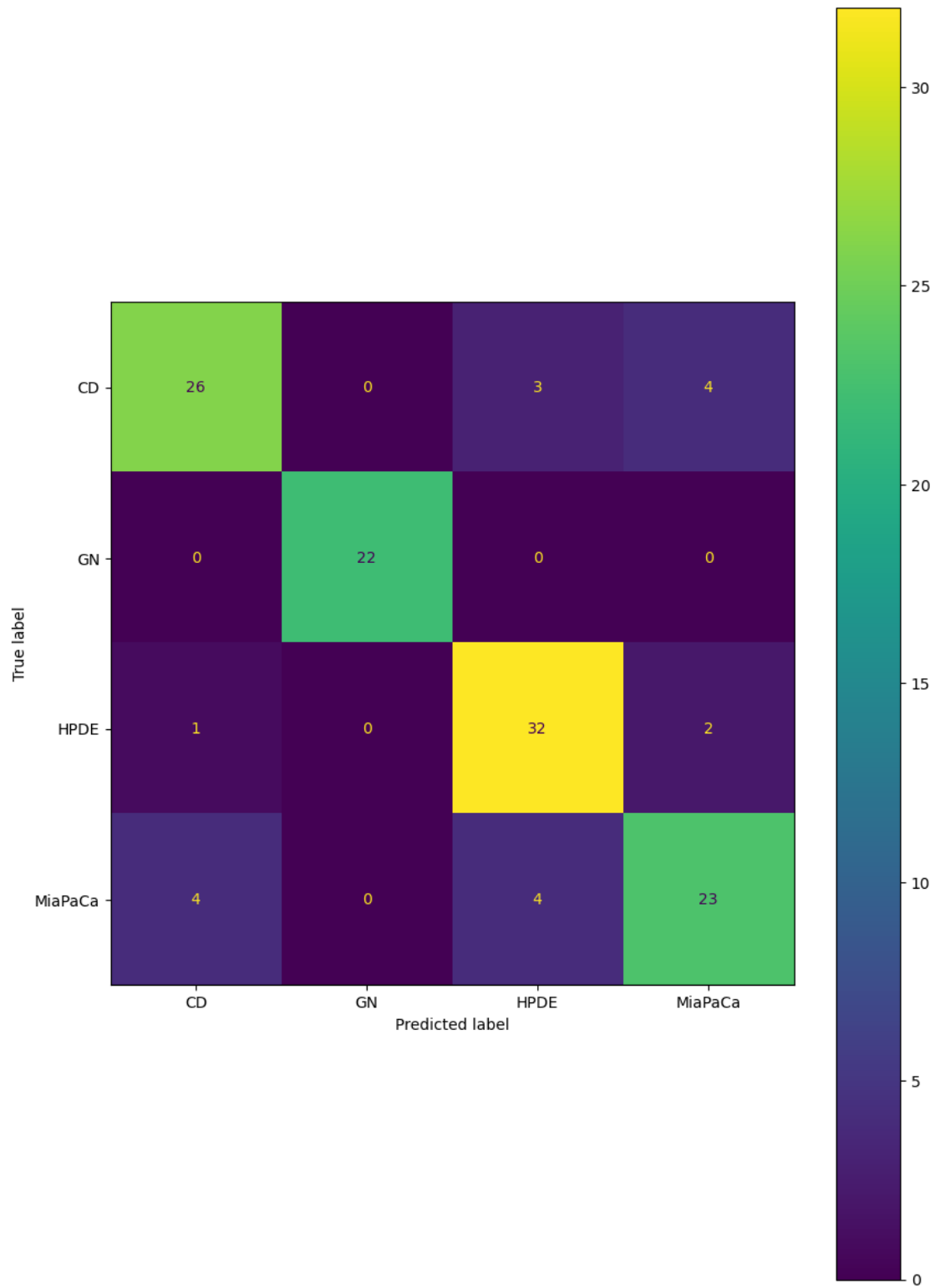
```

0.6      0.8      0.8      0.8      0.6      1.
0.8      0.8      0.8      1.      1.      0.8
0.6      1.      1.      1.      1.      0.6      ]
mean cross-validation score: 0.8513888888888889

C:\Users\brian\Anaconda3\Lib\site-
packages\sklearn\model_selection\_split.py:737: UserWarning: The least populated
class in y has only 22 members, which is less than n_splits=24.
  warnings.warn(

Specificity:
      label  specificity
0        CD    0.943182
1        GN    1.000000
2       HPDE    0.918605
3  MiaPaCa    0.933333
Sensitivity:
      label  sensitivity
0        CD    0.787879
1        GN    1.000000
2       HPDE    0.914286
3  MiaPaCa    0.741935
Overall Specificity:
      specificity    0.94878
dtype: float64
Overall Sensitivity:
      sensitivity    0.861025
dtype: float64

```



The cross-validation method also shows a worse results across the board.


```

[81]: DA1 = X_lda_noPCA[:,0]
      DA2 = X_lda_noPCA[:,1]
      DA3 = X_lda_noPCA[:,2]

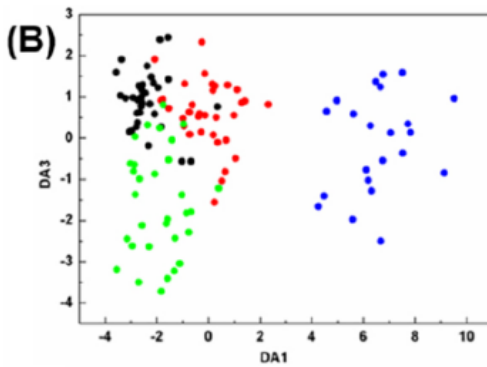
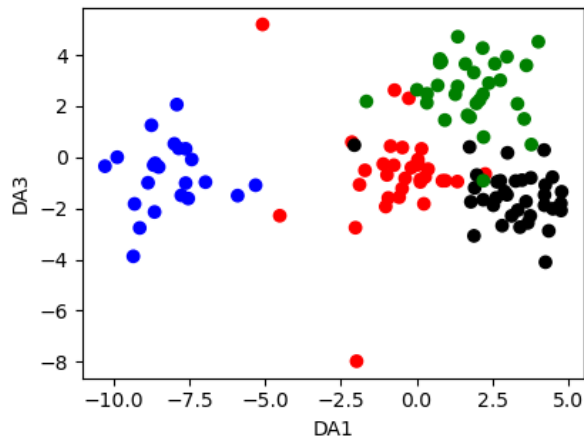
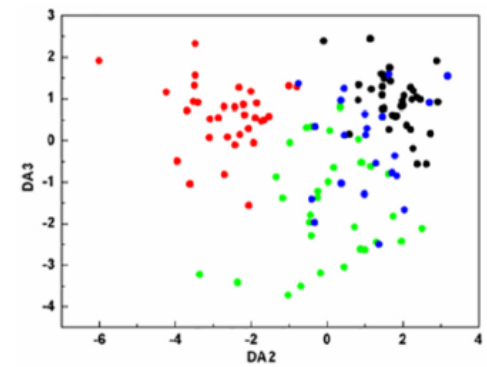
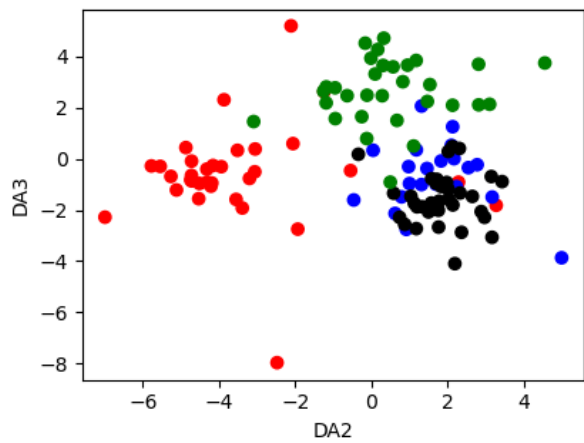
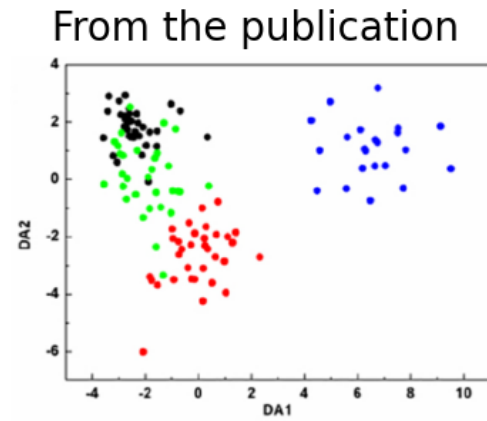
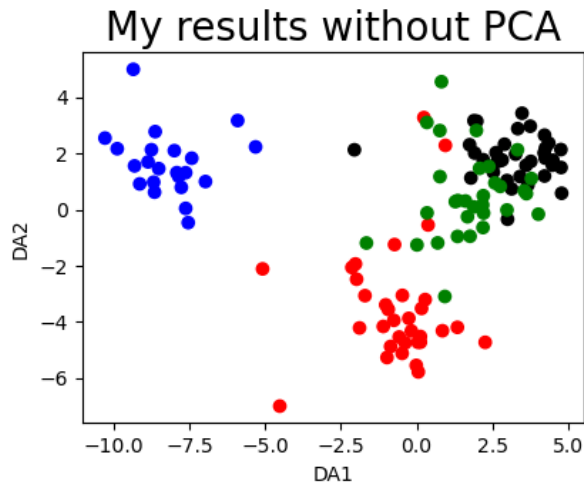
      fig, ax = plt.subplots(3,2,figsize=(8,10))
      ax[0,0].set_title('My results without PCA',fontsize=20)
      ax[0,1].set_title('From the publication',fontsize=20)
      ax[0,0].scatter(DA1,DA2*-1,c=df_master.iloc[:,-1].apply(lambda x: 'red' if x==0_
      ↪else 'blue' if x==1 else 'black' if x==2 else 'green'))
      ax[0,0].set_xlabel('DA1')
      ax[0,0].set_ylabel('DA2')
      ax[0,1].imshow(DA12_pubfig)
      ax[0,1].axis('off')

      ax[1,0].scatter(DA2*-1,DA3,c=df_master.iloc[:,-1].apply(lambda x: 'red' if x==0_
      ↪else 'blue' if x==1 else 'black' if x==2 else 'green'))
      ax[1,0].set_xlabel('DA2')
      ax[1,0].set_ylabel('DA3')
      ax[1,1].imshow(DA23_pubfig)
      ax[1,1].axis('off')

      ax[2,0].scatter(DA1,DA3,c=df_master.iloc[:,-1].apply(lambda x: 'red' if x==0_
      ↪else 'blue' if x==1 else 'black' if x==2 else 'green'))
      ax[2,0].set_xlabel('DA1')
      ax[2,0].set_ylabel('DA3')
      ax[2,1].imshow(DA13_pubfig)
      ax[2,1].axis('off')

      plt.tight_layout()
      plt.show()

```

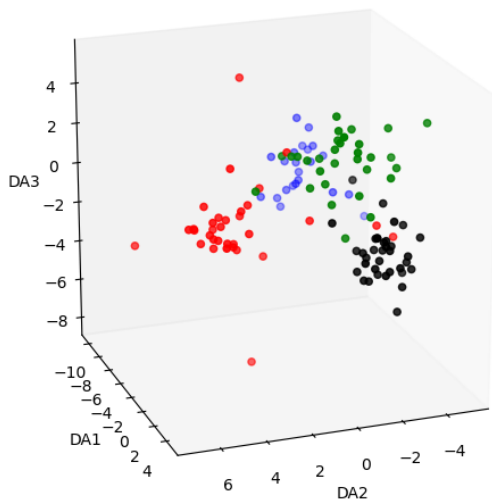


```
[82]: fig = plt.figure(figsize=(10,10))
ax = fig.add_subplot(1,2,1,projection='3d')
ax.scatter(DA2,DA1,DA3,c=df_master.iloc[:,-1].apply(lambda x: 'red' if x==0_
    ↪ else 'blue' if x==1 else 'black' if x==2 else 'green'))
ax.set(xlabel=('DA2'), ylabel=('DA1'), zlabel=('DA3'))
```

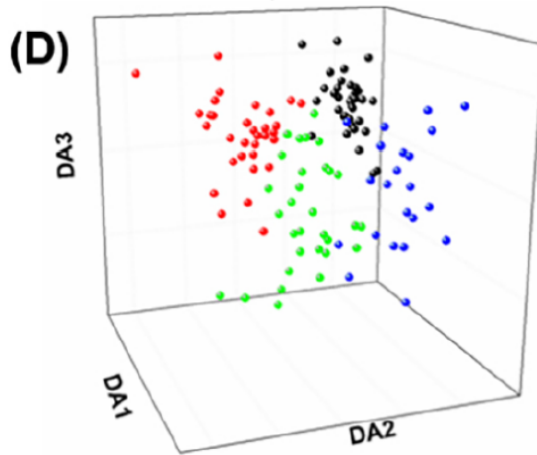
```
plt.tight_layout()
ax.set_box_aspect(aspect=(4,4,4), zoom=1)
ax.view_init(elev=20, azim=70)
ax.grid(False)
ax.set_title('My results without PCA',fontsize=20)

ax1 = fig.add_subplot(1,2,2)
ax1.imshow(DA123_pubfig)
ax1.axis(False)
ax1.set_title('From the publication',fontsize=20)
plt.show()
```

My results without PCA



From the publication



We can use different models to experiment whether we can increase the accuracy, specificity, and sensitivity.

```
[83]: from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV

rf = RandomForestClassifier()
param_grid = {
    'n_estimators': [10,100,200],
    'max_features': ["sqrt", "log2",None],
    'max_depth' : [1,2,3,4,5,6,7,8],
    'criterion' :['gini', 'entropy']
}

CV_rf = GridSearchCV(estimator=rf, param_grid=param_grid,cv=8)
```

```
CV_rf.fit(X_train, y_train.to_numpy().ravel())
CV_rf.best_params_
```

```
[83]: {'criterion': 'entropy',
      'max_depth': 5,
      'max_features': 'log2',
      'n_estimators': 100}
```

```
[84]: rf = RandomForestClassifier(n_estimators=CV_rf.best_params_['n_estimators'],
                                max_features=CV_rf.best_params_['max_features'],
                                max_depth=CV_rf.best_params_['max_depth'],
                                criterion=CV_rf.best_params_['criterion'])
rf.fit(X_train, y_train.to_numpy().ravel())
rf.score(X_test, y_test)
```

```
[84]: 0.8378378378378378
```

```
[85]: split = 21

scores = cross_val_score(rf, X, y.to_numpy().ravel(), cv=split)
print('cross-validation scores: ', scores)
print('mean cross-validation score: ', scores.mean())

y_pred = cross_val_predict(rf, X, y.to_numpy().ravel(), cv=split)
conf_mat = confusion_matrix(y, y_pred, labels=[0,1,2,3])

res = []
for l in [0,1,2,3]:
    prec, recall, _, _ = precision_recall_fscore_support(y.to_numpy().ravel()==l,
                                                         y_pred==l)
    res.append([l, recall[0], recall[1]])

statistics_df = pd.DataFrame(res, columns = [
    'class', 'specificity', 'sensitivity'])
statistics_df['label'] = statistics_df['class'].apply(lambda x: 'CD' if x==0
    else 'GN' if x==1 else 'HPDE' if x==2 else 'MiaPaCa')

print('Specificity: \n', statistics_df[['label', 'specificity']])
print('Sensitivity: \n', statistics_df[['label', 'sensitivity']])
print('Overall Specificity: \n', statistics_df[['specificity']].mean())
print('Overall Sensitivity: \n', statistics_df[['sensitivity']].mean())

cm_display = metrics.ConfusionMatrixDisplay(confusion_matrix = conf_mat,
    display_labels = statistics_df['label'].to_list())
```

```
cm_display.plot()  
plt.show()
```

```
cross-validation scores: [0.83333333 0.83333333 0.66666667 0.83333333  
0.66666667 1.
```

```
0.5      0.66666667 0.66666667 1.      0.83333333 0.66666667  
0.83333333 0.83333333 1.      0.66666667 0.8      0.8  
1.      0.6      0.6      ]
```

```
mean cross-validation score: 0.7761904761904762
```

```
Specificity:
```

	label	specificity
0	CD	0.886364
1	GN	1.000000
2	HPDE	0.953488
3	MiaPaCa	0.877778

```
Sensitivity:
```

	label	sensitivity
0	CD	0.787879
1	GN	0.863636
2	HPDE	0.800000
3	MiaPaCa	0.741935

```
Overall Specificity:
```

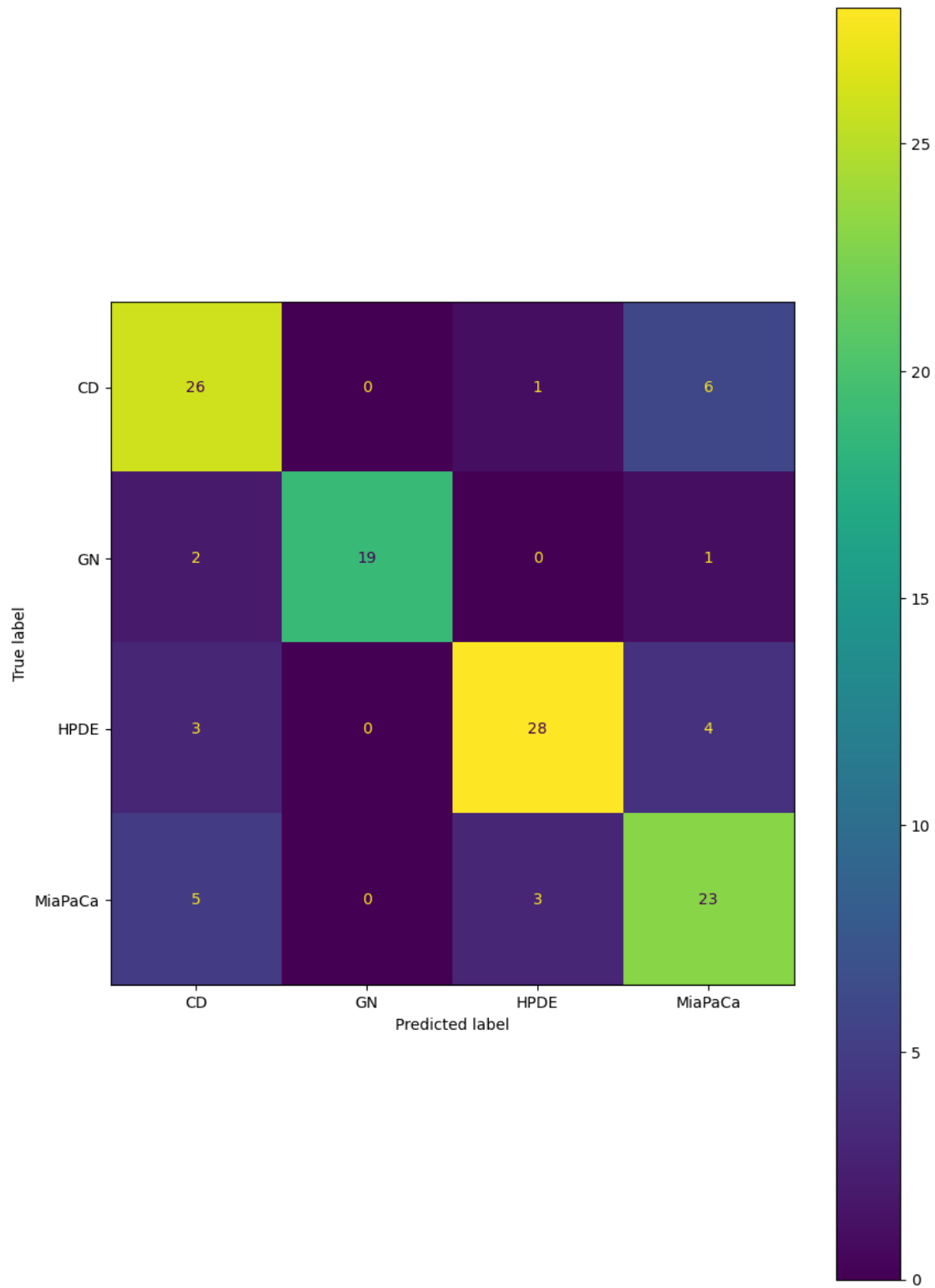
```
specificity    0.929407
```

```
dtype: float64
```

```
Overall Sensitivity:
```

```
sensitivity    0.798363
```

```
dtype: float64
```



The random forest classifier model does not score well. LDA seems to perform better with higher

accuracy and shorter latency.

```
[241]: rf = RandomForestClassifier(n_estimators=CV_rf.best_params_['n_estimators'],
                                max_features=CV_rf.best_params_['max_features'],
                                max_depth=CV_rf.best_params_['max_depth'],
                                criterion=CV_rf.best_params_['criterion'])
rf.fit(X_train_noPCA,y_train_noPCA.to_numpy().ravel())
rf.score(X_test_noPCA,y_test_noPCA.to_numpy().ravel())
```

```
[241]: 0.8108108108108109
```

```
[86]: split = 21

scores = cross_val_score(rf, df_master.drop(columns=['Target']), y.to_numpy().
    ↪ravel(), cv=split)
print('cross-validation scores: ', scores)
print('mean cross-validation score: ', scores.mean())

y_pred = cross_val_predict(rf, df_master.drop(columns=['Target']), y.to_numpy().
    ↪ravel(), cv=split)
conf_mat = confusion_matrix(y, y_pred, labels=[0,1,2,3])

res = []
for l in [0,1,2,3]:
    prec,recall,_,_ = precision_recall_fscore_support(y.to_numpy().ravel()==l,
    ↪y_pred==l)
    res.append([l,recall[0],recall[1]])

statistics_df = pd.DataFrame(res,columns =_
    ↪['class','specificity','sensitivity'])
statistics_df['label'] = statistics_df['class'].apply(lambda x: 'CD' if x==0_
    ↪else 'GN' if x==1 else 'HPDE' if x==2 else 'MiaPaCa')

print('Specificity: \n', statistics_df[['label','specificity']])
print('Sensitivity: \n', statistics_df[['label','sensitivity']])
print('Overall Specificity: \n', statistics_df[['specificity']].mean())
print('Overall Sensitivity: \n', statistics_df[['sensitivity']].mean())

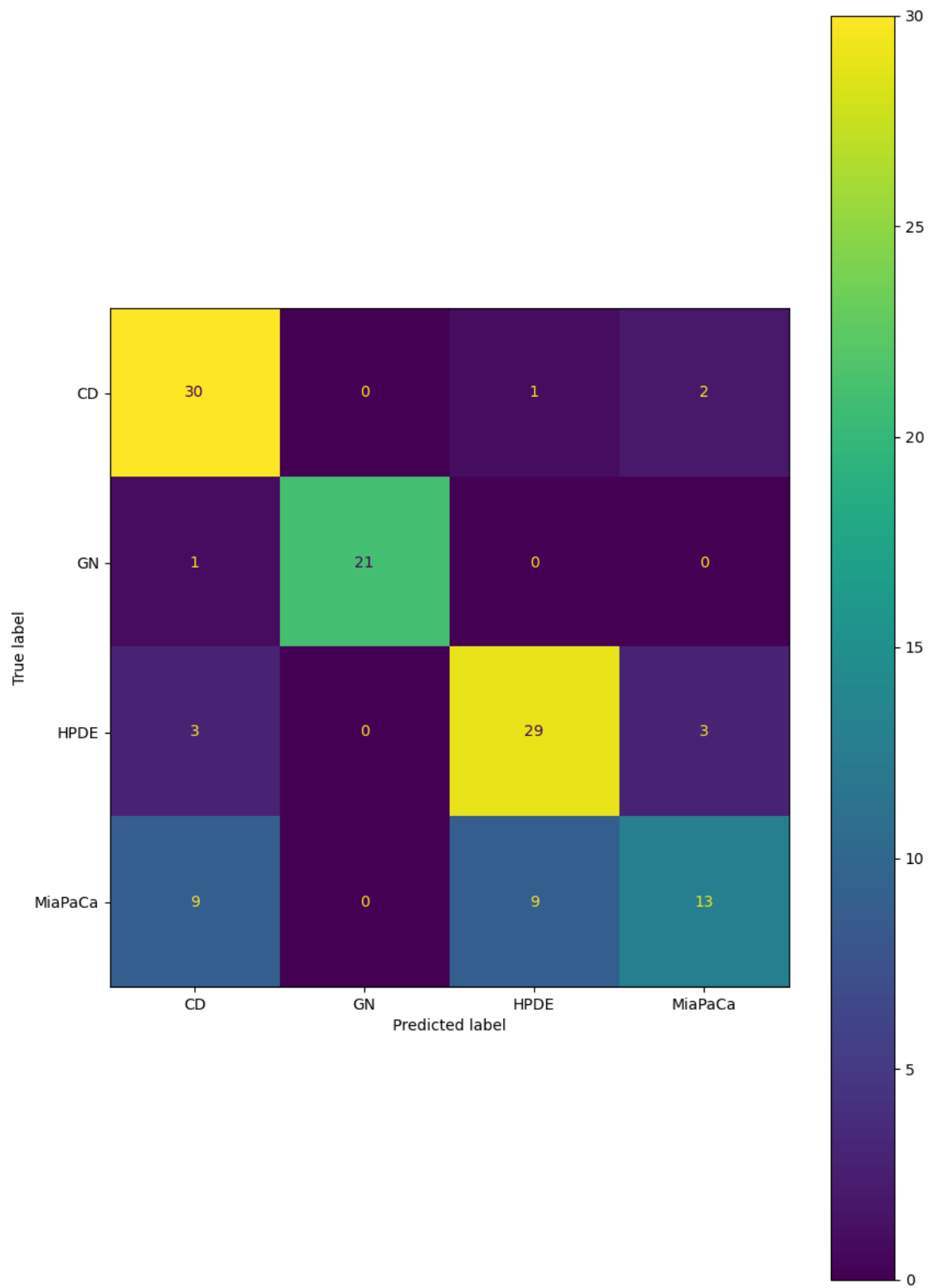
cm_display = metrics.ConfusionMatrixDisplay(confusion_matrix = conf_mat,_
    ↪display_labels = statistics_df['label'].to_list())
cm_display.plot()
plt.show()
```

```
cross-validation scores: [0.66666667 1.          0.83333333 1.]
```

```

0.66666667 1.
0.83333333 0.5          0.66666667 0.83333333 0.33333333 0.66666667
0.83333333 0.83333333 0.66666667 0.83333333 0.8          0.6
1.          1.          0.8          ]
mean cross-validation score: 0.7793650793650794
Specificity:
      label  specificity
0         CD    0.852273
1         GN    1.000000
2        HPDE    0.883721
3  MiaPaCa    0.944444
Sensitivity:
      label  sensitivity
0         CD    0.909091
1         GN    0.954545
2        HPDE    0.828571
3  MiaPaCa    0.419355
Overall Specificity:
      specificity    0.92011
dtype: float64
Overall Sensitivity:
      sensitivity    0.777891
dtype: float64

```

```
[87]: import torch
      from torch import nn
```

```
[88]: device = (
      "cuda"
      if torch.cuda.is_available()
      else "mps"
      if torch.backends.mps.is_available()
      else "cpu"
      )
      print(f"Using {device} device")
```

Using cpu device

```
[440]: class NeuralNetwork(nn.Module):
      def __init__(self):
          super().__init__()
          self.linear_relu_stack = nn.Sequential(
              nn.Linear(20, 30),
              nn.Linear(30, 30),
              nn.Linear(30, 10),
              nn.Linear(10, 4),
              nn.Softmax()
          )

      def forward(self, x):
          x = torch.from_numpy(x).to(torch.float32)
          logits = self.linear_relu_stack(x)
          return logits

def train_loop(X, y, model, epoch, batch, loss_fn, optimizer, printFn=True):
    model.train()

    y = turnYinto(y)
    y = torch.tensor(y).to(torch.float32)

    loss_plot = []
    plotx = []
    counter = 0
    for i in range(epoch):
        for k in range(X.shape[0]):
            # Compute prediction and loss
            pred = model(X[k,:])
            loss = loss_fn(pred, y[k])

            # Backpropagation
            loss.backward()
```

```

optimizer.step()
optimizer.zero_grad()
loss = loss.item()

if counter % 10 == 0 and printFn==True:
    print('\n')
    print('epoch {}: '.format(i))
    print('-'*100)
    print(f"{k}/{X.shape[0]} ----> loss: {loss:>7f}")
else:
    pass

loss_plot.append(loss)
counter += 1
plotx.append(counter)
if printFn==True:
    plt.plot(plotx,loss_plot)
    plt.xlabel('loss')
    plt.ylabel('iterations')
    plt.show()
else:
    pass
return loss, plotx

def testing(X_test,y_test,model,printFn=True):
    correct = 0
    preds = []
    for i in range(X_test.shape[0]):
        logits = model(X_test[i,:])
        pred_probab = nn.Softmax(dim=0)(logits)
        y_pred = pred_probab.argmax(0)
        preds.append(y_pred)
        if printFn==True:
            print(f"Predicted class: {y_pred}")
            print(f"Actual class: {y_test[i]}")
        else:
            pass
    t = y_test[i]
    t = int(t)
    if y_pred == t:
        correct += 1
    if printFn==True:
        print('accuracy: ', correct/(i+1))
        print('count: ', correct, '/', (i+1))
        print('-'*100, '\n')
    else:
        pass

```

```

        print('Accuracy: ', correct/(i+1))

    return correct/(i+1), preds

def turnYinto(y):
    try:
        Y = []
        for i in y.values:
            if i == 0:
                Y.append([1.0,0.0,0.0,0.0])
            elif i == 1:
                Y.append([0.0,1.0,0.0,0.0])
            elif i == 2:
                Y.append([0.0,0.0,1.0,0.0])
            else:
                Y.append([0.0,0.0,0.0,1.0])
        return np.array(Y)
    except:
        Y = []
        for i in y:
            if i == 0:
                Y.append([1.0,0.0,0.0,0.0])
            elif i == 1:
                Y.append([0.0,1.0,0.0,0.0])
            elif i == 2:
                Y.append([0.0,0.0,1.0,0.0])
            else:
                Y.append([0.0,0.0,0.0,1.0])
        return np.array(Y)

```

```

[306]: model = NeuralNetwork().to(device)
        print(model)

        learning_rate = 0.01
        epoch = 300
        batch = 11

        loss_fn = nn.CrossEntropyLoss()

        optimizer = torch.optim.SGD(model.parameters(), lr=learning_rate)

        loss_count, count = train_loop(X_train, y_train, model, epoch, batch, loss_fn,
        ↪optimizer, printFn=True)

```

NeuralNetwork(

```

(linear_relu_stack): Sequential(
  (0): Linear(in_features=20, out_features=30, bias=True)
  (1): Linear(in_features=30, out_features=30, bias=True)
  (2): Linear(in_features=30, out_features=10, bias=True)
  (3): Linear(in_features=10, out_features=4, bias=True)
  (4): Softmax(dim=None)
)
)

```

epoch 0:

```

-----
-----

```

0/84 ----> loss: 1.515288

epoch 0:

```

-----
-----

```

10/84 ----> loss: 1.426557

epoch 0:

```

-----
-----

```

20/84 ----> loss: 1.526613

epoch 0:

```

-----
-----

```

30/84 ----> loss: 1.291614

epoch 0:

```

-----
-----

```

40/84 ----> loss: 1.531961

epoch 0:

```

-----
-----

```

50/84 ----> loss: 1.310615

epoch 0:

```

-----
-----

```

```
-----  
60/84 ----> loss: 1.440917
```

```
epoch 0:
```

```
-----  
-----  
70/84 ----> loss: 1.088457
```

```
epoch 0:
```

```
-----  
-----  
80/84 ----> loss: 1.364361
```

```
epoch 1:
```

```
-----  
-----  
6/84 ----> loss: 1.049090
```

```
epoch 1:
```

```
-----  
-----  
16/84 ----> loss: 1.176778
```

```
epoch 1:
```

```
-----  
-----  
26/84 ----> loss: 1.135465
```

```
C:\Users\brian\Anaconda3\Lib\site-packages\torch\nn\modules\module.py:1518:  
UserWarning: Implicit dimension choice for softmax has been deprecated. Change  
the call to include dim=X as an argument.  
    return self._call_impl(*args, **kwargs)
```

```
epoch 1:
```

```
-----  
-----  
36/84 ----> loss: 1.017341
```

```
epoch 1:
```

46/84 ----> loss: 1.367784

epoch 1:

56/84 ----> loss: 1.288284

epoch 1:

66/84 ----> loss: 1.118008

epoch 1:

76/84 ----> loss: 1.096199

epoch 2:

2/84 ----> loss: 0.867312

epoch 2:

12/84 ----> loss: 0.812835

epoch 2:

22/84 ----> loss: 1.098505

epoch 2:

32/84 ----> loss: 1.630198

epoch 2:

42/84 ----> loss: 1.350734

epoch 2:

52/84 ----> loss: 0.797361

epoch 2:

62/84 ----> loss: 0.811508

epoch 2:

72/84 ----> loss: 0.788416

epoch 2:

82/84 ----> loss: 1.072305

epoch 3:

8/84 ----> loss: 1.440779

epoch 3:

18/84 ----> loss: 0.771015

epoch 3:

28/84 ----> loss: 1.212340

epoch 3:

38/84 ----> loss: 0.884953

epoch 3:

48/84 ----> loss: 0.765120

epoch 3:

58/84 ----> loss: 0.867796

epoch 3:

68/84 ----> loss: 0.818896

epoch 3:

78/84 ----> loss: 0.918123

epoch 4:

4/84 ----> loss: 0.777322

epoch 4:

14/84 ----> loss: 0.780414

epoch 4:

24/84 ----> loss: 0.806624

epoch 4:

34/84 ----> loss: 0.970118

epoch 4:

44/84 ----> loss: 1.337020

epoch 4:

54/84 ----> loss: 1.576498

epoch 4:

64/84 ----> loss: 1.367633

epoch 4:

74/84 ----> loss: 0.890826

epoch 5:

0/84 ----> loss: 0.749081

epoch 5:

10/84 ----> loss: 0.816943

epoch 5:

20/84 ----> loss: 0.752476

epoch 5:

30/84 ----> loss: 0.989824

epoch 5:

40/84 ----> loss: 0.870560

epoch 5:

50/84 ----> loss: 1.295663

epoch 5:

60/84 ----> loss: 1.232409

epoch 5:

70/84 ----> loss: 0.801703

epoch 5:

80/84 ----> loss: 0.761080

epoch 6:

6/84 ----> loss: 0.744013

epoch 6:

16/84 ----> loss: 0.746543

epoch 6:

26/84 ----> loss: 0.810548

epoch 6:

36/84 ----> loss: 0.789037

epoch 6:

46/84 ----> loss: 1.103470

epoch 6:

56/84 ----> loss: 0.820224

epoch 6:

66/84 ----> loss: 0.765625

epoch 6:

76/84 ----> loss: 0.802655

epoch 7:

2/84 ----> loss: 0.905642

epoch 7:

12/84 ----> loss: 0.776766

epoch 7:

22/84 ----> loss: 0.830703

epoch 7:

32/84 ----> loss: 0.773456

epoch 7:

42/84 ----> loss: 0.774894

epoch 7:

52/84 ----> loss: 0.842918

epoch 7:

62/84 ----> loss: 1.047609

epoch 7:

72/84 ----> loss: 0.799736

epoch 7:

82/84 ----> loss: 0.777673

epoch 8:

8/84 ----> loss: 0.949737

epoch 8:

18/84 ----> loss: 0.759061

epoch 8:

28/84 ----> loss: 0.756494

epoch 8:

38/84 ----> loss: 0.905860

epoch 8:

48/84 ----> loss: 0.745548

epoch 8:

58/84 ----> loss: 0.760533

epoch 8:

68/84 ----> loss: 0.771103

epoch 8:

78/84 ----> loss: 0.745941

epoch 9:

4/84 ----> loss: 0.778492

epoch 9:

14/84 ----> loss: 0.748566

epoch 9:

24/84 ----> loss: 0.748569

epoch 9:

34/84 ----> loss: 0.745317

epoch 9:

44/84 ----> loss: 0.769483

epoch 9:

54/84 ----> loss: 0.904303

epoch 9:

64/84 ----> loss: 0.781872

epoch 9:

74/84 ----> loss: 0.747088

epoch 10:

0/84 ----> loss: 0.743794

epoch 10:

10/84 ----> loss: 0.749549

epoch 10:

20/84 ----> loss: 0.745270

epoch 10:

30/84 ----> loss: 0.753164

epoch 10:

40/84 ----> loss: 0.745280

epoch 10:

50/84 ----> loss: 0.801919

epoch 10:

60/84 ----> loss: 0.869869

epoch 10:

70/84 ----> loss: 0.748270

epoch 10:

80/84 ----> loss: 0.746622

epoch 11:

6/84 ----> loss: 0.743686

epoch 11:

16/84 ----> loss: 0.743671

epoch 11:

26/84 ----> loss: 0.798232

epoch 11:

36/84 ----> loss: 0.744425

epoch 11:

46/84 ----> loss: 0.818172

epoch 11:

56/84 ----> loss: 0.752781

epoch 11:

66/84 ----> loss: 0.744523

epoch 11:

76/84 ----> loss: 0.744613

epoch 12:

2/84 ----> loss: 1.002750

epoch 12:

12/84 ----> loss: 0.745565

epoch 12:

22/84 ----> loss: 0.753274

epoch 12:

32/84 ----> loss: 0.744066

epoch 12:

42/84 ----> loss: 0.744975

epoch 12:

52/84 ----> loss: 0.887307

epoch 12:

62/84 ----> loss: 0.806701

epoch 12:

72/84 ----> loss: 0.800281

epoch 12:

82/84 ----> loss: 0.766243

epoch 13:

8/84 ----> loss: 0.843868

epoch 13:

18/84 ----> loss: 0.744517

epoch 13:

28/84 ----> loss: 0.748548

epoch 13:

38/84 ----> loss: 0.784753

epoch 13:

48/84 ----> loss: 0.743764

epoch 13:

58/84 ----> loss: 0.746929

epoch 13:

68/84 ----> loss: 0.748766

epoch 13:

78/84 ----> loss: 0.744128

epoch 14:

4/84 ----> loss: 0.762627

epoch 14:

14/84 ----> loss: 0.744179

epoch 14:

24/84 ----> loss: 0.744874

epoch 14:

34/84 ----> loss: 0.743877

epoch 14:

44/84 ----> loss: 0.747679

epoch 14:

54/84 ----> loss: 0.785609

epoch 14:

64/84 ----> loss: 0.770050

epoch 14:

74/84 ----> loss: 0.743859

epoch 15:

0/84 ----> loss: 0.743686

epoch 15:

10/84 ----> loss: 0.744832

epoch 15:

20/84 ----> loss: 0.744135

epoch 15:

30/84 ----> loss: 0.747662

epoch 15:

40/84 ----> loss: 0.744398

epoch 15:

50/84 ----> loss: 0.755160

epoch 15:

60/84 ----> loss: 0.766355

epoch 15:

70/84 ----> loss: 0.744642

epoch 15:

80/84 ----> loss: 0.745946

epoch 16:

6/84 ----> loss: 0.743669

epoch 16:

16/84 ----> loss: 0.743668

epoch 16:

26/84 ----> loss: 0.764953

epoch 16:

36/84 ----> loss: 0.743754

epoch 16:

46/84 ----> loss: 0.770743

epoch 16:

56/84 ----> loss: 0.749873

epoch 16:

66/84 ----> loss: 0.743943

epoch 16:

76/84 ----> loss: 0.743772

epoch 17:

2/84 ----> loss: 0.912008

epoch 17:

12/84 ----> loss: 0.744080

epoch 17:

22/84 ----> loss: 0.751738

epoch 17:

32/84 ----> loss: 0.743787

epoch 17:

42/84 ----> loss: 0.743806

epoch 17:

52/84 ----> loss: 0.843219

epoch 17:

62/84 ----> loss: 0.759445

epoch 17:

72/84 ----> loss: 0.800672

epoch 17:

82/84 ----> loss: 0.754952

epoch 18:

8/84 ----> loss: 0.774116

epoch 18:

18/84 ----> loss: 0.743930

epoch 18:

28/84 ----> loss: 0.747650

epoch 18:

38/84 ----> loss: 0.761381

epoch 18:

48/84 ----> loss: 0.743674

epoch 18:

58/84 ----> loss: 0.744990

epoch 18:

68/84 ----> loss: 0.744379

epoch 18:

78/84 ----> loss: 0.744266

epoch 19:

4/84 ----> loss: 0.752186

epoch 19:

14/84 ----> loss: 0.743788

epoch 19:

24/84 ----> loss: 0.744142

epoch 19:

34/84 ----> loss: 0.743703

epoch 19:

44/84 ----> loss: 0.744653

epoch 19:

54/84 ----> loss: 0.762302

epoch 19:

64/84 ----> loss: 0.770420

epoch 19:

74/84 ----> loss: 0.743685

epoch 20:

0/84 ----> loss: 0.743678

epoch 20:

10/84 ----> loss: 0.744480

epoch 20:

20/84 ----> loss: 0.743755

epoch 20:

30/84 ----> loss: 0.745936

epoch 20:

40/84 ----> loss: 0.744553

epoch 20:

50/84 ----> loss: 0.747090

epoch 20:

60/84 ----> loss: 0.749704

epoch 20:

70/84 ----> loss: 0.743919

epoch 20:

80/84 ----> loss: 0.746339

epoch 21:

6/84 ----> loss: 0.743668

epoch 21:

16/84 ----> loss: 0.743668

epoch 21:

26/84 ----> loss: 0.762492

epoch 21:

36/84 ----> loss: 0.743669

epoch 21:

46/84 ----> loss: 0.767848

epoch 21:

56/84 ----> loss: 0.747940

epoch 21:

66/84 ----> loss: 0.743722

epoch 21:

76/84 ----> loss: 0.743678

epoch 22:

2/84 ----> loss: 0.775496

epoch 22:

12/84 ----> loss: 0.743851

epoch 22:

22/84 ----> loss: 0.789736

epoch 22:

32/84 ----> loss: 0.743833

epoch 22:

42/84 ----> loss: 0.743788

epoch 22:

52/84 ----> loss: 0.762608

epoch 22:

62/84 ----> loss: 0.749240

epoch 22:

72/84 ----> loss: 0.788524

epoch 22:

82/84 ----> loss: 0.761246

epoch 23:

8/84 ----> loss: 0.768277

epoch 23:

18/84 ----> loss: 0.744028

epoch 23:

28/84 ----> loss: 0.746811

epoch 23:

38/84 ----> loss: 0.760911

epoch 23:

48/84 ----> loss: 0.743669

epoch 23:

58/84 ----> loss: 0.744884

epoch 23:

68/84 ----> loss: 0.743749

epoch 23:

78/84 ----> loss: 0.744343

epoch 24:

4/84 ----> loss: 0.751857

epoch 24:

14/84 ----> loss: 0.743675

epoch 24:

24/84 ----> loss: 0.759988

epoch 24:

34/84 ----> loss: 0.743672

epoch 24:

44/84 ----> loss: 0.744449

epoch 24:

54/84 ----> loss: 0.753391

epoch 24:

64/84 ----> loss: 0.755692

epoch 24:

74/84 ----> loss: 0.743676

epoch 25:

0/84 ----> loss: 0.743669

epoch 25:

10/84 ----> loss: 0.746666

epoch 25:

20/84 ----> loss: 0.743673

epoch 25:

30/84 ----> loss: 0.744625

epoch 25:

40/84 ----> loss: 0.743771

epoch 25:

50/84 ----> loss: 0.748623

epoch 25:

60/84 ----> loss: 0.747907

epoch 25:

70/84 ----> loss: 0.743948

epoch 25:

80/84 ----> loss: 0.747406

epoch 26:

6/84 ----> loss: 0.743668

epoch 26:

16/84 ----> loss: 0.743668

epoch 26:

26/84 ----> loss: 0.751272

epoch 26:

36/84 ----> loss: 0.743669

epoch 26:

46/84 ----> loss: 0.754729

epoch 26:

56/84 ----> loss: 0.747953

epoch 26:

66/84 ----> loss: 0.743683

epoch 26:

76/84 ----> loss: 0.743669

epoch 27:

2/84 ----> loss: 0.748525

epoch 27:

12/84 ----> loss: 0.743698

epoch 27:

22/84 ----> loss: 0.745317

epoch 27:

32/84 ----> loss: 0.745162

epoch 27:

42/84 ----> loss: 0.743992

epoch 27:

52/84 ----> loss: 0.824514

epoch 27:

