MLP

450-5

sets of experiments2 SGD(lr=0.0001, decay=1e-6, momentum=0.9, nesterov=True)

epochs=100, batch\_size=20 train\_time:397.63885736465454 test\_time:0.3899562358856201 Test loss:0.41825563192367554 Test accuracy:**0.8880000114440918**

Precise: 0.8596491228070176,0.9347826086956522,0.88,0.9148936170212766,0.86,

Recall: 0.8305084745762712,0.86,0.8979591836734694,0.8958333333333334,0.9772727272727273, F1 Score: 0.8448275862068966,0.8958333333333334,0.8888888888888888,0.9052631578947369,0.9148936170212765,

equirectangular\_projection\_map96.jpg,1,0

equirectangular\_projection\_map18.jpg,1,0

mercator\_projection\_map84.jpg,2,3

225px-Craster\_parabolic\_projection\_SW.jpg,0,4

hqdefault.jpg,0,4

map1470.png,2,3

equirectangular\_projection\_map43.jpg,1,2

51fYtlSy9tL.\_SR600,315\_PIWhiteStrip,BottomLeft,0,35\_PIStarRatingFOUR,BottomLeft,360,-6\_SR600,315\_ZA(14 Reviews),445,291,400,400,a - Copy.jpg,3,4

Augmented\_cylindrical-equal-area-300x177.png,3,2

mercator\_projection\_map15.jpg,2,1

Poster-World-Map\_Original-Map-1.jpg,0,2

robinson\_projection\_map96.jpg,4,0

equirectangular\_projection\_map52.jpg,1,0

images (2).jpg,3,4

225px-Gall�Peters\_projection\_SW.jpg,0,3

equirectangular\_projection\_map81.jpg,1,0

108271\_1.jpg,0,1

mercator\_projection\_map6.jpg,2,0

world-map-countries-geography-vector-9920386.jpg,0,1

620px-Oceans\_base\_map.svg - Copy.png,3,2

225px-Equal\_Earth\_projection\_SW.jpg,0,4

mercator\_