62/84 ----> loss: 0.747996

epoch 27:

72/84 ----> loss: 0.788581

epoch 27:

82/84 ----> loss: 0.748589

epoch 28:

8/84 ----> loss: 0.758448

epoch 28:

18/84 ----> loss: 0.743819

epoch 28:

28/84 ----> loss: 0.752623

epoch 28:

38/84 ----> loss: 0.755763

epoch 28:

48/84 ----> loss: 0.743669

epoch 28:

58/84 ----> loss: 0.745053

epoch 28:

68/84 ----> loss: 0.743690

epoch 28:

78/84 ----> loss: 0.744677

epoch 29:

4/84 ----> loss: 0.747849

epoch 29:

14/84 ----> loss: 0.743669

epoch 29:

24/84 ----> loss: 0.745196

epoch 29:

34/84 ----> loss: 0.743669

epoch 29:

44/84 ----> loss: 0.743962

epoch 29:

54/84 ----> loss: 0.746298

epoch 29:

64/84 ----> loss: 0.753576

epoch 29:

74/84 ----> loss: 0.743671

epoch 30:

0/84 ----> loss: 0.743669

epoch 30:

10/84 ----> loss: 0.745812

epoch 30:

20/84 ----> loss: 0.743672

epoch 30:

30/84 ----> loss: 0.744263

epoch 30:

40/84 ----> loss: 0.743746

epoch 30:

50/84 ----> loss: 0.747162

epoch 30:

60/84 ----> loss: 0.754571

epoch 30:

70/84 ----> loss: 0.743797

epoch 30:

80/84 ----> loss: 0.744823

epoch 31:

6/84 ----> loss: 0.743668

epoch 31:

16/84 ----> loss: 0.743668

epoch 31:

26/84 ----> loss: 0.748575

epoch 31:

36/84 ----> loss: 0.743668

epoch 31:

46/84 ----> loss: 0.752297

epoch 31:

56/84 ----> loss: 0.746706

epoch 31:

66/84 ----> loss: 0.743674

epoch 31:

76/84 ----> loss: 0.743668

epoch 32:

2/84 ----> loss: 0.745584

epoch 32:

12/84 ----> loss: 0.743676

epoch 32:

22/84 ----> loss: 0.743821

epoch 32:

32/84 ----> loss: 0.744746

epoch 32:

42/84 ----> loss: 0.743902

epoch 32:

52/84 ----> loss: 0.788267

epoch 32:

62/84 ----> loss: 0.748238

epoch 32:

72/84 ----> loss: 0.798503

epoch 32:

82/84 ----> loss: 0.746308

epoch 33:

8/84 ----> loss: 0.753751

epoch 33:

18/84 ----> loss: 0.743730

epoch 33:

28/84 ----> loss: 0.746500

epoch 33:

38/84 ----> loss: 0.750057

epoch 33:

48/84 ----> loss: 0.743669

epoch 33:

58/84 ----> loss: 0.744883

epoch 33:

68/84 ----> loss: 0.743678

epoch 33:

78/84 ----> loss: 0.744860

epoch 34:

4/84 ----> loss: 0.746628

epoch 34:

14/84 ----> loss: 0.743669

epoch 34:

24/84 ----> loss: 0.744732

epoch 34:

34/84 ----> loss: 0.743669

epoch 34:

44/84 ----> loss: 0.743780

epoch 34:

54/84 ----> loss: 0.745588

epoch 34:

64/84 ----> loss: 0.751267

epoch 34:

74/84 ----> loss: 0.743670

epoch 35:

0/84 ----> loss: 0.743668

epoch 35:

10/84 ----> loss: 0.745568

epoch 35:

20/84 ----> loss: 0.743671

epoch 35:

30/84 ----> loss: 0.744035

epoch 35:

40/84 ----> loss: 0.743741

epoch 35:

50/84 ----> loss: 0.746209

epoch 35:

60/84 ----> loss: 0.749714

epoch 35:

70/84 ----> loss: 0.743753

epoch 35:

80/84 ----> loss: 0.744282

epoch 36:

6/84 ----> loss: 0.743668

epoch 36:

16/84 ----> loss: 0.743668

epoch 36:

26/84 ----> loss: 0.747323

epoch 36:

36/84 ----> loss: 0.743668

epoch 36:

46/84 ----> loss: 0.750026

epoch 36:

56/84 ----> loss: 0.745754

epoch 36:

66/84 ----> loss: 0.743671

epoch 36:

76/84 ----> loss: 0.743668

epoch 37:

2/84 ----> loss: 0.744839

epoch 37:

12/84 ----> loss: 0.743672

epoch 37:

22/84 ----> loss: 0.743727

epoch 37:

32/84 ----> loss: 0.744316

epoch 37:

42/84 ----> loss: 0.743788

epoch 37:

52/84 ----> loss: 0.767104

epoch 37:

62/84 ----> loss: 0.746909

epoch 37:

72/84 ----> loss: 0.792168

epoch 37:

82/84 ----> loss: 0.745383

epoch 38:

8/84 ----> loss: 0.751281

epoch 38:

18/84 ----> loss: 0.743705

epoch 38:

28/84 ----> loss: 0.744671

epoch 38:

38/84 ----> loss: 0.747960

epoch 38:

48/84 ----> loss: 0.743668

epoch 38:

58/84 ----> loss: 0.744640

epoch 38:

68/84 ----> loss: 0.743672

epoch 38:

78/84 ----> loss: 0.745169

epoch 39:

4/84 ----> loss: 0.745834

epoch 39:

14/84 ----> loss: 0.743669

epoch 39:

24/84 ----> loss: 0.744406

epoch 39:

34/84 ----> loss: 0.743669

epoch 39:

44/84 ----> loss: 0.743716

epoch 39:

54/84 ----> loss: 0.745362

epoch 39:

64/84 ----> loss: 0.748960

epoch 39:

74/84 ----> loss: 0.743669

epoch 40:

0/84 ----> loss: 0.743668

epoch 40:

10/84 ----> loss: 0.745551

epoch 40:

20/84 ----> loss: 0.743670

epoch 40:

30/84 ----> loss: 0.743895

epoch 40:

40/84 ----> loss: 0.743752

epoch 40:

50/84 ----> loss: 0.745560

epoch 40:

60/84 ----> loss: 0.747504

epoch 40:

70/84 ----> loss: 0.743724

epoch 40:

80/84 ----> loss: 0.744064

epoch 41:

6/84 ----> loss: 0.743668

epoch 41:

16/84 ----> loss: 0.743668

epoch 41:

26/84 ----> loss: 0.746585

epoch 41:

36/84 ----> loss: 0.743668

epoch 41:

46/84 ----> loss: 0.748522

epoch 41:

56/84 ----> loss: 0.745136

epoch 41:

66/84 ----> loss: 0.743670

epoch 41:

76/84 ----> loss: 0.743668

epoch 42:

2/84 ----> loss: 0.744620

epoch 42:

12/84 ----> loss: 0.743670

epoch 42:

22/84 ----> loss: 0.743708

epoch 42:

32/84 ----> loss: 0.744049

epoch 42:

42/84 ----> loss: 0.743735

epoch 42:

52/84 ----> loss: 0.756139

epoch 42:

62/84 ----> loss: 0.745466

epoch 42:

72/84 ----> loss: 0.777715

epoch 42:

82/84 ----> loss: 0.745010

epoch 43:

8/84 ----> loss: 0.750036

epoch 43:

18/84 ----> loss: 0.743699

epoch 43:

28/84 ----> loss: 0.744134

epoch 43:

38/84 ----> loss: 0.746883

epoch 43:

48/84 ----> loss: 0.743668

epoch 43:

58/84 ----> loss: 0.744432

epoch 43:

68/84 ----> loss: 0.743670

epoch 43:

78/84 ----> loss: 0.745144

epoch 44:

4/84 ----> loss: 0.745209

epoch 44:

14/84 ----> loss: 0.743668

epoch 44:

24/84 ----> loss: 0.744174

epoch 44:

34/84 ----> loss: 0.743669

epoch 44:

44/84 ----> loss: 0.743691

epoch 44:

54/84 ----> loss: 0.745217

epoch 44:

64/84 ----> loss: 0.746992

epoch 44:

74/84 ----> loss: 0.743669

epoch 45:

0/84 ----> loss: 0.743668

epoch 45:

10/84 ----> loss: 0.745228

epoch 45:

20/84 ----> loss: 0.743670

epoch 45:

30/84 ----> loss: 0.743813

epoch 45:

40/84 ----> loss: 0.743764

epoch 45:

50/84 ----> loss: 0.745167

epoch 45:

60/84 ----> loss: 0.746318

epoch 45:

70/84 ----> loss: 0.743703

epoch 45:

80/84 ----> loss: 0.743959

epoch 46:

6/84 ----> loss: 0.743668

epoch 46:

16/84 ----> loss: 0.743668

epoch 46:

26/84 ----> loss: 0.745956

epoch 46:

36/84 ----> loss: 0.743668

epoch 46:

46/84 ----> loss: 0.747368

epoch 46:

56/84 ----> loss: 0.744769

epoch 46:

66/84 ----> loss: 0.743670

epoch 46:

76/84 ----> loss: 0.743668

epoch 47:

2/84 ----> loss: 0.744539

epoch 47:

12/84 ----> loss: 0.743670

epoch 47:

22/84 ----> loss: 0.743701

epoch 47:

32/84 ----> loss: 0.743909

epoch 47:

42/84 ----> loss: 0.743711

epoch 47:

52/84 ----> loss: 0.752266

epoch 47:

62/84 ----> loss: 0.744732

epoch 47:

72/84 ----> loss: 0.767587

epoch 47:

82/84 ----> loss: 0.744832

epoch 48:

8/84 ----> loss: 0.748961

epoch 48:

18/84 ----> loss: 0.743695

epoch 48:

28/84 ----> loss: 0.743945

epoch 48:

38/84 ----> loss: 0.746219

epoch 48:

48/84 ----> loss: 0.743668

epoch 48:

58/84 ----> loss: 0.744292

epoch 48:

68/84 ----> loss: 0.743669

epoch 48:

78/84 ----> loss: 0.744904

epoch 49:

4/84 ----> loss: 0.744839

epoch 49:

14/84 ----> loss: 0.743668

epoch 49:

24/84 ----> loss: 0.744057

epoch 49:

34/84 ----> loss: 0.743669

epoch 49:

44/84 ----> loss: 0.743681

epoch 49:

54/84 ----> loss: 0.745079

epoch 49:

64/84 ----> loss: 0.745971

epoch 49:

74/84 ----> loss: 0.743669

epoch 50:

0/84 ----> loss: 0.743668

epoch 50:

10/84 ----> loss: 0.744885

epoch 50:

20/84 ----> loss: 0.743669

epoch 50:

30/84 ----> loss: 0.743769

epoch 50:

40/84 ----> loss: 0.743771

epoch 50:

50/84 ----> loss: 0.744903

epoch 50:

60/84 ----> loss: 0.745615

epoch 50:

70/84 ----> loss: 0.743692

epoch 50:

80/84 ----> loss: 0.743892

epoch 51:

6/84 ----> loss: 0.743668

epoch 51:

16/84 ----> loss: 0.743668

epoch 51:

26/84 ----> loss: 0.745495

epoch 51:

36/84 ----> loss: 0.743668

epoch 51:

46/84 ----> loss: 0.746572

epoch 51:

56/84 ----> loss: 0.744534

epoch 51:

66/84 ----> loss: 0.743669

epoch 51:

76/84 ----> loss: 0.743668

epoch 52:

2/84 ----> loss: 0.744458

epoch 52:

12/84 ----> loss: 0.743670

epoch 52:

22/84 ----> loss: 0.743697

epoch 52:

32/84 ----> loss: 0.743836

epoch 52:

42/84 ----> loss: 0.743698

epoch 52:

52/84 ----> loss: 0.750607

epoch 52:

62/84 ----> loss: 0.744385

epoch 52:

72/84 ----> loss: 0.761799

epoch 52:

82/84 ----> loss: 0.744711

epoch 53:

8/84 ----> loss: 0.748038

epoch 53:

18/84 ----> loss: 0.743692

epoch 53:

28/84 ----> loss: 0.743857

epoch 53:

38/84 ----> loss: 0.745762

epoch 53:

48/84 ----> loss: 0.743668

epoch 53:

58/84 ----> loss: 0.744201

epoch 53:

68/84 ----> loss: 0.743669

epoch 53:

78/84 ----> loss: 0.744676

epoch 54:

4/84 ----> loss: 0.744617

epoch 54:

14/84 ----> loss: 0.743668

epoch 54:

24/84 ----> loss: 0.743993

epoch 54:

34/84 ----> loss: 0.743669

epoch 54:

44/84 ----> loss: 0.743676

epoch 54:

54/84 ----> loss: 0.744951

epoch 54:

64/84 ----> loss: 0.745431

epoch 54:

74/84 ----> loss: 0.743669

epoch 55:

0/84 ----> loss: 0.743668

epoch 55:

10/84 ----> loss: 0.744634

epoch 55:

20/84 ----> loss: 0.743669

epoch 55:

30/84 ----> loss: 0.743743

epoch 55:

40/84 ----> loss: 0.743774

epoch 55:

50/84 ----> loss: 0.744714

epoch 55:

60/84 ----> loss: 0.745184

epoch 55:

70/84 ----> loss: 0.743685

epoch 55:

80/84 ----> loss: 0.743845

epoch 56:

6/84 ----> loss: 0.743668

epoch 56:

16/84 ----> loss: 0.743668

epoch 56:

26/84 ----> loss: 0.745178

epoch 56:

36/84 ----> loss: 0.743668

epoch 56:

46/84 ----> loss: 0.746038

epoch 56:

56/84 ----> loss: 0.744376

epoch 56:

66/84 ----> loss: 0.743669

epoch 56:

76/84 ----> loss: 0.743668

epoch 57:

2/84 ----> loss: 0.744377

epoch 57:

12/84 ----> loss: 0.743669

epoch 57:

22/84 ----> loss: 0.743693

epoch 57:

32/84 ----> loss: 0.743795

epoch 57:

42/84 ----> loss: 0.743691

epoch 57:

52/84 ----> loss: 0.749651

epoch 57:

62/84 ----> loss: 0.744193

epoch 57:

72/84 ----> loss: 0.758177

epoch 57:

82/84 ----> loss: 0.744608

epoch 58:

8/84 ----> loss: 0.747328

epoch 58:

18/84 ----> loss: 0.743688

epoch 58:

28/84 ----> loss: 0.743807

epoch 58:

38/84 ----> loss: 0.745426

epoch 58:

48/84 ----> loss: 0.743668

epoch 58:

58/84 ----> loss: 0.744137

epoch 58:

68/84 ----> loss: 0.743669

epoch 58:

78/84 ----> loss: 0.744504

epoch 59:

4/84 ----> loss: 0.744468

epoch 59:

14/84 ----> loss: 0.743668

epoch 59:

24/84 ----> loss: 0.743954

epoch 59:

34/84 ----> loss: 0.743668

epoch 59:

44/84 ----> loss: 0.743674

epoch 59:

54/84 ----> loss: 0.744838

epoch 59:

64/84 ----> loss: 0.745103

epoch 59:

74/84 ----> loss: 0.743669

epoch 60:

0/84 ----> loss: 0.743668

epoch 60:

10/84 ----> loss: 0.744457

epoch 60:

20/84 ----> loss: 0.743669

epoch 60:

30/84 ----> loss: 0.743726

epoch 60:

40/84 ----> loss: 0.743774

epoch 60:

50/84 ----> loss: 0.744572

epoch 60:

60/84 ----> loss: 0.744900

epoch 60:

70/84 ----> loss: 0.743680

epoch 60:

80/84 ----> loss: 0.743811

epoch 61:

6/84 ----> loss: 0.743668

epoch 61:

16/84 ----> loss: 0.743668

epoch 61:

26/84 ----> loss: 0.744952

epoch 61:

36/84 ----> loss: 0.743668

epoch 61:

46/84 ----> loss: 0.745663

epoch 61:

56/84 ----> loss: 0.744262

epoch 61:

66/84 ----> loss: 0.743669

epoch 61:

76/84 ----> loss: 0.743668

epoch 62:

2/84 ----> loss: 0.744304

epoch 62:

12/84 ----> loss: 0.743669

epoch 62:

22/84 ----> loss: 0.743690

epoch 62:

32/84 ----> loss: 0.743768

epoch 62:

42/84 ----> loss: 0.743686

epoch 62:

52/84 ----> loss: 0.748991

epoch 62:

62/84 ----> loss: 0.744072

epoch 62:

72/84 ----> loss: 0.755704

epoch 62:

82/84 ----> loss: 0.744516

epoch 63:

8/84 ----> loss: 0.746792

epoch 63:

18/84 ----> loss: 0.743686

epoch 63:

28/84 ----> loss: 0.743775

epoch 63:

38/84 ----> loss: 0.745171

epoch 63:

48/84 ----> loss: 0.743668

epoch 63:

58/84 ----> loss: 0.744089

epoch 63:

68/84 ----> loss: 0.743669

epoch 63:

78/84 ----> loss: 0.744376

epoch 64:

4/84 ----> loss: 0.744360

epoch 64:

14/84 ----> loss: 0.743668

epoch 64:

24/84 ----> loss: 0.743926

epoch 64:

34/84 ----> loss: 0.743668

epoch 64:

44/84 ----> loss: 0.743672

epoch 64:

54/84 ----> loss: 0.744740

epoch 64:

64/84 ----> loss: 0.744883

epoch 64:

74/84 ----> loss: 0.743669

epoch 65:

0/84 ----> loss: 0.743668

epoch 65:

10/84 ----> loss: 0.744328

epoch 65:

20/84 ----> loss: 0.743669

epoch 65:

30/84 ----> loss: 0.743715

epoch 65:

40/84 ----> loss: 0.743773

epoch 65:

50/84 ----> loss: 0.744463

epoch 65:

60/84 ----> loss: 0.744701

epoch 65:

70/84 ----> loss: 0.743677

epoch 65:

80/84 ----> loss: 0.743785

epoch 66:

6/84 ----> loss: 0.743668

epoch 66:

16/84 ----> loss: 0.743668

epoch 66:

26/84 ----> loss: 0.744784

epoch 66:

36/84 ----> loss: 0.743668

epoch 66:

46/84 ----> loss: 0.745388

epoch 66:

56/84 ----> loss: 0.744177

epoch 66:

66/84 ----> loss: 0.743669

epoch 66:

76/84 ----> loss: 0.743668

epoch 67:

2/84 ----> loss: 0.744240

epoch 67:

12/84 ----> loss: 0.743669

epoch 67:

22/84 ----> loss: 0.743688

epoch 67:

32/84 ----> loss: 0.743749

epoch 67:

42/84 ----> loss: 0.743683

epoch 67:

52/84 ----> loss: 0.748488

epoch 67:

62/84 ----> loss: 0.743991

epoch 67:

72/84 ----> loss: 0.753913

epoch 67:

82/84 ----> loss: 0.744434

epoch 68:

8/84 ----> loss: 0.746380

epoch 68:

18/84 ----> loss: 0.743683

epoch 68:

28/84 ----> loss: 0.743753

epoch 68:

38/84 ----> loss: 0.744972

epoch 68:

48/84 ----> loss: 0.743668

epoch 68:

58/84 ----> loss: 0.744051

epoch 68:

68/84 ----> loss: 0.743669

epoch 68:

78/84 ----> loss: 0.744279

epoch 69:

4/84 ----> loss: 0.744277

epoch 69:

14/84 ----> loss: 0.743668

epoch 69:

24/84 ----> loss: 0.743904

epoch 69:

34/84 ----> loss: 0.743668

epoch 69:

44/84 ----> loss: 0.743671

epoch 69:

54/84 ----> loss: 0.744655

epoch 69:

64/84 ----> loss: 0.744724

epoch 69:

74/84 ----> loss: 0.743669

epoch 70:

0/84 ----> loss: 0.743668

epoch 70:

10/84 ----> loss: 0.744231

epoch 70:

20/84 ----> loss: 0.743669

epoch 70:

30/84 ----> loss: 0.743707

epoch 70:

40/84 ----> loss: 0.743771

epoch 70:

50/84 ----> loss: 0.744377

epoch 70:

60/84 ----> loss: 0.744555

epoch 70:

70/84 ----> loss: 0.743675

epoch 70:

80/84 ----> loss: 0.743766

epoch 71:

6/84 ----> loss: 0.743668

epoch 71:

16/84 ----> loss: 0.743668

epoch 71:

26/84 ----> loss: 0.744654

epoch 71:

36/84 ----> loss: 0.743668

epoch 71:

46/84 ----> loss: 0.745179

epoch 71:

56/84 ----> loss: 0.744112

epoch 71:

66/84 ----> loss: 0.743669

epoch 71:

76/84 ----> loss: 0.743668

epoch 72:

2/84 ----> loss: 0.744185

epoch 72:

12/84 ----> loss: 0.743669

epoch 72:

22/84 ----> loss: 0.743686

epoch 72:

32/84 ----> loss: 0.743736

epoch 72:

42/84 ----> loss: 0.743680

epoch 72:

52/84 ----> loss: 0.748081

epoch 72:

62/84 ----> loss: 0.743933

epoch 72:

72/84 ----> loss: 0.752560

epoch 72:

82/84 ----> loss: 0.744363

epoch 73:

8/84 ----> loss: 0.746056

epoch 73:

18/84 ----> loss: 0.743681

epoch 73:

28/84 ----> loss: 0.743738

epoch 73:

38/84 ----> loss: 0.744814

epoch 73:

48/84 ----> loss: 0.743668

epoch 73:

58/84 ----> loss: 0.744019

epoch 73:

68/84 ----> loss: 0.743669

epoch 73:

78/84 ----> loss: 0.744203

epoch 74:

4/84 ----> loss: 0.744211

epoch 74:

14/84 ----> loss: 0.743668

epoch 74:

24/84 ----> loss: 0.743887

epoch 74:

34/84 ----> loss: 0.743668

epoch 74:

44/84 ----> loss: 0.743670

epoch 74:

54/84 ----> loss: 0.744580

epoch 74:

64/84 ----> loss: 0.744603

epoch 74:

74/84 ----> loss: 0.743668

epoch 75:

0/84 ----> loss: 0.743668

epoch 75:

10/84 ----> loss: 0.744156

epoch 75:

20/84 ----> loss: 0.743669

epoch 75:

30/84 ----> loss: 0.743701

epoch 75:

40/84 ----> loss: 0.743768

epoch 75:

50/84 ----> loss: 0.744307

epoch 75:

60/84 ----> loss: 0.744444

epoch 75:

70/84 ----> loss: 0.743674

epoch 75:

80/84 ----> loss: 0.743751

epoch 76:

6/84 ----> loss: 0.743668

epoch 76:

16/84 ----> loss: 0.743668

epoch 76:

26/84 ----> loss: 0.744550

epoch 76:

36/84 ----> loss: 0.743668

epoch 76:

46/84 ----> loss: 0.745013

epoch 76:

56/84 ----> loss: 0.744060

epoch 76:

66/84 ----> loss: 0.743669

epoch 76:

76/84 ----> loss: 0.743668

epoch 77:

2/84 ----> loss: 0.744137

epoch 77:

12/84 ----> loss: 0.743669

epoch 77:

22/84 ----> loss: 0.743684

epoch 77:

32/84 ----> loss: 0.743726

epoch 77:

42/84 ----> loss: 0.743678

epoch 77:

52/84 ----> loss: 0.747741

epoch 77:

62/84 ----> loss: 0.743890

epoch 77:

72/84 ----> loss: 0.751503

epoch 77:

82/84 ----> loss: 0.744301

epoch 78:

8/84 ----> loss: 0.745797

epoch 78:

18/84 ----> loss: 0.743680

epoch 78:

28/84 ----> loss: 0.743727

epoch 78:

38/84 ----> loss: 0.744685

epoch 78:

48/84 ----> loss: 0.743668

epoch 78:

58/84 ----> loss: 0.743992

epoch 78:

68/84 ----> loss: 0.743669

epoch 78:

78/84 ----> loss: 0.744143

epoch 79:

4/84 ----> loss: 0.744158

epoch 79:

14/84 ----> loss: 0.743668

epoch 79:

24/84 ----> loss: 0.743872

epoch 79:

34/84 ----> loss: 0.743668

epoch 79:

44/84 ----> loss: 0.743670

epoch 79:

54/84 ----> loss: 0.744515

epoch 79:

64/84 ----> loss: 0.744508

epoch 79:

74/84 ----> loss: 0.743668

epoch 80:

0/84 ----> loss: 0.743668

epoch 80:

10/84 ----> loss: 0.744097

epoch 80:

20/84 ----> loss: 0.743669

epoch 80:

30/84 ----> loss: 0.743696

epoch 80:

40/84 ----> loss: 0.743765

epoch 80:

50/84 ----> loss: 0.744248

epoch 80:

60/84 ----> loss: 0.744357

epoch 80:

70/84 ----> loss: 0.743673

epoch 80:

80/84 ----> loss: 0.743740

epoch 81:

6/84 ----> loss: 0.743668

epoch 81:

16/84 ----> loss: 0.743668

epoch 81:

26/84 ----> loss: 0.744465

epoch 81:

36/84 ----> loss: 0.743668

epoch 81:

46/84 ----> loss: 0.744880

epoch 81:

56/84 ----> loss: 0.744018

epoch 81:

66/84 ----> loss: 0.743669

epoch 81:

76/84 ----> loss: 0.743668

epoch 82:

2/84 ----> loss: 0.744096

epoch 82:

12/84 ----> loss: 0.743669

epoch 82:

22/84 ----> loss: 0.743682

epoch 82:

32/84 ----> loss: 0.743718

epoch 82:

42/84 ----> loss: 0.743677

epoch 82:

52/84 ----> loss: 0.747451

epoch 82:

62/84 ----> loss: 0.743857

epoch 82:

72/84 ----> loss: 0.750657

epoch 82:

82/84 ----> loss: 0.744247

epoch 83:

8/84 ----> loss: 0.745586

epoch 83:

18/84 ----> loss: 0.743678

epoch 83:

28/84 ----> loss: 0.743718

epoch 83:

38/84 ----> loss: 0.744579

epoch 83:

48/84 ----> loss: 0.743668

epoch 83:

58/84 ----> loss: 0.743969

epoch 83:

68/84 ----> loss: 0.743669

epoch 83:

78/84 ----> loss: 0.744094

epoch 84:

4/84 ----> loss: 0.744113

epoch 84:

14/84 ----> loss: 0.743668

epoch 84:

24/84 ----> loss: 0.743860

epoch 84:

34/84 ----> loss: 0.743668

epoch 84:

44/84 ----> loss: 0.743670

epoch 84:

54/84 ----> loss: 0.744458

epoch 84:

64/84 ----> loss: 0.744431

epoch 84:

74/84 ----> loss: 0.743668

epoch 85:

0/84 ----> loss: 0.743668

epoch 85:

10/84 ----> loss: 0.744049

epoch 85:

20/84 ----> loss: 0.743669

epoch 85:

30/84 ----> loss: 0.743692

epoch 85:

40/84 ----> loss: 0.743762

epoch 85:

50/84 ----> loss: 0.744200

epoch 85:

60/84 ----> loss: 0.744287

epoch 85:

70/84 ----> loss: 0.743672

epoch 85:

80/84 ----> loss: 0.743731

epoch 86:

6/84 ----> loss: 0.743668

epoch 86:

16/84 ----> loss: 0.743668

epoch 86:

26/84 ----> loss: 0.744395

epoch 86:

36/84 ----> loss: 0.743668

epoch 86:

46/84 ----> loss: 0.744770

epoch 86:

56/84 ----> loss: 0.743983

epoch 86:

66/84 ----> loss: 0.743669

epoch 86:

76/84 ----> loss: 0.743668

epoch 87:

2/84 ----> loss: 0.744060

epoch 87:

12/84 ----> loss: 0.743669

epoch 87:

22/84 ----> loss: 0.743681

epoch 87:

32/84 ----> loss: 0.743712

epoch 87:

42/84 ----> loss: 0.743676

epoch 87:

52/84 ----> loss: 0.747198

epoch 87:

62/84 ----> loss: 0.743831

epoch 87:

72/84 ----> loss: 0.749965

epoch 87:

82/84 ----> loss: 0.744200

epoch 88:

8/84 ----> loss: 0.745410

epoch 88:

18/84 ----> loss: 0.743677

epoch 88:

28/84 ----> loss: 0.743711

epoch 88:

38/84 ----> loss: 0.744490

epoch 88:

48/84 ----> loss: 0.743668

epoch 88:

58/84 ----> loss: 0.743948

epoch 88:

68/84 ----> loss: 0.743669

epoch 88:

78/84 ----> loss: 0.744054

epoch 89:

4/84 ----> loss: 0.744075

epoch 89:

14/84 ----> loss: 0.743668

epoch 89:

24/84 ----> loss: 0.743849

epoch 89:

34/84 ----> loss: 0.743668

epoch 89:

44/84 ----> loss: 0.743669

epoch 89:

54/84 ----> loss: 0.744408

epoch 89:

64/84 ----> loss: 0.744367

epoch 89:

74/84 ----> loss: 0.743668

epoch 90:

0/84 ----> loss: 0.743668

epoch 90:

10/84 ----> loss: 0.744009

epoch 90:

20/84 ----> loss: 0.743669

epoch 90:

30/84 ----> loss: 0.743689

epoch 90:

40/84 ----> loss: 0.743759

epoch 90:

50/84 ----> loss: 0.744158

epoch 90:

60/84 ----> loss: 0.744229

epoch 90:

70/84 ----> loss: 0.743671

epoch 90:

80/84 ----> loss: 0.743723

epoch 91:

6/84 ----> loss: 0.743668

epoch 91:

16/84 ----> loss: 0.743668

epoch 91:

26/84 ----> loss: 0.744335

epoch 91:

36/84 ----> loss: 0.743668

epoch 91:

46/84 ----> loss: 0.744678

epoch 91:

56/84 ----> loss: 0.743953

epoch 91:

66/84 ----> loss: 0.743669

epoch 91:

76/84 ----> loss: 0.743668

epoch 92:

2/84 ----> loss: 0.744028

epoch 92:

12/84 ----> loss: 0.743669

epoch 92:

22/84 ----> loss: 0.743679

epoch 92:

32/84 ----> loss: 0.743707

epoch 92:

42/84 ----> loss: 0.743675

epoch 92:

52/84 ----> loss: 0.746977

epoch 92:

62/84 ----> loss: 0.743810

epoch 92:

72/84 ----> loss: 0.749391

epoch 92:

82/84 ----> loss: 0.744159

epoch 93:

8/84 ----> loss: 0.745262

epoch 93:

18/84 ----> loss: 0.743676

epoch 93:

28/84 ----> loss: 0.743706

epoch 93:

38/84 ----> loss: 0.744415

epoch 93:

48/84 ----> loss: 0.743668

epoch 93:

58/84 ----> loss: 0.743930

epoch 93:

68/84 ----> loss: 0.743668

epoch 93:

78/84 ----> loss: 0.744020

epoch 94:

4/84 ----> loss: 0.744043

epoch 94:

14/84 ----> loss: 0.743668

epoch 94:

24/84 ----> loss: 0.743839

epoch 94:

34/84 ----> loss: 0.743668

epoch 94:

44/84 ----> loss: 0.743669

epoch 94:

54/84 ----> loss: 0.744362

epoch 94:

64/84 ----> loss: 0.744313

epoch 94:

74/84 ----> loss: 0.743668

epoch 95:

0/84 ----> loss: 0.743668

epoch 95:

10/84 ----> loss: 0.743976

epoch 95:

20/84 ----> loss: 0.743669

epoch 95:

30/84 ----> loss: 0.743687

epoch 95:

40/84 ----> loss: 0.743756

epoch 95:

50/84 ----> loss: 0.744122

epoch 95:

60/84 ----> loss: 0.744181

epoch 95:

70/84 ----> loss: 0.743671

epoch 95:

80/84 ----> loss: 0.743717

epoch 96:

6/84 ----> loss: 0.743668

epoch 96:

16/84 ----> loss: 0.743668

epoch 96:

26/84 ----> loss: 0.744284

epoch 96:

36/84 ----> loss: 0.743668

epoch 96:

46/84 ----> loss: 0.744600

epoch 96:

56/84 ----> loss: 0.743928

epoch 96:

66/84 ----> loss: 0.743669

epoch 96:

76/84 ----> loss: 0.743668

epoch 97:

2/84 ----> loss: 0.744001

epoch 97:

12/84 ----> loss: 0.743669

epoch 97:

22/84 ----> loss: 0.743678

epoch 97:

32/84 ----> loss: 0.743703

epoch 97:

42/84 ----> loss: 0.743674

epoch 97:

52/84 ----> loss: 0.746780

epoch 97:

62/84 ----> loss: 0.743793

epoch 97:

72/84 ----> loss: 0.748906

epoch 97:

82/84 ----> loss: 0.744122

epoch 98:

8/84 ----> loss: 0.745136

epoch 98:

18/84 ----> loss: 0.743675

epoch 98:

28/84 ----> loss: 0.743701

epoch 98:

38/84 ----> loss: 0.744351

epoch 98:

48/84 ----> loss: 0.743668

epoch 98:

58/84 ----> loss: 0.743914

epoch 98:

68/84 ----> loss: 0.743668

epoch 98:

78/84 ----> loss: 0.743991

epoch 99:

4/84 ----> loss: 0.744016

epoch 99:

14/84 ----> loss: 0.743668

epoch 99:

24/84 ----> loss: 0.743830

epoch 99:

34/84 ----> loss: 0.743668

epoch 99:

44/84 ----> loss: 0.743669

epoch 99:

54/84 ----> loss: 0.744322

epoch 99:

64/84 ----> loss: 0.744267

epoch 99:

74/84 ----> loss: 0.743668

epoch 100:

0/84 ----> loss: 0.743668

epoch 100:

10/84 ----> loss: 0.743948

epoch 100:

20/84 ----> loss: 0.743669

epoch 100:

30/84 ----> loss: 0.743685

epoch 100:

40/84 ----> loss: 0.743753

epoch 100:

50/84 ----> loss: 0.744090

epoch 100:

60/84 ----> loss: 0.744141

epoch 100:

70/84 ----> loss: 0.743670

epoch 100:

80/84 ----> loss: 0.743711

epoch 101:

6/84 ----> loss: 0.743668

epoch 101:

16/84 ----> loss: 0.743668

epoch 101:

26/84 ----> loss: 0.744240

epoch 101:

36/84 ----> loss: 0.743668

epoch 101:

46/84 ----> loss: 0.744532

epoch 101:

56/84 ----> loss: 0.743907

epoch 101:

66/84 ----> loss: 0.743669

epoch 101:

76/84 ----> loss: 0.743668

epoch 102:

2/84 ----> loss: 0.743977

epoch 102:

12/84 ----> loss: 0.743669

epoch 102:

22/84 ----> loss: 0.743677

epoch 102:

32/84 ----> loss: 0.743699

epoch 102:

42/84 ----> loss: 0.743673

epoch 102:

52/84 ----> loss: 0.746605

epoch 102:

62/84 ----> loss: 0.743779

epoch 102:

72/84 ----> loss: 0.748492

epoch 102:

82/84 ----> loss: 0.744091

epoch 103:

8/84 ----> loss: 0.745028

epoch 103:

18/84 ----> loss: 0.743675

epoch 103:

28/84 ----> loss: 0.743698

epoch 103:

38/84 ----> loss: 0.744296

epoch 103:

48/84 ----> loss: 0.743668

epoch 103:

58/84 ----> loss: 0.743899

epoch 103:

68/84 ----> loss: 0.743668

epoch 103:

78/84 ----> loss: 0.743966

epoch 104:

4/84 ----> loss: 0.743991

epoch 104:

14/84 ----> loss: 0.743668

epoch 104:

24/84 ----> loss: 0.743822

epoch 104:

34/84 ----> loss: 0.743668

epoch 104:

44/84 ----> loss: 0.743669

epoch 104:

54/84 ----> loss: 0.744286

epoch 104:

64/84 ----> loss: 0.744226

epoch 104:

74/84 ----> loss: 0.743668

epoch 105:

0/84 ----> loss: 0.743668

epoch 105:

10/84 ----> loss: 0.743924

epoch 105:

20/84 ----> loss: 0.743669

epoch 105:

30/84 ----> loss: 0.743683

epoch 105:

40/84 ----> loss: 0.743750

epoch 105:

50/84 ----> loss: 0.744063

epoch 105:

60/84 ----> loss: 0.744106

epoch 105:

70/84 ----> loss: 0.743670

epoch 105:

80/84 ----> loss: 0.743707

epoch 106:

6/84 ----> loss: 0.743668

epoch 106:

16/84 ----> loss: 0.743668

epoch 106:

26/84 ----> loss: 0.744202

epoch 106:

36/84 ----> loss: 0.743668

epoch 106:

46/84 ----> loss: 0.744474

epoch 106:

56/84 ----> loss: 0.743888

epoch 106:

66/84 ----> loss: 0.743669

epoch 106:

76/84 ----> loss: 0.743668

epoch 107:

2/84 ----> loss: 0.743955

epoch 107:

12/84 ----> loss: 0.743669

epoch 107:

22/84 ----> loss: 0.743677

epoch 107:

32/84 ----> loss: 0.743696

epoch 107:

42/84 ----> loss: 0.743673

epoch 107:

52/84 ----> loss: 0.746447

epoch 107:

62/84 ----> loss: 0.743768

epoch 107:

72/84 ----> loss: 0.748135

epoch 107:

82/84 ----> loss: 0.744062

epoch 108:

8/84 ----> loss: 0.744933

epoch 108:

18/84 ----> loss: 0.743674

epoch 108:

28/84 ----> loss: 0.743695

epoch 108:

38/84 ----> loss: 0.744248

epoch 108:

48/84 ----> loss: 0.743668

epoch 108:

58/84 ----> loss: 0.743886

epoch 108:

68/84 ----> loss: 0.743668

epoch 108:

78/84 ----> loss: 0.743945

epoch 109:

4/84 ----> loss: 0.743970

epoch 109:

14/84 ----> loss: 0.743668

epoch 109:

24/84 ----> loss: 0.743814

epoch 109:

34/84 ----> loss: 0.743668

epoch 109:

44/84 ----> loss: 0.743669

epoch 109:

54/84 ----> loss: 0.744253

epoch 109:

64/84 ----> loss: 0.744191

epoch 109:

74/84 ----> loss: 0.743668

epoch 110:

0/84 ----> loss: 0.743668

epoch 110:

10/84 ----> loss: 0.743904

epoch 110:

20/84 ----> loss: 0.743669

epoch 110:

30/84 ----> loss: 0.743682

epoch 110:

40/84 ----> loss: 0.743747

epoch 110:

50/84 ----> loss: 0.744038

epoch 110:

60/84 ----> loss: 0.744075

epoch 110:

70/84 ----> loss: 0.743670

epoch 110:

80/84 ----> loss: 0.743703

epoch 111:

6/84 ----> loss: 0.743668

epoch 111:

16/84 ----> loss: 0.743668

epoch 111:

26/84 ----> loss: 0.744168

epoch 111:

36/84 ----> loss: 0.743668

epoch 111:

46/84 ----> loss: 0.744422

epoch 111:

56/84 ----> loss: 0.743872

epoch 111:

66/84 ----> loss: 0.743669

epoch 111:

76/84 ----> loss: 0.743668

epoch 112:

2/84 ----> loss: 0.743936

epoch 112:

12/84 ----> loss: 0.743669

epoch 112:

22/84 ----> loss: 0.743676

epoch 112:

32/84 ----> loss: 0.743694

epoch 112:

42/84 ----> loss: 0.743672

epoch 112:

52/84 ----> loss: 0.746305

epoch 112:

62/84 ----> loss: 0.743758

epoch 112:

72/84 ----> loss: 0.747824

epoch 112:

82/84 ----> loss: 0.744037

epoch 113:

8/84 ----> loss: 0.744850

epoch 113:

18/84 ----> loss: 0.743674

epoch 113:

28/84 ----> loss: 0.743692

epoch 113:

38/84 ----> loss: 0.744206

epoch 113:

48/84 ----> loss: 0.743668

epoch 113:

58/84 ----> loss: 0.743874

epoch 113:

68/84 ----> loss: 0.743668

epoch 113:

78/84 ----> loss: 0.743926

epoch 114:

4/84 ----> loss: 0.743951

epoch 114:

14/84 ----> loss: 0.743668

epoch 114:

24/84 ----> loss: 0.743807

epoch 114:

34/84 ----> loss: 0.743668

epoch 114:

44/84 ----> loss: 0.743669

epoch 114:

54/84 ----> loss: 0.744223

epoch 114:

64/84 ----> loss: 0.744160

epoch 114:

74/84 ----> loss: 0.743668

epoch 115:

0/84 ----> loss: 0.743668

epoch 115:

10/84 ----> loss: 0.743886

epoch 115:

20/84 ----> loss: 0.743669

epoch 115:

30/84 ----> loss: 0.743681

epoch 115:

40/84 ----> loss: 0.743744

epoch 115:

50/84 ----> loss: 0.744017

epoch 115:

60/84 ----> loss: 0.744049

epoch 115:

70/84 ----> loss: 0.743670

epoch 115:

80/84 ----> loss: 0.743700

epoch 116:

6/84 ----> loss: 0.743668

epoch 116:

16/84 ----> loss: 0.743668

epoch 116:

26/84 ----> loss: 0.744138

epoch 116:

36/84 ----> loss: 0.743668

epoch 116:

46/84 ----> loss: 0.744377

epoch 116:

56/84 ----> loss: 0.743858

epoch 116:

66/84 ----> loss: 0.743669

epoch 116:

76/84 ----> loss: 0.743668

epoch 117:

2/84 ----> loss: 0.743919

epoch 117:

12/84 ----> loss: 0.743669

epoch 117:

22/84 ----> loss: 0.743675

epoch 117:

32/84 ----> loss: 0.743692

epoch 117:

42/84 ----> loss: 0.743672

epoch 117:

52/84 ----> loss: 0.746175

epoch 117:

62/84 ----> loss: 0.743750

epoch 117:

72/84 ----> loss: 0.747551

epoch 117:

82/84 ----> loss: 0.744015

epoch 118:

8/84 ----> loss: 0.744777

epoch 118:

18/84 ----> loss: 0.743673

epoch 118:

28/84 ----> loss: 0.743690

epoch 118:

38/84 ----> loss: 0.744169

epoch 118:

48/84 ----> loss: 0.743668

epoch 118:

58/84 ----> loss: 0.743864

epoch 118:

68/84 ----> loss: 0.743668

epoch 118:

78/84 ----> loss: 0.743910

epoch 119:

4/84 ----> loss: 0.743934

epoch 119:

14/84 ----> loss: 0.743668

epoch 119:

24/84 ----> loss: 0.743801

epoch 119:

34/84 ----> loss: 0.743668

epoch 119:

44/84 ----> loss: 0.743669

epoch 119:

54/84 ----> loss: 0.744196

epoch 119:

64/84 ----> loss: 0.744132

epoch 119:

74/84 ----> loss: 0.743668

epoch 120:

0/84 ----> loss: 0.743668

epoch 120:

10/84 ----> loss: 0.743870

epoch 120:

20/84 ----> loss: 0.743669

epoch 120:

30/84 ----> loss: 0.743680

epoch 120:

40/84 ----> loss: 0.743742

epoch 120:

50/84 ----> loss: 0.743997

epoch 120:

60/84 ----> loss: 0.744025

epoch 120:

70/84 ----> loss: 0.743669

epoch 120:

80/84 ----> loss: 0.743697

epoch 121:

6/84 ----> loss: 0.743668

epoch 121:

16/84 ----> loss: 0.743668

epoch 121:

26/84 ----> loss: 0.744111

epoch 121:

36/84 ----> loss: 0.743668

epoch 121:

46/84 ----> loss: 0.744336

epoch 121:

56/84 ----> loss: 0.743845

epoch 121:

66/84 ----> loss: 0.743669

epoch 121:

76/84 ----> loss: 0.743668

epoch 122:

2/84 ----> loss: 0.743904

epoch 122:

12/84 ----> loss: 0.743669

epoch 122:

22/84 ----> loss: 0.743675

epoch 122:

32/84 ----> loss: 0.743690

epoch 122:

42/84 ----> loss: 0.743672

epoch 122:

52/84 ----> loss: 0.746057

epoch 122:

62/84 ----> loss: 0.743742

epoch 122:

72/84 ----> loss: 0.747309

epoch 122:

82/84 ----> loss: 0.743994

epoch 123:

8/84 ----> loss: 0.744712

epoch 123:

18/84 ----> loss: 0.743673

epoch 123:

28/84 ----> loss: 0.743688

epoch 123:

38/84 ----> loss: 0.744136

epoch 123:

48/84 ----> loss: 0.743668

epoch 123:

58/84 ----> loss: 0.743854

epoch 123:

68/84 ----> loss: 0.743668

epoch 123:

78/84 ----> loss: 0.743895

epoch 124:

4/84 ----> loss: 0.743919

epoch 124:

14/84 ----> loss: 0.743668

epoch 124:

24/84 ----> loss: 0.743795

epoch 124:

34/84 ----> loss: 0.743668

epoch 124:

44/84 ----> loss: 0.743669

epoch 124:

54/84 ----> loss: 0.744171

epoch 124:

64/84 ----> loss: 0.744107

epoch 124:

74/84 ----> loss: 0.743668

epoch 125:

0/84 ----> loss: 0.743668

epoch 125:

10/84 ----> loss: 0.743856

epoch 125:

20/84 ----> loss: 0.743669

epoch 125:

30/84 ----> loss: 0.743679

epoch 125:

40/84 ----> loss: 0.743739

epoch 125:

50/84 ----> loss: 0.743980

epoch 125:

60/84 ----> loss: 0.744005

epoch 125:

70/84 ----> loss: 0.743669

epoch 125:

80/84 ----> loss: 0.743695

epoch 126:

6/84 ----> loss: 0.743668

epoch 126:

16/84 ----> loss: 0.743668

epoch 126:

26/84 ----> loss: 0.744086

epoch 126:

36/84 ----> loss: 0.743668

epoch 126:

46/84 ----> loss: 0.744300

epoch 126:

56/84 ----> loss: 0.743834

epoch 126:

66/84 ----> loss: 0.743668

epoch 126:

76/84 ----> loss: 0.743668

epoch 127:

2/84 ----> loss: 0.743890

epoch 127:

12/84 ----> loss: 0.743669

epoch 127:

22/84 ----> loss: 0.743674

epoch 127:

32/84 ----> loss: 0.743688

epoch 127:

42/84 ----> loss: 0.743671

epoch 127:

52/84 ----> loss: 0.745949

epoch 127:

62/84 ----> loss: 0.743736

epoch 127:

72/84 ----> loss: 0.747093

epoch 127:

82/84 ----> loss: 0.743976

epoch 128:

8/84 ----> loss: 0.744654

epoch 128:

18/84 ----> loss: 0.743672

epoch 128:

28/84 ----> loss: 0.743686

epoch 128:

38/84 ----> loss: 0.744106

epoch 128:

48/84 ----> loss: 0.743668

epoch 128:

58/84 ----> loss: 0.743845

epoch 128:

68/84 ----> loss: 0.743668

epoch 128:

78/84 ----> loss: 0.743882

epoch 129:

4/84 ----> loss: 0.743906

epoch 129:

14/84 ----> loss: 0.743668

epoch 129:

24/84 ----> loss: 0.743790

epoch 129:

34/84 ----> loss: 0.743668

epoch 129:

44/84 ----> loss: 0.743669

epoch 129:

54/84 ----> loss: 0.744149

epoch 129:

64/84 ----> loss: 0.744085

epoch 129:

74/84 ----> loss: 0.743668

epoch 130:

0/84 ----> loss: 0.743668

epoch 130:

10/84 ----> loss: 0.743843

epoch 130:

20/84 ----> loss: 0.743669

epoch 130:

30/84 ----> loss: 0.743678

epoch 130:

40/84 ----> loss: 0.743737

epoch 130:

50/84 ----> loss: 0.743964

epoch 130:

60/84 ----> loss: 0.743986

epoch 130:

70/84 ----> loss: 0.743669

epoch 130:

80/84 ----> loss: 0.743693

epoch 131:

6/84 ----> loss: 0.743668

epoch 131:

16/84 ----> loss: 0.743668

epoch 131:

26/84 ----> loss: 0.744065

epoch 131:

36/84 ----> loss: 0.743668

epoch 131:

46/84 ----> loss: 0.744267

epoch 131:

56/84 ----> loss: 0.743824

epoch 131:

66/84 ----> loss: 0.743668

epoch 131:

76/84 ----> loss: 0.743668

epoch 132:

2/84 ----> loss: 0.743877

epoch 132:

12/84 ----> loss: 0.743669

epoch 132:

22/84 ----> loss: 0.743674

epoch 132:

32/84 ----> loss: 0.743687

epoch 132:

42/84 ----> loss: 0.743671

epoch 132:

52/84 ----> loss: 0.745850

epoch 132:

62/84 ----> loss: 0.743731

epoch 132:

72/84 ----> loss: 0.746900

epoch 132:

82/84 ----> loss: 0.743959

epoch 133:

8/84 ----> loss: 0.744601

epoch 133:

18/84 ----> loss: 0.743672

epoch 133:

28/84 ----> loss: 0.743685

epoch 133:

38/84 ----> loss: 0.744080

epoch 133:

48/84 ----> loss: 0.743668

epoch 133:

58/84 ----> loss: 0.743836

epoch 133:

68/84 ----> loss: 0.743668

epoch 133:

78/84 ----> loss: 0.743870

epoch 134:

4/84 ----> loss: 0.743893

epoch 134:

14/84 ----> loss: 0.743668

epoch 134:

24/84 ----> loss: 0.743785

epoch 134:

34/84 ----> loss: 0.743668

epoch 134:

44/84 ----> loss: 0.743669

epoch 134:

54/84 ----> loss: 0.744128

epoch 134:

64/84 ----> loss: 0.744065

epoch 134:

74/84 ----> loss: 0.743668

epoch 135:

0/84 ----> loss: 0.743668

epoch 135:

10/84 ----> loss: 0.743832

epoch 135:

20/84 ----> loss: 0.743668

epoch 135:

30/84 ----> loss: 0.743677

epoch 135:

40/84 ----> loss: 0.743734

epoch 135:

50/84 ----> loss: 0.743949

epoch 135:

60/84 ----> loss: 0.743969

epoch 135:

70/84 ----> loss: 0.743669

epoch 135:

80/84 ----> loss: 0.743691

epoch 136:

6/84 ----> loss: 0.743668

epoch 136:

16/84 ----> loss: 0.743668

epoch 136:

26/84 ----> loss: 0.744045

epoch 136:

36/84 ----> loss: 0.743668

epoch 136:

46/84 ----> loss: 0.744237

epoch 136:

56/84 ----> loss: 0.743815

epoch 136:

66/84 ----> loss: 0.743668

epoch 136:

76/84 ----> loss: 0.743668

epoch 137:

2/84 ----> loss: 0.743866

epoch 137:

12/84 ----> loss: 0.743669

epoch 137:

22/84 ----> loss: 0.743674

epoch 137:

32/84 ----> loss: 0.743685

epoch 137:

42/84 ----> loss: 0.743671

epoch 137:

52/84 ----> loss: 0.745759

epoch 137:

62/84 ----> loss: 0.743726

epoch 137:

72/84 ----> loss: 0.746727

epoch 137:

82/84 ----> loss: 0.743944

epoch 138:

8/84 ----> loss: 0.744553

epoch 138:

18/84 ----> loss: 0.743672

epoch 138:

28/84 ----> loss: 0.743684

epoch 138:

38/84 ----> loss: 0.744056

epoch 138:

48/84 ----> loss: 0.743668

epoch 138:

58/84 ----> loss: 0.743829

epoch 138:

68/84 ----> loss: 0.743668

epoch 138:

78/84 ----> loss: 0.743859

epoch 139:

4/84 ----> loss: 0.743882

epoch 139:

14/84 ----> loss: 0.743668

epoch 139:

24/84 ----> loss: 0.743780

epoch 139:

34/84 ----> loss: 0.743668

epoch 139:

44/84 ----> loss: 0.743669

epoch 139:

54/84 ----> loss: 0.744108

epoch 139:

64/84 ----> loss: 0.744046

epoch 139:

74/84 ----> loss: 0.743668

epoch 140:

0/84 ----> loss: 0.743668

epoch 140:

10/84 ----> loss: 0.743822

epoch 140:

20/84 ----> loss: 0.743668

epoch 140:

30/84 ----> loss: 0.743677

epoch 140:

40/84 ----> loss: 0.743732

epoch 140:

50/84 ----> loss: 0.743936

epoch 140:

60/84 ----> loss: 0.743954

epoch 140:

70/84 ----> loss: 0.743669

epoch 140:

80/84 ----> loss: 0.743689

epoch 141:

6/84 ----> loss: 0.743668

epoch 141:

16/84 ----> loss: 0.743668

epoch 141:

26/84 ----> loss: 0.744027

epoch 141:

36/84 ----> loss: 0.743668

epoch 141:

46/84 ----> loss: 0.744210

epoch 141:

56/84 ----> loss: 0.743807

epoch 141:

66/84 ----> loss: 0.743668

epoch 141:

76/84 ----> loss: 0.743668

epoch 142:

2/84 ----> loss: 0.743855

epoch 142:

12/84 ----> loss: 0.743669

epoch 142:

22/84 ----> loss: 0.743673

epoch 142:

32/84 ----> loss: 0.743684

epoch 142:

42/84 ----> loss: 0.743671

epoch 142:

52/84 ----> loss: 0.745674

epoch 142:

62/84 ----> loss: 0.743722

epoch 142:

72/84 ----> loss: 0.746570

epoch 142:

82/84 ----> loss: 0.743930

epoch 143:

8/84 ----> loss: 0.744510

epoch 143:

18/84 ----> loss: 0.743671

epoch 143:

28/84 ----> loss: 0.743682

epoch 143:

38/84 ----> loss: 0.744035

epoch 143:

48/84 ----> loss: 0.743668

epoch 143:

58/84 ----> loss: 0.743822

epoch 143:

68/84 ----> loss: 0.743668

epoch 143:

78/84 ----> loss: 0.743850

epoch 144:

4/84 ----> loss: 0.743872

epoch 144:

14/84 ----> loss: 0.743668

epoch 144:

24/84 ----> loss: 0.743776

epoch 144:

34/84 ----> loss: 0.743668

epoch 144:

44/84 ----> loss: 0.743669

epoch 144:

54/84 ----> loss: 0.744090

epoch 144:

64/84 ----> loss: 0.744029

epoch 144:

74/84 ----> loss: 0.743668

epoch 145:

0/84 ----> loss: 0.743668

epoch 145:

10/84 ----> loss: 0.743813

epoch 145:

20/84 ----> loss: 0.743668

epoch 145:

30/84 ----> loss: 0.743676

epoch 145:

40/84 ----> loss: 0.743730

epoch 145:

50/84 ----> loss: 0.743924

epoch 145:

60/84 ----> loss: 0.743940

epoch 145:

70/84 ----> loss: 0.743669

epoch 145:

80/84 ----> loss: 0.743688

epoch 146:

6/84 ----> loss: 0.743668

epoch 146:

16/84 ----> loss: 0.743668

epoch 146:

26/84 ----> loss: 0.744010

epoch 146:

36/84 ----> loss: 0.743668

epoch 146:

46/84 ----> loss: 0.744186

epoch 146:

56/84 ----> loss: 0.743799

epoch 146:

66/84 ----> loss: 0.743668

epoch 146:

76/84 ----> loss: 0.743668

epoch 147:

2/84 ----> loss: 0.743846

epoch 147:

12/84 ----> loss: 0.743669

epoch 147:

22/84 ----> loss: 0.743673

epoch 147:

32/84 ----> loss: 0.743683

epoch 147:

42/84 ----> loss: 0.743670

epoch 147:

52/84 ----> loss: 0.745596

epoch 147:

62/84 ----> loss: 0.743718

epoch 147:

72/84 ----> loss: 0.746427

epoch 147:

82/84 ----> loss: 0.743918

epoch 148:

8/84 ----> loss: 0.744471

epoch 148:

18/84 ----> loss: 0.743671

epoch 148:

28/84 ----> loss: 0.743681

epoch 148:

38/84 ----> loss: 0.744015

epoch 148:

48/84 ----> loss: 0.743668

epoch 148:

58/84 ----> loss: 0.743815

epoch 148:

68/84 ----> loss: 0.743668

epoch 148:

78/84 ----> loss: 0.743841

epoch 149:

4/84 ----> loss: 0.743862

epoch 149:

14/84 ----> loss: 0.743668

epoch 149:

24/84 ----> loss: 0.743772

epoch 149:

34/84 ----> loss: 0.743668

epoch 149:

44/84 ----> loss: 0.743669

epoch 149:

54/84 ----> loss: 0.744074

epoch 149:

64/84 ----> loss: 0.744013

epoch 149:

74/84 ----> loss: 0.743668

epoch 150:

0/84 ----> loss: 0.743668

epoch 150:

10/84 ----> loss: 0.743805

epoch 150:

20/84 ----> loss: 0.743668

epoch 150:

30/84 ----> loss: 0.743676

epoch 150:

40/84 ----> loss: 0.743728

epoch 150:

50/84 ----> loss: 0.743913

epoch 150:

60/84 ----> loss: 0.743928

epoch 150:

70/84 ----> loss: 0.743669

epoch 150:

80/84 ----> loss: 0.743686

epoch 151:

6/84 ----> loss: 0.743668

epoch 151:

16/84 ----> loss: 0.743668

epoch 151:

26/84 ----> loss: 0.743995

epoch 151:

36/84 ----> loss: 0.743668

epoch 151:

46/84 ----> loss: 0.744163

epoch 151:

56/84 ----> loss: 0.743792

epoch 151:

66/84 ----> loss: 0.743668

epoch 151:

76/84 ----> loss: 0.743668

epoch 152:

2/84 ----> loss: 0.743837

epoch 152:

12/84 ----> loss: 0.743669

epoch 152:

22/84 ----> loss: 0.743672

epoch 152:

32/84 ----> loss: 0.743682

epoch 152:

42/84 ----> loss: 0.743670

epoch 152:

52/84 ----> loss: 0.745523

epoch 152:

62/84 ----> loss: 0.743714

epoch 152:

72/84 ----> loss: 0.746296

epoch 152:

82/84 ----> loss: 0.743906

epoch 153:

8/84 ----> loss: 0.744435

epoch 153:

18/84 ----> loss: 0.743671

epoch 153:

28/84 ----> loss: 0.743680

epoch 153:

38/84 ----> loss: 0.743997

epoch 153:

48/84 ----> loss: 0.743668

epoch 153:

58/84 ----> loss: 0.743809

epoch 153:

68/84 ----> loss: 0.743668

epoch 153:

78/84 ----> loss: 0.743833

epoch 154:

4/84 ----> loss: 0.743854

epoch 154:

14/84 ----> loss: 0.743668

epoch 154:

24/84 ----> loss: 0.743769

epoch 154:

34/84 ----> loss: 0.743668

epoch 154:

44/84 ----> loss: 0.743669

epoch 154:

54/84 ----> loss: 0.744059

epoch 154:

64/84 ----> loss: 0.743999

epoch 154:

74/84 ----> loss: 0.743668

epoch 155:

0/84 ----> loss: 0.743668

epoch 155:

10/84 ----> loss: 0.743798

epoch 155:

20/84 ----> loss: 0.743668

epoch 155:

30/84 ----> loss: 0.743675

epoch 155:

40/84 ----> loss: 0.743726

epoch 155:

50/84 ----> loss: 0.743903

epoch 155:

60/84 ----> loss: 0.743916

epoch 155:

70/84 ----> loss: 0.743669

epoch 155:

80/84 ----> loss: 0.743685

epoch 156:

6/84 ----> loss: 0.743668

epoch 156:

16/84 ----> loss: 0.743668

epoch 156:

26/84 ----> loss: 0.743981

epoch 156:

36/84 ----> loss: 0.743668

epoch 156:

46/84 ----> loss: 0.744142

epoch 156:

56/84 ----> loss: 0.743786

epoch 156:

66/84 ----> loss: 0.743668

epoch 156:

76/84 ----> loss: 0.743668

epoch 157:

2/84 ----> loss: 0.743829

epoch 157:

12/84 ----> loss: 0.743668

epoch 157:

22/84 ----> loss: 0.743672

epoch 157:

32/84 ----> loss: 0.743681

epoch 157:

42/84 ----> loss: 0.743670

epoch 157:

52/84 ----> loss: 0.745455

epoch 157:

62/84 ----> loss: 0.743711

epoch 157:

72/84 ----> loss: 0.746177

epoch 157:

82/84 ----> loss: 0.743895

epoch 158:

8/84 ----> loss: 0.744401

epoch 158:

18/84 ----> loss: 0.743671

epoch 158:

28/84 ----> loss: 0.743680

epoch 158:

38/84 ----> loss: 0.743981

epoch 158:

48/84 ----> loss: 0.743668

epoch 158:

58/84 ----> loss: 0.743803

epoch 158:

68/84 ----> loss: 0.743668

epoch 158:

78/84 ----> loss: 0.743825

epoch 159:

4/84 ----> loss: 0.743846

epoch 159:

14/84 ----> loss: 0.743668

epoch 159:

24/84 ----> loss: 0.743765

epoch 159:

34/84 ----> loss: 0.743668

epoch 159:

44/84 ----> loss: 0.743669

epoch 159:

54/84 ----> loss: 0.744044

epoch 159:

64/84 ----> loss: 0.743986

epoch 159:

74/84 ----> loss: 0.743668

epoch 160:

0/84 ----> loss: 0.743668

epoch 160:

10/84 ----> loss: 0.743791

epoch 160:

20/84 ----> loss: 0.743668

epoch 160:

30/84 ----> loss: 0.743675

epoch 160:

40/84 ----> loss: 0.743725

epoch 160:

50/84 ----> loss: 0.743893

epoch 160:

60/84 ----> loss: 0.743905

epoch 160:

70/84 ----> loss: 0.743669

epoch 160:

80/84 ----> loss: 0.743684

epoch 161:

6/84 ----> loss: 0.743668

epoch 161:

16/84 ----> loss: 0.743668

epoch 161:

26/84 ----> loss: 0.743968

epoch 161:

36/84 ----> loss: 0.743668

epoch 161:

46/84 ----> loss: 0.744123

epoch 161:

56/84 ----> loss: 0.743781

epoch 161:

66/84 ----> loss: 0.743668

epoch 161:

76/84 ----> loss: 0.743668

epoch 162:

2/84 ----> loss: 0.743822

epoch 162:

12/84 ----> loss: 0.743668

epoch 162:

22/84 ----> loss: 0.743672

epoch 162:

32/84 ----> loss: 0.743681

epoch 162:

42/84 ----> loss: 0.743670

epoch 162:

52/84 ----> loss: 0.745392

epoch 162:

62/84 ----> loss: 0.743709

epoch 162:

72/84 ----> loss: 0.746067

epoch 162:

82/84 ----> loss: 0.743885

epoch 163:

8/84 ----> loss: 0.744371

epoch 163:

18/84 ----> loss: 0.743671

epoch 163:

28/84 ----> loss: 0.743679

epoch 163:

38/84 ----> loss: 0.743966

epoch 163:

48/84 ----> loss: 0.743668

epoch 163:

58/84 ----> loss: 0.743798

epoch 163:

68/84 ----> loss: 0.743668

epoch 163:

78/84 ----> loss: 0.743818

epoch 164:

4/84 ----> loss: 0.743839

epoch 164:

14/84 ----> loss: 0.743668

epoch 164:

24/84 ----> loss: 0.743762

epoch 164:

34/84 ----> loss: 0.743668

epoch 164:

44/84 ----> loss: 0.743669

epoch 164:

54/84 ----> loss: 0.744031

epoch 164:

64/84 ----> loss: 0.743974

epoch 164:

74/84 ----> loss: 0.743668

epoch 165:

0/84 ----> loss: 0.743668

epoch 165:

10/84 ----> loss: 0.743785

epoch 165:

20/84 ----> loss: 0.743668

epoch 165:

30/84 ----> loss: 0.743674

epoch 165:

40/84 ----> loss: 0.743723

epoch 165:

50/84 ----> loss: 0.743884

epoch 165:

60/84 ----> loss: 0.743896

epoch 165:

70/84 ----> loss: 0.743669

epoch 165:

80/84 ----> loss: 0.743683

epoch 166:

6/84 ----> loss: 0.743668

epoch 166:

16/84 ----> loss: 0.743668

epoch 166:

26/84 ----> loss: 0.743956

epoch 166:

36/84 ----> loss: 0.743668

epoch 166:

46/84 ----> loss: 0.744105

epoch 166:

56/84 ----> loss: 0.743775

epoch 166:

66/84 ----> loss: 0.743668

epoch 166:

76/84 ----> loss: 0.743668

epoch 167:

2/84 ----> loss: 0.743815

epoch 167:

12/84 ----> loss: 0.743668

epoch 167:

22/84 ----> loss: 0.743672

epoch 167:

32/84 ----> loss: 0.743680

epoch 167:

42/84 ----> loss: 0.743670

epoch 167:

52/84 ----> loss: 0.745333

epoch 167:

62/84 ----> loss: 0.743706

epoch 167:

72/84 ----> loss: 0.745966

epoch 167:

82/84 ----> loss: 0.743876

epoch 168:

8/84 ----> loss: 0.744343

epoch 168:

18/84 ----> loss: 0.743670

epoch 168:

28/84 ----> loss: 0.743678

epoch 168:

38/84 ----> loss: 0.743952

epoch 168:

48/84 ----> loss: 0.743668

epoch 168:

58/84 ----> loss: 0.743793

epoch 168:

68/84 ----> loss: 0.743668

epoch 168:

78/84 ----> loss: 0.743812

epoch 169:

4/84 ----> loss: 0.743832

epoch 169:

14/84 ----> loss: 0.743668

epoch 169:

24/84 ----> loss: 0.743758

epoch 169:

34/84 ----> loss: 0.743668

epoch 169:

44/84 ----> loss: 0.743669

epoch 169:

54/84 ----> loss: 0.744018

epoch 169:

64/84 ----> loss: 0.743962

epoch 169:

74/84 ----> loss: 0.743668

epoch 170:

0/84 ----> loss: 0.743668

epoch 170:

10/84 ----> loss: 0.743779

epoch 170:

20/84 ----> loss: 0.743668

epoch 170:

30/84 ----> loss: 0.743674

epoch 170:

40/84 ----> loss: 0.743721

epoch 170:

50/84 ----> loss: 0.743876

epoch 170:

60/84 ----> loss: 0.743887

epoch 170:

70/84 ----> loss: 0.743669

epoch 170:

80/84 ----> loss: 0.743682

epoch 171:

6/84 ----> loss: 0.743668

epoch 171:

16/84 ----> loss: 0.743668

epoch 171:

26/84 ----> loss: 0.743945

epoch 171:

36/84 ----> loss: 0.743668

epoch 171:

46/84 ----> loss: 0.744089

epoch 171:

56/84 ----> loss: 0.743771

epoch 171:

66/84 ----> loss: 0.743668

epoch 171:

76/84 ----> loss: 0.743668

epoch 172:

2/84 ----> loss: 0.743809

epoch 172:

12/84 ----> loss: 0.743668

epoch 172:

22/84 ----> loss: 0.743672

epoch 172:

32/84 ----> loss: 0.743679

epoch 172:

42/84 ----> loss: 0.743670

epoch 172:

52/84 ----> loss: 0.745277

epoch 172:

62/84 ----> loss: 0.743704

epoch 172:

72/84 ----> loss: 0.745872

epoch 172:

82/84 ----> loss: 0.743868

epoch 173:

8/84 ----> loss: 0.744316

epoch 173:

18/84 ----> loss: 0.743670

epoch 173:

28/84 ----> loss: 0.743678

epoch 173:

38/84 ----> loss: 0.743940

epoch 173:

48/84 ----> loss: 0.743668

epoch 173:

58/84 ----> loss: 0.743788

epoch 173:

68/84 ----> loss: 0.743668

epoch 173:

78/84 ----> loss: 0.743806

epoch 174:

4/84 ----> loss: 0.743825

epoch 174:

14/84 ----> loss: 0.743668

epoch 174:

24/84 ----> loss: 0.743756

epoch 174:

34/84 ----> loss: 0.743668

epoch 174:

44/84 ----> loss: 0.743669

epoch 174:

54/84 ----> loss: 0.744006

epoch 174:

64/84 ----> loss: 0.743952

epoch 174:

74/84 ----> loss: 0.743668

epoch 175:

0/84 ----> loss: 0.743668

epoch 175:

10/84 ----> loss: 0.743774

epoch 175:

20/84 ----> loss: 0.743668

epoch 175:

30/84 ----> loss: 0.743674

epoch 175:

40/84 ----> loss: 0.743720

epoch 175:

50/84 ----> loss: 0.743869

epoch 175:

60/84 ----> loss: 0.743878

epoch 175:

70/84 ----> loss: 0.743669

epoch 175:

80/84 ----> loss: 0.743681

epoch 176:

6/84 ----> loss: 0.743668

epoch 176:

16/84 ----> loss: 0.743668

epoch 176:

26/84 ----> loss: 0.743935

epoch 176:

36/84 ----> loss: 0.743668

epoch 176:

46/84 ----> loss: 0.744073

epoch 176:

56/84 ----> loss: 0.743766

epoch 176:

66/84 ----> loss: 0.743668

epoch 176:

76/84 ----> loss: 0.743668

epoch 177:

2/84 ----> loss: 0.743803

epoch 177:

12/84 ----> loss: 0.743668

epoch 177:

22/84 ----> loss: 0.743671

epoch 177:

32/84 ----> loss: 0.743679

epoch 177:

42/84 ----> loss: 0.743670

epoch 177:

52/84 ----> loss: 0.745225

epoch 177:

62/84 ----> loss: 0.743702

epoch 177:

72/84 ----> loss: 0.745785

epoch 177:

82/84 ----> loss: 0.743860

epoch 178:

8/84 ----> loss: 0.744292

epoch 178:

18/84 ----> loss: 0.743670

epoch 178:

28/84 ----> loss: 0.743677

epoch 178:

38/84 ----> loss: 0.743928

epoch 178:

48/84 ----> loss: 0.743668

epoch 178:

58/84 ----> loss: 0.743784

epoch 178:

68/84 ----> loss: 0.743668

epoch 178:

78/84 ----> loss: 0.743801

epoch 179:

4/84 ----> loss: 0.743819

epoch 179:

14/84 ----> loss: 0.743668

epoch 179:

24/84 ----> loss: 0.743753

epoch 179:

34/84 ----> loss: 0.743668

epoch 179:

44/84 ----> loss: 0.743669

epoch 179:

54/84 ----> loss: 0.743995

epoch 179:

64/84 ----> loss: 0.743942

epoch 179:

74/84 ----> loss: 0.743668

epoch 180:

0/84 ----> loss: 0.743668

epoch 180:

10/84 ----> loss: 0.743769

epoch 180:

20/84 ----> loss: 0.743668

epoch 180:

30/84 ----> loss: 0.743673

epoch 180:

40/84 ----> loss: 0.743719

epoch 180:

50/84 ----> loss: 0.743861

epoch 180:

60/84 ----> loss: 0.743870

epoch 180:

70/84 ----> loss: 0.743669

epoch 180:

80/84 ----> loss: 0.743681

epoch 181:

6/84 ----> loss: 0.743668

epoch 181:

16/84 ----> loss: 0.743668

epoch 181:

26/84 ----> loss: 0.743925

epoch 181:

36/84 ----> loss: 0.743668

epoch 181:

46/84 ----> loss: 0.744059

epoch 181:

56/84 ----> loss: 0.743762

epoch 181:

66/84 ----> loss: 0.743668

epoch 181:

76/84 ----> loss: 0.743668

epoch 182:

2/84 ----> loss: 0.743797

epoch 182:

12/84 ----> loss: 0.743668

epoch 182:

22/84 ----> loss: 0.743671

epoch 182:

32/84 ----> loss: 0.743678

epoch 182:

42/84 ----> loss: 0.743670

epoch 182:

52/84 ----> loss: 0.745176

epoch 182:

62/84 ----> loss: 0.743700

epoch 182:

72/84 ----> loss: 0.745705

epoch 182:

82/84 ----> loss: 0.743852

epoch 183:

8/84 ----> loss: 0.744269

epoch 183:

18/84 ----> loss: 0.743670

epoch 183:

28/84 ----> loss: 0.743677

epoch 183:

38/84 ----> loss: 0.743917

epoch 183:

48/84 ----> loss: 0.743668

epoch 183:

58/84 ----> loss: 0.743780

epoch 183:

68/84 ----> loss: 0.743668

epoch 183:

78/84 ----> loss: 0.743796

epoch 184:

4/84 ----> loss: 0.743814

epoch 184:

14/84 ----> loss: 0.743668

epoch 184:

24/84 ----> loss: 0.743750

epoch 184:

34/84 ----> loss: 0.743668

epoch 184:

44/84 ----> loss: 0.743669

epoch 184:

54/84 ----> loss: 0.743985

epoch 184:

64/84 ----> loss: 0.743932

epoch 184:

74/84 ----> loss: 0.743668

epoch 185:

0/84 ----> loss: 0.743668

epoch 185:

10/84 ----> loss: 0.743765

epoch 185:

20/84 ----> loss: 0.743668

epoch 185:

30/84 ----> loss: 0.743673

epoch 185:

40/84 ----> loss: 0.743717

epoch 185:

50/84 ----> loss: 0.743855

epoch 185:

60/84 ----> loss: 0.743863

epoch 185:

70/84 ----> loss: 0.743669

epoch 185:

80/84 ----> loss: 0.743680

epoch 186:

6/84 ----> loss: 0.743668

epoch 186:

16/84 ----> loss: 0.743668

epoch 186:

26/84 ----> loss: 0.743917

epoch 186:

36/84 ----> loss: 0.743668

epoch 186:

46/84 ----> loss: 0.744046

epoch 186:

56/84 ----> loss: 0.743758

epoch 186:

66/84 ----> loss: 0.743668

epoch 186:

76/84 ----> loss: 0.743668

epoch 187:

2/84 ----> loss: 0.743792

epoch 187:

12/84 ----> loss: 0.743668

epoch 187:

22/84 ----> loss: 0.743671

epoch 187:

32/84 ----> loss: 0.743678

epoch 187:

42/84 ----> loss: 0.743670

epoch 187:

52/84 ----> loss: 0.745130

epoch 187:

62/84 ----> loss: 0.743698

epoch 187:

72/84 ----> loss: 0.745629

epoch 187:

82/84 ----> loss: 0.743846

epoch 188:

8/84 ----> loss: 0.744248

epoch 188:

18/84 ----> loss: 0.743670

epoch 188:

28/84 ----> loss: 0.743676

epoch 188:

38/84 ----> loss: 0.743907

epoch 188:

48/84 ----> loss: 0.743668

epoch 188:

58/84 ----> loss: 0.743776

epoch 188:

68/84 ----> loss: 0.743668

epoch 188:

78/84 ----> loss: 0.743791

epoch 189:

4/84 ----> loss: 0.743809

epoch 189:

14/84 ----> loss: 0.743668

epoch 189:

24/84 ----> loss: 0.743748

epoch 189:

34/84 ----> loss: 0.743668

epoch 189:

44/84 ----> loss: 0.743669

epoch 189:

54/84 ----> loss: 0.743975

epoch 189:

64/84 ----> loss: 0.743924

epoch 189:

74/84 ----> loss: 0.743668

epoch 190:

0/84 ----> loss: 0.743668

epoch 190:

10/84 ----> loss: 0.743761

epoch 190:

20/84 ----> loss: 0.743668

epoch 190:

30/84 ----> loss: 0.743673

epoch 190:

40/84 ----> loss: 0.743716

epoch 190:

50/84 ----> loss: 0.743848

epoch 190:

60/84 ----> loss: 0.743856

epoch 190:

70/84 ----> loss: 0.743669

epoch 190:

80/84 ----> loss: 0.743679

epoch 191:

6/84 ----> loss: 0.743668

epoch 191:

16/84 ----> loss: 0.743668

epoch 191:

26/84 ----> loss: 0.743908

epoch 191:

36/84 ----> loss: 0.743668

epoch 191:

46/84 ----> loss: 0.744033

epoch 191:

56/84 ----> loss: 0.743754

epoch 191:

66/84 ----> loss: 0.743668

epoch 191:

76/84 ----> loss: 0.743668

epoch 192:

2/84 ----> loss: 0.743787

epoch 192:

12/84 ----> loss: 0.743668

epoch 192:

22/84 ----> loss: 0.743671

epoch 192:

32/84 ----> loss: 0.743677

epoch 192:

42/84 ----> loss: 0.743670

epoch 192:

52/84 ----> loss: 0.745086

epoch 192:

62/84 ----> loss: 0.743697

epoch 192:

72/84 ----> loss: 0.745559

epoch 192:

82/84 ----> loss: 0.743839

epoch 193:

8/84 ----> loss: 0.744228

epoch 193:

18/84 ----> loss: 0.743670

epoch 193:

28/84 ----> loss: 0.743676

epoch 193:

38/84 ----> loss: 0.743898

epoch 193:

48/84 ----> loss: 0.743668

epoch 193:

58/84 ----> loss: 0.743772

epoch 193:

68/84 ----> loss: 0.743668

epoch 193:

78/84 ----> loss: 0.743787

epoch 194:

4/84 ----> loss: 0.743804

epoch 194:

14/84 ----> loss: 0.743668

epoch 194:

24/84 ----> loss: 0.743746

epoch 194:

34/84 ----> loss: 0.743668

epoch 194:

44/84 ----> loss: 0.743669

epoch 194:

54/84 ----> loss: 0.743966

epoch 194:

64/84 ----> loss: 0.743915

epoch 194:

74/84 ----> loss: 0.743668

epoch 195:

0/84 ----> loss: 0.743668

epoch 195:

10/84 ----> loss: 0.743757

epoch 195:

20/84 ----> loss: 0.743668

epoch 195:

30/84 ----> loss: 0.743673

epoch 195:

40/84 ----> loss: 0.743715

epoch 195:

50/84 ----> loss: 0.743843

epoch 195:

60/84 ----> loss: 0.743850

epoch 195:

70/84 ----> loss: 0.743669

epoch 195:

80/84 ----> loss: 0.743679

epoch 196:

6/84 ----> loss: 0.743668

epoch 196:

16/84 ----> loss: 0.743668

epoch 196:

26/84 ----> loss: 0.743900

epoch 196:

36/84 ----> loss: 0.743668

epoch 196:

46/84 ----> loss: 0.744021

epoch 196:

56/84 ----> loss: 0.743751

epoch 196:

66/84 ----> loss: 0.743668

epoch 196:

76/84 ----> loss: 0.743668

epoch 197:

2/84 ----> loss: 0.743783

epoch 197:

12/84 ----> loss: 0.743668

epoch 197:

22/84 ----> loss: 0.743671

epoch 197:

32/84 ----> loss: 0.743677

epoch 197:

42/84 ----> loss: 0.743669

epoch 197:

52/84 ----> loss: 0.745044

epoch 197:

62/84 ----> loss: 0.743695

epoch 197:

72/84 ----> loss: 0.745493

epoch 197:

82/84 ----> loss: 0.743833

epoch 198:

8/84 ----> loss: 0.744209

epoch 198:

18/84 ----> loss: 0.743670

epoch 198:

28/84 ----> loss: 0.743675

epoch 198:

38/84 ----> loss: 0.743889

epoch 198:

48/84 ----> loss: 0.743668

epoch 198:

58/84 ----> loss: 0.743769

epoch 198:

68/84 ----> loss: 0.743668

epoch 198:

78/84 ----> loss: 0.743783

epoch 199:

4/84 ----> loss: 0.743799

epoch 199:

14/84 ----> loss: 0.743668

epoch 199:

24/84 ----> loss: 0.743743

epoch 199:

34/84 ----> loss: 0.743668

epoch 199:

44/84 ----> loss: 0.743669

epoch 199:

54/84 ----> loss: 0.743957

epoch 199:

64/84 ----> loss: 0.743908

epoch 199:

74/84 ----> loss: 0.743668

epoch 200:

0/84 ----> loss: 0.743668

epoch 200:

10/84 ----> loss: 0.743753

epoch 200:

20/84 ----> loss: 0.743668

epoch 200:

30/84 ----> loss: 0.743672

epoch 200:

40/84 ----> loss: 0.743713

epoch 200:

50/84 ----> loss: 0.743837

epoch 200:

60/84 ----> loss: 0.743844

epoch 200:

70/84 ----> loss: 0.743669

epoch 200:

80/84 ----> loss: 0.743678

epoch 201:

6/84 ----> loss: 0.743668

epoch 201:

16/84 ----> loss: 0.743668

epoch 201:

26/84 ----> loss: 0.743893

epoch 201:

36/84 ----> loss: 0.743668

epoch 201:

46/84 ----> loss: 0.744010

epoch 201:

56/84 ----> loss: 0.743748

epoch 201:

66/84 ----> loss: 0.743668

epoch 201:

76/84 ----> loss: 0.743668

epoch 202:

2/84 ----> loss: 0.743779

epoch 202:

12/84 ----> loss: 0.743668

epoch 202:

22/84 ----> loss: 0.743671

epoch 202:

32/84 ----> loss: 0.743676

epoch 202:

42/84 ----> loss: 0.743669

epoch 202:

52/84 ----> loss: 0.745005

epoch 202:

62/84 ----> loss: 0.743694

epoch 202:

72/84 ----> loss: 0.745432

epoch 202:

82/84 ----> loss: 0.743827

epoch 203:

8/84 ----> loss: 0.744192

epoch 203:

18/84 ----> loss: 0.743670

epoch 203:

28/84 ----> loss: 0.743675

epoch 203:

38/84 ----> loss: 0.743881

epoch 203:

48/84 ----> loss: 0.743668

epoch 203:

58/84 ----> loss: 0.743766

epoch 203:

68/84 ----> loss: 0.743668

epoch 203:

78/84 ----> loss: 0.743779

epoch 204:

4/84 ----> loss: 0.743795

epoch 204:

14/84 ----> loss: 0.743668

epoch 204:

24/84 ----> loss: 0.743741

epoch 204:

34/84 ----> loss: 0.743668

epoch 204:

44/84 ----> loss: 0.743669

epoch 204:

54/84 ----> loss: 0.743949

epoch 204:

64/84 ----> loss: 0.743900

epoch 204:

74/84 ----> loss: 0.743668

epoch 205:

0/84 ----> loss: 0.743668

epoch 205:

10/84 ----> loss: 0.743750

epoch 205:

20/84 ----> loss: 0.743668

epoch 205:

30/84 ----> loss: 0.743672

epoch 205:

40/84 ----> loss: 0.743712

epoch 205:

50/84 ----> loss: 0.743832

epoch 205:

60/84 ----> loss: 0.743838

epoch 205:

70/84 ----> loss: 0.743669

epoch 205:

80/84 ----> loss: 0.743678

epoch 206:

6/84 ----> loss: 0.743668

epoch 206:

16/84 ----> loss: 0.743668

epoch 206:

26/84 ----> loss: 0.743885

epoch 206:

36/84 ----> loss: 0.743668

epoch 206:

46/84 ----> loss: 0.744000

epoch 206:

56/84 ----> loss: 0.743745

epoch 206:

66/84 ----> loss: 0.743668

epoch 206:

76/84 ----> loss: 0.743668

epoch 207:

2/84 ----> loss: 0.743775

epoch 207:

12/84 ----> loss: 0.743668

epoch 207:

22/84 ----> loss: 0.743671

epoch 207:

32/84 ----> loss: 0.743676

epoch 207:

42/84 ----> loss: 0.743669

epoch 207:

52/84 ----> loss: 0.744968

epoch 207:

62/84 ----> loss: 0.743693

epoch 207:

72/84 ----> loss: 0.745374

epoch 207:

82/84 ----> loss: 0.743822

epoch 208:

8/84 ----> loss: 0.744175

epoch 208:

18/84 ----> loss: 0.743670

epoch 208:

28/84 ----> loss: 0.743675

epoch 208:

38/84 ----> loss: 0.743873

epoch 208:

48/84 ----> loss: 0.743668

epoch 208:

58/84 ----> loss: 0.743763

epoch 208:

68/84 ----> loss: 0.743668

epoch 208:

78/84 ----> loss: 0.743775

epoch 209:

4/84 ----> loss: 0.743791

epoch 209:

14/84 ----> loss: 0.743668

epoch 209:

24/84 ----> loss: 0.743739

epoch 209:

34/84 ----> loss: 0.743668

epoch 209:

44/84 ----> loss: 0.743669

epoch 209:

54/84 ----> loss: 0.743941

epoch 209:

64/84 ----> loss: 0.743894

epoch 209:

74/84 ----> loss: 0.743668

epoch 210:

0/84 ----> loss: 0.743668

epoch 210:

10/84 ----> loss: 0.743747

epoch 210:

20/84 ----> loss: 0.743668

epoch 210:

30/84 ----> loss: 0.743672

epoch 210:

40/84 ----> loss: 0.743711

epoch 210:

50/84 ----> loss: 0.743827

epoch 210:

60/84 ----> loss: 0.743833

epoch 210:

70/84 ----> loss: 0.743669

epoch 210:

80/84 ----> loss: 0.743677

epoch 211:

6/84 ----> loss: 0.743668

epoch 211:

16/84 ----> loss: 0.743668

epoch 211:

26/84 ----> loss: 0.743879

epoch 211:

36/84 ----> loss: 0.743668

epoch 211:

46/84 ----> loss: 0.743990

epoch 211:

56/84 ----> loss: 0.743742

epoch 211:

66/84 ----> loss: 0.743668

epoch 211:

76/84 ----> loss: 0.743668

epoch 212:

2/84 ----> loss: 0.743771

epoch 212:

12/84 ----> loss: 0.743668

epoch 212:

22/84 ----> loss: 0.743670

epoch 212:

32/84 ----> loss: 0.743676

epoch 212:

42/84 ----> loss: 0.743669

epoch 212:

52/84 ----> loss: 0.744933

epoch 212:

62/84 ----> loss: 0.743691

epoch 212:

72/84 ----> loss: 0.745319

epoch 212:

82/84 ----> loss: 0.743817

epoch 213:

8/84 ----> loss: 0.744160

epoch 213:

18/84 ----> loss: 0.743670

epoch 213:

28/84 ----> loss: 0.743675

epoch 213:

38/84 ----> loss: 0.743866

epoch 213:

48/84 ----> loss: 0.743668

epoch 213:

58/84 ----> loss: 0.743760

epoch 213:

68/84 ----> loss: 0.743668

epoch 213:

78/84 ----> loss: 0.743772

epoch 214:

4/84 ----> loss: 0.743787

epoch 214:

14/84 ----> loss: 0.743668

epoch 214:

24/84 ----> loss: 0.743737

epoch 214:

34/84 ----> loss: 0.743668

epoch 214:

44/84 ----> loss: 0.743669

epoch 214:

54/84 ----> loss: 0.743933

epoch 214:

64/84 ----> loss: 0.743887

epoch 214:

74/84 ----> loss: 0.743668

epoch 215:

0/84 ----> loss: 0.743668

epoch 215:

10/84 ----> loss: 0.743744

epoch 215:

20/84 ----> loss: 0.743668

epoch 215:

30/84 ----> loss: 0.743672

epoch 215:

40/84 ----> loss: 0.743710

epoch 215:

50/84 ----> loss: 0.743822

epoch 215:

60/84 ----> loss: 0.743828

epoch 215:

70/84 ----> loss: 0.743669

epoch 215:

80/84 ----> loss: 0.743677

epoch 216:

6/84 ----> loss: 0.743668

epoch 216:

16/84 ----> loss: 0.743668

epoch 216:

26/84 ----> loss: 0.743873

epoch 216:

36/84 ----> loss: 0.743668

epoch 216:

46/84 ----> loss: 0.743980

epoch 216:

56/84 ----> loss: 0.743740

epoch 216:

66/84 ----> loss: 0.743668

epoch 216:

76/84 ----> loss: 0.743668

epoch 217:

2/84 ----> loss: 0.743768

epoch 217:

12/84 ----> loss: 0.743668

epoch 217:

```
-----  
-----  
22/84 ----> loss: 0.743670  
  
epoch 217:  
-----  
-----  
32/84 ----> loss: 0.743675  
  
epoch 217:  
-----  
-----  
42/84 ----> loss: 0.743669  
  
epoch 217:  
-----  
-----  
52/84 ----> loss: 0.744900  
  
epoch 217:  
-----  
-----  
62/84 ----> loss: 0.743691  
  
epoch 217:  
-----  
-----  
72/84 ----> loss: 0.745268  
  
epoch 217:  
-----  
-----  
82/84 ----> loss: 0.743812  
  
epoch 218:  
-----  
-----  
8/84 ----> loss: 0.744145  
  
epoch 218:
```

```
-----  
-----  
18/84 ----> loss: 0.743670  
  
epoch 218:  
-----  
-----  
28/84 ----> loss: 0.743674  
  
epoch 218:  
-----  
-----  
38/84 ----> loss: 0.743859  
  
epoch 218:  
-----  
-----  
48/84 ----> loss: 0.743668  
  
epoch 218:  
-----  
-----  
58/84 ----> loss: 0.743757  
  
epoch 218:  
-----  
-----  
68/84 ----> loss: 0.743668  
  
epoch 218:  
-----  
-----  
78/84 ----> loss: 0.743768  
  
epoch 219:  
-----  
-----  
4/84 ----> loss: 0.743784  
  
epoch 219:
```


14/84 ----> loss: 0.743668

epoch 219:

24/84 ----> loss: 0.743735

epoch 219:

34/84 ----> loss: 0.743668

epoch 219:

44/84 ----> loss: 0.743669

epoch 219:

54/84 ----> loss: 0.743926

epoch 219:

64/84 ----> loss: 0.743881

epoch 219:

74/84 ----> loss: 0.743668

epoch 220:

0/84 ----> loss: 0.743668

epoch 220:

10/84 ----> loss: 0.743741

epoch 220:

20/84 ----> loss: 0.743668

epoch 220:

30/84 ----> loss: 0.743672

epoch 220:

40/84 ----> loss: 0.743709

epoch 220:

50/84 ----> loss: 0.743818

epoch 220:

60/84 ----> loss: 0.743823

epoch 220:

70/84 ----> loss: 0.743669

epoch 220:

80/84 ----> loss: 0.743677

epoch 221:

6/84 ----> loss: 0.743668

epoch 221:

16/84 ----> loss: 0.743668

epoch 221:

26/84 ----> loss: 0.743867

epoch 221:

36/84 ----> loss: 0.743668

epoch 221:

46/84 ----> loss: 0.743972

epoch 221:

56/84 ----> loss: 0.743737

epoch 221:

66/84 ----> loss: 0.743668

epoch 221:

76/84 ----> loss: 0.743668

epoch 222:

2/84 ----> loss: 0.743764

epoch 222:

12/84 ----> loss: 0.743668

epoch 222:

22/84 ----> loss: 0.743670

epoch 222:

32/84 ----> loss: 0.743675

epoch 222:

42/84 ----> loss: 0.743669

epoch 222:

52/84 ----> loss: 0.744868

epoch 222:

62/84 ----> loss: 0.743689

epoch 222:

72/84 ----> loss: 0.745220

epoch 222:

82/84 ----> loss: 0.743808

epoch 223:

8/84 ----> loss: 0.744132

epoch 223:

18/84 ----> loss: 0.743669

epoch 223:

28/84 ----> loss: 0.743674

epoch 223:

38/84 ----> loss: 0.743852

epoch 223:

48/84 ----> loss: 0.743668

epoch 223:

58/84 ----> loss: 0.743754

epoch 223:

68/84 ----> loss: 0.743668

epoch 223:

78/84 ----> loss: 0.743765

epoch 224:

4/84 ----> loss: 0.743780

epoch 224:

14/84 ----> loss: 0.743668

epoch 224:

24/84 ----> loss: 0.743734

epoch 224:

34/84 ----> loss: 0.743668

epoch 224:

44/84 ----> loss: 0.743669

epoch 224:

54/84 ----> loss: 0.743919

epoch 224:

64/84 ----> loss: 0.743875

epoch 224:

74/84 ----> loss: 0.743668

epoch 225:

0/84 ----> loss: 0.743668

epoch 225:

10/84 ----> loss: 0.743738

epoch 225:

20/84 ----> loss: 0.743668

epoch 225:

30/84 ----> loss: 0.743671

epoch 225:

40/84 ----> loss: 0.743708

epoch 225:

50/84 ----> loss: 0.743814

epoch 225:

60/84 ----> loss: 0.743819

epoch 225:

70/84 ----> loss: 0.743669

epoch 225:

80/84 ----> loss: 0.743676

epoch 226:

6/84 ----> loss: 0.743668

epoch 226:

16/84 ----> loss: 0.743668

epoch 226:

26/84 ----> loss: 0.743861

epoch 226:

36/84 ----> loss: 0.743668

epoch 226:

46/84 ----> loss: 0.743963

epoch 226:

56/84 ----> loss: 0.743735

epoch 226:

66/84 ----> loss: 0.743668

epoch 226:

76/84 ----> loss: 0.743668

epoch 227:

2/84 ----> loss: 0.743761

epoch 227:

12/84 ----> loss: 0.743668

epoch 227:

22/84 ----> loss: 0.743670

epoch 227:

32/84 ----> loss: 0.743675

epoch 227:

42/84 ----> loss: 0.743669

epoch 227:

52/84 ----> loss: 0.744837

epoch 227:

62/84 ----> loss: 0.743689

epoch 227:

72/84 ----> loss: 0.745174

epoch 227:

82/84 ----> loss: 0.743803

epoch 228:

8/84 ----> loss: 0.744118

epoch 228:

18/84 ----> loss: 0.743669

epoch 228:

28/84 ----> loss: 0.743674

epoch 228:

38/84 ----> loss: 0.743846

epoch 228:

48/84 ----> loss: 0.743668

epoch 228:

58/84 ----> loss: 0.743752

epoch 228:

68/84 ----> loss: 0.743668

epoch 228:

78/84 ----> loss: 0.743762

epoch 229:

4/84 ----> loss: 0.743777

epoch 229:

14/84 ----> loss: 0.743668

epoch 229:

24/84 ----> loss: 0.743732

epoch 229:

34/84 ----> loss: 0.743668

epoch 229:

44/84 ----> loss: 0.743669

epoch 229:

54/84 ----> loss: 0.743913

epoch 229:

64/84 ----> loss: 0.743869

epoch 229:

74/84 ----> loss: 0.743668

epoch 230:

0/84 ----> loss: 0.743668

epoch 230:

10/84 ----> loss: 0.743736

epoch 230:

20/84 ----> loss: 0.743668

epoch 230:

30/84 ----> loss: 0.743671

epoch 230:

40/84 ----> loss: 0.743707

epoch 230:

50/84 ----> loss: 0.743810

epoch 230:

60/84 ----> loss: 0.743815

epoch 230:

70/84 ----> loss: 0.743669

epoch 230:

80/84 ----> loss: 0.743676

epoch 231:

6/84 ----> loss: 0.743668

epoch 231:

16/84 ----> loss: 0.743668

epoch 231:

26/84 ----> loss: 0.743856

epoch 231:

36/84 ----> loss: 0.743668

epoch 231:

46/84 ----> loss: 0.743955

epoch 231:

56/84 ----> loss: 0.743733

epoch 231:

66/84 ----> loss: 0.743668

epoch 231:

76/84 ----> loss: 0.743668

epoch 232:

2/84 ----> loss: 0.743758

epoch 232:

12/84 ----> loss: 0.743668

epoch 232:

22/84 ----> loss: 0.743670

epoch 232:

32/84 ----> loss: 0.743675

epoch 232:

42/84 ----> loss: 0.743669

epoch 232:

52/84 ----> loss: 0.744808

epoch 232:

62/84 ----> loss: 0.743688

epoch 232:

72/84 ----> loss: 0.745130

epoch 232:

82/84 ----> loss: 0.743799

epoch 233:

8/84 ----> loss: 0.744106

epoch 233:

18/84 ----> loss: 0.743669

epoch 233:

28/84 ----> loss: 0.743674

epoch 233:

38/84 ----> loss: 0.743841

epoch 233:

48/84 ----> loss: 0.743668

epoch 233:

58/84 ----> loss: 0.743749

epoch 233:

68/84 ----> loss: 0.743668

epoch 233:

78/84 ----> loss: 0.743760

epoch 234:

4/84 ----> loss: 0.743774

epoch 234:

14/84 ----> loss: 0.743668

epoch 234:

24/84 ----> loss: 0.743731

epoch 234:

34/84 ----> loss: 0.743668

epoch 234:

44/84 ----> loss: 0.743668

epoch 234:

54/84 ----> loss: 0.743907

epoch 234:

64/84 ----> loss: 0.743864

epoch 234:

74/84 ----> loss: 0.743668

epoch 235:

0/84 ----> loss: 0.743668

epoch 235:

10/84 ----> loss: 0.743733

epoch 235:

20/84 ----> loss: 0.743668

epoch 235:

30/84 ----> loss: 0.743671

epoch 235:

40/84 ----> loss: 0.743706

epoch 235:

50/84 ----> loss: 0.743806

epoch 235:

60/84 ----> loss: 0.743810

epoch 235:

70/84 ----> loss: 0.743669

epoch 235:

80/84 ----> loss: 0.743676

epoch 236:

6/84 ----> loss: 0.743668

epoch 236:

16/84 ----> loss: 0.743668

epoch 236:

26/84 ----> loss: 0.743851

epoch 236:

36/84 ----> loss: 0.743668

epoch 236:

46/84 ----> loss: 0.743948

epoch 236:

56/84 ----> loss: 0.743731

epoch 236:

66/84 ----> loss: 0.743668

epoch 236:

76/84 ----> loss: 0.743668

epoch 237:

2/84 ----> loss: 0.743756

epoch 237:

12/84 ----> loss: 0.743668

epoch 237:

22/84 ----> loss: 0.743670

epoch 237:

32/84 ----> loss: 0.743674

epoch 237:

42/84 ----> loss: 0.743669

epoch 237:

52/84 ----> loss: 0.744781

epoch 237:

62/84 ----> loss: 0.743687

epoch 237:

72/84 ----> loss: 0.745089

epoch 237:

82/84 ----> loss: 0.743795

epoch 238:

8/84 ----> loss: 0.744094

epoch 238:

18/84 ----> loss: 0.743669

epoch 238:

28/84 ----> loss: 0.743673

epoch 238:

38/84 ----> loss: 0.743835

epoch 238:

48/84 ----> loss: 0.743668

epoch 238:

58/84 ----> loss: 0.743747

epoch 238:

68/84 ----> loss: 0.743668

epoch 238:

78/84 ----> loss: 0.743757

epoch 239:

4/84 ----> loss: 0.743771

epoch 239:

14/84 ----> loss: 0.743668

epoch 239:

24/84 ----> loss: 0.743729

epoch 239:

34/84 ----> loss: 0.743668

epoch 239:

44/84 ----> loss: 0.743668

epoch 239:

54/84 ----> loss: 0.743901

epoch 239:

64/84 ----> loss: 0.743859

epoch 239:

74/84 ----> loss: 0.743668

epoch 240:

0/84 ----> loss: 0.743668

epoch 240:

10/84 ----> loss: 0.743731

epoch 240:

20/84 ----> loss: 0.743668

epoch 240:

30/84 ----> loss: 0.743671

epoch 240:

40/84 ----> loss: 0.743706

epoch 240:

50/84 ----> loss: 0.743802

epoch 240:

60/84 ----> loss: 0.743807

epoch 240:

70/84 ----> loss: 0.743669

epoch 240:

80/84 ----> loss: 0.743675

epoch 241:

6/84 ----> loss: 0.743668

epoch 241:

16/84 ----> loss: 0.743668

epoch 241:

26/84 ----> loss: 0.743846

epoch 241:

36/84 ----> loss: 0.743668

epoch 241:

46/84 ----> loss: 0.743941

epoch 241:

56/84 ----> loss: 0.743729

epoch 241:

66/84 ----> loss: 0.743668

epoch 241:

76/84 ----> loss: 0.743668

epoch 242:

2/84 ----> loss: 0.743753

epoch 242:

12/84 ----> loss: 0.743668

epoch 242:

22/84 ----> loss: 0.743670

epoch 242:

32/84 ----> loss: 0.743674

epoch 242:

42/84 ----> loss: 0.743669

epoch 242:

52/84 ----> loss: 0.744754

epoch 242:

62/84 ----> loss: 0.743686

epoch 242:

72/84 ----> loss: 0.745050

epoch 242:

82/84 ----> loss: 0.743792

epoch 243:

8/84 ----> loss: 0.744083

epoch 243:

18/84 ----> loss: 0.743669

epoch 243:

28/84 ----> loss: 0.743673

epoch 243:

38/84 ----> loss: 0.743830

epoch 243:

48/84 ----> loss: 0.743668

epoch 243:

58/84 ----> loss: 0.743745

epoch 243:

68/84 ----> loss: 0.743668

epoch 243:

78/84 ----> loss: 0.743755

epoch 244:

4/84 ----> loss: 0.743768

epoch 244:

14/84 ----> loss: 0.743668

epoch 244:

24/84 ----> loss: 0.743728

epoch 244:

34/84 ----> loss: 0.743668

epoch 244:

44/84 ----> loss: 0.743668

epoch 244:

54/84 ----> loss: 0.743895

epoch 244:

64/84 ----> loss: 0.743854

epoch 244:

74/84 ----> loss: 0.743668

epoch 245:

0/84 ----> loss: 0.743668

epoch 245:

10/84 ----> loss: 0.743729

epoch 245:

20/84 ----> loss: 0.743668

epoch 245:

30/84 ----> loss: 0.743671

epoch 245:

40/84 ----> loss: 0.743705

epoch 245:

50/84 ----> loss: 0.743799

epoch 245:

60/84 ----> loss: 0.743803

epoch 245:

70/84 ----> loss: 0.743669

epoch 245:

80/84 ----> loss: 0.743675

epoch 246:

6/84 ----> loss: 0.743668

epoch 246:

16/84 ----> loss: 0.743668

epoch 246:

26/84 ----> loss: 0.743841

epoch 246:

36/84 ----> loss: 0.743668

epoch 246:

46/84 ----> loss: 0.743934

epoch 246:

56/84 ----> loss: 0.743727

epoch 246:

66/84 ----> loss: 0.743668

epoch 246:

76/84 ----> loss: 0.743668

epoch 247:

2/84 ----> loss: 0.743750

epoch 247:

12/84 ----> loss: 0.743668

epoch 247:

22/84 ----> loss: 0.743670

epoch 247:

32/84 ----> loss: 0.743674

epoch 247:

42/84 ----> loss: 0.743669

epoch 247:

52/84 ----> loss: 0.744729

epoch 247:

62/84 ----> loss: 0.743685

epoch 247:

72/84 ----> loss: 0.745013

epoch 247:

82/84 ----> loss: 0.743788

epoch 248:

8/84 ----> loss: 0.744072

epoch 248:

18/84 ----> loss: 0.743669

epoch 248:

28/84 ----> loss: 0.743673

epoch 248:

38/84 ----> loss: 0.743825

epoch 248:

48/84 ----> loss: 0.743668

epoch 248:

58/84 ----> loss: 0.743743

epoch 248:

68/84 ----> loss: 0.743668

epoch 248:

78/84 ----> loss: 0.743752

epoch 249:

4/84 ----> loss: 0.743766

epoch 249:

14/84 ----> loss: 0.743668

epoch 249:

24/84 ----> loss: 0.743726

epoch 249:

34/84 ----> loss: 0.743668

epoch 249:

44/84 ----> loss: 0.743668

epoch 249:

54/84 ----> loss: 0.743890

epoch 249:

64/84 ----> loss: 0.743850

epoch 249:

74/84 ----> loss: 0.743668

epoch 250:

0/84 ----> loss: 0.743668

epoch 250:

10/84 ----> loss: 0.743727

epoch 250:

20/84 ----> loss: 0.743668

epoch 250:

30/84 ----> loss: 0.743671

epoch 250:

40/84 ----> loss: 0.743704

epoch 250:

50/84 ----> loss: 0.743795

epoch 250:

60/84 ----> loss: 0.743800

epoch 250:

70/84 ----> loss: 0.743669

epoch 250:

80/84 ----> loss: 0.743675

epoch 251:

6/84 ----> loss: 0.743668

epoch 251:

16/84 ----> loss: 0.743668

epoch 251:

26/84 ----> loss: 0.743837

epoch 251:

36/84 ----> loss: 0.743668

epoch 251:

46/84 ----> loss: 0.743927

epoch 251:

56/84 ----> loss: 0.743725

epoch 251:

66/84 ----> loss: 0.743668

epoch 251:

76/84 ----> loss: 0.743668

epoch 252:

2/84 ----> loss: 0.743748

epoch 252:

12/84 ----> loss: 0.743668

epoch 252:

22/84 ----> loss: 0.743670

epoch 252:

32/84 ----> loss: 0.743674

epoch 252:

42/84 ----> loss: 0.743669

epoch 252:

52/84 ----> loss: 0.744705

epoch 252:

62/84 ----> loss: 0.743685

epoch 252:

72/84 ----> loss: 0.744978

epoch 252:

82/84 ----> loss: 0.743785

epoch 253:

8/84 ----> loss: 0.744062

epoch 253:

18/84 ----> loss: 0.743669

epoch 253:

28/84 ----> loss: 0.743673

epoch 253:

38/84 ----> loss: 0.743821

epoch 253:

48/84 ----> loss: 0.743668

epoch 253:

58/84 ----> loss: 0.743741

epoch 253:

68/84 ----> loss: 0.743668

epoch 253:

78/84 ----> loss: 0.743750

epoch 254:

4/84 ----> loss: 0.743763

epoch 254:

14/84 ----> loss: 0.743668

epoch 254:

24/84 ----> loss: 0.743725

epoch 254:

34/84 ----> loss: 0.743668

epoch 254:

44/84 ----> loss: 0.743668

epoch 254:

54/84 ----> loss: 0.743885

epoch 254:

64/84 ----> loss: 0.743845

epoch 254:

74/84 ----> loss: 0.743668

epoch 255:

0/84 ----> loss: 0.743668

epoch 255:

10/84 ----> loss: 0.743725

epoch 255:

20/84 ----> loss: 0.743668

epoch 255:

30/84 ----> loss: 0.743671

epoch 255:

40/84 ----> loss: 0.743703

epoch 255:

50/84 ----> loss: 0.743792

epoch 255:

60/84 ----> loss: 0.743796

epoch 255:

70/84 ----> loss: 0.743669

epoch 255:

80/84 ----> loss: 0.743674

epoch 256:

6/84 ----> loss: 0.743668

epoch 256:

16/84 ----> loss: 0.743668

epoch 256:

26/84 ----> loss: 0.743833

epoch 256:

36/84 ----> loss: 0.743668

epoch 256:

46/84 ----> loss: 0.743921

epoch 256:

56/84 ----> loss: 0.743724

epoch 256:

66/84 ----> loss: 0.743668

epoch 256:

76/84 ----> loss: 0.743668

epoch 257:

2/84 ----> loss: 0.743746

epoch 257:

12/84 ----> loss: 0.743668

epoch 257:

22/84 ----> loss: 0.743670

epoch 257:

32/84 ----> loss: 0.743674

epoch 257:

42/84 ----> loss: 0.743669

epoch 257:

52/84 ----> loss: 0.744682

epoch 257:

62/84 ----> loss: 0.743684

epoch 257:

72/84 ----> loss: 0.744944

epoch 257:

82/84 ----> loss: 0.743782

epoch 258:

8/84 ----> loss: 0.744052

epoch 258:

18/84 ----> loss: 0.743669

epoch 258:

28/84 ----> loss: 0.743673

epoch 258:

38/84 ----> loss: 0.743816

epoch 258:

48/84 ----> loss: 0.743668

epoch 258:

58/84 ----> loss: 0.743739

epoch 258:

68/84 ----> loss: 0.743668

epoch 258:

78/84 ----> loss: 0.743748

epoch 259:

4/84 ----> loss: 0.743761

epoch 259:

14/84 ----> loss: 0.743668

epoch 259:

24/84 ----> loss: 0.743724

epoch 259:

34/84 ----> loss: 0.743668

epoch 259:

44/84 ----> loss: 0.743668

epoch 259:

54/84 ----> loss: 0.743880

epoch 259:

64/84 ----> loss: 0.743841

epoch 259:

74/84 ----> loss: 0.743668

epoch 260:

0/84 ----> loss: 0.743668

epoch 260:

10/84 ----> loss: 0.743724

epoch 260:

20/84 ----> loss: 0.743668

epoch 260:

30/84 ----> loss: 0.743671

epoch 260:

40/84 ----> loss: 0.743703

epoch 260:

50/84 ----> loss: 0.743789

epoch 260:

60/84 ----> loss: 0.743793

epoch 260:

70/84 ----> loss: 0.743669

epoch 260:

80/84 ----> loss: 0.743674

epoch 261:

6/84 ----> loss: 0.743668

epoch 261:

16/84 ----> loss: 0.743668

epoch 261:

26/84 ----> loss: 0.743829

epoch 261:

36/84 ----> loss: 0.743668

epoch 261:

46/84 ----> loss: 0.743915

epoch 261:

56/84 ----> loss: 0.743722

epoch 261:

66/84 ----> loss: 0.743668

epoch 261:

76/84 ----> loss: 0.743668

epoch 262:

2/84 ----> loss: 0.743744

epoch 262:

12/84 ----> loss: 0.743668

epoch 262:

22/84 ----> loss: 0.743670

epoch 262:

32/84 ----> loss: 0.743673

epoch 262:

42/84 ----> loss: 0.743669

epoch 262:

52/84 ----> loss: 0.744660

epoch 262:

62/84 ----> loss: 0.743684

epoch 262:

72/84 ----> loss: 0.744912

epoch 262:

82/84 ----> loss: 0.743779

epoch 263:

8/84 ----> loss: 0.744043

epoch 263:

18/84 ----> loss: 0.743669

epoch 263:

28/84 ----> loss: 0.743672

epoch 263:

38/84 ----> loss: 0.743812

epoch 263:

48/84 ----> loss: 0.743668

epoch 263:

58/84 ----> loss: 0.743737

epoch 263:

68/84 ----> loss: 0.743668

epoch 263:

78/84 ----> loss: 0.743746

epoch 264:

4/84 ----> loss: 0.743758

epoch 264:

14/84 ----> loss: 0.743668

epoch 264:

24/84 ----> loss: 0.743722

epoch 264:

34/84 ----> loss: 0.743668

epoch 264:

44/84 ----> loss: 0.743668

epoch 264:

54/84 ----> loss: 0.743875

epoch 264:

64/84 ----> loss: 0.743837

epoch 264:

74/84 ----> loss: 0.743668

epoch 265:

0/84 ----> loss: 0.743668

epoch 265:

10/84 ----> loss: 0.743722

epoch 265:

20/84 ----> loss: 0.743668

epoch 265:

30/84 ----> loss: 0.743671

epoch 265:

40/84 ----> loss: 0.743702

epoch 265:

50/84 ----> loss: 0.743787

epoch 265:

60/84 ----> loss: 0.743790

epoch 265:

70/84 ----> loss: 0.743669

epoch 265:

80/84 ----> loss: 0.743674

epoch 266:

6/84 ----> loss: 0.743668

epoch 266:

16/84 ----> loss: 0.743668

epoch 266:

26/84 ----> loss: 0.743825

epoch 266:

36/84 ----> loss: 0.743668

epoch 266:

46/84 ----> loss: 0.743909

epoch 266:

56/84 ----> loss: 0.743720

epoch 266:

66/84 ----> loss: 0.743668

epoch 266:

76/84 ----> loss: 0.743668

epoch 267:

2/84 ----> loss: 0.743742

epoch 267:

12/84 ----> loss: 0.743668

epoch 267:

22/84 ----> loss: 0.743670

epoch 267:

32/84 ----> loss: 0.743673

epoch 267:

42/84 ----> loss: 0.743669

epoch 267:

52/84 ----> loss: 0.744638

epoch 267:

62/84 ----> loss: 0.743683

epoch 267:

72/84 ----> loss: 0.744881

epoch 267:

82/84 ----> loss: 0.743776

epoch 268:

8/84 ----> loss: 0.744034

epoch 268:

18/84 ----> loss: 0.743669

epoch 268:

28/84 ----> loss: 0.743672

epoch 268:

38/84 ----> loss: 0.743808

epoch 268:

48/84 ----> loss: 0.743668

epoch 268:

58/84 ----> loss: 0.743736

epoch 268:

68/84 ----> loss: 0.743668

epoch 268:

78/84 ----> loss: 0.743744

epoch 269:

4/84 ----> loss: 0.743756

epoch 269:

14/84 ----> loss: 0.743668

epoch 269:

24/84 ----> loss: 0.743721

epoch 269:

34/84 ----> loss: 0.743668

epoch 269:

44/84 ----> loss: 0.743668

epoch 269:

54/84 ----> loss: 0.743871

epoch 269:

64/84 ----> loss: 0.743833

epoch 269:

74/84 ----> loss: 0.743668

epoch 270:

0/84 ----> loss: 0.743668

epoch 270:

10/84 ----> loss: 0.743720

epoch 270:

20/84 ----> loss: 0.743668

epoch 270:

30/84 ----> loss: 0.743671

epoch 270:

40/84 ----> loss: 0.743701

epoch 270:

50/84 ----> loss: 0.743784

epoch 270:

60/84 ----> loss: 0.743787

epoch 270:

70/84 ----> loss: 0.743669

epoch 270:

80/84 ----> loss: 0.743674

epoch 271:

6/84 ----> loss: 0.743668

epoch 271:

16/84 ----> loss: 0.743668

epoch 271:

26/84 ----> loss: 0.743821

epoch 271:

36/84 ----> loss: 0.743668

epoch 271:

46/84 ----> loss: 0.743904

epoch 271:

56/84 ----> loss: 0.743719

epoch 271:

66/84 ----> loss: 0.743668

epoch 271:

76/84 ----> loss: 0.743668

epoch 272:

2/84 ----> loss: 0.743740

epoch 272:

12/84 ----> loss: 0.743668

epoch 272:

22/84 ----> loss: 0.743670

epoch 272:

32/84 ----> loss: 0.743673

epoch 272:

42/84 ----> loss: 0.743669

epoch 272:

52/84 ----> loss: 0.744618

epoch 272:

62/84 ----> loss: 0.743682

epoch 272:

72/84 ----> loss: 0.744852

epoch 272:

82/84 ----> loss: 0.743773

epoch 273:

8/84 ----> loss: 0.744025

epoch 273:

18/84 ----> loss: 0.743669

epoch 273:

28/84 ----> loss: 0.743672

epoch 273:

38/84 ----> loss: 0.743805

epoch 273:

48/84 ----> loss: 0.743668

epoch 273:

58/84 ----> loss: 0.743734

epoch 273:

68/84 ----> loss: 0.743668

epoch 273:

78/84 ----> loss: 0.743742

epoch 274:

4/84 ----> loss: 0.743754

epoch 274:

14/84 ----> loss: 0.743668

epoch 274:

24/84 ----> loss: 0.743720

epoch 274:

34/84 ----> loss: 0.743668

epoch 274:

44/84 ----> loss: 0.743668

epoch 274:

54/84 ----> loss: 0.743866

epoch 274:

64/84 ----> loss: 0.743830

epoch 274:

74/84 ----> loss: 0.743668

epoch 275:

0/84 ----> loss: 0.743668

epoch 275:

10/84 ----> loss: 0.743719

epoch 275:

20/84 ----> loss: 0.743668

epoch 275:

30/84 ----> loss: 0.743671

epoch 275:

40/84 ----> loss: 0.743701

epoch 275:

50/84 ----> loss: 0.743781

epoch 275:

60/84 ----> loss: 0.743784

epoch 275:

70/84 ----> loss: 0.743669

epoch 275:

80/84 ----> loss: 0.743674

epoch 276:

6/84 ----> loss: 0.743668

epoch 276:

16/84 ----> loss: 0.743668

epoch 276:

26/84 ----> loss: 0.743818

epoch 276:

36/84 ----> loss: 0.743668

epoch 276:

46/84 ----> loss: 0.743899

epoch 276:

56/84 ----> loss: 0.743718

epoch 276:

66/84 ----> loss: 0.743668

epoch 276:

76/84 ----> loss: 0.743668

epoch 277:

2/84 ----> loss: 0.743738

epoch 277:

12/84 ----> loss: 0.743668

epoch 277:

22/84 ----> loss: 0.743670

epoch 277:

32/84 ----> loss: 0.743673

epoch 277:

42/84 ----> loss: 0.743669

epoch 277:

52/84 ----> loss: 0.744598

epoch 277:

62/84 ----> loss: 0.743682

epoch 277:

72/84 ----> loss: 0.744824

epoch 277:

82/84 ----> loss: 0.743771

epoch 278:

8/84 ----> loss: 0.744017

epoch 278:

18/84 ----> loss: 0.743669

epoch 278:

28/84 ----> loss: 0.743672

epoch 278:

38/84 ----> loss: 0.743801

epoch 278:

48/84 ----> loss: 0.743668

epoch 278:

58/84 ----> loss: 0.743732

epoch 278:

68/84 ----> loss: 0.743668

epoch 278:

78/84 ----> loss: 0.743740

epoch 279:

4/84 ----> loss: 0.743752

epoch 279:

14/84 ----> loss: 0.743668

epoch 279:

24/84 ----> loss: 0.743719

epoch 279:

34/84 ----> loss: 0.743668

epoch 279:

44/84 ----> loss: 0.743668

epoch 279:

54/84 ----> loss: 0.743862

epoch 279:

64/84 ----> loss: 0.743826

epoch 279:

74/84 ----> loss: 0.743668

epoch 280:

0/84 ----> loss: 0.743668

epoch 280:

10/84 ----> loss: 0.743717

epoch 280:

20/84 ----> loss: 0.743668

epoch 280:

30/84 ----> loss: 0.743670

epoch 280:

40/84 ----> loss: 0.743700

epoch 280:

50/84 ----> loss: 0.743779

epoch 280:

60/84 ----> loss: 0.743782

epoch 280:

70/84 ----> loss: 0.743669

epoch 280:

80/84 ----> loss: 0.743673

epoch 281:

6/84 ----> loss: 0.743668

epoch 281:

16/84 ----> loss: 0.743668

epoch 281:

26/84 ----> loss: 0.743814

epoch 281:

36/84 ----> loss: 0.743668

epoch 281:

46/84 ----> loss: 0.743894

epoch 281:

56/84 ----> loss: 0.743716

epoch 281:

66/84 ----> loss: 0.743668

epoch 281:

76/84 ----> loss: 0.743668

epoch 282:

2/84 ----> loss: 0.743736

epoch 282:

12/84 ----> loss: 0.743668

epoch 282:

22/84 ----> loss: 0.743670

epoch 282:

32/84 ----> loss: 0.743673

epoch 282:

42/84 ----> loss: 0.743669

epoch 282:

52/84 ----> loss: 0.744579

epoch 282:

62/84 ----> loss: 0.743681

epoch 282:

72/84 ----> loss: 0.744797

epoch 282:

82/84 ----> loss: 0.743768

epoch 283:

8/84 ----> loss: 0.744010

epoch 283:

18/84 ----> loss: 0.743669

epoch 283:

28/84 ----> loss: 0.743672

epoch 283:

38/84 ----> loss: 0.743797

epoch 283:

48/84 ----> loss: 0.743668

epoch 283:

58/84 ----> loss: 0.743731

epoch 283:

68/84 ----> loss: 0.743668

epoch 283:

78/84 ----> loss: 0.743739

epoch 284:

4/84 ----> loss: 0.743750

epoch 284:

14/84 ----> loss: 0.743668

epoch 284:

24/84 ----> loss: 0.743718

epoch 284:

34/84 ----> loss: 0.743668

epoch 284:

44/84 ----> loss: 0.743668

epoch 284:

54/84 ----> loss: 0.743858

epoch 284:

64/84 ----> loss: 0.743823

epoch 284:

74/84 ----> loss: 0.743668

epoch 285:

0/84 ----> loss: 0.743668

epoch 285:

10/84 ----> loss: 0.743716

epoch 285:

20/84 ----> loss: 0.743668

epoch 285:

30/84 ----> loss: 0.743670

epoch 285:

40/84 ----> loss: 0.743699

epoch 285:

50/84 ----> loss: 0.743776

epoch 285:

60/84 ----> loss: 0.743779

epoch 285:

70/84 ----> loss: 0.743669

epoch 285:

80/84 ----> loss: 0.743673

epoch 286:

6/84 ----> loss: 0.743668

epoch 286:

16/84 ----> loss: 0.743668

epoch 286:

26/84 ----> loss: 0.743811

epoch 286:

36/84 ----> loss: 0.743668

epoch 286:

46/84 ----> loss: 0.743889

epoch 286:

56/84 ----> loss: 0.743715

epoch 286:

66/84 ----> loss: 0.743668

epoch 286:

76/84 ----> loss: 0.743668

epoch 287:

2/84 ----> loss: 0.743734

epoch 287:

12/84 ----> loss: 0.743668

epoch 287:

22/84 ----> loss: 0.743669

epoch 287:

32/84 ----> loss: 0.743673

epoch 287:

42/84 ----> loss: 0.743669

epoch 287:

52/84 ----> loss: 0.744561

epoch 287:

62/84 ----> loss: 0.743681

epoch 287:

72/84 ----> loss: 0.744772

epoch 287:

82/84 ----> loss: 0.743766

epoch 288:

8/84 ----> loss: 0.744002

epoch 288:

18/84 ----> loss: 0.743669

epoch 288:

28/84 ----> loss: 0.743672

epoch 288:

38/84 ----> loss: 0.743794

epoch 288:

48/84 ----> loss: 0.743668

epoch 288:

58/84 ----> loss: 0.743730

epoch 288:

68/84 ----> loss: 0.743668

epoch 288:

78/84 ----> loss: 0.743737

epoch 289:

4/84 ----> loss: 0.743748

epoch 289:

14/84 ----> loss: 0.743668

epoch 289:

24/84 ----> loss: 0.743717

epoch 289:

34/84 ----> loss: 0.743668

epoch 289:

44/84 ----> loss: 0.743668

epoch 289:

54/84 ----> loss: 0.743854

epoch 289:

64/84 ----> loss: 0.743819

epoch 289:

74/84 ----> loss: 0.743668

epoch 290:

0/84 ----> loss: 0.743668

epoch 290:

10/84 ----> loss: 0.743715

epoch 290:

20/84 ----> loss: 0.743668

epoch 290:

30/84 ----> loss: 0.743670

epoch 290:

40/84 ----> loss: 0.743699

epoch 290:

50/84 ----> loss: 0.743774

epoch 290:

60/84 ----> loss: 0.743777

epoch 290:

70/84 ----> loss: 0.743669

epoch 290:

80/84 ----> loss: 0.743673

epoch 291:

6/84 ----> loss: 0.743668

epoch 291:

16/84 ----> loss: 0.743668

epoch 291:

26/84 ----> loss: 0.743808

epoch 291:

36/84 ----> loss: 0.743668

epoch 291:

46/84 ----> loss: 0.743884

epoch 291:

56/84 ----> loss: 0.743714

epoch 291:

66/84 ----> loss: 0.743668

epoch 291:

76/84 ----> loss: 0.743668

epoch 292:

2/84 ----> loss: 0.743733

epoch 292:

12/84 ----> loss: 0.743668

epoch 292:

22/84 ----> loss: 0.743669

epoch 292:

32/84 ----> loss: 0.743672

epoch 292:

42/84 ----> loss: 0.743669

epoch 292:

52/84 ----> loss: 0.744543

epoch 292:

62/84 ----> loss: 0.743681

epoch 292:

72/84 ----> loss: 0.744747

epoch 292:

82/84 ----> loss: 0.743764

epoch 293:

8/84 ----> loss: 0.743995

epoch 293:

18/84 ----> loss: 0.743669

epoch 293:

28/84 ----> loss: 0.743672

epoch 293:

38/84 ----> loss: 0.743791

epoch 293:

48/84 ----> loss: 0.743668

epoch 293:

58/84 ----> loss: 0.743728

epoch 293:

68/84 ----> loss: 0.743668

epoch 293:

78/84 ----> loss: 0.743736

epoch 294:

4/84 ----> loss: 0.743747

epoch 294:

14/84 ----> loss: 0.743668

epoch 294:

24/84 ----> loss: 0.743716

epoch 294:

34/84 ----> loss: 0.743668

epoch 294:

44/84 ----> loss: 0.743668

epoch 294:

54/84 ----> loss: 0.743851

epoch 294:

64/84 ----> loss: 0.743816

epoch 294:

74/84 ----> loss: 0.743668

epoch 295:

0/84 ----> loss: 0.743668

epoch 295:

10/84 ----> loss: 0.743713

epoch 295:

20/84 ----> loss: 0.743668

epoch 295:

30/84 ----> loss: 0.743670

epoch 295:

40/84 ----> loss: 0.743698

epoch 295:

50/84 ----> loss: 0.743772

epoch 295:

60/84 ----> loss: 0.743774

epoch 295:

70/84 ----> loss: 0.743669

epoch 295:

80/84 ----> loss: 0.743673

epoch 296:

6/84 ----> loss: 0.743668

epoch 296:

16/84 ----> loss: 0.743668

epoch 296:

26/84 ----> loss: 0.743805

epoch 296:

36/84 ----> loss: 0.743668

epoch 296:

46/84 ----> loss: 0.743880

epoch 296:

56/84 ----> loss: 0.743713

epoch 296:

66/84 ----> loss: 0.743668

epoch 296:

76/84 ----> loss: 0.743668

epoch 297:

2/84 ----> loss: 0.743731

epoch 297:

12/84 ----> loss: 0.743668

epoch 297:

22/84 ----> loss: 0.743669

epoch 297:

32/84 ----> loss: 0.743672

epoch 297:

42/84 ----> loss: 0.743669

epoch 297:

52/84 ----> loss: 0.744527

epoch 297:

62/84 ----> loss: 0.743680

epoch 297:

72/84 ----> loss: 0.744723

epoch 297:

82/84 ----> loss: 0.743761

epoch 298:

8/84 ----> loss: 0.743988

epoch 298:

18/84 ----> loss: 0.743669

epoch 298:

28/84 ----> loss: 0.743672

epoch 298:

38/84 ----> loss: 0.743788

epoch 298:

48/84 ----> loss: 0.743668

epoch 298:

58/84 ----> loss: 0.743727

epoch 298:

68/84 ----> loss: 0.743668

epoch 298:

78/84 ----> loss: 0.743734

epoch 299:

4/84 ----> loss: 0.743745

epoch 299:

14/84 ----> loss: 0.743668

epoch 299:

24/84 ----> loss: 0.743715

epoch 299:

34/84 ----> loss: 0.743668

epoch 299:

44/84 ----> loss: 0.743668

epoch 299:

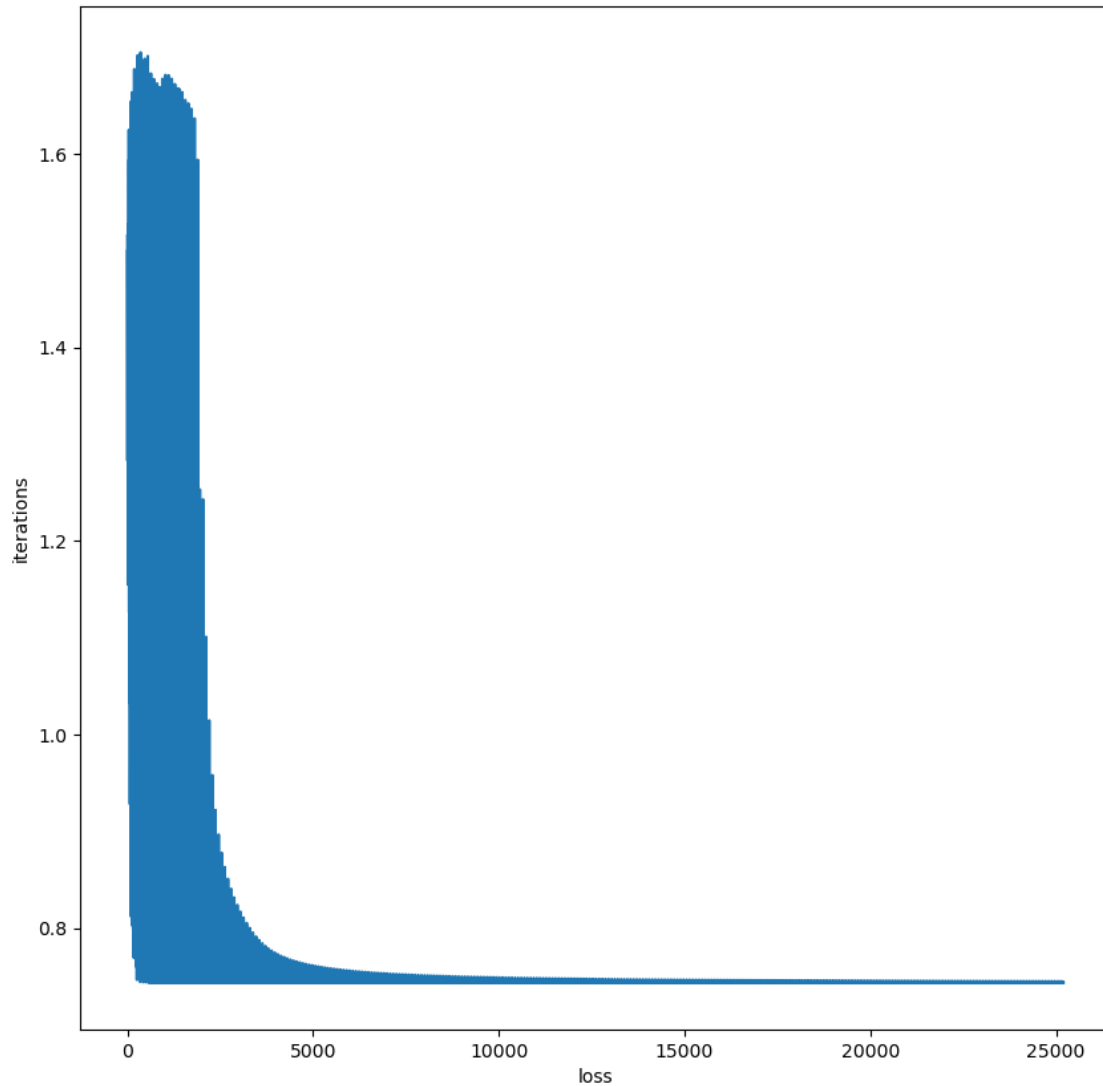
54/84 ----> loss: 0.743847

epoch 299:

64/84 ----> loss: 0.743813

epoch 299:

74/84 ----> loss: 0.743668



```
[307]: accuracy = testing(X_test,y_test.to_numpy().ravel(),model,printFn=False)
        print(accuracy)
```

```
Accuracy: 0.9459459459459459
(0.9459459459459459, [tensor(2), tensor(3), tensor(1), tensor(0), tensor(0),
tensor(2), tensor(2), tensor(0), tensor(0), tensor(0), tensor(2), tensor(0),
tensor(3), tensor(2), tensor(1), tensor(0), tensor(2), tensor(3), tensor(2),
tensor(2), tensor(3), tensor(3), tensor(1), tensor(0), tensor(1), tensor(1),
tensor(2), tensor(1), tensor(1), tensor(2), tensor(3), tensor(0), tensor(2),
tensor(2), tensor(0), tensor(2), tensor(3)])
```

```
[308]: #torch.save(model.state_dict(), "model.pth")
        #print("Saved PyTorch Model State to model.pth")
```

```
[474]: model = NeuralNetwork().to(device)
        model.load_state_dict(torch.load("model.pth"))
        model.eval()
```

```
[474]: NeuralNetwork(
      (linear_relu_stack): Sequential(
        (0): Linear(in_features=20, out_features=30, bias=True)
        (1): Linear(in_features=30, out_features=30, bias=True)
        (2): Linear(in_features=30, out_features=10, bias=True)
        (3): Linear(in_features=10, out_features=4, bias=True)
        (4): Softmax(dim=None)
      )
    )
```

```
[475]: accuracy,preds = testing(X_test,y_test.to_numpy().ravel(),model,printFn=False)
        print(accuracy)
```

```
Accuracy:  0.9459459459459459
0.9459459459459459
```

```
C:\Users\brian\Anaconda3\Lib\site-packages\torch\nn\modules\module.py:1518:
UserWarning: Implicit dimension choice for softmax has been deprecated. Change
the call to include dim=X as an argument.
    return self._call_impl(*args, **kwargs)
```

```
[476]: res = []
        for l in [0,1,2,3]:
            prec,recall,_,_ = precision_recall_fscore_support(np.array(y_test)==l,
                                                              np.array(preds)==l,
                                                              pos_label=True,average=None)

            res.append([l,recall[0],recall[1]])

statistics_df = pd.DataFrame(res,columns =_
    ↳ ['class','specificity','sensitivity'])
statistics_df['label'] = statistics_df['class'].apply(lambda x: 'CD' if x==0_
    ↳ else 'GN' if x==1 else 'HPDE' if x==2 else 'MiaPaCa')

confusion_mat = metrics.confusion_matrix(y_test.values.ravel(), np.
    ↳ array(preds),labels=[0,1,2,3])

print('Specificity: \n', statistics_df[['label','specificity']])
print('Sensitivity: \n', statistics_df[['label','sensitivity']])
```

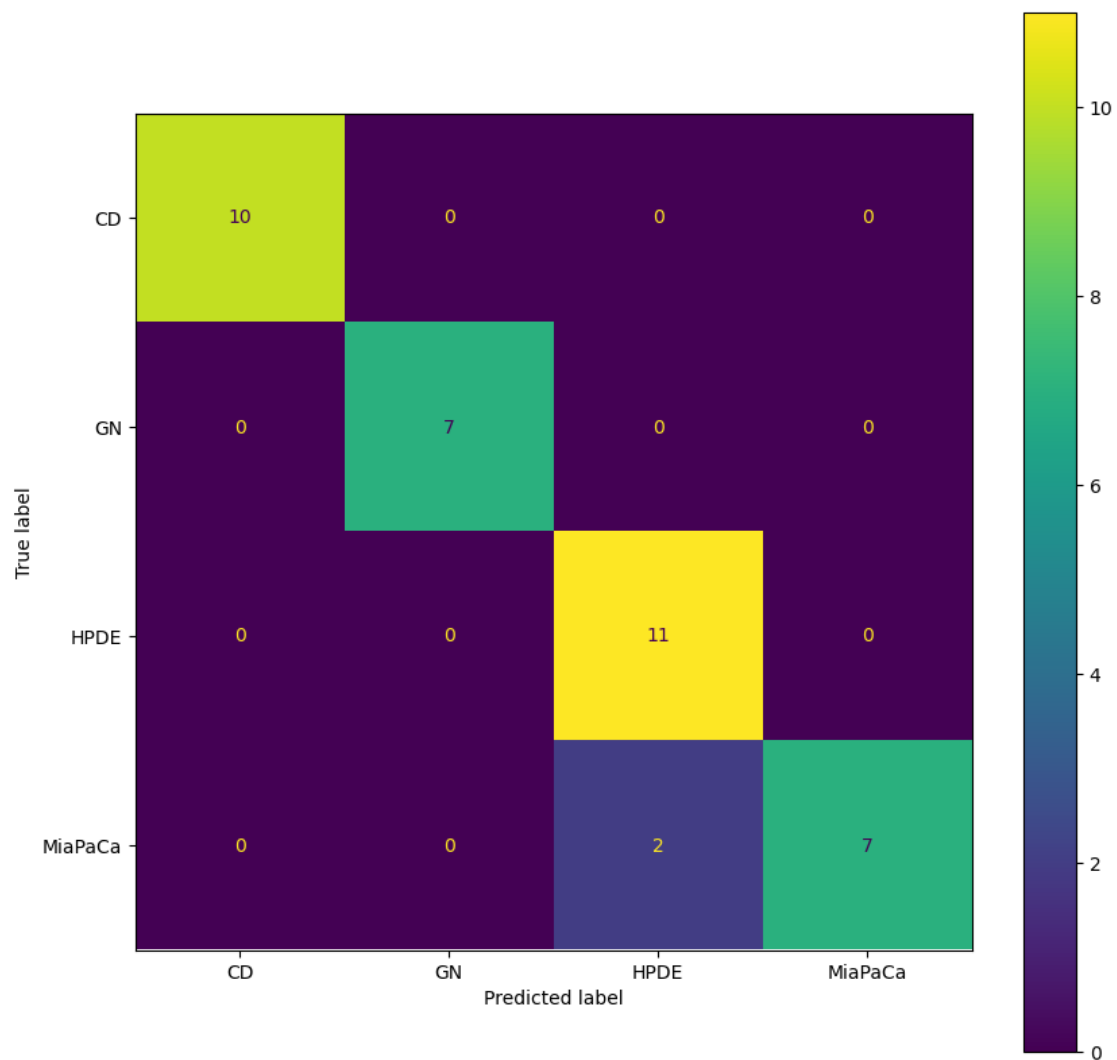
```
cm_display = metrics.ConfusionMatrixDisplay(confusion_matrix = confusion_mat,
display_labels = statistics_df['label'].to_list())
cm_display.plot()
plt.show()
```

Specificity:

	label	specificity
0	CD	1.000000
1	GN	1.000000
2	HPDE	0.923077
3	MiaPaCa	1.000000

Sensitivity:

	label	sensitivity
0	CD	1.000000
1	GN	1.000000
2	HPDE	1.000000
3	MiaPaCa	0.777778



```
[477]: print('Overall specificity: ', statistics_df['specificity'].mean())
print('Overall sensitivity: ', statistics_df['sensitivity'].mean())
```

```
Overall specificity:  0.9807692307692308
Overall sensitivity:  0.9444444444444444
```

This results display better accuracy, sensitivity, and specificity. My accuracy: 94% whereas the study's accuracy is 90%. My specificity: 98% whereas the study's specificity is 97%. Finally, my sensitivity: 95% whereas the study's sensitivity is 91%. Overall, the neural network seems to work better!

```
[478]: model
```

```
[478]: NeuralNetwork(
  (linear_relu_stack): Sequential(
    (0): Linear(in_features=20, out_features=30, bias=True)
    (1): Linear(in_features=30, out_features=30, bias=True)
    (2): Linear(in_features=30, out_features=10, bias=True)
    (3): Linear(in_features=10, out_features=4, bias=True)
    (4): Softmax(dim=None)
  )
)
```

```
[479]: from sklearn.model_selection import KFold

split = 25

#kfold = KFold(n_splits=X.shape[0], shuffle=True)
kfold = KFold(n_splits=split, shuffle=True)

all_pred = np.array([])
y_match = np.array([])
accuracies = []
for fold, (train_ids, test_ids) in enumerate(kfold.split(X)):

    model = NeuralNetwork().to(device)
    learning_rate = 0.01
    epoch = 300
    batch = 11

    loss_fn = nn.CrossEntropyLoss()

    optimizer = torch.optim.SGD(model.parameters(), lr=learning_rate)

    loss_count, count = train_loop(X[train_ids],
```

```

        y.to_numpy().ravel()[train_ids],
        model,
        epoch, batch,
        loss_fn,
        optimizer,
        printFn=False)

    accuracy, preds = testing(X[test_ids], y.to_numpy().
    ↪ ravel()[test_ids], model, printFn=False)
    accuracies.append(accuracy)
    all_pred = np.append(all_pred, preds)
    y_match = np.append(y_match, y.to_numpy().ravel()[test_ids])

print('Overall Accuracy: ', np.array(accuracies).mean())
confusion_mat = confusion_matrix(y_match, all_pred, labels=[0,1,2,3])

res = []
for l in [0,1,2,3]:
    prec, recall, _, _ = precision_recall_fscore_support(y_match==l,
                                                         all_pred==l,
                                                         labels=[0,1,2,3],
                                                         pos_label=True,
                                                         average=None)

    res.append([l, recall[0], recall[1]])

statistics_df = pd.DataFrame(res, columns = [
    ↪ ['class', 'specificity', 'sensitivity'])
statistics_df['label'] = statistics_df['class'].apply(lambda x: 'CD' if x==0,
    ↪ else 'GN' if x==1 else 'HPDE' if x==2 else 'MiaPaCa')

print('Specificity: \n', statistics_df[['label', 'specificity']])
print('Sensitivity: \n', statistics_df[['label', 'sensitivity']])
print('Overall Specificity: \n', statistics_df[['specificity']].mean())
print('Overall Sensitivity: \n', statistics_df[['sensitivity']].mean())

cm_display = metrics.ConfusionMatrixDisplay(confusion_matrix = confusion_mat,
    ↪ display_labels = statistics_df['label'].to_list())
cm_display.plot()
plt.show()

```

C:\Users\brian\Anaconda3\Lib\site-packages\torch\nn\modules\module.py:1518:
 UserWarning: Implicit dimension choice for softmax has been deprecated. Change
 the call to include dim=X as an argument.

```
    return self._call_impl(*args, **kwargs)
```

Accuracy: 1.0

Accuracy: 0.8

```

Accuracy: 0.8
Accuracy: 0.8
Accuracy: 0.6
Accuracy: 0.8
Accuracy: 0.8
Accuracy: 1.0
Accuracy: 1.0
Accuracy: 0.8
Accuracy: 1.0
Accuracy: 1.0
Accuracy: 0.8
Accuracy: 0.6
Accuracy: 1.0
Accuracy: 1.0
Accuracy: 0.8
Accuracy: 1.0
Accuracy: 1.0
Accuracy: 1.0
Accuracy: 1.0
Accuracy: 1.0
Accuracy: 1.0
Accuracy: 1.0
Accuracy: 0.75
Overall Accuracy: 0.894
Specificity:
      label  specificity
0        CD    0.965909
1        GN    0.969697
2       HPDE    0.953488
3  MiaPaCa    0.966667
Sensitivity:
      label  sensitivity
0        CD    0.848485
1        GN    0.909091
2       HPDE    0.971429
3  MiaPaCa    0.838710
Overall Specificity:
      specificity    0.96394
dtype: float64
Overall Sensitivity:
      sensitivity    0.891929
dtype: float64

```

```

C:\Users\brian\Anaconda3\Lib\site-
packages\sklearn\metrics\_classification.py:1509: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))

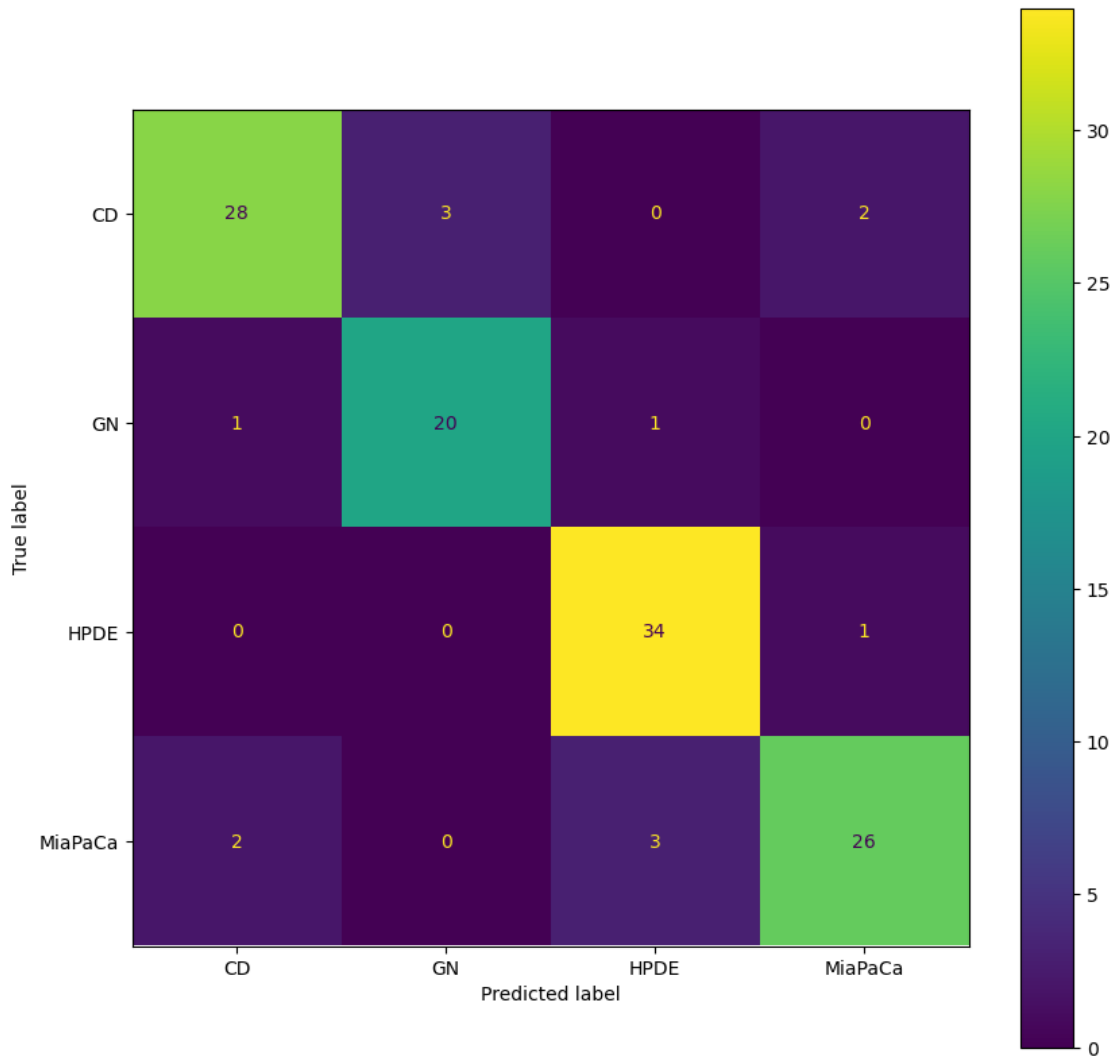
```

```

C:\Users\brian\Anaconda3\Lib\site-
packages\sklearn\metrics\_classification.py:1509: UndefinedMetricWarning: Recall
is ill-defined and being set to 0.0 in labels with no true samples. Use
`zero_division` parameter to control this behavior.
    _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
C:\Users\brian\Anaconda3\Lib\site-
packages\sklearn\metrics\_classification.py:1509: UndefinedMetricWarning:
F-score is ill-defined and being set to 0.0 in labels with no true nor predicted
samples. Use `zero_division` parameter to control this behavior.
    _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
C:\Users\brian\Anaconda3\Lib\site-
packages\sklearn\metrics\_classification.py:1509: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
    _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
C:\Users\brian\Anaconda3\Lib\site-
packages\sklearn\metrics\_classification.py:1509: UndefinedMetricWarning: Recall
is ill-defined and being set to 0.0 in labels with no true samples. Use
`zero_division` parameter to control this behavior.
    _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
C:\Users\brian\Anaconda3\Lib\site-
packages\sklearn\metrics\_classification.py:1509: UndefinedMetricWarning:
F-score is ill-defined and being set to 0.0 in labels with no true nor predicted
samples. Use `zero_division` parameter to control this behavior.
    _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
C:\Users\brian\Anaconda3\Lib\site-
packages\sklearn\metrics\_classification.py:1509: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
    _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
C:\Users\brian\Anaconda3\Lib\site-
packages\sklearn\metrics\_classification.py:1509: UndefinedMetricWarning: Recall
is ill-defined and being set to 0.0 in labels with no true samples. Use
`zero_division` parameter to control this behavior.
    _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
C:\Users\brian\Anaconda3\Lib\site-
packages\sklearn\metrics\_classification.py:1509: UndefinedMetricWarning:
F-score is ill-defined and being set to 0.0 in labels with no true nor predicted
samples. Use `zero_division` parameter to control this behavior.
    _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
C:\Users\brian\Anaconda3\Lib\site-
packages\sklearn\metrics\_classification.py:1509: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
    _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
C:\Users\brian\Anaconda3\Lib\site-
packages\sklearn\metrics\_classification.py:1509: UndefinedMetricWarning: Recall
is ill-defined and being set to 0.0 in labels with no true samples. Use

```

```
`zero_division` parameter to control this behavior.
_warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
C:\Users\brian\Anaconda3\Lib\site-
packages\sklearn\metrics\_classification.py:1509: UndefinedMetricWarning:
F-score is ill-defined and being set to 0.0 in labels with no true nor predicted
samples. Use `zero_division` parameter to control this behavior.
_warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```



Let us see whether non-PCA transformed data works better with the neural network.

```
[494]: model
```

```
[494]: NeuralNetwork(
  (linear_relu_stack): Sequential(
    (0): Linear(in_features=1013, out_features=30, bias=True)
```



```

        (1): Linear(in_features=30, out_features=30, bias=True)
        (2): Linear(in_features=30, out_features=10, bias=True)
        (3): Linear(in_features=10, out_features=4, bias=True)
        (4): Softmax(dim=None)
    )
)

```

```

[495]: model.linear_relu_stack.add_module('0', nn.Linear(1013,30))
#model.linear_relu_stack.add_module('1', nn.ReLU())
#model.linear_relu_stack.add_module('2', nn.Linear(30,30))
#model.linear_relu_stack.add_module('3', nn.Linear(30,10))
#model.linear_relu_stack.add_module('4', nn.Linear(10,4))
#model.linear_relu_stack.add_module('5', nn.Softmax(dim=0))

```

```

[496]: print(model)

learning_rate = 0.01
epoch = 300
batch = 11

loss_fn = nn.CrossEntropyLoss()

optimizer = torch.optim.SGD(model.parameters(), lr=learning_rate)

loss_count, count = train_loop(X_train_noPCA.values, y_train_noPCA.to_numpy().
    ↪ravel(), model, epoch, batch, loss_fn, optimizer, printFn=True)

```

```

NeuralNetwork(
  (linear_relu_stack): Sequential(
    (0): Linear(in_features=1013, out_features=30, bias=True)
    (1): Linear(in_features=30, out_features=30, bias=True)
    (2): Linear(in_features=30, out_features=10, bias=True)
    (3): Linear(in_features=10, out_features=4, bias=True)
    (4): Softmax(dim=None)
  )
)

```

epoch 0:

```

-----
-----

```

0/84 ----> loss: 1.281213

epoch 0:

```

-----

```

10/84 ----> loss: 0.743937

epoch 0:

20/84 ----> loss: 1.581696

epoch 0:

30/84 ----> loss: 1.743650

epoch 0:

40/84 ----> loss: 0.825755

epoch 0:

50/84 ----> loss: 0.754118

epoch 0:

60/84 ----> loss: 1.505596

epoch 0:

70/84 ----> loss: 1.694448

epoch 0:

80/84 ----> loss: 0.745640

epoch 1:

```
-----  
6/84 ----> loss: 1.702444
```

```
epoch 1:  
-----  
-----
```

```
16/84 ----> loss: 0.743671
```

```
epoch 1:  
-----  
-----
```

```
26/84 ----> loss: 0.743676
```

```
C:\Users\brian\Anaconda3\Lib\site-packages\torch\nn\modules\module.py:1518:  
UserWarning: Implicit dimension choice for softmax has been deprecated. Change  
the call to include dim=X as an argument.  
    return self._call_impl(*args, **kwargs)
```

```
epoch 1:  
-----  
-----
```

```
36/84 ----> loss: 0.821890
```

```
epoch 1:  
-----  
-----
```

```
46/84 ----> loss: 0.743680
```

```
epoch 1:  
-----  
-----
```

```
56/84 ----> loss: 1.166392
```

```
epoch 1:  
-----  
-----
```

```
66/84 ----> loss: 0.774919
```

```
epoch 1:  
-----  
-----
```

76/84 ----> loss: 0.743670

epoch 2:

2/84 ----> loss: 0.743669

epoch 2:

12/84 ----> loss: 1.743587

epoch 2:

22/84 ----> loss: 1.677501

epoch 2:

32/84 ----> loss: 0.743668

epoch 2:

42/84 ----> loss: 0.750224

epoch 2:

52/84 ----> loss: 0.743669

epoch 2:

62/84 ----> loss: 0.746304

epoch 2:

72/84 ----> loss: 0.743671

epoch 2:

82/84 ----> loss: 1.277410

epoch 3:

8/84 ----> loss: 1.390721

epoch 3:

18/84 ----> loss: 1.738103

epoch 3:

28/84 ----> loss: 0.743671

epoch 3:

38/84 ----> loss: 1.743215

epoch 3:

48/84 ----> loss: 0.770878

epoch 3:

58/84 ----> loss: 0.743671

epoch 3:

68/84 ----> loss: 0.743669

epoch 3:

78/84 ----> loss: 0.743670

epoch 4:

4/84 ----> loss: 1.743667

epoch 4:

14/84 ----> loss: 1.743668

epoch 4:

24/84 ----> loss: 1.743668

epoch 4:

34/84 ----> loss: 0.743668

epoch 4:

44/84 ----> loss: 0.743668

epoch 4:

54/84 ----> loss: 1.743668

epoch 4:

64/84 ----> loss: 1.684607

epoch 4:

74/84 ----> loss: 0.743668

epoch 5:

0/84 ----> loss: 0.743668

epoch 5:

10/84 ----> loss: 0.743669

epoch 5:

20/84 ----> loss: 0.748420

epoch 5:

30/84 ----> loss: 1.743599

epoch 5:

40/84 ----> loss: 0.743669

epoch 5:

50/84 ----> loss: 0.743669

epoch 5:

60/84 ----> loss: 0.743706

epoch 5:

70/84 ----> loss: 0.747257

epoch 5:

80/84 ----> loss: 0.743670

epoch 6:

6/84 ----> loss: 0.743682

epoch 6:

16/84 ----> loss: 0.743668

epoch 6:

26/84 ----> loss: 0.743669

epoch 6:

36/84 ----> loss: 1.320114

epoch 6:

46/84 ----> loss: 0.743671

epoch 6:

56/84 ----> loss: 0.751883

epoch 6:

66/84 ----> loss: 0.743668

epoch 6:

76/84 ----> loss: 0.743673

epoch 7:

2/84 ----> loss: 0.743668

epoch 7:

12/84 ----> loss: 1.741231

epoch 7:

22/84 ----> loss: 0.743668

epoch 7:

32/84 ----> loss: 0.743668

epoch 7:

42/84 ----> loss: 0.751994

epoch 7:

52/84 ----> loss: 0.743668

epoch 7:

62/84 ----> loss: 0.743668

epoch 7:

72/84 ----> loss: 0.743669

epoch 7:

82/84 ----> loss: 0.743684

epoch 8:

8/84 ----> loss: 0.743668

epoch 8:

18/84 ----> loss: 1.735373

epoch 8:

28/84 ----> loss: 0.743668

epoch 8:

38/84 ----> loss: 1.743619

epoch 8:

48/84 ----> loss: 0.743671

epoch 8:

58/84 ----> loss: 0.743668

epoch 8:

68/84 ----> loss: 0.743669

epoch 8:

78/84 ----> loss: 0.743736

epoch 9:

4/84 ----> loss: 1.743668

epoch 9:

14/84 ----> loss: 1.743668

epoch 9:

24/84 ----> loss: 1.743668

epoch 9:

34/84 ----> loss: 0.743668

epoch 9:

44/84 ----> loss: 0.743668

epoch 9:

54/84 ----> loss: 1.743668

epoch 9:

64/84 ----> loss: 1.667233

epoch 9:

74/84 ----> loss: 0.743668

epoch 10:

0/84 ----> loss: 0.743668

epoch 10:

10/84 ----> loss: 0.743668

epoch 10:

20/84 ----> loss: 0.744740

epoch 10:

30/84 ----> loss: 1.743668

epoch 10:

40/84 ----> loss: 0.743669

epoch 10:

50/84 ----> loss: 0.743668

epoch 10:

60/84 ----> loss: 0.743684

epoch 10:

70/84 ----> loss: 0.743669

epoch 10:

80/84 ----> loss: 0.743668

epoch 11:

6/84 ----> loss: 0.743681

epoch 11:

16/84 ----> loss: 0.743669

epoch 11:

26/84 ----> loss: 0.743668

epoch 11:

36/84 ----> loss: 0.760100

epoch 11:

46/84 ----> loss: 0.743668

epoch 11:

56/84 ----> loss: 1.488797

epoch 11:

66/84 ----> loss: 0.743669

epoch 11:

76/84 ----> loss: 0.743767

epoch 12:

2/84 ----> loss: 0.743668

epoch 12:

12/84 ----> loss: 1.743407

epoch 12:

22/84 ----> loss: 0.743668

epoch 12:

32/84 ----> loss: 0.743668

epoch 12:

42/84 ----> loss: 0.743669

epoch 12:

52/84 ----> loss: 0.743669

epoch 12:

62/84 ----> loss: 0.743668

epoch 12:

72/84 ----> loss: 0.743668

epoch 12:

82/84 ----> loss: 0.744449

epoch 13:

8/84 ----> loss: 0.743668

epoch 13:

18/84 ----> loss: 0.753493

epoch 13:

28/84 ----> loss: 0.743668

epoch 13:

38/84 ----> loss: 1.743647

epoch 13:

48/84 ----> loss: 0.743669

epoch 13:

58/84 ----> loss: 0.743668

epoch 13:

68/84 ----> loss: 0.743668

epoch 13:

78/84 ----> loss: 0.745221

epoch 14:

4/84 ----> loss: 1.743668

epoch 14:

14/84 ----> loss: 1.743668

epoch 14:

24/84 ----> loss: 1.743668

epoch 14:

34/84 ----> loss: 0.743668

epoch 14:

44/84 ----> loss: 0.743668

epoch 14:

54/84 ----> loss: 1.743668

epoch 14:

64/84 ----> loss: 1.684358

epoch 14:

74/84 ----> loss: 0.743668

epoch 15:

0/84 ----> loss: 0.743668

epoch 15:

10/84 ----> loss: 0.743668

epoch 15:

20/84 ----> loss: 0.743670

epoch 15:

30/84 ----> loss: 1.743668

epoch 15:

40/84 ----> loss: 0.743668

epoch 15:

50/84 ----> loss: 0.743668

epoch 15:

60/84 ----> loss: 0.743670

epoch 15:

70/84 ----> loss: 0.743670

epoch 15:

80/84 ----> loss: 0.743668

epoch 16:

6/84 ----> loss: 0.743707

epoch 16:

16/84 ----> loss: 0.743668

epoch 16:

26/84 ----> loss: 0.743668

epoch 16:

36/84 ----> loss: 0.747592

epoch 16:

46/84 ----> loss: 0.743668

epoch 16:

56/84 ----> loss: 0.743669

epoch 16:

66/84 ----> loss: 0.743669

epoch 16:

76/84 ----> loss: 0.743714

epoch 17:

2/84 ----> loss: 0.743668

epoch 17:

12/84 ----> loss: 1.743247

epoch 17:

22/84 ----> loss: 0.743668

epoch 17:

32/84 ----> loss: 0.743668

epoch 17:

42/84 ----> loss: 0.743675

epoch 17:

52/84 ----> loss: 0.743669

epoch 17:

62/84 ----> loss: 0.743668

epoch 17:

72/84 ----> loss: 0.743668

epoch 17:

82/84 ----> loss: 0.744409

epoch 18:

8/84 ----> loss: 0.743668

epoch 18:

18/84 ----> loss: 0.746143

epoch 18:

28/84 ----> loss: 0.743668

epoch 18:

38/84 ----> loss: 1.743664

epoch 18:

48/84 ----> loss: 0.743669

epoch 18:

58/84 ----> loss: 0.743669

epoch 18:

68/84 ----> loss: 0.743668

epoch 18:

78/84 ----> loss: 0.745020

epoch 19:

4/84 ----> loss: 1.743668

epoch 19:

14/84 ----> loss: 1.743668

epoch 19:

24/84 ----> loss: 1.743668

epoch 19:

34/84 ----> loss: 0.743668

epoch 19:

44/84 ----> loss: 0.743668

epoch 19:

54/84 ----> loss: 1.743668

epoch 19:

64/84 ----> loss: 1.675752

epoch 19:

74/84 ----> loss: 0.743668

epoch 20:

0/84 ----> loss: 0.743668

epoch 20:

10/84 ----> loss: 0.743668

epoch 20:

20/84 ----> loss: 0.743671

epoch 20:

30/84 ----> loss: 1.743667

epoch 20:

40/84 ----> loss: 0.743668

epoch 20:

50/84 ----> loss: 0.743668

epoch 20:

60/84 ----> loss: 0.743669

epoch 20:

70/84 ----> loss: 0.743670

epoch 20:

80/84 ----> loss: 0.743668

epoch 21:

6/84 ----> loss: 0.743718

epoch 21:

16/84 ----> loss: 0.743668

epoch 21:

26/84 ----> loss: 0.743668

epoch 21:

36/84 ----> loss: 0.744638

epoch 21:

46/84 ----> loss: 0.743668

epoch 21:

56/84 ----> loss: 0.743669

epoch 21:

66/84 ----> loss: 0.743669

epoch 21:

76/84 ----> loss: 0.743694

epoch 22:

2/84 ----> loss: 0.743668

epoch 22:

12/84 ----> loss: 1.743263

epoch 22:

22/84 ----> loss: 0.743668

epoch 22:

32/84 ----> loss: 0.743668

epoch 22:

42/84 ----> loss: 0.743672

epoch 22:

52/84 ----> loss: 0.743669

epoch 22:

62/84 ----> loss: 0.743668

epoch 22:

72/84 ----> loss: 0.743668

epoch 22:

82/84 ----> loss: 0.744160

epoch 23:

8/84 ----> loss: 0.743668

epoch 23:

18/84 ----> loss: 0.746837

epoch 23:

28/84 ----> loss: 0.743668

epoch 23:

38/84 ----> loss: 1.743644

epoch 23:

48/84 ----> loss: 0.743669

epoch 23:

58/84 ----> loss: 0.743668

epoch 23:

68/84 ----> loss: 0.743668

epoch 23:

78/84 ----> loss: 0.744910

epoch 24:

4/84 ----> loss: 1.743668

epoch 24:

14/84 ----> loss: 1.743668

epoch 24:

24/84 ----> loss: 1.743668

epoch 24:

34/84 ----> loss: 0.743668

epoch 24:

44/84 ----> loss: 0.743668

epoch 24:

54/84 ----> loss: 1.743668

epoch 24:

64/84 ----> loss: 1.689591

epoch 24:

74/84 ----> loss: 0.743668

epoch 25:

0/84 ----> loss: 0.743668

epoch 25:

10/84 ----> loss: 0.743668

epoch 25:

20/84 ----> loss: 0.743670

epoch 25:

30/84 ----> loss: 1.743668

epoch 25:

40/84 ----> loss: 0.743668

epoch 25:

50/84 ----> loss: 0.743668

epoch 25:

```
-----  
-----  
60/84 ----> loss: 0.743671  
  
epoch 25:  
-----  
-----  
70/84 ----> loss: 0.743670  
  
epoch 25:  
-----  
-----  
80/84 ----> loss: 0.743668  
  
epoch 26:  
-----  
-----  
6/84 ----> loss: 0.743696  
  
epoch 26:  
-----  
-----  
16/84 ----> loss: 0.743668  
  
epoch 26:  
-----  
-----  
26/84 ----> loss: 0.743668  
  
epoch 26:  
-----  
-----  
36/84 ----> loss: 0.745437  
  
epoch 26:  
-----  
-----  
46/84 ----> loss: 0.743668
```

epoch 26:

56/84 ----> loss: 0.743669

epoch 26:

66/84 ----> loss: 0.743669

epoch 26:

76/84 ----> loss: 0.743713

epoch 27:

2/84 ----> loss: 0.743668

epoch 27:

12/84 ----> loss: 1.742986

epoch 27:

22/84 ----> loss: 0.743668

epoch 27:

32/84 ----> loss: 0.743668

epoch 27:

42/84 ----> loss: 0.743676

epoch 27:

52/84 ----> loss: 0.743669

epoch 27:

62/84 ----> loss: 0.743668

epoch 27:

72/84 ----> loss: 0.743668

epoch 27:

82/84 ----> loss: 0.744159

epoch 28:

8/84 ----> loss: 0.743668

epoch 28:

18/84 ----> loss: 0.745868

epoch 28:

28/84 ----> loss: 0.743668

epoch 28:

38/84 ----> loss: 1.743644

epoch 28:

48/84 ----> loss: 0.743669

epoch 28:

58/84 ----> loss: 0.743668

epoch 28:

68/84 ----> loss: 0.743668

epoch 28:

78/84 ----> loss: 0.744692

epoch 29:

4/84 ----> loss: 1.743668

epoch 29:

14/84 ----> loss: 1.743668

epoch 29:

24/84 ----> loss: 1.743668

epoch 29:

34/84 ----> loss: 0.743668

epoch 29:

44/84 ----> loss: 0.743668

epoch 29:

54/84 ----> loss: 1.743668

epoch 29:

64/84 ----> loss: 1.668758

epoch 29:

74/84 ----> loss: 0.743668

epoch 30:

0/84 ----> loss: 0.743668

epoch 30:

10/84 ----> loss: 0.743668

epoch 30:

20/84 ----> loss: 0.743671

epoch 30:

30/84 ----> loss: 1.743667

epoch 30:

40/84 ----> loss: 0.743669

epoch 30:

50/84 ----> loss: 0.743668

epoch 30:

60/84 ----> loss: 0.743670

epoch 30:

70/84 ----> loss: 0.743670

epoch 30:

80/84 ----> loss: 0.743668

epoch 31:

6/84 ----> loss: 0.743692

epoch 31:

16/84 ----> loss: 0.743669

epoch 31:

26/84 ----> loss: 0.743668

epoch 31:

36/84 ----> loss: 0.744189

epoch 31:

46/84 ----> loss: 0.743668

epoch 31:

56/84 ----> loss: 0.743669

epoch 31:

66/84 ----> loss: 0.743669

epoch 31:

76/84 ----> loss: 0.743692

epoch 32:

2/84 ----> loss: 0.743668

epoch 32:

12/84 ----> loss: 1.742080

epoch 32:

22/84 ----> loss: 0.743668

epoch 32:

32/84 ----> loss: 0.743668

epoch 32:

42/84 ----> loss: 0.743673

epoch 32:

52/84 ----> loss: 0.743669

epoch 32:

62/84 ----> loss: 0.743668

epoch 32:

72/84 ----> loss: 0.743668

epoch 32:

82/84 ----> loss: 0.744182

epoch 33:

8/84 ----> loss: 0.743668

epoch 33:

18/84 ----> loss: 0.746676

epoch 33:

28/84 ----> loss: 0.743668

epoch 33:

38/84 ----> loss: 1.743642

epoch 33:

48/84 ----> loss: 0.743669

epoch 33:

58/84 ----> loss: 0.743668

epoch 33:

68/84 ----> loss: 0.743668

epoch 33:

78/84 ----> loss: 0.744437

epoch 34:

4/84 ----> loss: 1.743668

epoch 34:

14/84 ----> loss: 1.743668

epoch 34:

24/84 ----> loss: 1.743668

epoch 34:

34/84 ----> loss: 0.743668

epoch 34:

44/84 ----> loss: 0.743668

epoch 34:

54/84 ----> loss: 1.743668

epoch 34:

64/84 ----> loss: 1.677995

epoch 34:

74/84 ----> loss: 0.743668

epoch 35:

0/84 ----> loss: 0.743668

epoch 35:

10/84 ----> loss: 0.743668

epoch 35:

20/84 ----> loss: 0.743670

epoch 35:

30/84 ----> loss: 1.743668

epoch 35:

40/84 ----> loss: 0.743669

epoch 35:

50/84 ----> loss: 0.743668

epoch 35:

60/84 ----> loss: 0.743672

epoch 35:

70/84 ----> loss: 0.743670

epoch 35:

80/84 ----> loss: 0.743668

epoch 36:

6/84 ----> loss: 0.743686

epoch 36:

16/84 ----> loss: 0.743669

epoch 36:

26/84 ----> loss: 0.743668

epoch 36:

36/84 ----> loss: 0.744811

epoch 36:

46/84 ----> loss: 0.743668

epoch 36:

56/84 ----> loss: 0.743669

epoch 36:

66/84 ----> loss: 0.743669

epoch 36:

76/84 ----> loss: 0.743712

epoch 37:

2/84 ----> loss: 0.743668

epoch 37:

12/84 ----> loss: 1.741207

epoch 37:

22/84 ----> loss: 0.743668

epoch 37:

32/84 ----> loss: 0.743668

epoch 37:

42/84 ----> loss: 0.743681

epoch 37:

52/84 ----> loss: 0.743669

epoch 37:

62/84 ----> loss: 0.743668

epoch 37:

72/84 ----> loss: 0.743668

epoch 37:

82/84 ----> loss: 0.744181

epoch 38:

8/84 ----> loss: 0.743668

epoch 38:

18/84 ----> loss: 0.745348

epoch 38:

28/84 ----> loss: 0.743668

epoch 38:

38/84 ----> loss: 1.743661

epoch 38:

48/84 ----> loss: 0.743669

epoch 38:

58/84 ----> loss: 0.743669

epoch 38:

68/84 ----> loss: 0.743668

epoch 38:

78/84 ----> loss: 0.744289

epoch 39:

4/84 ----> loss: 1.743668

epoch 39:

14/84 ----> loss: 1.743668

epoch 39:

24/84 ----> loss: 1.743668

epoch 39:

34/84 ----> loss: 0.743668

epoch 39:

44/84 ----> loss: 0.743668

epoch 39:

54/84 ----> loss: 1.743668

epoch 39:

64/84 ----> loss: 1.687332

epoch 39:

74/84 ----> loss: 0.743668

epoch 40:

0/84 ----> loss: 0.743668

epoch 40:

10/84 ----> loss: 0.743668

epoch 40:

20/84 ----> loss: 0.743670

epoch 40:

30/84 ----> loss: 1.743668

epoch 40:

40/84 ----> loss: 0.743669

epoch 40:

50/84 ----> loss: 0.743668

epoch 40:

60/84 ----> loss: 0.743670

epoch 40:

70/84 ----> loss: 0.743670

epoch 40:

80/84 ----> loss: 0.743668

epoch 41:

6/84 ----> loss: 0.743691

epoch 41:

16/84 ----> loss: 0.743668

epoch 41:

26/84 ----> loss: 0.743668

epoch 41:

36/84 ----> loss: 0.744074

epoch 41:

46/84 ----> loss: 0.743668

epoch 41:

56/84 ----> loss: 0.743669

epoch 41:

66/84 ----> loss: 0.743669

epoch 41:

76/84 ----> loss: 0.743694

epoch 42:

2/84 ----> loss: 0.743668

epoch 42:

12/84 ----> loss: 1.741467

epoch 42:

22/84 ----> loss: 0.743668

epoch 42:

32/84 ----> loss: 0.743668

epoch 42:

42/84 ----> loss: 0.743676

epoch 42:

52/84 ----> loss: 0.743669

epoch 42:

62/84 ----> loss: 0.743668

epoch 42:

72/84 ----> loss: 0.743668

epoch 42:

82/84 ----> loss: 0.744077

epoch 43:

8/84 ----> loss: 0.743668

epoch 43:

18/84 ----> loss: 0.745474

epoch 43:

28/84 ----> loss: 0.743668

epoch 43:

38/84 ----> loss: 1.743660

epoch 43:

48/84 ----> loss: 0.743669

epoch 43:

58/84 ----> loss: 0.743669

epoch 43:

68/84 ----> loss: 0.743668

epoch 43:

78/84 ----> loss: 0.744209

epoch 44:

4/84 ----> loss: 1.743668

epoch 44:

14/84 ----> loss: 1.743668

epoch 44:

24/84 ----> loss: 1.743668

epoch 44:

34/84 ----> loss: 0.743668

epoch 44:

44/84 ----> loss: 0.743668

epoch 44:

54/84 ----> loss: 1.743668

epoch 44:

64/84 ----> loss: 1.669429

epoch 44:

74/84 ----> loss: 0.743668

epoch 45:

0/84 ----> loss: 0.743668

epoch 45:

10/84 ----> loss: 0.743668

epoch 45:

20/84 ----> loss: 0.743670

epoch 45:

30/84 ----> loss: 1.743668

epoch 45:

40/84 ----> loss: 0.743669

epoch 45:

50/84 ----> loss: 0.743668

epoch 45:

60/84 ----> loss: 0.743672

epoch 45:

70/84 ----> loss: 0.743670

epoch 45:

80/84 ----> loss: 0.743668

epoch 46:

6/84 ----> loss: 0.743693

epoch 46:

16/84 ----> loss: 0.743668

epoch 46:

26/84 ----> loss: 0.743668

epoch 46:

36/84 ----> loss: 0.744596

epoch 46:

46/84 ----> loss: 0.743668

epoch 46:

56/84 ----> loss: 0.743669

epoch 46:

66/84 ----> loss: 0.743669

epoch 46:

76/84 ----> loss: 0.743714

epoch 47:

2/84 ----> loss: 0.743668

epoch 47:

12/84 ----> loss: 1.742731

epoch 47:

22/84 ----> loss: 0.743668

epoch 47:

32/84 ----> loss: 0.743668

epoch 47:

42/84 ----> loss: 0.743686

epoch 47:

52/84 ----> loss: 0.743669

epoch 47:

62/84 ----> loss: 0.743668

epoch 47:

72/84 ----> loss: 0.743668

epoch 47:

82/84 ----> loss: 0.744007

epoch 48:

8/84 ----> loss: 0.743668

epoch 48:

18/84 ----> loss: 0.744764

epoch 48:

28/84 ----> loss: 0.743668

epoch 48:

38/84 ----> loss: 1.743661

epoch 48:

48/84 ----> loss: 0.743669

epoch 48:

58/84 ----> loss: 0.743669

epoch 48:

68/84 ----> loss: 0.743668

epoch 48:

78/84 ----> loss: 0.744218

epoch 49:

4/84 ----> loss: 1.743668

epoch 49:

14/84 ----> loss: 1.743668

epoch 49:

24/84 ----> loss: 1.743668

epoch 49:

34/84 ----> loss: 0.743668

epoch 49:

44/84 ----> loss: 0.743668

epoch 49:

54/84 ----> loss: 1.743668

epoch 49:

64/84 ----> loss: 1.672434

epoch 49:

74/84 ----> loss: 0.743668

epoch 50:

0/84 ----> loss: 0.743668

epoch 50:

10/84 ----> loss: 0.743668

epoch 50:

20/84 ----> loss: 0.743670

epoch 50:

30/84 ----> loss: 1.743667

epoch 50:

40/84 ----> loss: 0.743669

epoch 50:

50/84 ----> loss: 0.743668

epoch 50:

60/84 ----> loss: 0.743670

epoch 50:

70/84 ----> loss: 0.743670

epoch 50:

80/84 ----> loss: 0.743668

epoch 51:

6/84 ----> loss: 0.743697

epoch 51:

16/84 ----> loss: 0.743668

epoch 51:

26/84 ----> loss: 0.743668

epoch 51:

36/84 ----> loss: 0.743997

epoch 51:

46/84 ----> loss: 0.743668

epoch 51:

56/84 ----> loss: 0.743669

epoch 51:

66/84 ----> loss: 0.743669

epoch 51:

76/84 ----> loss: 0.743693

epoch 52:

2/84 ----> loss: 0.743668

epoch 52:

12/84 ----> loss: 1.742904

epoch 52:

22/84 ----> loss: 0.743668

epoch 52:

32/84 ----> loss: 0.743668

epoch 52:

42/84 ----> loss: 0.743677

epoch 52:

52/84 ----> loss: 0.743669

epoch 52:

62/84 ----> loss: 0.743668

epoch 52:

72/84 ----> loss: 0.743668

epoch 52:

82/84 ----> loss: 0.743951

epoch 53:

8/84 ----> loss: 0.743668

epoch 53:

18/84 ----> loss: 0.745266

epoch 53:

28/84 ----> loss: 0.743668

epoch 53:

38/84 ----> loss: 1.743639

epoch 53:

48/84 ----> loss: 0.743669

epoch 53:

58/84 ----> loss: 0.743669

epoch 53:

68/84 ----> loss: 0.743668

epoch 53:

78/84 ----> loss: 0.744196

epoch 54:

4/84 ----> loss: 1.743668

epoch 54:

14/84 ----> loss: 1.743668

epoch 54:

24/84 ----> loss: 1.743668

epoch 54:

34/84 ----> loss: 0.743668

epoch 54:

44/84 ----> loss: 0.743668

epoch 54:

54/84 ----> loss: 1.743668

epoch 54:

64/84 ----> loss: 1.678937

epoch 54:

74/84 ----> loss: 0.743668

epoch 55:

0/84 ----> loss: 0.743668

epoch 55:

10/84 ----> loss: 0.743668

epoch 55:

20/84 ----> loss: 0.743669

epoch 55:

30/84 ----> loss: 1.743667

epoch 55:

40/84 ----> loss: 0.743669

epoch 55:

50/84 ----> loss: 0.743668

epoch 55:

60/84 ----> loss: 0.743673

epoch 55:

70/84 ----> loss: 0.743671

epoch 55:

80/84 ----> loss: 0.743669

epoch 56:

6/84 ----> loss: 0.743690

epoch 56:

16/84 ----> loss: 0.743669

epoch 56:

26/84 ----> loss: 0.743668

epoch 56:

36/84 ----> loss: 0.744382

epoch 56:

46/84 ----> loss: 0.743668

epoch 56:

56/84 ----> loss: 0.743669

epoch 56:

66/84 ----> loss: 0.743669

epoch 56:

76/84 ----> loss: 0.743713

epoch 57:

2/84 ----> loss: 0.743668

epoch 57:

12/84 ----> loss: 1.742807

epoch 57:

22/84 ----> loss: 0.743669

epoch 57:

32/84 ----> loss: 0.743668

epoch 57:

42/84 ----> loss: 0.743687

epoch 57:

52/84 ----> loss: 0.743669

epoch 57:

62/84 ----> loss: 0.743668

epoch 57:

72/84 ----> loss: 0.743668

epoch 57:

82/84 ----> loss: 0.743969

epoch 58:

8/84 ----> loss: 0.743668

epoch 58:

18/84 ----> loss: 0.744899

epoch 58:

28/84 ----> loss: 0.743668

epoch 58:

38/84 ----> loss: 1.743635

epoch 58:

48/84 ----> loss: 0.743669

epoch 58:

58/84 ----> loss: 0.743669

epoch 58:

68/84 ----> loss: 0.743668

epoch 58:

78/84 ----> loss: 0.744161

epoch 59:

4/84 ----> loss: 1.743668

epoch 59:

14/84 ----> loss: 1.743668

epoch 59:

24/84 ----> loss: 1.743668

epoch 59:

34/84 ----> loss: 0.743668

epoch 59:

44/84 ----> loss: 0.743668

epoch 59:

54/84 ----> loss: 1.743668

epoch 59:

64/84 ----> loss: 1.675012

epoch 59:

74/84 ----> loss: 0.743668

epoch 60:

0/84 ----> loss: 0.743668

epoch 60:

10/84 ----> loss: 0.743668

epoch 60:

20/84 ----> loss: 0.743670

epoch 60:

30/84 ----> loss: 1.743667

epoch 60:

40/84 ----> loss: 0.743669

epoch 60:

50/84 ----> loss: 0.743668

epoch 60:

60/84 ----> loss: 0.743671

epoch 60:

70/84 ----> loss: 0.743671

epoch 60:

80/84 ----> loss: 0.743669

epoch 61:

6/84 ----> loss: 0.743686

epoch 61:

16/84 ----> loss: 0.743669

epoch 61:

26/84 ----> loss: 0.743668

epoch 61:

36/84 ----> loss: 0.743923

epoch 61:

46/84 ----> loss: 0.743668

epoch 61:

56/84 ----> loss: 0.743669

epoch 61:

66/84 ----> loss: 0.743669

epoch 61:

76/84 ----> loss: 0.743693

epoch 62:

2/84 ----> loss: 0.743668

epoch 62:

12/84 ----> loss: 1.741573

epoch 62:

22/84 ----> loss: 0.743668

epoch 62:

32/84 ----> loss: 0.743668

epoch 62:

42/84 ----> loss: 0.743679

epoch 62:

52/84 ----> loss: 0.743669

epoch 62:

62/84 ----> loss: 0.743668

epoch 62:

72/84 ----> loss: 0.743668

epoch 62:

82/84 ----> loss: 0.743965

epoch 63:

8/84 ----> loss: 0.743668

epoch 63:

18/84 ----> loss: 0.745398

epoch 63:

28/84 ----> loss: 0.743668

epoch 63:

38/84 ----> loss: 1.743628

epoch 63:

48/84 ----> loss: 0.743669

epoch 63:

58/84 ----> loss: 0.743669

epoch 63:

68/84 ----> loss: 0.743668

epoch 63:

78/84 ----> loss: 0.744071

epoch 64:

4/84 ----> loss: 1.743668

epoch 64:

14/84 ----> loss: 1.743668

epoch 64:

24/84 ----> loss: 1.743668

epoch 64:

34/84 ----> loss: 0.743668

epoch 64:

44/84 ----> loss: 0.743668

epoch 64:

54/84 ----> loss: 1.743668

epoch 64:

64/84 ----> loss: 1.668297

epoch 64:

74/84 ----> loss: 0.743668

epoch 65:

0/84 ----> loss: 0.743668

epoch 65:

10/84 ----> loss: 0.743668

epoch 65:

20/84 ----> loss: 0.743669

epoch 65:

30/84 ----> loss: 1.743667

epoch 65:

40/84 ----> loss: 0.743669

epoch 65:

50/84 ----> loss: 0.743668

epoch 65:

60/84 ----> loss: 0.743675

epoch 65:

70/84 ----> loss: 0.743671

epoch 65:

80/84 ----> loss: 0.743669

epoch 66:

6/84 ----> loss: 0.743684

epoch 66:

16/84 ----> loss: 0.743669

epoch 66:

26/84 ----> loss: 0.743668

epoch 66:

36/84 ----> loss: 0.744255

epoch 66:

46/84 ----> loss: 0.743668

epoch 66:

56/84 ----> loss: 0.743669

epoch 66:

66/84 ----> loss: 0.743669

epoch 66:

76/84 ----> loss: 0.743714

epoch 67:

2/84 ----> loss: 0.743668

epoch 67:

12/84 ----> loss: 1.740310

epoch 67:

22/84 ----> loss: 0.743668

epoch 67:

32/84 ----> loss: 0.743668

epoch 67:

42/84 ----> loss: 0.743694

epoch 67:

52/84 ----> loss: 0.743669

epoch 67:

62/84 ----> loss: 0.743668

epoch 67:

72/84 ----> loss: 0.743668

epoch 67:

82/84 ----> loss: 0.743991

epoch 68:

8/84 ----> loss: 0.743668

epoch 68:

18/84 ----> loss: 0.744784

epoch 68:

28/84 ----> loss: 0.743668

epoch 68:

38/84 ----> loss: 1.743644

epoch 68:

48/84 ----> loss: 0.743669

epoch 68:

58/84 ----> loss: 0.743669

epoch 68:

68/84 ----> loss: 0.743668

epoch 68:

78/84 ----> loss: 0.744044

epoch 69:

4/84 ----> loss: 1.743668

epoch 69:

14/84 ----> loss: 1.743668

epoch 69:

24/84 ----> loss: 1.743668

epoch 69:

34/84 ----> loss: 0.743668

epoch 69:

44/84 ----> loss: 0.743668

epoch 69:

54/84 ----> loss: 1.743668

epoch 69:

64/84 ----> loss: 1.671753

epoch 69:

74/84 ----> loss: 0.743668

epoch 70:

0/84 ----> loss: 0.743668

epoch 70:

10/84 ----> loss: 0.743668

epoch 70:

20/84 ----> loss: 0.743670

epoch 70:

30/84 ----> loss: 1.743667

epoch 70:

40/84 ----> loss: 0.743669

epoch 70:

50/84 ----> loss: 0.743668

epoch 70:

60/84 ----> loss: 0.743672

epoch 70:

70/84 ----> loss: 0.743671

epoch 70:

80/84 ----> loss: 0.743669

epoch 71:

6/84 ----> loss: 0.743682

epoch 71:

16/84 ----> loss: 0.743669

epoch 71:

26/84 ----> loss: 0.743668

epoch 71:

36/84 ----> loss: 0.743891

epoch 71:

46/84 ----> loss: 0.743668

epoch 71:

56/84 ----> loss: 0.743669

epoch 71:

66/84 ----> loss: 0.743669

epoch 71:

76/84 ----> loss: 0.743695

epoch 72:

2/84 ----> loss: 0.743668

epoch 72:

12/84 ----> loss: 1.739448

epoch 72:

22/84 ----> loss: 0.743668

epoch 72:

32/84 ----> loss: 0.743668

epoch 72:

42/84 ----> loss: 0.743684

epoch 72:

52/84 ----> loss: 0.743669

epoch 72:

62/84 ----> loss: 0.743668

epoch 72:

72/84 ----> loss: 0.743668

epoch 72:

82/84 ----> loss: 0.743960

epoch 73:

8/84 ----> loss: 0.743668

epoch 73:

18/84 ----> loss: 0.744954

epoch 73:

28/84 ----> loss: 0.743668

epoch 73:

38/84 ----> loss: 1.743651

epoch 73:

48/84 ----> loss: 0.743669

epoch 73:

58/84 ----> loss: 0.743669

epoch 73:

68/84 ----> loss: 0.743668

epoch 73:

78/84 ----> loss: 0.743978

epoch 74:

4/84 ----> loss: 1.743668

epoch 74:

14/84 ----> loss: 1.743668

epoch 74:

24/84 ----> loss: 1.743668

epoch 74:

34/84 ----> loss: 0.743668

epoch 74:

44/84 ----> loss: 0.743668

epoch 74:

54/84 ----> loss: 1.743668

epoch 74:

64/84 ----> loss: 1.677091

epoch 74:

74/84 ----> loss: 0.743668

epoch 75:

0/84 ----> loss: 0.743668

epoch 75:

10/84 ----> loss: 0.743668

epoch 75:

20/84 ----> loss: 0.743670

epoch 75:

30/84 ----> loss: 1.743667

epoch 75:

40/84 ----> loss: 0.743669

epoch 75:

50/84 ----> loss: 0.743668

epoch 75:

60/84 ----> loss: 0.743676

epoch 75:

70/84 ----> loss: 0.743670

epoch 75:

80/84 ----> loss: 0.743669

epoch 76:

6/84 ----> loss: 0.743683

epoch 76:

16/84 ----> loss: 0.743669

epoch 76:

26/84 ----> loss: 0.743668

epoch 76:

36/84 ----> loss: 0.744187

epoch 76:

46/84 ----> loss: 0.743668

epoch 76:

56/84 ----> loss: 0.743669

epoch 76:

66/84 ----> loss: 0.743669

epoch 76:

76/84 ----> loss: 0.743717

epoch 77:

2/84 ----> loss: 0.743668

epoch 77:

12/84 ----> loss: 1.738236

epoch 77:

22/84 ----> loss: 0.743668

epoch 77:

32/84 ----> loss: 0.743668

epoch 77:

42/84 ----> loss: 0.743708

epoch 77:

52/84 ----> loss: 0.743669

epoch 77:

62/84 ----> loss: 0.743668

epoch 77:

72/84 ----> loss: 0.743668

epoch 77:

82/84 ----> loss: 0.743946

epoch 78:

8/84 ----> loss: 0.743668

epoch 78:

18/84 ----> loss: 0.744495

epoch 78:

28/84 ----> loss: 0.743668

epoch 78:

38/84 ----> loss: 1.743652

epoch 78:

48/84 ----> loss: 0.743669

epoch 78:

58/84 ----> loss: 0.743669

epoch 78:

68/84 ----> loss: 0.743668

epoch 78:

78/84 ----> loss: 0.743971

epoch 79:

4/84 ----> loss: 1.743668

epoch 79:

14/84 ----> loss: 1.743668

epoch 79:

24/84 ----> loss: 1.743668

epoch 79:

34/84 ----> loss: 0.743668

epoch 79:

44/84 ----> loss: 0.743668

epoch 79:

54/84 ----> loss: 1.743668

epoch 79:

64/84 ----> loss: 1.680914

epoch 79:

74/84 ----> loss: 0.743668

epoch 80:

0/84 ----> loss: 0.743668

epoch 80:

10/84 ----> loss: 0.743668

epoch 80:

20/84 ----> loss: 0.743670

epoch 80:

30/84 ----> loss: 1.743667

epoch 80:

40/84 ----> loss: 0.743669

epoch 80:

50/84 ----> loss: 0.743668

epoch 80:

60/84 ----> loss: 0.743672

epoch 80:

70/84 ----> loss: 0.743671

epoch 80:

80/84 ----> loss: 0.743669

epoch 81:

6/84 ----> loss: 0.743681

epoch 81:

16/84 ----> loss: 0.743669

epoch 81:

26/84 ----> loss: 0.743668

epoch 81:

36/84 ----> loss: 0.743875

epoch 81:

46/84 ----> loss: 0.743668

epoch 81:

56/84 ----> loss: 0.743669

epoch 81:

66/84 ----> loss: 0.743669

epoch 81:

76/84 ----> loss: 0.743698

epoch 82:

2/84 ----> loss: 0.743668

epoch 82:

12/84 ----> loss: 1.738405

epoch 82:

22/84 ----> loss: 0.743668

epoch 82:

32/84 ----> loss: 0.743668

epoch 82:

42/84 ----> loss: 0.743694

epoch 82:

52/84 ----> loss: 0.743669

epoch 82:

62/84 ----> loss: 0.743668

epoch 82:

72/84 ----> loss: 0.743668

epoch 82:

82/84 ----> loss: 0.743910

epoch 83:

8/84 ----> loss: 0.743668

epoch 83:

18/84 ----> loss: 0.744623

epoch 83:

28/84 ----> loss: 0.743668

epoch 83:

38/84 ----> loss: 1.743649

epoch 83:

48/84 ----> loss: 0.743669

epoch 83:

58/84 ----> loss: 0.743669

epoch 83:

68/84 ----> loss: 0.743668

epoch 83:

78/84 ----> loss: 0.743932

epoch 84:

4/84 ----> loss: 1.743668

epoch 84:

14/84 ----> loss: 1.743668

epoch 84:

24/84 ----> loss: 1.743668

epoch 84:

34/84 ----> loss: 0.743668

epoch 84:

44/84 ----> loss: 0.743668

epoch 84:

54/84 ----> loss: 1.743668

epoch 84:

64/84 ----> loss: 1.673918

epoch 84:

74/84 ----> loss: 0.743668

epoch 85:

0/84 ----> loss: 0.743668

epoch 85:

10/84 ----> loss: 0.743668

epoch 85:

20/84 ----> loss: 0.743670

epoch 85:

30/84 ----> loss: 1.743667

epoch 85:

40/84 ----> loss: 0.743669

epoch 85:

50/84 ----> loss: 0.743668

epoch 85:

60/84 ----> loss: 0.743677

epoch 85:

70/84 ----> loss: 0.743671

epoch 85:

80/84 ----> loss: 0.743669

epoch 86:

6/84 ----> loss: 0.743681

epoch 86:

16/84 ----> loss: 0.743669

epoch 86:

26/84 ----> loss: 0.743668

epoch 86:

36/84 ----> loss: 0.744125

epoch 86:

46/84 ----> loss: 0.743668

epoch 86:

56/84 ----> loss: 0.743669

epoch 86:

66/84 ----> loss: 0.743669

epoch 86:

76/84 ----> loss: 0.743723

epoch 87:

2/84 ----> loss: 0.743668

epoch 87:

12/84 ----> loss: 1.738945

epoch 87:

22/84 ----> loss: 0.743668

epoch 87:

32/84 ----> loss: 0.743668

epoch 87:

42/84 ----> loss: 0.743741

epoch 87:

52/84 ----> loss: 0.743669

epoch 87:

62/84 ----> loss: 0.743668

epoch 87:

72/84 ----> loss: 0.743668

epoch 87:

82/84 ----> loss: 0.743897

epoch 88:

8/84 ----> loss: 0.743668

epoch 88:

18/84 ----> loss: 0.744255

epoch 88:

28/84 ----> loss: 0.743668

epoch 88:

38/84 ----> loss: 1.743647

epoch 88:

48/84 ----> loss: 0.743669

epoch 88:

58/84 ----> loss: 0.743669

epoch 88:

68/84 ----> loss: 0.743668

epoch 88:

78/84 ----> loss: 0.743925

epoch 89:

4/84 ----> loss: 1.743668

epoch 89:

14/84 ----> loss: 1.743668

epoch 89:

24/84 ----> loss: 1.743668

epoch 89:

34/84 ----> loss: 0.743668

epoch 89:

44/84 ----> loss: 0.743668

epoch 89:

54/84 ----> loss: 1.743668

epoch 89:

64/84 ----> loss: 1.667815

epoch 89:

74/84 ----> loss: 0.743668

epoch 90:

0/84 ----> loss: 0.743668

epoch 90:

10/84 ----> loss: 0.743668

epoch 90:

20/84 ----> loss: 0.743671

epoch 90:

30/84 ----> loss: 1.743667

epoch 90:

40/84 ----> loss: 0.743669

epoch 90:

50/84 ----> loss: 0.743668

epoch 90:

60/84 ----> loss: 0.743673

epoch 90:

70/84 ----> loss: 0.743671

epoch 90:

80/84 ----> loss: 0.743669

epoch 91:

6/84 ----> loss: 0.743677

epoch 91:

16/84 ----> loss: 0.743669

epoch 91:

26/84 ----> loss: 0.743668

epoch 91:

36/84 ----> loss: 0.743862

epoch 91:

46/84 ----> loss: 0.743668

epoch 91:

56/84 ----> loss: 0.743669

epoch 91:

66/84 ----> loss: 0.743669

epoch 91:

76/84 ----> loss: 0.743710

epoch 92:

2/84 ----> loss: 0.743668

epoch 92:

12/84 ----> loss: 1.738652

epoch 92:

22/84 ----> loss: 0.743668

epoch 92:

32/84 ----> loss: 0.743668

epoch 92:

42/84 ----> loss: 0.743757

epoch 92:

52/84 ----> loss: 0.743669

epoch 92:

62/84 ----> loss: 0.743668

epoch 92:

72/84 ----> loss: 0.743668

epoch 92:

82/84 ----> loss: 0.743862

epoch 93:

8/84 ----> loss: 0.743668

epoch 93:

18/84 ----> loss: 0.744105

epoch 93:

28/84 ----> loss: 0.743668

epoch 93:

38/84 ----> loss: 1.743638

epoch 93:

48/84 ----> loss: 0.743669

epoch 93:

58/84 ----> loss: 0.743669

epoch 93:

68/84 ----> loss: 0.743669

epoch 93:

78/84 ----> loss: 0.743886

epoch 94:

4/84 ----> loss: 1.743667

epoch 94:

14/84 ----> loss: 1.743668

epoch 94:

24/84 ----> loss: 1.743668

epoch 94:

34/84 ----> loss: 0.743668

epoch 94:

44/84 ----> loss: 0.743668

epoch 94:

54/84 ----> loss: 1.743668

epoch 94:

64/84 ----> loss: 1.667236

epoch 94:

74/84 ----> loss: 0.743668

epoch 95:

0/84 ----> loss: 0.743668

epoch 95:

10/84 ----> loss: 0.743668

epoch 95:

20/84 ----> loss: 0.743671

epoch 95:

30/84 ----> loss: 1.743667

epoch 95:

40/84 ----> loss: 0.743669

epoch 95:

50/84 ----> loss: 0.743669

epoch 95:

60/84 ----> loss: 0.743676

epoch 95:

70/84 ----> loss: 0.743670

epoch 95:

80/84 ----> loss: 0.743669

epoch 96:

6/84 ----> loss: 0.743672

epoch 96:

16/84 ----> loss: 0.743669

epoch 96:

26/84 ----> loss: 0.743668

epoch 96:

36/84 ----> loss: 0.743945

epoch 96:

46/84 ----> loss: 0.743668

epoch 96:

56/84 ----> loss: 0.743669

epoch 96:

66/84 ----> loss: 0.743669

epoch 96:

76/84 ----> loss: 0.743736

epoch 97:

2/84 ----> loss: 0.743668

epoch 97:

12/84 ----> loss: 1.738018

epoch 97:

22/84 ----> loss: 0.743668

epoch 97:

32/84 ----> loss: 0.743668

epoch 97:

42/84 ----> loss: 0.743887

epoch 97:

52/84 ----> loss: 0.743669

epoch 97:

62/84 ----> loss: 0.743668

epoch 97:

72/84 ----> loss: 0.743668

epoch 97:

82/84 ----> loss: 0.743831

epoch 98:

8/84 ----> loss: 0.743668

epoch 98:

18/84 ----> loss: 0.744101

epoch 98:

28/84 ----> loss: 0.743668

epoch 98:

38/84 ----> loss: 1.743632

epoch 98:

48/84 ----> loss: 0.743669

epoch 98:

58/84 ----> loss: 0.743669

epoch 98:

68/84 ----> loss: 0.743668

epoch 98:

78/84 ----> loss: 0.743849

epoch 99:

4/84 ----> loss: 1.743667

epoch 99:

14/84 ----> loss: 1.743667

epoch 99:

24/84 ----> loss: 1.743668

epoch 99:

34/84 ----> loss: 0.743668

epoch 99:

44/84 ----> loss: 0.743668

epoch 99:

54/84 ----> loss: 1.743668

epoch 99:

64/84 ----> loss: 1.668049

epoch 99:

74/84 ----> loss: 0.743668

epoch 100:

0/84 ----> loss: 0.743668

epoch 100:

10/84 ----> loss: 0.743668

epoch 100:

20/84 ----> loss: 0.743671

epoch 100:

30/84 ----> loss: 1.743667

epoch 100:

40/84 ----> loss: 0.743669

epoch 100:

50/84 ----> loss: 0.743669

epoch 100:

60/84 ----> loss: 0.743676

epoch 100:

70/84 ----> loss: 0.743671

epoch 100:

80/84 ----> loss: 0.743669

epoch 101:

6/84 ----> loss: 0.743674

epoch 101:

16/84 ----> loss: 0.743669

epoch 101:

26/84 ----> loss: 0.743668

epoch 101:

36/84 ----> loss: 0.743918

epoch 101:

46/84 ----> loss: 0.743668

epoch 101:

56/84 ----> loss: 0.743669

epoch 101:

66/84 ----> loss: 0.743669

epoch 101:

76/84 ----> loss: 0.743725

epoch 102:

2/84 ----> loss: 0.743668

epoch 102:

12/84 ----> loss: 1.737277

epoch 102:

22/84 ----> loss: 0.743668

epoch 102:

32/84 ----> loss: 0.743668

epoch 102:

42/84 ----> loss: 0.743859

epoch 102:

52/84 ----> loss: 0.743669

epoch 102:

62/84 ----> loss: 0.743668

epoch 102:

72/84 ----> loss: 0.743668

epoch 102:

82/84 ----> loss: 0.743808

epoch 103:

8/84 ----> loss: 0.743668

epoch 103:

18/84 ----> loss: 0.744221

epoch 103:

28/84 ----> loss: 0.743668

epoch 103:

38/84 ----> loss: 1.743621

epoch 103:

48/84 ----> loss: 0.743669

epoch 103:

58/84 ----> loss: 0.743669

epoch 103:

68/84 ----> loss: 0.743669

epoch 103:

78/84 ----> loss: 0.743828

epoch 104:

4/84 ----> loss: 1.743666

epoch 104:

14/84 ----> loss: 1.743667

epoch 104:

24/84 ----> loss: 1.743667

epoch 104:

34/84 ----> loss: 0.743668

epoch 104:

44/84 ----> loss: 0.743668

epoch 104:

54/84 ----> loss: 1.743668

epoch 104:

64/84 ----> loss: 1.670386

epoch 104:

74/84 ----> loss: 0.743668

epoch 105:

0/84 ----> loss: 0.743668

epoch 105:

10/84 ----> loss: 0.743668

epoch 105:

20/84 ----> loss: 0.743671

epoch 105:

30/84 ----> loss: 1.743666

epoch 105:

40/84 ----> loss: 0.743669

epoch 105:

50/84 ----> loss: 0.743669

epoch 105:

60/84 ----> loss: 0.743677

epoch 105:

70/84 ----> loss: 0.743671

epoch 105:

80/84 ----> loss: 0.743669

epoch 106:

6/84 ----> loss: 0.743674

epoch 106:

16/84 ----> loss: 0.743669

epoch 106:

26/84 ----> loss: 0.743668

epoch 106:

36/84 ----> loss: 0.743897

epoch 106:

46/84 ----> loss: 0.743668

epoch 106:

56/84 ----> loss: 0.743669

epoch 106:

66/84 ----> loss: 0.743669

epoch 106:

76/84 ----> loss: 0.743720

epoch 107:

2/84 ----> loss: 0.743668

epoch 107:

12/84 ----> loss: 1.734317

epoch 107:

22/84 ----> loss: 0.743668

epoch 107:

32/84 ----> loss: 0.743668

epoch 107:

42/84 ----> loss: 0.743854

epoch 107:

52/84 ----> loss: 0.743669

epoch 107:

62/84 ----> loss: 0.743668

epoch 107:

72/84 ----> loss: 0.743668

epoch 107:

82/84 ----> loss: 0.743794

epoch 108:

8/84 ----> loss: 0.743668

epoch 108:

18/84 ----> loss: 0.744304

epoch 108:

28/84 ----> loss: 0.743668

epoch 108:

38/84 ----> loss: 1.743600

epoch 108:

48/84 ----> loss: 0.743669

epoch 108:

58/84 ----> loss: 0.743669

epoch 108:

68/84 ----> loss: 0.743669

epoch 108:

78/84 ----> loss: 0.743814

epoch 109:

4/84 ----> loss: 1.743665

epoch 109:

14/84 ----> loss: 1.743666

epoch 109:

24/84 ----> loss: 1.743666

epoch 109:

34/84 ----> loss: 0.743668

epoch 109:

44/84 ----> loss: 0.743668

epoch 109:

54/84 ----> loss: 1.743668

epoch 109:

64/84 ----> loss: 1.673446

epoch 109:

74/84 ----> loss: 0.743668

epoch 110:

0/84 ----> loss: 0.743668

epoch 110:

10/84 ----> loss: 0.743668

epoch 110:

20/84 ----> loss: 0.743671

epoch 110:

30/84 ----> loss: 1.743665

epoch 110:

40/84 ----> loss: 0.743669

epoch 110:

50/84 ----> loss: 0.743670

epoch 110:

60/84 ----> loss: 0.743678

epoch 110:

70/84 ----> loss: 0.743672

epoch 110:

80/84 ----> loss: 0.743670

epoch 111:

6/84 ----> loss: 0.743673

epoch 111:

16/84 ----> loss: 0.743669

epoch 111:

26/84 ----> loss: 0.743668

epoch 111:

36/84 ----> loss: 0.743875

epoch 111:

46/84 ----> loss: 0.743668

epoch 111:

56/84 ----> loss: 0.743669

epoch 111:

66/84 ----> loss: 0.743669

epoch 111:

76/84 ----> loss: 0.743716

epoch 112:

2/84 ----> loss: 0.743668

epoch 112:

12/84 ----> loss: 1.717012

epoch 112:

22/84 ----> loss: 0.743668

epoch 112:

32/84 ----> loss: 0.743668

epoch 112:

42/84 ----> loss: 0.743875

epoch 112:

52/84 ----> loss: 0.743669

epoch 112:

62/84 ----> loss: 0.743668

epoch 112:

72/84 ----> loss: 0.743668

epoch 112:

82/84 ----> loss: 0.743791

epoch 113:

8/84 ----> loss: 0.743668

epoch 113:

18/84 ----> loss: 0.744403

epoch 113:

28/84 ----> loss: 0.743669

epoch 113:

38/84 ----> loss: 1.743556

epoch 113:

48/84 ----> loss: 0.743669

epoch 113:

58/84 ----> loss: 0.743669

epoch 113:

68/84 ----> loss: 0.743669

epoch 113:

78/84 ----> loss: 0.743801

epoch 114:

4/84 ----> loss: 1.743661

epoch 114:

14/84 ----> loss: 1.743662

epoch 114:

24/84 ----> loss: 1.743661

epoch 114:

34/84 ----> loss: 0.743668

epoch 114:

44/84 ----> loss: 0.743668

epoch 114:

54/84 ----> loss: 1.743668

epoch 114:

64/84 ----> loss: 1.674323

epoch 114:

74/84 ----> loss: 0.743668

epoch 115:

0/84 ----> loss: 0.743668

epoch 115:

10/84 ----> loss: 0.743668

epoch 115:

20/84 ----> loss: 0.743672

epoch 115:

30/84 ----> loss: 1.743662

epoch 115:

40/84 ----> loss: 0.743669

epoch 115:

50/84 ----> loss: 0.743675

epoch 115:

60/84 ----> loss: 0.743682

epoch 115:

70/84 ----> loss: 0.743674

epoch 115:

80/84 ----> loss: 0.743671

epoch 116:

6/84 ----> loss: 0.743672

epoch 116:

16/84 ----> loss: 0.743669

epoch 116:

26/84 ----> loss: 0.743668

epoch 116:

36/84 ----> loss: 0.743856

epoch 116:

46/84 ----> loss: 0.743669

epoch 116:

56/84 ----> loss: 0.743669

epoch 116:

66/84 ----> loss: 0.743669

epoch 116:

76/84 ----> loss: 0.743718

epoch 117:

2/84 ----> loss: 0.743669

epoch 117:

12/84 ----> loss: 1.686188

epoch 117:

22/84 ----> loss: 0.743668

epoch 117:

32/84 ----> loss: 0.743669

epoch 117:

42/84 ----> loss: 0.743936

epoch 117:

52/84 ----> loss: 0.743669

epoch 117:

62/84 ----> loss: 0.743668

epoch 117:

72/84 ----> loss: 0.743668

epoch 117:

82/84 ----> loss: 0.743768

epoch 118:

8/84 ----> loss: 0.743668

epoch 118:

18/84 ----> loss: 0.744366

epoch 118:

28/84 ----> loss: 0.743669

epoch 118:

38/84 ----> loss: 1.743439

epoch 118:

48/84 ----> loss: 0.743669

epoch 118:

58/84 ----> loss: 0.743671

epoch 118:

68/84 ----> loss: 0.743669

epoch 118:

78/84 ----> loss: 0.743793

epoch 119:

4/84 ----> loss: 1.743654

epoch 119:

14/84 ----> loss: 1.743658

epoch 119:

24/84 ----> loss: 1.743652

epoch 119:

34/84 ----> loss: 0.743668

epoch 119:

44/84 ----> loss: 0.743669

epoch 119:

54/84 ----> loss: 1.743667

epoch 119:

64/84 ----> loss: 1.668450

epoch 119:

74/84 ----> loss: 0.743668

epoch 120:

0/84 ----> loss: 0.743668

epoch 120:

10/84 ----> loss: 0.743668

epoch 120:

20/84 ----> loss: 0.743672

epoch 120:

30/84 ----> loss: 1.743658

epoch 120:

40/84 ----> loss: 0.743669

epoch 120:

50/84 ----> loss: 0.743687

epoch 120:

60/84 ----> loss: 0.743689

epoch 120:

70/84 ----> loss: 0.743676

epoch 120:

80/84 ----> loss: 0.743671

epoch 121:

6/84 ----> loss: 0.743671

epoch 121:

16/84 ----> loss: 0.743669

epoch 121:

26/84 ----> loss: 0.743669

epoch 121:

36/84 ----> loss: 0.743846

epoch 121:

46/84 ----> loss: 0.743670

epoch 121:

56/84 ----> loss: 0.743669

epoch 121:

66/84 ----> loss: 0.743669

epoch 121:

76/84 ----> loss: 0.743716

epoch 122:

2/84 ----> loss: 0.743669

epoch 122:

12/84 ----> loss: 1.682139

epoch 122:

22/84 ----> loss: 0.743668

epoch 122:

32/84 ----> loss: 0.743669

epoch 122:

42/84 ----> loss: 0.743952

epoch 122:

52/84 ----> loss: 0.743669

epoch 122:

62/84 ----> loss: 0.743668

epoch 122:

72/84 ----> loss: 0.743668

epoch 122:

82/84 ----> loss: 0.743752

epoch 123:

8/84 ----> loss: 0.743668

epoch 123:

18/84 ----> loss: 0.744355

epoch 123:

28/84 ----> loss: 0.743669

epoch 123:

38/84 ----> loss: 1.742998

epoch 123:

48/84 ----> loss: 0.743669

epoch 123:

58/84 ----> loss: 0.743673

epoch 123:

68/84 ----> loss: 0.743670

epoch 123:

78/84 ----> loss: 0.743789

epoch 124:

4/84 ----> loss: 1.743652

epoch 124:

14/84 ----> loss: 1.743658

epoch 124:

24/84 ----> loss: 1.743648

epoch 124:

34/84 ----> loss: 0.743668

epoch 124:

44/84 ----> loss: 0.743670

epoch 124:

54/84 ----> loss: 1.743665

epoch 124:

64/84 ----> loss: 1.670101

epoch 124:

74/84 ----> loss: 0.743668

epoch 125:

0/84 ----> loss: 0.743668

epoch 125:

10/84 ----> loss: 0.743668

epoch 125:

20/84 ----> loss: 0.743672

epoch 125:

30/84 ----> loss: 1.743654

epoch 125:

40/84 ----> loss: 0.743669

epoch 125:

50/84 ----> loss: 0.743728

epoch 125:

60/84 ----> loss: 0.743702

epoch 125:

70/84 ----> loss: 0.743678

epoch 125:

80/84 ----> loss: 0.743671

epoch 126:

6/84 ----> loss: 0.743671

epoch 126:

16/84 ----> loss: 0.743669

epoch 126:

26/84 ----> loss: 0.743669

epoch 126:

```
-----  
-----  
36/84 ----> loss: 0.743840  
  
epoch 126:  
-----  
-----  
46/84 ----> loss: 0.743672  
  
epoch 126:  
-----  
-----  
56/84 ----> loss: 0.743669  
  
epoch 126:  
-----  
-----  
66/84 ----> loss: 0.743669  
  
epoch 126:  
-----  
-----  
76/84 ----> loss: 0.743710  
  
epoch 127:  
-----  
-----  
2/84 ----> loss: 0.743669  
  
epoch 127:  
-----  
-----  
12/84 ----> loss: 1.675084  
  
epoch 127:  
-----  
-----  
22/84 ----> loss: 0.743668  
  
epoch 127:
```


32/84 ----> loss: 0.743669

epoch 127:

42/84 ----> loss: 0.743926

epoch 127:

52/84 ----> loss: 0.743669

epoch 127:

62/84 ----> loss: 0.743668

epoch 127:

72/84 ----> loss: 0.743668

epoch 127:

82/84 ----> loss: 0.743762

epoch 128:

8/84 ----> loss: 0.743668

epoch 128:

18/84 ----> loss: 0.744483

epoch 128:


```
-----  
-----  
28/84 ----> loss: 0.743669  
  
epoch 128:  
-----  
-----  
38/84 ----> loss: 1.742551  
  
epoch 128:  
-----  
-----  
48/84 ----> loss: 0.743669  
  
epoch 128:  
-----  
-----  
58/84 ----> loss: 0.743677  
  
epoch 128:  
-----  
-----  
68/84 ----> loss: 0.743672  
  
epoch 128:  
-----  
-----  
78/84 ----> loss: 0.743777  
  
epoch 129:  
-----  
-----  
4/84 ----> loss: 1.743638  
  
epoch 129:  
-----  
-----  
14/84 ----> loss: 1.743654  
  
epoch 129:
```


24/84 ----> loss: 1.743643

epoch 129:

34/84 ----> loss: 0.743668

epoch 129:

44/84 ----> loss: 0.743671

epoch 129:

54/84 ----> loss: 1.743662

epoch 129:

64/84 ----> loss: 1.676580

epoch 129:

74/84 ----> loss: 0.743668

epoch 130:

0/84 ----> loss: 0.743668

epoch 130:

10/84 ----> loss: 0.743669

epoch 130:

20/84 ----> loss: 0.743673

epoch 130:

30/84 ----> loss: 1.743650

epoch 130:

40/84 ----> loss: 0.743670

epoch 130:

50/84 ----> loss: 0.743787

epoch 130:

60/84 ----> loss: 0.743711

epoch 130:

70/84 ----> loss: 0.743683

epoch 130:

80/84 ----> loss: 0.743676

epoch 131:

6/84 ----> loss: 0.743672

epoch 131:

```
-----  
-----  
16/84 ----> loss: 0.743669  
  
epoch 131:  
-----  
-----  
26/84 ----> loss: 0.743669  
  
epoch 131:  
-----  
-----  
36/84 ----> loss: 0.743842  
  
epoch 131:  
-----  
-----  
46/84 ----> loss: 0.743673  
  
epoch 131:  
-----  
-----  
56/84 ----> loss: 0.743669  
  
epoch 131:  
-----  
-----  
66/84 ----> loss: 0.743669  
  
epoch 131:  
-----  
-----  
76/84 ----> loss: 0.743705  
  
epoch 132:  
-----  
-----  
2/84 ----> loss: 0.743669  
  
epoch 132:
```


12/84 ----> loss: 1.667438

epoch 132:

22/84 ----> loss: 0.743668

epoch 132:

32/84 ----> loss: 0.743669

epoch 132:

42/84 ----> loss: 0.743863

epoch 132:

52/84 ----> loss: 0.743670

epoch 132:

62/84 ----> loss: 0.743668

epoch 132:

72/84 ----> loss: 0.743668

epoch 132:

82/84 ----> loss: 0.743794

epoch 133:

8/84 ----> loss: 0.743668

epoch 133:

18/84 ----> loss: 0.744719

epoch 133:

28/84 ----> loss: 0.743669

epoch 133:

38/84 ----> loss: 1.742422

epoch 133:

48/84 ----> loss: 0.743669

epoch 133:

58/84 ----> loss: 0.743679

epoch 133:

68/84 ----> loss: 0.743673

epoch 133:

78/84 ----> loss: 0.743771

epoch 134:

4/84 ----> loss: 1.743611

epoch 134:

14/84 ----> loss: 1.743655

epoch 134:

24/84 ----> loss: 1.743648

epoch 134:

34/84 ----> loss: 0.743668

epoch 134:

44/84 ----> loss: 0.743671

epoch 134:

54/84 ----> loss: 1.743661

epoch 134:

64/84 ----> loss: 1.686738

epoch 134:

74/84 ----> loss: 0.743669

epoch 135:

0/84 ----> loss: 0.743669

epoch 135:

10/84 ----> loss: 0.743669

epoch 135:

20/84 ----> loss: 0.743672

epoch 135:

30/84 ----> loss: 1.743649

epoch 135:

40/84 ----> loss: 0.743670

epoch 135:

50/84 ----> loss: 0.743774

epoch 135:

60/84 ----> loss: 0.743703

epoch 135:

70/84 ----> loss: 0.743689

epoch 135:

80/84 ----> loss: 0.743684

epoch 136:

6/84 ----> loss: 0.743673

epoch 136:

16/84 ----> loss: 0.743669

epoch 136:

26/84 ----> loss: 0.743669

epoch 136:

36/84 ----> loss: 0.743853

epoch 136:

46/84 ----> loss: 0.743672

epoch 136:

56/84 ----> loss: 0.743669

epoch 136:

66/84 ----> loss: 0.743669

epoch 136:

76/84 ----> loss: 0.743703

epoch 137:

2/84 ----> loss: 0.743669

epoch 137:

12/84 ----> loss: 1.668621

epoch 137:

22/84 ----> loss: 0.743668

epoch 137:

32/84 ----> loss: 0.743669

epoch 137:

42/84 ----> loss: 0.743817

epoch 137:

52/84 ----> loss: 0.743670

epoch 137:

62/84 ----> loss: 0.743668

epoch 137:

72/84 ----> loss: 0.743668

epoch 137:

82/84 ----> loss: 0.743831

epoch 138:

8/84 ----> loss: 0.743668

epoch 138:

18/84 ----> loss: 0.744857

epoch 138:

28/84 ----> loss: 0.743669

epoch 138:

38/84 ----> loss: 1.742526

epoch 138:

48/84 ----> loss: 0.743669

epoch 138:

58/84 ----> loss: 0.743677

epoch 138:

68/84 ----> loss: 0.743672

epoch 138:

78/84 ----> loss: 0.743774

epoch 139:

4/84 ----> loss: 1.743602

epoch 139:

14/84 ----> loss: 1.743655

epoch 139:

24/84 ----> loss: 1.743649

epoch 139:

34/84 ----> loss: 0.743668

epoch 139:

44/84 ----> loss: 0.743670

epoch 139:

54/84 ----> loss: 1.743661

epoch 139:

64/84 ----> loss: 1.675038

epoch 139:

74/84 ----> loss: 0.743669

epoch 140:

0/84 ----> loss: 0.743669

epoch 140:

10/84 ----> loss: 0.743669

epoch 140:

20/84 ----> loss: 0.743672

epoch 140:

30/84 ----> loss: 1.743649

epoch 140:

40/84 ----> loss: 0.743671

epoch 140:

50/84 ----> loss: 0.743743

epoch 140:

60/84 ----> loss: 0.743694

epoch 140:

70/84 ----> loss: 0.743691

epoch 140:

80/84 ----> loss: 0.743690

epoch 141:

6/84 ----> loss: 0.743674

epoch 141:

16/84 ----> loss: 0.743669

epoch 141:

26/84 ----> loss: 0.743669

epoch 141:

36/84 ----> loss: 0.743864

epoch 141:

46/84 ----> loss: 0.743671

epoch 141:

56/84 ----> loss: 0.743669

epoch 141:

66/84 ----> loss: 0.743669

epoch 141:

76/84 ----> loss: 0.743704

epoch 142:

2/84 ----> loss: 0.743669

epoch 142:

12/84 ----> loss: 1.669672

epoch 142:

22/84 ----> loss: 0.743668

epoch 142:

32/84 ----> loss: 0.743669

epoch 142:

42/84 ----> loss: 0.743790

epoch 142:

52/84 ----> loss: 0.743670

epoch 142:

62/84 ----> loss: 0.743668

epoch 142:

72/84 ----> loss: 0.743668

epoch 142:

82/84 ----> loss: 0.743860

epoch 143:

8/84 ----> loss: 0.743668

epoch 143:

18/84 ----> loss: 0.744870

epoch 143:

28/84 ----> loss: 0.743669

epoch 143:

38/84 ----> loss: 1.742823

epoch 143:

48/84 ----> loss: 0.743669

epoch 143:

58/84 ----> loss: 0.743676

epoch 143:

68/84 ----> loss: 0.743671

epoch 143:

78/84 ----> loss: 0.743780

epoch 144:

4/84 ----> loss: 1.743593

epoch 144:

14/84 ----> loss: 1.743654

epoch 144:

24/84 ----> loss: 1.743650

epoch 144:

34/84 ----> loss: 0.743668

epoch 144:

44/84 ----> loss: 0.743669

epoch 144:

54/84 ----> loss: 1.743663

epoch 144:

64/84 ----> loss: 1.668778

epoch 144:

74/84 ----> loss: 0.743669

epoch 145:

0/84 ----> loss: 0.743669

epoch 145:

10/84 ----> loss: 0.743669

epoch 145:

20/84 ----> loss: 0.743672

epoch 145:

30/84 ----> loss: 1.743650

epoch 145:

40/84 ----> loss: 0.743670

epoch 145:

50/84 ----> loss: 0.743713

epoch 145:

60/84 ----> loss: 0.743685

epoch 145:

70/84 ----> loss: 0.743693

epoch 145:

80/84 ----> loss: 0.743698

epoch 146:

6/84 ----> loss: 0.743675

epoch 146:

16/84 ----> loss: 0.743669

epoch 146:

26/84 ----> loss: 0.743669

epoch 146:

36/84 ----> loss: 0.743875

epoch 146:

46/84 ----> loss: 0.743670

epoch 146:

56/84 ----> loss: 0.743669

epoch 146:

66/84 ----> loss: 0.743669

epoch 146:

76/84 ----> loss: 0.743706

epoch 147:

2/84 ----> loss: 0.743670

epoch 147:

12/84 ----> loss: 1.671485

epoch 147:

22/84 ----> loss: 0.743668

epoch 147:

32/84 ----> loss: 0.743669

epoch 147:

42/84 ----> loss: 0.743765

epoch 147:

52/84 ----> loss: 0.743669

epoch 147:

62/84 ----> loss: 0.743668

epoch 147:

72/84 ----> loss: 0.743668

epoch 147:

82/84 ----> loss: 0.743876

epoch 148:

8/84 ----> loss: 0.743668

epoch 148:

18/84 ----> loss: 0.744848

epoch 148:

28/84 ----> loss: 0.743669

epoch 148:

38/84 ----> loss: 1.743079

epoch 148:

48/84 ----> loss: 0.743669

epoch 148:

58/84 ----> loss: 0.743675

epoch 148:

68/84 ----> loss: 0.743670

epoch 148:

78/84 ----> loss: 0.743788

epoch 149:

4/84 ----> loss: 1.743586

epoch 149:

14/84 ----> loss: 1.743653

epoch 149:

24/84 ----> loss: 1.743651

epoch 149:

34/84 ----> loss: 0.743668

epoch 149:

44/84 ----> loss: 0.743669

epoch 149:

54/84 ----> loss: 1.743664

epoch 149:

64/84 ----> loss: 1.667380

epoch 149:

74/84 ----> loss: 0.743669

epoch 150:

0/84 ----> loss: 0.743669

epoch 150:

10/84 ----> loss: 0.743669

epoch 150:

20/84 ----> loss: 0.743672

epoch 150:

30/84 ----> loss: 1.743650

epoch 150:

40/84 ----> loss: 0.743670

epoch 150:

50/84 ----> loss: 0.743692

epoch 150:

60/84 ----> loss: 0.743680

epoch 150:

70/84 ----> loss: 0.743694

epoch 150:

80/84 ----> loss: 0.743701

epoch 151:

6/84 ----> loss: 0.743676

epoch 151:

16/84 ----> loss: 0.743669

epoch 151:

26/84 ----> loss: 0.743669

epoch 151:

36/84 ----> loss: 0.743881

epoch 151:

46/84 ----> loss: 0.743669

epoch 151:

56/84 ----> loss: 0.743669

epoch 151:

66/84 ----> loss: 0.743669

epoch 151:

76/84 ----> loss: 0.743708

epoch 152:

2/84 ----> loss: 0.743670

epoch 152:

12/84 ----> loss: 1.670411

epoch 152:

22/84 ----> loss: 0.743668

epoch 152:

32/84 ----> loss: 0.743669

epoch 152:

42/84 ----> loss: 0.743749

epoch 152:

52/84 ----> loss: 0.743669

epoch 152:

62/84 ----> loss: 0.743668

epoch 152:

72/84 ----> loss: 0.743668

epoch 152:

82/84 ----> loss: 0.743869

epoch 153:

8/84 ----> loss: 0.743668

epoch 153:

18/84 ----> loss: 0.744738

epoch 153:

28/84 ----> loss: 0.743670

epoch 153:

38/84 ----> loss: 1.743191

epoch 153:

48/84 ----> loss: 0.743669

epoch 153:

58/84 ----> loss: 0.743674

epoch 153:

68/84 ----> loss: 0.743669

epoch 153:

78/84 ----> loss: 0.743794

epoch 154:

4/84 ----> loss: 1.743590

epoch 154:

14/84 ----> loss: 1.743651

epoch 154:

24/84 ----> loss: 1.743650

epoch 154:

34/84 ----> loss: 0.743668

epoch 154:

44/84 ----> loss: 0.743669

epoch 154:

54/84 ----> loss: 1.743665

epoch 154:

64/84 ----> loss: 1.670160

epoch 154:

74/84 ----> loss: 0.743669

epoch 155:

0/84 ----> loss: 0.743669

epoch 155:

10/84 ----> loss: 0.743669

epoch 155:

20/84 ----> loss: 0.743671

epoch 155:

30/84 ----> loss: 1.743649

epoch 155:

40/84 ----> loss: 0.743670

epoch 155:

50/84 ----> loss: 0.743683

epoch 155:

60/84 ----> loss: 0.743678

epoch 155:

70/84 ----> loss: 0.743692

epoch 155:

80/84 ----> loss: 0.743696

epoch 156:

6/84 ----> loss: 0.743677

epoch 156:

16/84 ----> loss: 0.743669

epoch 156:

26/84 ----> loss: 0.743669

epoch 156:

36/84 ----> loss: 0.743877

epoch 156:

46/84 ----> loss: 0.743669

epoch 156:

56/84 ----> loss: 0.743669

epoch 156:

66/84 ----> loss: 0.743669

epoch 156:

76/84 ----> loss: 0.743711

epoch 157:

2/84 ----> loss: 0.743670

epoch 157:

12/84 ----> loss: 1.667695

epoch 157:

22/84 ----> loss: 0.743668

epoch 157:

32/84 ----> loss: 0.743669

epoch 157:

42/84 ----> loss: 0.743744

epoch 157:

52/84 ----> loss: 0.743669

epoch 157:

62/84 ----> loss: 0.743668

epoch 157:

72/84 ----> loss: 0.743668

epoch 157:

82/84 ----> loss: 0.743844

epoch 158:

8/84 ----> loss: 0.743668

epoch 158:

18/84 ----> loss: 0.744569

epoch 158:

28/84 ----> loss: 0.743670

epoch 158:

38/84 ----> loss: 1.743152

epoch 158:

48/84 ----> loss: 0.743669

epoch 158:

58/84 ----> loss: 0.743674

epoch 158:

68/84 ----> loss: 0.743669

epoch 158:

78/84 ----> loss: 0.743799

epoch 159:

4/84 ----> loss: 1.743599

epoch 159:

14/84 ----> loss: 1.743647

epoch 159:

24/84 ----> loss: 1.743644

epoch 159:

34/84 ----> loss: 0.743668

epoch 159:

44/84 ----> loss: 0.743669

epoch 159:

54/84 ----> loss: 1.743664

epoch 159:

64/84 ----> loss: 1.672949

epoch 159:

74/84 ----> loss: 0.743669

epoch 160:

0/84 ----> loss: 0.743669

epoch 160:

10/84 ----> loss: 0.743669

epoch 160:

20/84 ----> loss: 0.743671

epoch 160:

30/84 ----> loss: 1.743646

epoch 160:

40/84 ----> loss: 0.743669

epoch 160:

50/84 ----> loss: 0.743681

epoch 160:

60/84 ----> loss: 0.743677

epoch 160:

70/84 ----> loss: 0.743692

epoch 160:

80/84 ----> loss: 0.743689

epoch 161:

6/84 ----> loss: 0.743676

epoch 161:

16/84 ----> loss: 0.743669

epoch 161:

26/84 ----> loss: 0.743669

epoch 161:

36/84 ----> loss: 0.743866

epoch 161:

46/84 ----> loss: 0.743670

epoch 161:

56/84 ----> loss: 0.743669

epoch 161:

66/84 ----> loss: 0.743669

epoch 161:

76/84 ----> loss: 0.743713

epoch 162:

2/84 ----> loss: 0.743670

epoch 162:

12/84 ----> loss: 1.667489

epoch 162:

22/84 ----> loss: 0.743668

epoch 162:

32/84 ----> loss: 0.743669

epoch 162:

42/84 ----> loss: 0.743746

epoch 162:

52/84 ----> loss: 0.743670

epoch 162:

62/84 ----> loss: 0.743668

epoch 162:

72/84 ----> loss: 0.743668

epoch 162:

82/84 ----> loss: 0.743819

epoch 163:

8/84 ----> loss: 0.743668

epoch 163:

18/84 ----> loss: 0.744429

epoch 163:

28/84 ----> loss: 0.743671

epoch 163:

38/84 ----> loss: 1.742929

epoch 163:

48/84 ----> loss: 0.743669

epoch 163:

58/84 ----> loss: 0.743676

epoch 163:

68/84 ----> loss: 0.743669

epoch 163:

78/84 ----> loss: 0.743800

epoch 164:

4/84 ----> loss: 1.743598

epoch 164:

14/84 ----> loss: 1.743641

epoch 164:

24/84 ----> loss: 1.743635

epoch 164:

34/84 ----> loss: 0.743668

epoch 164:

44/84 ----> loss: 0.743669

epoch 164:

54/84 ----> loss: 1.743663

epoch 164:

64/84 ----> loss: 1.670682

epoch 164:

74/84 ----> loss: 0.743669

epoch 165:

0/84 ----> loss: 0.743669

epoch 165:

10/84 ----> loss: 0.743669

epoch 165:

20/84 ----> loss: 0.743671

epoch 165:

30/84 ----> loss: 1.743639

epoch 165:

40/84 ----> loss: 0.743669

epoch 165:

50/84 ----> loss: 0.743685

epoch 165:

60/84 ----> loss: 0.743679

epoch 165:

70/84 ----> loss: 0.743694

epoch 165:

80/84 ----> loss: 0.743685

epoch 166:

6/84 ----> loss: 0.743675

epoch 166:

16/84 ----> loss: 0.743669

epoch 166:

26/84 ----> loss: 0.743669

epoch 166:

36/84 ----> loss: 0.743857

epoch 166:

46/84 ----> loss: 0.743671

epoch 166:

56/84 ----> loss: 0.743669

epoch 166:

66/84 ----> loss: 0.743669

epoch 166:

76/84 ----> loss: 0.743716

epoch 167:

2/84 ----> loss: 0.743670

epoch 167:

12/84 ----> loss: 1.668719

epoch 167:

22/84 ----> loss: 0.743668

epoch 167:

32/84 ----> loss: 0.743669

epoch 167:

42/84 ----> loss: 0.743751

epoch 167:

52/84 ----> loss: 0.743670

epoch 167:

62/84 ----> loss: 0.743668

epoch 167:

72/84 ----> loss: 0.743668

epoch 167:

82/84 ----> loss: 0.743801

epoch 168:

8/84 ----> loss: 0.743668

epoch 168:

18/84 ----> loss: 0.744338

epoch 168:

28/84 ----> loss: 0.743671

epoch 168:

38/84 ----> loss: 1.742221

epoch 168:

48/84 ----> loss: 0.743669

epoch 168:

58/84 ----> loss: 0.743681

epoch 168:

68/84 ----> loss: 0.743669

epoch 168:

78/84 ----> loss: 0.743799

epoch 169:

4/84 ----> loss: 1.743585

epoch 169:

14/84 ----> loss: 1.743634

epoch 169:

24/84 ----> loss: 1.743620

epoch 169:

34/84 ----> loss: 0.743669

epoch 169:

44/84 ----> loss: 0.743671

epoch 169:

54/84 ----> loss: 1.743658

epoch 169:

64/84 ----> loss: 1.667446

epoch 169:

74/84 ----> loss: 0.743669

epoch 170:

0/84 ----> loss: 0.743669

epoch 170:

10/84 ----> loss: 0.743669

epoch 170:

20/84 ----> loss: 0.743672

epoch 170:

30/84 ----> loss: 1.743623

epoch 170:

40/84 ----> loss: 0.743669

epoch 170:

50/84 ----> loss: 0.743701

epoch 170:

60/84 ----> loss: 0.743686

epoch 170:

70/84 ----> loss: 0.743702

epoch 170:

80/84 ----> loss: 0.743685

epoch 171:

6/84 ----> loss: 0.743674

epoch 171:

16/84 ----> loss: 0.743669

epoch 171:

26/84 ----> loss: 0.743669

epoch 171:

36/84 ----> loss: 0.743883

epoch 171:

46/84 ----> loss: 0.743677

epoch 171:

56/84 ----> loss: 0.743669

epoch 171:

66/84 ----> loss: 0.743669

epoch 171:

76/84 ----> loss: 0.743732

epoch 172:

2/84 ----> loss: 0.743670

epoch 172:

12/84 ----> loss: 1.667812

epoch 172:

22/84 ----> loss: 0.743668

epoch 172:

32/84 ----> loss: 0.743670

epoch 172:

42/84 ----> loss: 0.743786

epoch 172:

52/84 ----> loss: 0.743674

epoch 172:

62/84 ----> loss: 0.743668

epoch 172:

72/84 ----> loss: 0.743668

epoch 172:

82/84 ----> loss: 0.743778

epoch 173:

8/84 ----> loss: 0.743668

epoch 173:

18/84 ----> loss: 0.744040

epoch 173:

28/84 ----> loss: 0.743679

epoch 173:

38/84 ----> loss: 1.731465

epoch 173:

48/84 ----> loss: 0.743669

epoch 173:

58/84 ----> loss: 0.743741

epoch 173:

68/84 ----> loss: 0.743669

epoch 173:

78/84 ----> loss: 0.743799

epoch 174:

4/84 ----> loss: 1.743336

epoch 174:

14/84 ----> loss: 1.743550

epoch 174:

24/84 ----> loss: 1.743508

epoch 174:

34/84 ----> loss: 0.743669

epoch 174:

44/84 ----> loss: 0.743686

epoch 174:

54/84 ----> loss: 1.743479

epoch 174:

64/84 ----> loss: 1.674360

epoch 174:

74/84 ----> loss: 0.743670

epoch 175:

0/84 ----> loss: 0.743670

epoch 175:

10/84 ----> loss: 0.743670

epoch 175:

20/84 ----> loss: 0.743673

epoch 175:

30/84 ----> loss: 1.743158

epoch 175:

40/84 ----> loss: 0.743669

epoch 175:

50/84 ----> loss: 0.743690

epoch 175:

60/84 ----> loss: 0.743726

epoch 175:

70/84 ----> loss: 0.743919

epoch 175:

80/84 ----> loss: 0.743729

epoch 176:

6/84 ----> loss: 0.743686

epoch 176:

16/84 ----> loss: 0.743669

epoch 176:

26/84 ----> loss: 0.743674

epoch 176:

36/84 ----> loss: 0.744419

epoch 176:

46/84 ----> loss: 0.743793

epoch 176:

56/84 ----> loss: 0.743669

epoch 176:

66/84 ----> loss: 0.743668

epoch 176:

76/84 ----> loss: 0.744154

epoch 177:

2/84 ----> loss: 0.743697

epoch 177:

12/84 ----> loss: 1.668061

epoch 177:

22/84 ----> loss: 0.743668

epoch 177:

32/84 ----> loss: 0.743678

epoch 177:

42/84 ----> loss: 0.743863

epoch 177:

52/84 ----> loss: 0.743779

epoch 177:

62/84 ----> loss: 0.743668

epoch 177:

72/84 ----> loss: 0.743668

epoch 177:

82/84 ----> loss: 0.744295

epoch 178:

8/84 ----> loss: 0.743668

epoch 178:

18/84 ----> loss: 0.744642

epoch 178:

28/84 ----> loss: 0.743720

epoch 178:

38/84 ----> loss: 1.670344

epoch 178:

48/84 ----> loss: 0.743669

epoch 178:

58/84 ----> loss: 0.744870

epoch 178:

68/84 ----> loss: 0.743671

epoch 178:

78/84 ----> loss: 0.743770

epoch 179:

4/84 ----> loss: 1.740347

epoch 179:

14/84 ----> loss: 1.743162

epoch 179:

24/84 ----> loss: 1.743077

epoch 179:

34/84 ----> loss: 0.743675

epoch 179:

44/84 ----> loss: 0.743718

epoch 179:

54/84 ----> loss: 1.741977

epoch 179:

64/84 ----> loss: 1.696728

epoch 179:

74/84 ----> loss: 0.743685

epoch 180:

0/84 ----> loss: 0.743712

epoch 180:

10/84 ----> loss: 0.743689

epoch 180:

20/84 ----> loss: 0.743674

epoch 180:

30/84 ----> loss: 1.741317

epoch 180:

40/84 ----> loss: 0.743669

epoch 180:

50/84 ----> loss: 0.743731

epoch 180:

60/84 ----> loss: 0.743699

epoch 180:

70/84 ----> loss: 0.746846

epoch 180:

80/84 ----> loss: 0.744001

epoch 181:

6/84 ----> loss: 0.743709

epoch 181:

16/84 ----> loss: 0.743669

epoch 181:

26/84 ----> loss: 0.743743

epoch 181:

36/84 ----> loss: 0.744381

epoch 181:

46/84 ----> loss: 0.743848

epoch 181:

56/84 ----> loss: 0.743669

epoch 181:

66/84 ----> loss: 0.743668

epoch 181:

76/84 ----> loss: 0.743865

epoch 182:

2/84 ----> loss: 0.743938

epoch 182:

12/84 ----> loss: 1.669822

epoch 182:

22/84 ----> loss: 0.743668

epoch 182:

32/84 ----> loss: 0.743715

epoch 182:

42/84 ----> loss: 0.743790

epoch 182:

52/84 ----> loss: 0.743976

epoch 182:

62/84 ----> loss: 0.743668

epoch 182:

72/84 ----> loss: 0.743668

epoch 182:

82/84 ----> loss: 0.744907

epoch 183:

8/84 ----> loss: 0.743668

epoch 183:

18/84 ----> loss: 0.745415

epoch 183:

28/84 ----> loss: 0.743833

epoch 183:

38/84 ----> loss: 1.667749

epoch 183:

48/84 ----> loss: 0.743669

epoch 183:

58/84 ----> loss: 0.745065

epoch 183:

68/84 ----> loss: 0.743671

epoch 183:

78/84 ----> loss: 0.743774

epoch 184:

4/84 ----> loss: 1.736510

epoch 184:

14/84 ----> loss: 1.742888

epoch 184:

24/84 ----> loss: 1.742725

epoch 184:

34/84 ----> loss: 0.743681

epoch 184:

44/84 ----> loss: 0.743770

epoch 184:

54/84 ----> loss: 1.739704

epoch 184:

64/84 ----> loss: 1.684150

epoch 184:

74/84 ----> loss: 0.743703

epoch 185:

0/84 ----> loss: 0.743727

epoch 185:

10/84 ----> loss: 0.743702

epoch 185:

20/84 ----> loss: 0.743674

epoch 185:

30/84 ----> loss: 1.736118

epoch 185:

40/84 ----> loss: 0.743670

epoch 185:

50/84 ----> loss: 0.743710

epoch 185:

60/84 ----> loss: 0.743709

epoch 185:

70/84 ----> loss: 0.751575

epoch 185:

80/84 ----> loss: 0.744166

epoch 186:

6/84 ----> loss: 0.743759

epoch 186:

16/84 ----> loss: 0.743669

epoch 186:

26/84 ----> loss: 0.743776

epoch 186:

36/84 ----> loss: 0.744604

epoch 186:

46/84 ----> loss: 0.743961

epoch 186:

56/84 ----> loss: 0.743669

epoch 186:

66/84 ----> loss: 0.743668

epoch 186:

76/84 ----> loss: 0.743898

epoch 187:

2/84 ----> loss: 0.743978

epoch 187:

12/84 ----> loss: 1.670305

epoch 187:

22/84 ----> loss: 0.743669

epoch 187:

32/84 ----> loss: 0.743751

epoch 187:

42/84 ----> loss: 0.743834

epoch 187:

52/84 ----> loss: 0.744491

epoch 187:

62/84 ----> loss: 0.743668

epoch 187:

72/84 ----> loss: 0.743668

epoch 187:

82/84 ----> loss: 0.746023

epoch 188:

8/84 ----> loss: 0.743668

epoch 188:

18/84 ----> loss: 0.746609

epoch 188:

28/84 ----> loss: 0.743984

epoch 188:

38/84 ----> loss: 1.658684

epoch 188:

48/84 ----> loss: 0.743669

epoch 188:

58/84 ----> loss: 0.943841

epoch 188:

68/84 ----> loss: 0.743671

epoch 188:

78/84 ----> loss: 0.743954

epoch 189:

4/84 ----> loss: 1.723660

epoch 189:

14/84 ----> loss: 1.742568

epoch 189:

24/84 ----> loss: 1.742437

epoch 189:

34/84 ----> loss: 0.743677

epoch 189:

44/84 ----> loss: 0.743769

epoch 189:

54/84 ----> loss: 1.740463

epoch 189:

64/84 ----> loss: 1.674920

epoch 189:

74/84 ----> loss: 0.743721

epoch 190:

0/84 ----> loss: 0.743726

epoch 190:

10/84 ----> loss: 0.743699

epoch 190:

20/84 ----> loss: 0.743695

epoch 190:

30/84 ----> loss: 1.708036

epoch 190:

40/84 ----> loss: 0.743670

epoch 190:

50/84 ----> loss: 0.743729

epoch 190:

60/84 ----> loss: 0.743750

epoch 190:

70/84 ----> loss: 0.785790

epoch 190:

80/84 ----> loss: 0.744942

epoch 191:

6/84 ----> loss: 0.745661

epoch 191:

16/84 ----> loss: 0.743724

epoch 191:

26/84 ----> loss: 0.743689

epoch 191:

36/84 ----> loss: 0.745051

epoch 191:

46/84 ----> loss: 0.744075

epoch 191:

56/84 ----> loss: 0.743669

epoch 191:

66/84 ----> loss: 0.743676

epoch 191:

76/84 ----> loss: 0.743671

epoch 192:

2/84 ----> loss: 0.751479

epoch 192:

12/84 ----> loss: 0.743672

epoch 192:

22/84 ----> loss: 0.743693

epoch 192:

32/84 ----> loss: 0.743671

epoch 192:

42/84 ----> loss: 0.743890

epoch 192:

52/84 ----> loss: 0.743736

epoch 192:

62/84 ----> loss: 0.743668

epoch 192:

72/84 ----> loss: 0.743668

epoch 192:

82/84 ----> loss: 0.743868

epoch 193:

8/84 ----> loss: 0.743669

epoch 193:

18/84 ----> loss: 0.743993

epoch 193:

28/84 ----> loss: 0.743672

epoch 193:

38/84 ----> loss: 0.743676

epoch 193:

48/84 ----> loss: 0.743692

epoch 193:

58/84 ----> loss: 1.233166

epoch 193:

68/84 ----> loss: 0.743668

epoch 193:

78/84 ----> loss: 0.743668

epoch 194:

4/84 ----> loss: 1.743531

epoch 194:

14/84 ----> loss: 1.743668

epoch 194:

24/84 ----> loss: 1.743627

epoch 194:

34/84 ----> loss: 0.743668

epoch 194:

44/84 ----> loss: 0.743668

epoch 194:

54/84 ----> loss: 1.725597

epoch 194:

64/84 ----> loss: 0.743686

epoch 194:

74/84 ----> loss: 0.743669

epoch 195:

0/84 ----> loss: 0.743669

epoch 195:

10/84 ----> loss: 0.743669

epoch 195:

20/84 ----> loss: 0.743668

epoch 195:

30/84 ----> loss: 1.637960

epoch 195:

40/84 ----> loss: 0.744824

epoch 195:

50/84 ----> loss: 0.743675

epoch 195:

60/84 ----> loss: 0.743669

epoch 195:

70/84 ----> loss: 0.747015

epoch 195:

80/84 ----> loss: 0.743705

epoch 196:

6/84 ----> loss: 0.744434

epoch 196:

16/84 ----> loss: 0.743672

epoch 196:

26/84 ----> loss: 0.803303

epoch 196:

36/84 ----> loss: 0.743829

epoch 196:

46/84 ----> loss: 0.743673

epoch 196:

56/84 ----> loss: 0.743915

epoch 196:

66/84 ----> loss: 0.743668

epoch 196:

76/84 ----> loss: 0.743769

epoch 197:

2/84 ----> loss: 0.743677

epoch 197:

12/84 ----> loss: 0.743668

epoch 197:

22/84 ----> loss: 0.745498

epoch 197:

32/84 ----> loss: 0.744286

epoch 197:

42/84 ----> loss: 0.743706

epoch 197:

52/84 ----> loss: 0.743686

epoch 197:

62/84 ----> loss: 0.743668

epoch 197:

72/84 ----> loss: 0.743668

epoch 197:

82/84 ----> loss: 0.744295

epoch 198:

8/84 ----> loss: 0.743668

epoch 198:

18/84 ----> loss: 0.743922

epoch 198:

28/84 ----> loss: 0.743926

epoch 198:

38/84 ----> loss: 0.743676

epoch 198:

48/84 ----> loss: 0.743691

epoch 198:

58/84 ----> loss: 0.743798

epoch 198:

68/84 ----> loss: 0.743669

epoch 198:

78/84 ----> loss: 0.743669

epoch 199:

4/84 ----> loss: 0.743957

epoch 199:

14/84 ----> loss: 1.682353

epoch 199:

24/84 ----> loss: 1.735611

epoch 199:

34/84 ----> loss: 0.772131

epoch 199:

44/84 ----> loss: 0.744057

epoch 199:

54/84 ----> loss: 0.744140

epoch 199:

64/84 ----> loss: 0.743675

epoch 199:

74/84 ----> loss: 0.743674

epoch 200:

0/84 ----> loss: 0.743669

epoch 200:

10/84 ----> loss: 0.743669

epoch 200:

20/84 ----> loss: 0.743668

epoch 200:

30/84 ----> loss: 0.744865

epoch 200:

40/84 ----> loss: 0.744774

epoch 200:

50/84 ----> loss: 0.743673

epoch 200:

60/84 ----> loss: 0.743669

epoch 200:

70/84 ----> loss: 0.750473

epoch 200:

80/84 ----> loss: 0.743829

epoch 201:

6/84 ----> loss: 0.744395

epoch 201:

16/84 ----> loss: 0.755358

epoch 201:

26/84 ----> loss: 1.716016

epoch 201:

36/84 ----> loss: 0.743847

epoch 201:

46/84 ----> loss: 0.743678

epoch 201:

56/84 ----> loss: 0.743862

epoch 201:

66/84 ----> loss: 0.743668

epoch 201:

76/84 ----> loss: 0.743936

epoch 202:

2/84 ----> loss: 0.743669

epoch 202:

12/84 ----> loss: 0.743670

epoch 202:

22/84 ----> loss: 0.748647

epoch 202:

32/84 ----> loss: 0.743669

epoch 202:

42/84 ----> loss: 0.743684

epoch 202:

52/84 ----> loss: 0.743708

epoch 202:

62/84 ----> loss: 0.743668

epoch 202:

72/84 ----> loss: 0.743668

epoch 202:

82/84 ----> loss: 0.744098

epoch 203:

8/84 ----> loss: 0.743669

epoch 203:

18/84 ----> loss: 0.743820

epoch 203:

28/84 ----> loss: 0.743669

epoch 203:

38/84 ----> loss: 0.743681

epoch 203:

48/84 ----> loss: 0.743674

epoch 203:

58/84 ----> loss: 0.745172

epoch 203:

68/84 ----> loss: 0.743669

epoch 203:

78/84 ----> loss: 0.743669

epoch 204:

4/84 ----> loss: 0.743684

epoch 204:

14/84 ----> loss: 1.700621

epoch 204:

24/84 ----> loss: 1.658134

epoch 204:

34/84 ----> loss: 0.748559

epoch 204:

44/84 ----> loss: 0.743691

epoch 204:

54/84 ----> loss: 0.743725

epoch 204:

64/84 ----> loss: 0.743727

epoch 204:

74/84 ----> loss: 0.743671

epoch 205:

0/84 ----> loss: 0.743670

epoch 205:

10/84 ----> loss: 0.743669

epoch 205:

20/84 ----> loss: 0.743668

epoch 205:

30/84 ----> loss: 0.743670

epoch 205:

40/84 ----> loss: 0.744597

epoch 205:

50/84 ----> loss: 0.743670

epoch 205:

60/84 ----> loss: 0.743669

epoch 205:

70/84 ----> loss: 0.753983

epoch 205:

80/84 ----> loss: 0.743677

epoch 206:

6/84 ----> loss: 0.745232

epoch 206:

16/84 ----> loss: 0.751650

epoch 206:

26/84 ----> loss: 0.743672

epoch 206:

36/84 ----> loss: 0.743778

epoch 206:

46/84 ----> loss: 0.743673

epoch 206:

56/84 ----> loss: 0.743721

epoch 206:

66/84 ----> loss: 0.743668

epoch 206:

76/84 ----> loss: 0.743746

epoch 207:

2/84 ----> loss: 0.743699

epoch 207:

12/84 ----> loss: 0.743669

epoch 207:

22/84 ----> loss: 0.745697

epoch 207:

32/84 ----> loss: 0.743674

epoch 207:

42/84 ----> loss: 0.743690

epoch 207:

52/84 ----> loss: 0.743851

epoch 207:

62/84 ----> loss: 0.743668

epoch 207:

72/84 ----> loss: 0.743668

epoch 207:

82/84 ----> loss: 0.743767

epoch 208:

8/84 ----> loss: 0.743668

epoch 208:

18/84 ----> loss: 0.743819

epoch 208:

28/84 ----> loss: 0.743669

epoch 208:

38/84 ----> loss: 0.743677

epoch 208:

48/84 ----> loss: 0.743679

epoch 208:

58/84 ----> loss: 0.743784

epoch 208:

68/84 ----> loss: 0.743669

epoch 208:

78/84 ----> loss: 0.743669

epoch 209:

4/84 ----> loss: 0.743774

epoch 209:

14/84 ----> loss: 1.633824

epoch 209:

24/84 ----> loss: 1.197700

epoch 209:

34/84 ----> loss: 0.743668

epoch 209:

44/84 ----> loss: 0.743668

epoch 209:

54/84 ----> loss: 1.332364

epoch 209:

64/84 ----> loss: 0.743977

epoch 209:

74/84 ----> loss: 0.743668

epoch 210:

0/84 ----> loss: 0.743668

epoch 210:

10/84 ----> loss: 0.743668

epoch 210:

20/84 ----> loss: 0.743669

epoch 210:

30/84 ----> loss: 0.743679

epoch 210:

40/84 ----> loss: 0.743668

epoch 210:

50/84 ----> loss: 0.743668

epoch 210:

60/84 ----> loss: 0.743668

epoch 210:

70/84 ----> loss: 0.758621

epoch 210:

80/84 ----> loss: 0.743669

epoch 211:

6/84 ----> loss: 0.743842

epoch 211:

16/84 ----> loss: 0.743669

epoch 211:

26/84 ----> loss: 0.743668

epoch 211:

36/84 ----> loss: 0.743764

epoch 211:

46/84 ----> loss: 0.743668

epoch 211:

56/84 ----> loss: 0.743671

epoch 211:

66/84 ----> loss: 0.743668

epoch 211:

76/84 ----> loss: 0.743678

epoch 212:

2/84 ----> loss: 0.743668

epoch 212:

12/84 ----> loss: 0.743668

epoch 212:

22/84 ----> loss: 0.750810

epoch 212:

32/84 ----> loss: 0.743672

epoch 212:

42/84 ----> loss: 0.743669

epoch 212:

52/84 ----> loss: 0.743676

epoch 212:

62/84 ----> loss: 0.743668

epoch 212:

72/84 ----> loss: 0.743668

epoch 212:

82/84 ----> loss: 0.743676

epoch 213:

8/84 ----> loss: 0.743668

epoch 213:

18/84 ----> loss: 0.744045

epoch 213:

28/84 ----> loss: 0.792800

epoch 213:

38/84 ----> loss: 0.744036

epoch 213:

48/84 ----> loss: 0.743671

epoch 213:

58/84 ----> loss: 0.744528

epoch 213:

68/84 ----> loss: 0.743668

epoch 213:

78/84 ----> loss: 0.743669

epoch 214:

4/84 ----> loss: 0.743670

epoch 214:

14/84 ----> loss: 1.425491

epoch 214:

24/84 ----> loss: 0.743670

epoch 214:

34/84 ----> loss: 0.743669

epoch 214:

44/84 ----> loss: 0.743718

epoch 214:

54/84 ----> loss: 0.743669

epoch 214:

64/84 ----> loss: 0.743730

epoch 214:

74/84 ----> loss: 0.743672

epoch 215:

0/84 ----> loss: 0.743669

epoch 215:

10/84 ----> loss: 0.743672

epoch 215:

20/84 ----> loss: 0.743668

epoch 215:

30/84 ----> loss: 0.743699

epoch 215:

40/84 ----> loss: 0.743668

epoch 215:

50/84 ----> loss: 0.743669

epoch 215:

60/84 ----> loss: 0.743669

epoch 215:

70/84 ----> loss: 0.745649

epoch 215:

80/84 ----> loss: 0.743673

epoch 216:

6/84 ----> loss: 0.743681

epoch 216:

16/84 ----> loss: 0.743668

epoch 216:

26/84 ----> loss: 0.744127

epoch 216:

36/84 ----> loss: 0.743781

epoch 216:

46/84 ----> loss: 0.743679

epoch 216:

56/84 ----> loss: 0.743670

epoch 216:

66/84 ----> loss: 0.743668

epoch 216:

76/84 ----> loss: 0.743670

epoch 217:

2/84 ----> loss: 0.743693

epoch 217:

12/84 ----> loss: 0.746802

epoch 217:

22/84 ----> loss: 0.743672

epoch 217:

32/84 ----> loss: 0.743670

epoch 217:

42/84 ----> loss: 0.743669

epoch 217:

52/84 ----> loss: 0.743669

epoch 217:

62/84 ----> loss: 0.743668

epoch 217:

72/84 ----> loss: 0.743668

epoch 217:

82/84 ----> loss: 0.743677

epoch 218:

8/84 ----> loss: 0.743668

epoch 218:

18/84 ----> loss: 0.744498

epoch 218:

28/84 ----> loss: 0.743669

epoch 218:

38/84 ----> loss: 0.743701

epoch 218:

48/84 ----> loss: 0.743669

epoch 218:

58/84 ----> loss: 0.743741

epoch 218:

68/84 ----> loss: 0.743668

epoch 218:

78/84 ----> loss: 0.743669

epoch 219:

4/84 ----> loss: 0.743669

epoch 219:

14/84 ----> loss: 0.798076

epoch 219:

24/84 ----> loss: 0.744786

epoch 219:

34/84 ----> loss: 0.743669

epoch 219:

44/84 ----> loss: 0.743699

epoch 219:

54/84 ----> loss: 0.743669

epoch 219:

64/84 ----> loss: 0.743718

epoch 219:

74/84 ----> loss: 0.743671

epoch 220:

0/84 ----> loss: 0.743669

epoch 220:

10/84 ----> loss: 0.758352

epoch 220:

20/84 ----> loss: 0.743668

epoch 220:

30/84 ----> loss: 0.743703

epoch 220:

40/84 ----> loss: 0.743669

epoch 220:

50/84 ----> loss: 0.743670

epoch 220:

60/84 ----> loss: 0.743669

epoch 220:

70/84 ----> loss: 0.745287

epoch 220:

80/84 ----> loss: 0.743750

epoch 221:

6/84 ----> loss: 0.743730

epoch 221:

16/84 ----> loss: 0.743668

epoch 221:

26/84 ----> loss: 1.743456

epoch 221:

36/84 ----> loss: 0.743761

epoch 221:

46/84 ----> loss: 0.743672

epoch 221:

56/84 ----> loss: 0.743669

epoch 221:

66/84 ----> loss: 0.743671

epoch 221:

76/84 ----> loss: 0.743670

epoch 222:

2/84 ----> loss: 0.743668

epoch 222:

12/84 ----> loss: 0.743680

epoch 222:

22/84 ----> loss: 0.743747

epoch 222:

32/84 ----> loss: 0.743669

epoch 222:

42/84 ----> loss: 0.743669

epoch 222:

52/84 ----> loss: 0.743668

epoch 222:

62/84 ----> loss: 0.743668

epoch 222:

72/84 ----> loss: 0.743668

epoch 222:

82/84 ----> loss: 0.743670

epoch 223:

8/84 ----> loss: 0.743668

epoch 223:

18/84 ----> loss: 0.744677

epoch 223:

28/84 ----> loss: 0.743669

epoch 223:

38/84 ----> loss: 0.743676

epoch 223:

48/84 ----> loss: 0.743670

epoch 223:

58/84 ----> loss: 0.743795

epoch 223:

68/84 ----> loss: 0.743668

epoch 223:

78/84 ----> loss: 0.743669

epoch 224:

4/84 ----> loss: 0.743669

epoch 224:

14/84 ----> loss: 0.747433

epoch 224:

24/84 ----> loss: 0.743685

epoch 224:

34/84 ----> loss: 0.743671

epoch 224:

44/84 ----> loss: 0.745812

epoch 224:

54/84 ----> loss: 0.743668

epoch 224:

64/84 ----> loss: 0.743670

epoch 224:

74/84 ----> loss: 0.743680

epoch 225:

0/84 ----> loss: 0.743674

epoch 225:

10/84 ----> loss: 0.743815

epoch 225:

20/84 ----> loss: 0.743668

epoch 225:

30/84 ----> loss: 0.743681

epoch 225:

40/84 ----> loss: 0.743669

epoch 225:

50/84 ----> loss: 0.743669

epoch 225:

60/84 ----> loss: 0.743669

epoch 225:

70/84 ----> loss: 0.745178

epoch 225:

80/84 ----> loss: 0.743695

epoch 226:

6/84 ----> loss: 0.743822

epoch 226:

16/84 ----> loss: 0.743670

epoch 226:

26/84 ----> loss: 0.746038

epoch 226:

36/84 ----> loss: 0.743743

epoch 226:

46/84 ----> loss: 0.743722

epoch 226:

56/84 ----> loss: 0.743669

epoch 226:

66/84 ----> loss: 0.743668

epoch 226:

76/84 ----> loss: 0.743670

epoch 227:

2/84 ----> loss: 0.743855

epoch 227:

12/84 ----> loss: 0.744257

epoch 227:

22/84 ----> loss: 0.743706

epoch 227:

32/84 ----> loss: 0.743673

epoch 227:

42/84 ----> loss: 0.743669

epoch 227:

52/84 ----> loss: 0.743668

epoch 227:

62/84 ----> loss: 0.743668

epoch 227:

72/84 ----> loss: 0.743668

epoch 227:

82/84 ----> loss: 0.743669

epoch 228:

8/84 ----> loss: 0.743668

epoch 228:

18/84 ----> loss: 0.744321

epoch 228:

28/84 ----> loss: 0.743669

epoch 228:

38/84 ----> loss: 0.743681

epoch 228:

48/84 ----> loss: 0.743669

epoch 228:

58/84 ----> loss: 0.743812

epoch 228:

68/84 ----> loss: 0.743668

epoch 228:

78/84 ----> loss: 0.743669

epoch 229:

4/84 ----> loss: 0.743669

epoch 229:

14/84 ----> loss: 0.745798

epoch 229:

24/84 ----> loss: 0.743681

epoch 229:

34/84 ----> loss: 0.743670

epoch 229:

44/84 ----> loss: 0.745192

epoch 229:

54/84 ----> loss: 0.743668

epoch 229:

64/84 ----> loss: 0.743670

epoch 229:

74/84 ----> loss: 0.743677

epoch 230:

0/84 ----> loss: 0.743672

epoch 230:

10/84 ----> loss: 0.743765

epoch 230:

20/84 ----> loss: 0.743668

epoch 230:

30/84 ----> loss: 0.743681

epoch 230:

40/84 ----> loss: 0.743669

epoch 230:

50/84 ----> loss: 0.743669

epoch 230:

60/84 ----> loss: 0.743668

epoch 230:

70/84 ----> loss: 0.744785

epoch 230:

80/84 ----> loss: 0.743687

epoch 231:

6/84 ----> loss: 0.743800

epoch 231:

16/84 ----> loss: 0.743670

epoch 231:

26/84 ----> loss: 0.745207

epoch 231:

36/84 ----> loss: 0.743749

epoch 231:

46/84 ----> loss: 0.743708

epoch 231:

56/84 ----> loss: 0.743669

epoch 231:

66/84 ----> loss: 0.743668

epoch 231:

76/84 ----> loss: 0.743670

epoch 232:

2/84 ----> loss: 0.743819

epoch 232:

12/84 ----> loss: 0.744346

epoch 232:

22/84 ----> loss: 0.743698

epoch 232:

32/84 ----> loss: 0.743672

epoch 232:

42/84 ----> loss: 0.743669

epoch 232:

52/84 ----> loss: 0.743668

epoch 232:

62/84 ----> loss: 0.743668

epoch 232:

72/84 ----> loss: 0.743668

epoch 232:

82/84 ----> loss: 0.743669

epoch 233:

8/84 ----> loss: 0.743668

epoch 233:

18/84 ----> loss: 0.744214

epoch 233:

28/84 ----> loss: 0.743669

epoch 233:

38/84 ----> loss: 0.743681

epoch 233:

48/84 ----> loss: 0.743669

epoch 233:

58/84 ----> loss: 0.743796

epoch 233:

68/84 ----> loss: 0.743668

epoch 233:

78/84 ----> loss: 0.743669

epoch 234:

4/84 ----> loss: 0.743669

epoch 234:

14/84 ----> loss: 0.745525

epoch 234:

24/84 ----> loss: 0.743680

epoch 234:

34/84 ----> loss: 0.743669

epoch 234:

44/84 ----> loss: 0.744841

epoch 234:

54/84 ----> loss: 0.743668

epoch 234:

64/84 ----> loss: 0.743670

epoch 234:

74/84 ----> loss: 0.743675

epoch 235:

0/84 ----> loss: 0.743671

epoch 235:

10/84 ----> loss: 0.743739

epoch 235:

20/84 ----> loss: 0.743668

epoch 235:

30/84 ----> loss: 0.743682

epoch 235:

40/84 ----> loss: 0.743668

epoch 235:

50/84 ----> loss: 0.743669

epoch 235:

60/84 ----> loss: 0.743668

epoch 235:

70/84 ----> loss: 0.744520

epoch 235:

80/84 ----> loss: 0.743684

epoch 236:

6/84 ----> loss: 0.743786

epoch 236:

16/84 ----> loss: 0.743670

epoch 236:

26/84 ----> loss: 0.744789

epoch 236:

36/84 ----> loss: 0.743751

epoch 236:

46/84 ----> loss: 0.743700

epoch 236:

56/84 ----> loss: 0.743669

epoch 236:

66/84 ----> loss: 0.743668

epoch 236:

76/84 ----> loss: 0.743670

epoch 237:

2/84 ----> loss: 0.743796

epoch 237:

12/84 ----> loss: 0.744373

epoch 237:

22/84 ----> loss: 0.743693

epoch 237:

32/84 ----> loss: 0.743671

epoch 237:

42/84 ----> loss: 0.743669

epoch 237:

52/84 ----> loss: 0.743668

epoch 237:

62/84 ----> loss: 0.743668

epoch 237:

72/84 ----> loss: 0.743668

epoch 237:

82/84 ----> loss: 0.743669

epoch 238:

8/84 ----> loss: 0.743668

epoch 238:

18/84 ----> loss: 0.744141

epoch 238:

28/84 ----> loss: 0.743669

epoch 238:

38/84 ----> loss: 0.743679

epoch 238:

48/84 ----> loss: 0.743669

epoch 238:

58/84 ----> loss: 0.743782

epoch 238:

68/84 ----> loss: 0.743668

epoch 238:

78/84 ----> loss: 0.743669

epoch 239:

4/84 ----> loss: 0.743669

epoch 239:

14/84 ----> loss: 0.745340

epoch 239:

24/84 ----> loss: 0.743680

epoch 239:

34/84 ----> loss: 0.743669

epoch 239:

44/84 ----> loss: 0.744622

epoch 239:

54/84 ----> loss: 0.743668

epoch 239:

64/84 ----> loss: 0.743670

epoch 239:

74/84 ----> loss: 0.743674

epoch 240:

0/84 ----> loss: 0.743671

epoch 240:

10/84 ----> loss: 0.743725

epoch 240:

20/84 ----> loss: 0.743668

epoch 240:

30/84 ----> loss: 0.743682

epoch 240:

40/84 ----> loss: 0.743668

epoch 240:

50/84 ----> loss: 0.743669

epoch 240:

60/84 ----> loss: 0.743668

epoch 240:

70/84 ----> loss: 0.744347

epoch 240:

80/84 ----> loss: 0.743681

epoch 241:

6/84 ----> loss: 0.743776

epoch 241:

16/84 ----> loss: 0.743670

epoch 241:

26/84 ----> loss: 0.744544

epoch 241:

36/84 ----> loss: 0.743750

epoch 241:

46/84 ----> loss: 0.743694

epoch 241:

56/84 ----> loss: 0.743669

epoch 241:

66/84 ----> loss: 0.743668

epoch 241:

76/84 ----> loss: 0.743669

epoch 242:

2/84 ----> loss: 0.743779

epoch 242:

12/84 ----> loss: 0.744375

epoch 242:

22/84 ----> loss: 0.743690

epoch 242:

32/84 ----> loss: 0.743670

epoch 242:

42/84 ----> loss: 0.743669

epoch 242:

52/84 ----> loss: 0.743668

epoch 242:

62/84 ----> loss: 0.743668

epoch 242:

72/84 ----> loss: 0.743668

epoch 242:

82/84 ----> loss: 0.743669

epoch 243:

8/84 ----> loss: 0.743668

epoch 243:

18/84 ----> loss: 0.744086

epoch 243:

28/84 ----> loss: 0.743669

epoch 243:

38/84 ----> loss: 0.743678

epoch 243:

48/84 ----> loss: 0.743669

epoch 243:

58/84 ----> loss: 0.743771

epoch 243:

68/84 ----> loss: 0.743668

epoch 243:

78/84 ----> loss: 0.743669

epoch 244:

4/84 ----> loss: 0.743669

epoch 244:

14/84 ----> loss: 0.745189

epoch 244:

24/84 ----> loss: 0.743679

epoch 244:

34/84 ----> loss: 0.743669

epoch 244:

44/84 ----> loss: 0.744473

epoch 244:

54/84 ----> loss: 0.743668

epoch 244:

64/84 ----> loss: 0.743670

epoch 244:

74/84 ----> loss: 0.743673

epoch 245:

0/84 ----> loss: 0.743670

epoch 245:

10/84 ----> loss: 0.743715

epoch 245:

20/84 ----> loss: 0.743668

epoch 245:

30/84 ----> loss: 0.743682

epoch 245:

40/84 ----> loss: 0.743668

epoch 245:

50/84 ----> loss: 0.743669

epoch 245:

60/84 ----> loss: 0.743668

epoch 245:

70/84 ----> loss: 0.744228

epoch 245:

80/84 ----> loss: 0.743679

epoch 246:

6/84 ----> loss: 0.743767

epoch 246:

16/84 ----> loss: 0.743670

epoch 246:

26/84 ----> loss: 0.744384

epoch 246:

36/84 ----> loss: 0.743749

epoch 246:

46/84 ----> loss: 0.743691

epoch 246:

56/84 ----> loss: 0.743669

epoch 246:

66/84 ----> loss: 0.743668

epoch 246:

76/84 ----> loss: 0.743669

epoch 247:

2/84 ----> loss: 0.743766

epoch 247:

12/84 ----> loss: 0.744362

epoch 247:

22/84 ----> loss: 0.743687

epoch 247:

32/84 ----> loss: 0.743670

epoch 247:

42/84 ----> loss: 0.743669

epoch 247:

52/84 ----> loss: 0.743668

epoch 247:

62/84 ----> loss: 0.743668

epoch 247:

72/84 ----> loss: 0.743668

epoch 247:

82/84 ----> loss: 0.743669

epoch 248:

8/84 ----> loss: 0.743668

epoch 248:

18/84 ----> loss: 0.744042

epoch 248:

28/84 ----> loss: 0.743669

epoch 248:

38/84 ----> loss: 0.743677

epoch 248:

48/84 ----> loss: 0.743669

epoch 248:

58/84 ----> loss: 0.743763

epoch 248:

68/84 ----> loss: 0.743668

epoch 248:

78/84 ----> loss: 0.743669

epoch 249:

4/84 ----> loss: 0.743669

epoch 249:

14/84 ----> loss: 0.745063

epoch 249:

24/84 ----> loss: 0.743679

epoch 249:

34/84 ----> loss: 0.743669

epoch 249:

44/84 ----> loss: 0.744364

epoch 249:

54/84 ----> loss: 0.743668

epoch 249:

64/84 ----> loss: 0.743670

epoch 249:

74/84 ----> loss: 0.743672

epoch 250:

0/84 ----> loss: 0.743670

epoch 250:

10/84 ----> loss: 0.743709

epoch 250:

20/84 ----> loss: 0.743668

epoch 250:

30/84 ----> loss: 0.743682

epoch 250:

40/84 ----> loss: 0.743668

epoch 250:

50/84 ----> loss: 0.743669

epoch 250:

60/84 ----> loss: 0.743668

epoch 250:

70/84 ----> loss: 0.744141

epoch 250:

80/84 ----> loss: 0.743678

epoch 251:

6/84 ----> loss: 0.743759

epoch 251:

16/84 ----> loss: 0.743670

epoch 251:

26/84 ----> loss: 0.744272

epoch 251:

36/84 ----> loss: 0.743748

epoch 251:

46/84 ----> loss: 0.743688

epoch 251:

56/84 ----> loss: 0.743669

epoch 251:

66/84 ----> loss: 0.743668

epoch 251:

76/84 ----> loss: 0.743669

epoch 252:

2/84 ----> loss: 0.743756

epoch 252:

12/84 ----> loss: 0.744342

epoch 252:

22/84 ----> loss: 0.743685

epoch 252:

32/84 ----> loss: 0.743670

epoch 252:

42/84 ----> loss: 0.743669

epoch 252:

52/84 ----> loss: 0.743668

epoch 252:

62/84 ----> loss: 0.743668

epoch 252:

72/84 ----> loss: 0.743668

epoch 252:

82/84 ----> loss: 0.743669

epoch 253:

8/84 ----> loss: 0.743668

epoch 253:

18/84 ----> loss: 0.744006

epoch 253:

28/84 ----> loss: 0.743669

epoch 253:

38/84 ----> loss: 0.743677

epoch 253:

48/84 ----> loss: 0.743669

epoch 253:

58/84 ----> loss: 0.743755

epoch 253:

68/84 ----> loss: 0.743668

epoch 253:

78/84 ----> loss: 0.743669

epoch 254:

4/84 ----> loss: 0.743669

epoch 254:

14/84 ----> loss: 0.744956

epoch 254:

24/84 ----> loss: 0.743678

epoch 254:

34/84 ----> loss: 0.743669

epoch 254:

44/84 ----> loss: 0.744281

epoch 254:

54/84 ----> loss: 0.743668

epoch 254:

64/84 ----> loss: 0.743670

epoch 254:

74/84 ----> loss: 0.743672

epoch 255:

0/84 ----> loss: 0.743670

epoch 255:

10/84 ----> loss: 0.743704

epoch 255:

20/84 ----> loss: 0.743668

epoch 255:

30/84 ----> loss: 0.743681

epoch 255:

40/84 ----> loss: 0.743668

epoch 255:

50/84 ----> loss: 0.743669

epoch 255:

60/84 ----> loss: 0.743668

epoch 255:

70/84 ----> loss: 0.744075

epoch 255:

80/84 ----> loss: 0.743677

epoch 256:

6/84 ----> loss: 0.743753

epoch 256:

16/84 ----> loss: 0.743670

epoch 256:

26/84 ----> loss: 0.744190

epoch 256:

36/84 ----> loss: 0.743746

epoch 256:

46/84 ----> loss: 0.743685

epoch 256:

56/84 ----> loss: 0.743669

epoch 256:

66/84 ----> loss: 0.743668

epoch 256:

76/84 ----> loss: 0.743669

epoch 257:

2/84 ----> loss: 0.743748

epoch 257:

12/84 ----> loss: 0.744317

epoch 257:

22/84 ----> loss: 0.743684

epoch 257:

32/84 ----> loss: 0.743670

epoch 257:

42/84 ----> loss: 0.743669

epoch 257:

52/84 ----> loss: 0.743668

epoch 257:

62/84 ----> loss: 0.743668

epoch 257:

72/84 ----> loss: 0.743668

epoch 257:

82/84 ----> loss: 0.743669

epoch 258:

8/84 ----> loss: 0.743668

epoch 258:

18/84 ----> loss: 0.743976

epoch 258:

28/84 ----> loss: 0.743668

epoch 258:

38/84 ----> loss: 0.743676

epoch 258:

48/84 ----> loss: 0.743669

epoch 258:

58/84 ----> loss: 0.743749

epoch 258:

68/84 ----> loss: 0.743668

epoch 258:

78/84 ----> loss: 0.743669

epoch 259:

4/84 ----> loss: 0.743669

epoch 259:

14/84 ----> loss: 0.744863

epoch 259:

24/84 ----> loss: 0.743678

epoch 259:

34/84 ----> loss: 0.743669

epoch 259:

44/84 ----> loss: 0.744217

epoch 259:

54/84 ----> loss: 0.743668

epoch 259:

64/84 ----> loss: 0.743670

epoch 259:

74/84 ----> loss: 0.743671

epoch 260:

0/84 ----> loss: 0.743670

epoch 260:

10/84 ----> loss: 0.743700

epoch 260:

20/84 ----> loss: 0.743668

epoch 260:

30/84 ----> loss: 0.743681

epoch 260:

40/84 ----> loss: 0.743668

epoch 260:

50/84 ----> loss: 0.743668

epoch 260:

60/84 ----> loss: 0.743668

epoch 260:

70/84 ----> loss: 0.744024

epoch 260:

80/84 ----> loss: 0.743676

epoch 261:

6/84 ----> loss: 0.743747

epoch 261:

16/84 ----> loss: 0.743670

epoch 261:

26/84 ----> loss: 0.744126

epoch 261:

36/84 ----> loss: 0.743744

epoch 261:

46/84 ----> loss: 0.743683

epoch 261:

56/84 ----> loss: 0.743669

epoch 261:

66/84 ----> loss: 0.743668

epoch 261:

76/84 ----> loss: 0.743669

epoch 262:

2/84 ----> loss: 0.743741

epoch 262:

12/84 ----> loss: 0.744290

epoch 262:

22/84 ----> loss: 0.743682

epoch 262:

32/84 ----> loss: 0.743669

epoch 262:

42/84 ----> loss: 0.743669

epoch 262:

52/84 ----> loss: 0.743668

epoch 262:

62/84 ----> loss: 0.743668

epoch 262:

72/84 ----> loss: 0.743668

epoch 262:

82/84 ----> loss: 0.743669

epoch 263:

8/84 ----> loss: 0.743668

epoch 263:

18/84 ----> loss: 0.743951

epoch 263:

28/84 ----> loss: 0.743668

epoch 263:

38/84 ----> loss: 0.743676

epoch 263:

48/84 ----> loss: 0.743669

epoch 263:

58/84 ----> loss: 0.743744

epoch 263:

68/84 ----> loss: 0.743668

epoch 263:

78/84 ----> loss: 0.743669

epoch 264:

4/84 ----> loss: 0.743669

epoch 264:

14/84 ----> loss: 0.744782

epoch 264:

24/84 ----> loss: 0.743678

epoch 264:

34/84 ----> loss: 0.743669

epoch 264:

44/84 ----> loss: 0.744164

epoch 264:

54/84 ----> loss: 0.743668

epoch 264:

64/84 ----> loss: 0.743670

epoch 264:

74/84 ----> loss: 0.743671

epoch 265:

0/84 ----> loss: 0.743669

epoch 265:

10/84 ----> loss: 0.743697

epoch 265:

20/84 ----> loss: 0.743668

epoch 265:

30/84 ----> loss: 0.743681

epoch 265:

40/84 ----> loss: 0.743668

epoch 265:

50/84 ----> loss: 0.743668

epoch 265:

60/84 ----> loss: 0.743668

epoch 265:

70/84 ----> loss: 0.743983

epoch 265:

80/84 ----> loss: 0.743675

epoch 266:

6/84 ----> loss: 0.743742

epoch 266:

16/84 ----> loss: 0.743670

epoch 266:

26/84 ----> loss: 0.744076

epoch 266:

36/84 ----> loss: 0.743741

epoch 266:

46/84 ----> loss: 0.743682

epoch 266:

56/84 ----> loss: 0.743669

epoch 266:

66/84 ----> loss: 0.743668

epoch 266:

76/84 ----> loss: 0.743669

epoch 267:

2/84 ----> loss: 0.743735

epoch 267:

12/84 ----> loss: 0.744262

epoch 267:

22/84 ----> loss: 0.743681

epoch 267:

32/84 ----> loss: 0.743669

epoch 267:

42/84 ----> loss: 0.743669

epoch 267:

52/84 ----> loss: 0.743668

epoch 267:

62/84 ----> loss: 0.743668

epoch 267:

72/84 ----> loss: 0.743668

epoch 267:

82/84 ----> loss: 0.743669

epoch 268:

8/84 ----> loss: 0.743668

epoch 268:

18/84 ----> loss: 0.743930

epoch 268:

28/84 ----> loss: 0.743668

epoch 268:

38/84 ----> loss: 0.743675

epoch 268:

48/84 ----> loss: 0.743669

epoch 268:

58/84 ----> loss: 0.743739

epoch 268:

68/84 ----> loss: 0.743668

epoch 268:

78/84 ----> loss: 0.743669

epoch 269:

4/84 ----> loss: 0.743669

epoch 269:

14/84 ----> loss: 0.744710

epoch 269:

24/84 ----> loss: 0.743677

epoch 269:

34/84 ----> loss: 0.743669

epoch 269:

44/84 ----> loss: 0.744121

epoch 269:

54/84 ----> loss: 0.743668

epoch 269:

64/84 ----> loss: 0.743670

epoch 269:

74/84 ----> loss: 0.743671

epoch 270:

0/84 ----> loss: 0.743669

epoch 270:

10/84 ----> loss: 0.743694

epoch 270:

20/84 ----> loss: 0.743668

epoch 270:

30/84 ----> loss: 0.743681

epoch 270:

40/84 ----> loss: 0.743668

epoch 270:

50/84 ----> loss: 0.743668

epoch 270:

60/84 ----> loss: 0.743668

epoch 270:

70/84 ----> loss: 0.743950

epoch 270:

80/84 ----> loss: 0.743674

epoch 271:

6/84 ----> loss: 0.743738

epoch 271:

16/84 ----> loss: 0.743670

epoch 271:

26/84 ----> loss: 0.744035

epoch 271:

36/84 ----> loss: 0.743739

epoch 271:

46/84 ----> loss: 0.743681

epoch 271:

56/84 ----> loss: 0.743669

epoch 271:

66/84 ----> loss: 0.743668

epoch 271:

76/84 ----> loss: 0.743669

epoch 272:

2/84 ----> loss: 0.743730

epoch 272:

12/84 ----> loss: 0.744236

epoch 272:

22/84 ----> loss: 0.743680

epoch 272:

32/84 ----> loss: 0.743669

epoch 272:

42/84 ----> loss: 0.743669

epoch 272:

52/84 ----> loss: 0.743668

epoch 272:

62/84 ----> loss: 0.743668

epoch 272:

72/84 ----> loss: 0.743668

epoch 272:

82/84 ----> loss: 0.743669

epoch 273:

8/84 ----> loss: 0.743668

epoch 273:

18/84 ----> loss: 0.743912

epoch 273:

28/84 ----> loss: 0.743668

epoch 273:

38/84 ----> loss: 0.743675

epoch 273:

48/84 ----> loss: 0.743669

epoch 273:

58/84 ----> loss: 0.743735

epoch 273:

68/84 ----> loss: 0.743668

epoch 273:

78/84 ----> loss: 0.743669

epoch 274:

4/84 ----> loss: 0.743669

epoch 274:

14/84 ----> loss: 0.744647

epoch 274:

24/84 ----> loss: 0.743677

epoch 274:

34/84 ----> loss: 0.743669

epoch 274:

44/84 ----> loss: 0.744084

epoch 274:

54/84 ----> loss: 0.743668

epoch 274:

64/84 ----> loss: 0.743670

epoch 274:

74/84 ----> loss: 0.743671

epoch 275:

0/84 ----> loss: 0.743669

epoch 275:

10/84 ----> loss: 0.743692

epoch 275:

20/84 ----> loss: 0.743668

epoch 275:

30/84 ----> loss: 0.743681

epoch 275:

40/84 ----> loss: 0.743668

epoch 275:

50/84 ----> loss: 0.743668

epoch 275:

60/84 ----> loss: 0.743668

epoch 275:

70/84 ----> loss: 0.743922

epoch 275:

80/84 ----> loss: 0.743674

epoch 276:

6/84 ----> loss: 0.743734

epoch 276:

16/84 ----> loss: 0.743670

epoch 276:

26/84 ----> loss: 0.744001

epoch 276:

36/84 ----> loss: 0.743737

epoch 276:

46/84 ----> loss: 0.743680

epoch 276:

56/84 ----> loss: 0.743669

epoch 276:

66/84 ----> loss: 0.743668

epoch 276:

76/84 ----> loss: 0.743669

epoch 277:

2/84 ----> loss: 0.743726

epoch 277:

12/84 ----> loss: 0.744210

epoch 277:

22/84 ----> loss: 0.743680

epoch 277:

32/84 ----> loss: 0.743669

epoch 277:

42/84 ----> loss: 0.743669

epoch 277:

52/84 ----> loss: 0.743668

epoch 277:

62/84 ----> loss: 0.743668

epoch 277:

72/84 ----> loss: 0.743668

epoch 277:

82/84 ----> loss: 0.743669

epoch 278:

8/84 ----> loss: 0.743668

epoch 278:

18/84 ----> loss: 0.743896

epoch 278:

28/84 ----> loss: 0.743668

epoch 278:

38/84 ----> loss: 0.743674

epoch 278:

48/84 ----> loss: 0.743669

epoch 278:

58/84 ----> loss: 0.743732

epoch 278:

68/84 ----> loss: 0.743668

epoch 278:

78/84 ----> loss: 0.743669

epoch 279:

4/84 ----> loss: 0.743669

epoch 279:

14/84 ----> loss: 0.744590

epoch 279:

24/84 ----> loss: 0.743677

epoch 279:

34/84 ----> loss: 0.743669

epoch 279:

44/84 ----> loss: 0.744053

epoch 279:

54/84 ----> loss: 0.743668

epoch 279:

64/84 ----> loss: 0.743669

epoch 279:

74/84 ----> loss: 0.743670

epoch 280:

0/84 ----> loss: 0.743669

epoch 280:

10/84 ----> loss: 0.743690

epoch 280:

20/84 ----> loss: 0.743668

epoch 280:

30/84 ----> loss: 0.743681

epoch 280:

40/84 ----> loss: 0.743668

epoch 280:

50/84 ----> loss: 0.743668

epoch 280:

60/84 ----> loss: 0.743668

epoch 280:

70/84 ----> loss: 0.743899

epoch 280:

80/84 ----> loss: 0.743673

epoch 281:

6/84 ----> loss: 0.743730

epoch 281:

16/84 ----> loss: 0.743670

epoch 281:

26/84 ----> loss: 0.743973

epoch 281:

36/84 ----> loss: 0.743734

epoch 281:

46/84 ----> loss: 0.743679

epoch 281:

56/84 ----> loss: 0.743669

epoch 281:

66/84 ----> loss: 0.743668

epoch 281:

76/84 ----> loss: 0.743669

epoch 282:

2/84 ----> loss: 0.743722

epoch 282:

12/84 ----> loss: 0.744185

epoch 282:

22/84 ----> loss: 0.743679

epoch 282:

32/84 ----> loss: 0.743669

epoch 282:

42/84 ----> loss: 0.743669

epoch 282:

52/84 ----> loss: 0.743668

epoch 282:

62/84 ----> loss: 0.743668

epoch 282:

72/84 ----> loss: 0.743668

epoch 282:

82/84 ----> loss: 0.743669

epoch 283:

8/84 ----> loss: 0.743668

epoch 283:

18/84 ----> loss: 0.743882

epoch 283:

28/84 ----> loss: 0.743668

epoch 283:

38/84 ----> loss: 0.743674

epoch 283:

48/84 ----> loss: 0.743669

epoch 283:

58/84 ----> loss: 0.743729

epoch 283:

68/84 ----> loss: 0.743668

epoch 283:

78/84 ----> loss: 0.743669

epoch 284:

4/84 ----> loss: 0.743669

epoch 284:

14/84 ----> loss: 0.744540

epoch 284:

24/84 ----> loss: 0.743677

epoch 284:

34/84 ----> loss: 0.743669

epoch 284:

44/84 ----> loss: 0.744027

epoch 284:

54/84 ----> loss: 0.743668

epoch 284:

64/84 ----> loss: 0.743669

epoch 284:

74/84 ----> loss: 0.743670

epoch 285:

0/84 ----> loss: 0.743669

epoch 285:

10/84 ----> loss: 0.743688

epoch 285:

20/84 ----> loss: 0.743668

epoch 285:

30/84 ----> loss: 0.743681

epoch 285:

40/84 ----> loss: 0.743668

epoch 285:

50/84 ----> loss: 0.743668

epoch 285:

60/84 ----> loss: 0.743668

epoch 285:

70/84 ----> loss: 0.743879

epoch 285:

80/84 ----> loss: 0.743673

epoch 286:

6/84 ----> loss: 0.743727

epoch 286:

16/84 ----> loss: 0.743669

epoch 286:

26/84 ----> loss: 0.743949

epoch 286:

36/84 ----> loss: 0.743732

epoch 286:

46/84 ----> loss: 0.743678

epoch 286:

56/84 ----> loss: 0.743669

epoch 286:

66/84 ----> loss: 0.743668

epoch 286:

76/84 ----> loss: 0.743669

epoch 287:

2/84 ----> loss: 0.743719

epoch 287:

12/84 ----> loss: 0.744162

epoch 287:

22/84 ----> loss: 0.743678

epoch 287:

32/84 ----> loss: 0.743669

epoch 287:

42/84 ----> loss: 0.743669

epoch 287:

52/84 ----> loss: 0.743668

epoch 287:

62/84 ----> loss: 0.743668

epoch 287:

72/84 ----> loss: 0.743668

epoch 287:

82/84 ----> loss: 0.743669

epoch 288:

8/84 ----> loss: 0.743668

epoch 288:

18/84 ----> loss: 0.743869

epoch 288:

28/84 ----> loss: 0.743668

epoch 288:

38/84 ----> loss: 0.743674

epoch 288:

48/84 ----> loss: 0.743669

epoch 288:

58/84 ----> loss: 0.743726

epoch 288:

68/84 ----> loss: 0.743668

epoch 288:

78/84 ----> loss: 0.743669

epoch 289:

4/84 ----> loss: 0.743669

epoch 289:

14/84 ----> loss: 0.744494

epoch 289:

24/84 ----> loss: 0.743676

epoch 289:

34/84 ----> loss: 0.743669

epoch 289:

44/84 ----> loss: 0.744003

epoch 289:

54/84 ----> loss: 0.743668

epoch 289:

64/84 ----> loss: 0.743669

epoch 289:

74/84 ----> loss: 0.743670

epoch 290:

0/84 ----> loss: 0.743669

epoch 290:

10/84 ----> loss: 0.743687

epoch 290:

20/84 ----> loss: 0.743668

epoch 290:

30/84 ----> loss: 0.743680

epoch 290:

40/84 ----> loss: 0.743668

epoch 290:

50/84 ----> loss: 0.743668

epoch 290:

60/84 ----> loss: 0.743668

epoch 290:

70/84 ----> loss: 0.743862

epoch 290:

80/84 ----> loss: 0.743672

epoch 291:

6/84 ----> loss: 0.743724

epoch 291:

16/84 ----> loss: 0.743669

epoch 291:

26/84 ----> loss: 0.743929

epoch 291:

36/84 ----> loss: 0.743730

epoch 291:

46/84 ----> loss: 0.743677

epoch 291:

56/84 ----> loss: 0.743669

epoch 291:

66/84 ----> loss: 0.743668

epoch 291:

76/84 ----> loss: 0.743669

epoch 292:

2/84 ----> loss: 0.743716

epoch 292:

12/84 ----> loss: 0.744140

epoch 292:

22/84 ----> loss: 0.743678

epoch 292:

32/84 ----> loss: 0.743669

epoch 292:

42/84 ----> loss: 0.743669

epoch 292:

52/84 ----> loss: 0.743668

epoch 292:

62/84 ----> loss: 0.743668

epoch 292:

72/84 ----> loss: 0.743668

epoch 292:

82/84 ----> loss: 0.743669

epoch 293:

8/84 ----> loss: 0.743668

epoch 293:

18/84 ----> loss: 0.743858

epoch 293:

28/84 ----> loss: 0.743668

epoch 293:

38/84 ----> loss: 0.743673

epoch 293:

48/84 ----> loss: 0.743669

epoch 293:

58/84 ----> loss: 0.743723

epoch 293:

68/84 ----> loss: 0.743668

epoch 293:

78/84 ----> loss: 0.743669

epoch 294:

4/84 ----> loss: 0.743669

epoch 294:

14/84 ----> loss: 0.744453

epoch 294:

24/84 ----> loss: 0.743676

epoch 294:

34/84 ----> loss: 0.743669

epoch 294:

44/84 ----> loss: 0.743983

epoch 294:

54/84 ----> loss: 0.743668

epoch 294:

64/84 ----> loss: 0.743669

epoch 294:

74/84 ----> loss: 0.743670

epoch 295:

0/84 ----> loss: 0.743669

epoch 295:

10/84 ----> loss: 0.743686

epoch 295:

20/84 ----> loss: 0.743668

epoch 295:

30/84 ----> loss: 0.743680

epoch 295:

40/84 ----> loss: 0.743668

epoch 295:

50/84 ----> loss: 0.743668

epoch 295:

60/84 ----> loss: 0.743668

epoch 295:

70/84 ----> loss: 0.743847

epoch 295:

80/84 ----> loss: 0.743672

epoch 296:

6/84 ----> loss: 0.743722

epoch 296:

16/84 ----> loss: 0.743669

epoch 296:

26/84 ----> loss: 0.743911

epoch 296:

36/84 ----> loss: 0.743728

epoch 296:

46/84 ----> loss: 0.743677

epoch 296:

56/84 ----> loss: 0.743669

epoch 296:

66/84 ----> loss: 0.743668

epoch 296:

76/84 ----> loss: 0.743669

epoch 297:

2/84 ----> loss: 0.743713

epoch 297:

12/84 ----> loss: 0.744120

epoch 297:

22/84 ----> loss: 0.743677

epoch 297:

32/84 ----> loss: 0.743669

epoch 297:

42/84 ----> loss: 0.743669

epoch 297:

52/84 ----> loss: 0.743668

epoch 297:

62/84 ----> loss: 0.743668

epoch 297:

72/84 ----> loss: 0.743668

epoch 297:

82/84 ----> loss: 0.743669

epoch 298:

8/84 ----> loss: 0.743668

epoch 298:

18/84 ----> loss: 0.743849

epoch 298:

28/84 ----> loss: 0.743668

epoch 298:

38/84 ----> loss: 0.743673

epoch 298:

48/84 ----> loss: 0.743669

epoch 298:

58/84 ----> loss: 0.743721

epoch 298:

68/84 ----> loss: 0.743668

epoch 298:

78/84 ----> loss: 0.743669

epoch 299:

4/84 ----> loss: 0.743669

epoch 299:

14/84 ----> loss: 0.744415

epoch 299:

24/84 ----> loss: 0.743676

epoch 299:

34/84 ----> loss: 0.743669

epoch 299:

44/84 ----> loss: 0.743965

epoch 299:

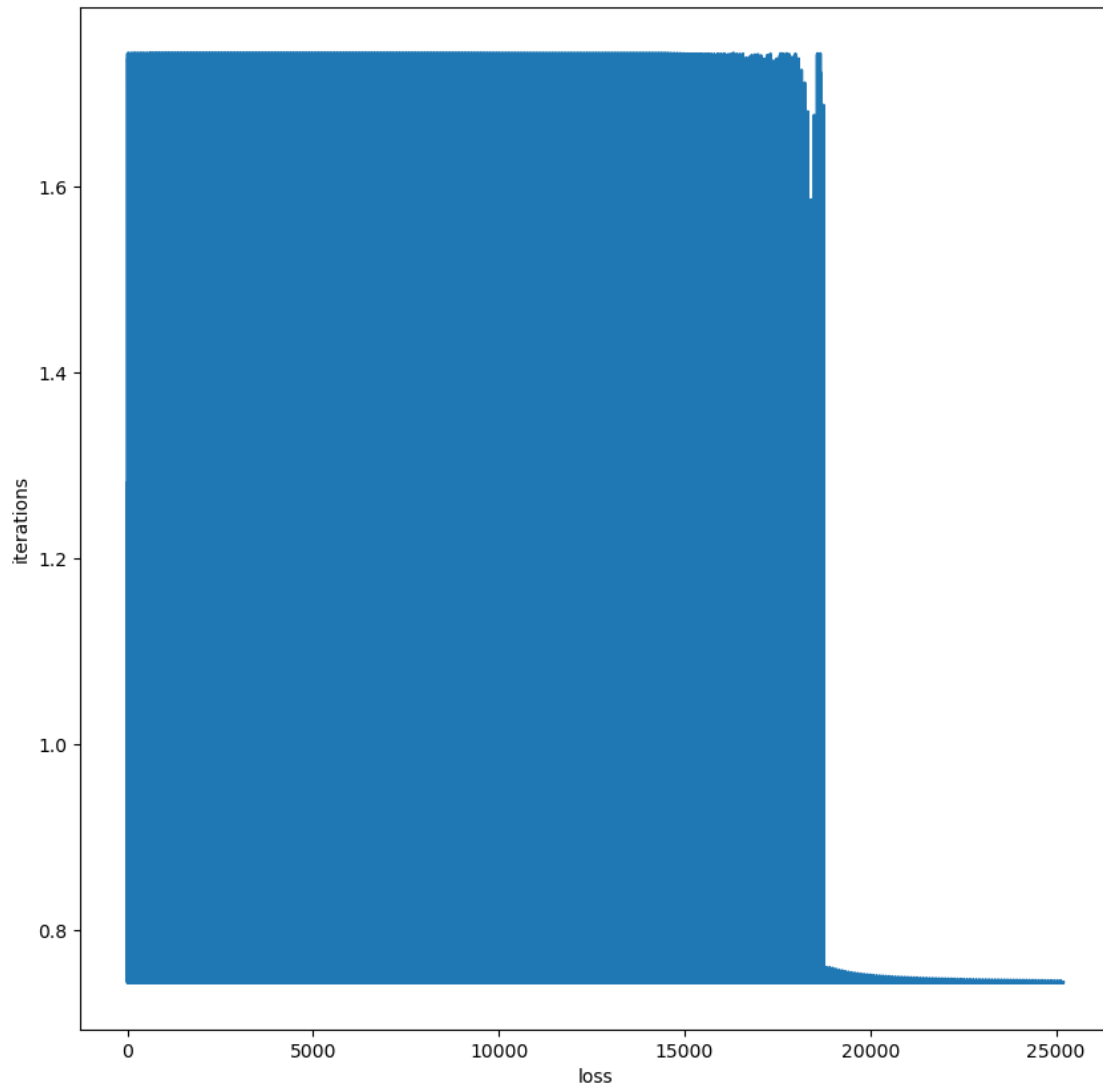
54/84 ----> loss: 0.743668

epoch 299:

64/84 ----> loss: 0.743669

epoch 299:

74/84 ----> loss: 0.743670



```
[497]: accuracy,preds = testing(X_test_noPCA.values,y_test_noPCA.to_numpy().
      ↪ ravel(),model,printFn=False)
      print(accuracy)
```

Accuracy: 0.8378378378378378
0.8378378378378378

```
[498]: res = []
      for l in [0,1,2,3]:
          prec,recall,_,_ = precision_recall_fscore_support(np.array(y_test)==1,
                                                            np.array(preds)==1,
                                                            pos_label=True,average=None)
          res.append([l,recall[0],recall[1]])
```

```

statistics_df = pd.DataFrame(res, columns = ['class', 'specificity', 'sensitivity'])
statistics_df['label'] = statistics_df['class'].apply(lambda x: 'CD' if x==0
else 'GN' if x==1 else 'HPDE' if x==2 else 'MiaPaCa')

confusion_mat = metrics.confusion_matrix(y_test.values.ravel(), np.
array(preds), labels=[0,1,2,3])

print('Specificity: \n', statistics_df[['label', 'specificity']])
print('Sensitivity: \n', statistics_df[['label', 'sensitivity']])

cm_display = metrics.ConfusionMatrixDisplay(confusion_matrix = confusion_mat,
display_labels = statistics_df['label'].to_list())
cm_display.plot()
plt.show()

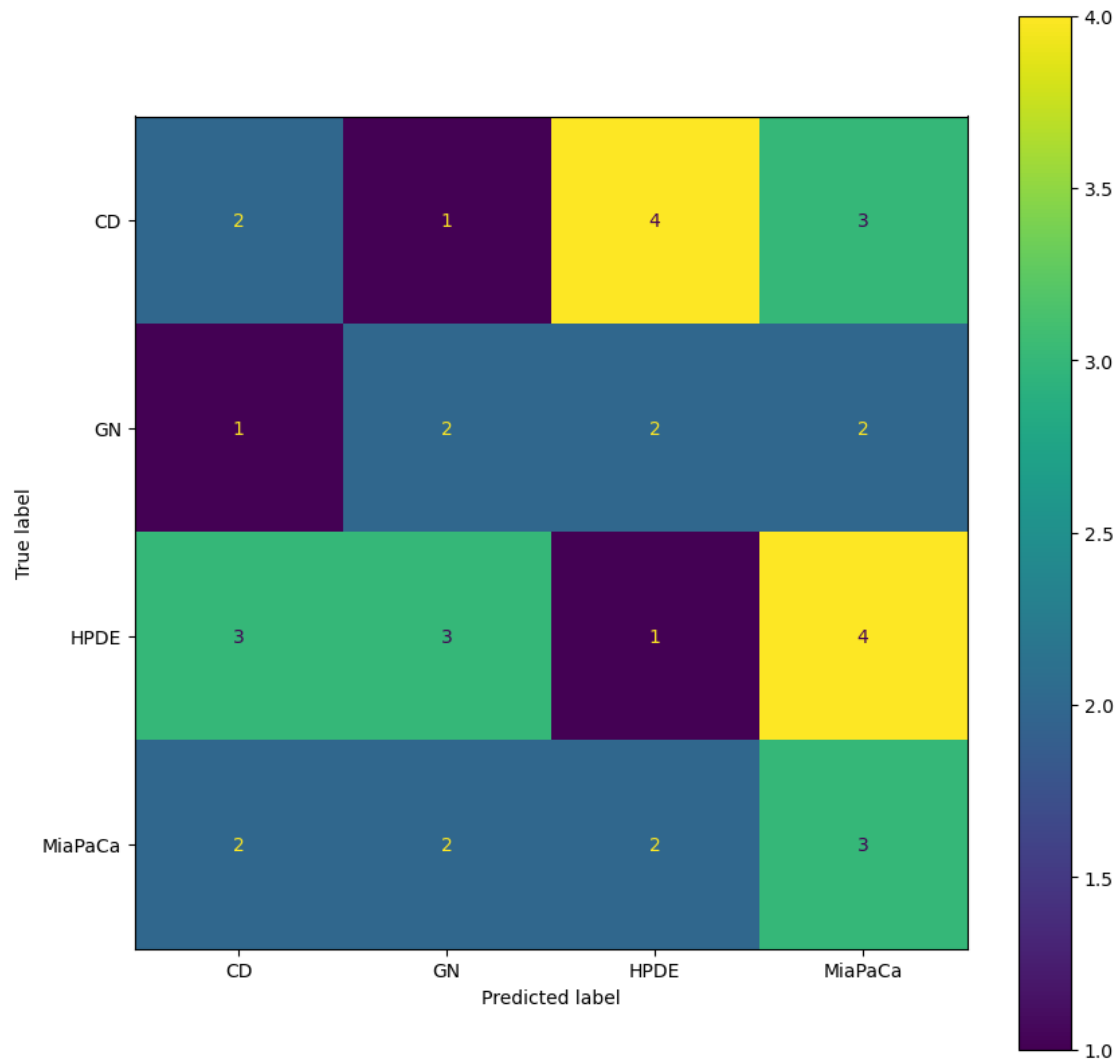
```

Specificity:

	label	specificity
0	CD	0.777778
1	GN	0.800000
2	HPDE	0.692308
3	MiaPaCa	0.678571

Sensitivity:

	label	sensitivity
0	CD	0.200000
1	GN	0.285714
2	HPDE	0.090909
3	MiaPaCa	0.333333



```
[499]: print('Overall specificity: ', statistics_df['specificity'].mean())
       print('Overall sensitivity: ', statistics_df['sensitivity'].mean())
```

```
Overall specificity: 0.7371642246642247
Overall sensitivity: 0.22748917748917746
```

```
[342]: X_noPCA = df_master.drop(columns=['Target']).reset_index().
       ↪ drop(columns=['index']).to_numpy()
```

```
[343]: split = 25

       #kfold = KFold(n_splits=X.shape[0], shuffle=True)
       kfold = KFold(n_splits=split, shuffle=True)
```



```

all_pred = np.array([])
y_match = np.array([])
accuracies = []
for fold, (train_ids, test_ids) in enumerate(kfold.split(X_noPCA)):

    learning_rate = 0.01
    epoch = 300
    batch = 11

    loss_fn = nn.CrossEntropyLoss()

    optimizer = torch.optim.SGD(model.parameters(), lr=learning_rate)

    loss_count, count = train_loop(X_noPCA[train_ids],
                                    y.to_numpy().ravel()[train_ids],
                                    model,
                                    epoch, batch,
                                    loss_fn,
                                    optimizer,
                                    printFn=False)

    accuracy, preds = testing(X_noPCA[test_ids], y.to_numpy().
    ↪ ravel()[test_ids], model, printFn=False)
    accuracies.append(accuracy)
    all_pred = np.append(all_pred, preds)
    y_match = np.append(y_match, y.to_numpy().ravel()[test_ids])

print('Overall Accuracy: ', np.array(accuracies).mean())
conf_mat = confusion_matrix(y_match, all_pred, labels=[0,1,2,3])

res = []
for l in [0,1,2,3]:
    prec, recall, _, _ = precision_recall_fscore_support(y_match==l,
                                                         all_pred==l,
                                                         labels=[0,1,2,3],
                                                         pos_label=True,
                                                         average=None)

    res.append([l, recall[0], recall[1]])

statistics_df = pd.DataFrame(res, columns =_
    ↪ ['class', 'specificity', 'sensitivity'])
statistics_df['label'] = statistics_df['class'].apply(lambda x: 'CD' if x==0_
    ↪ else 'GN' if x==1 else 'HPDE' if x==2 else 'MiaPaCa')

print('Specificity: \n', statistics_df[['label', 'specificity']])

```

```

print('Sensitivity: \n', statistics_df[['label', 'sensitivity']])
print('Overall Specificity: \n', statistics_df[['specificity']].mean())
print('Overall Sensitivity: \n', statistics_df[['sensitivity']].mean())

cm_display = metrics.ConfusionMatrixDisplay(confusion_matrix = conf_mat,
display_labels = statistics_df['label'].to_list())
cm_display.plot()
plt.show()

```

C:\Users\brian\Anaconda3\Lib\site-packages\torch\nn\modules\module.py:1518:
UserWarning: Implicit dimension choice for softmax has been deprecated. Change
the call to include dim=X as an argument.

```

return self._call_impl(*args, **kwargs)

```

```

Accuracy:  1.0
Accuracy:  1.0
Accuracy:  1.0
Accuracy:  1.0
Accuracy:  1.0
Accuracy:  1.0
Accuracy:  1.0
Accuracy:  1.0
Accuracy:  1.0
Accuracy:  1.0
Accuracy:  1.0
Accuracy:  1.0
Accuracy:  1.0
Accuracy:  1.0
Accuracy:  1.0
Accuracy:  1.0
Accuracy:  1.0
Accuracy:  1.0
Accuracy:  1.0
Accuracy:  1.0
Accuracy:  1.0
Accuracy:  1.0
Accuracy:  1.0
Accuracy:  1.0
Accuracy:  1.0
Accuracy:  1.0
Accuracy:  1.0
Accuracy:  1.0
Overall Accuracy:  1.0
Specificity:
      label  specificity
0         CD          1.0
1         GN          1.0
2        HPDE          1.0
3    MiaPaCa          1.0
Sensitivity:
      label  sensitivity

```

```

0      CD      1.0
1      GN      1.0
2      HPDE     1.0
3  MiaPaCa     1.0

```

Overall Specificity:

```
specificity    1.0
```

dtype: float64

Overall Sensitivity:

```
sensitivity    1.0
```

dtype: float64

C:\Users\brian\Anaconda3\Lib\site-

packages\sklearn\metrics_classification.py:1509: UndefinedMetricWarning:

Precision is ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.

```
_warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

C:\Users\brian\Anaconda3\Lib\site-

packages\sklearn\metrics_classification.py:1509: UndefinedMetricWarning: Recall

is ill-defined and being set to 0.0 in labels with no true samples. Use `zero_division` parameter to control this behavior.

```
_warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

C:\Users\brian\Anaconda3\Lib\site-

packages\sklearn\metrics_classification.py:1509: UndefinedMetricWarning:

F-score is ill-defined and being set to 0.0 in labels with no true nor predicted samples. Use `zero_division` parameter to control this behavior.

```
_warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

C:\Users\brian\Anaconda3\Lib\site-

packages\sklearn\metrics_classification.py:1509: UndefinedMetricWarning:

Precision is ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.

```
_warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

C:\Users\brian\Anaconda3\Lib\site-

packages\sklearn\metrics_classification.py:1509: UndefinedMetricWarning: Recall

is ill-defined and being set to 0.0 in labels with no true samples. Use `zero_division` parameter to control this behavior.

```
_warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

C:\Users\brian\Anaconda3\Lib\site-

packages\sklearn\metrics_classification.py:1509: UndefinedMetricWarning:

F-score is ill-defined and being set to 0.0 in labels with no true nor predicted samples. Use `zero_division` parameter to control this behavior.

```
_warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

C:\Users\brian\Anaconda3\Lib\site-

packages\sklearn\metrics_classification.py:1509: UndefinedMetricWarning:

Precision is ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.

```
_warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

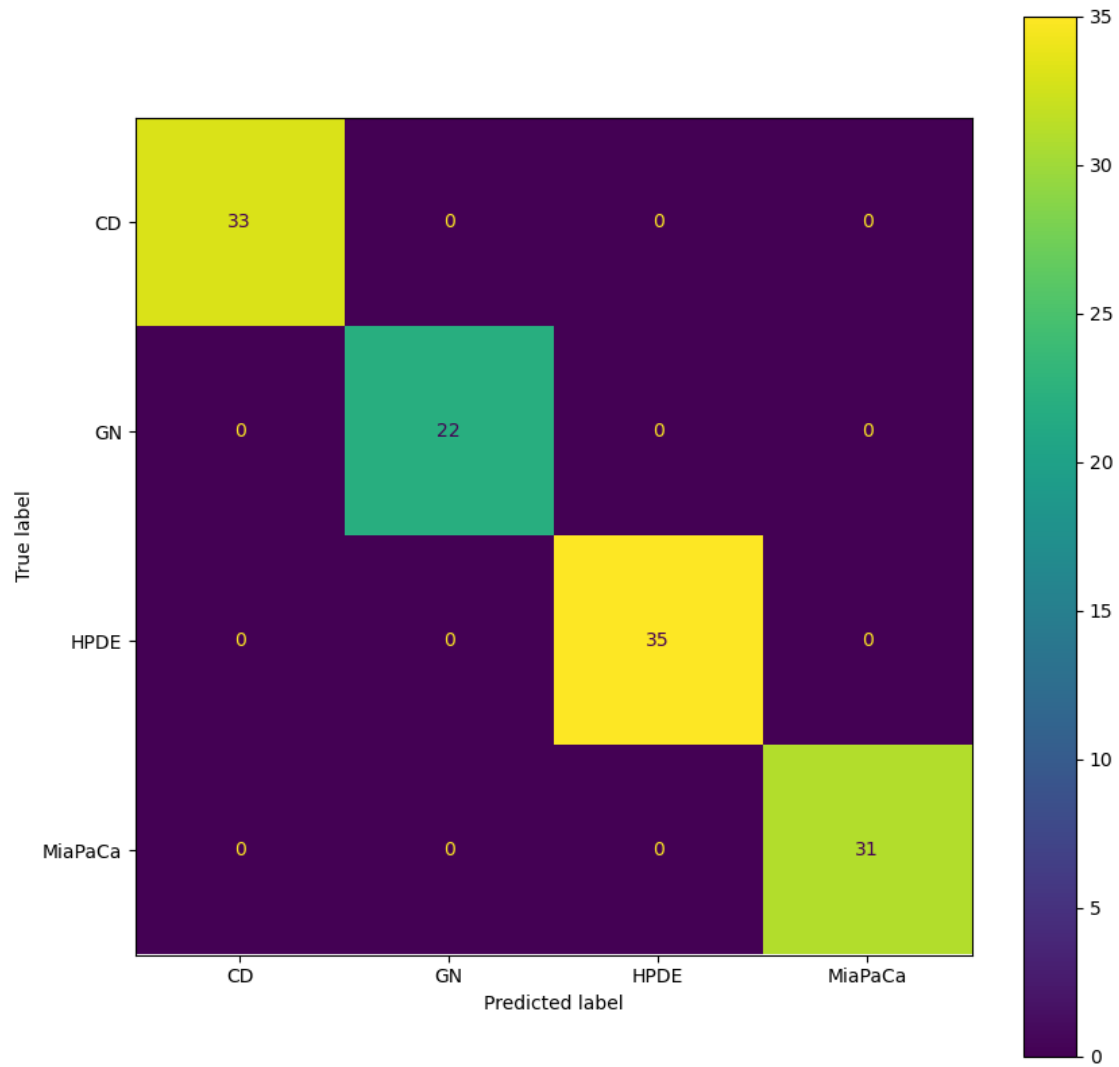
C:\Users\brian\Anaconda3\Lib\site-

packages\sklearn\metrics_classification.py:1509: UndefinedMetricWarning: Recall

```

is ill-defined and being set to 0.0 in labels with no true samples. Use
`zero_division` parameter to control this behavior.
    _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
C:\Users\brian\Anaconda3\Lib\site-
packages\sklearn\metrics\_classification.py:1509: UndefinedMetricWarning:
F-score is ill-defined and being set to 0.0 in labels with no true nor predicted
samples. Use `zero_division` parameter to control this behavior.
    _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
C:\Users\brian\Anaconda3\Lib\site-
packages\sklearn\metrics\_classification.py:1509: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
    _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
C:\Users\brian\Anaconda3\Lib\site-
packages\sklearn\metrics\_classification.py:1509: UndefinedMetricWarning: Recall
is ill-defined and being set to 0.0 in labels with no true samples. Use
`zero_division` parameter to control this behavior.
    _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
C:\Users\brian\Anaconda3\Lib\site-
packages\sklearn\metrics\_classification.py:1509: UndefinedMetricWarning:
F-score is ill-defined and being set to 0.0 in labels with no true nor predicted
samples. Use `zero_division` parameter to control this behavior.
    _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))

```



Summary: The LDA is a good method, which results in above 90% for all values. However, classical neural network model seems to do way better!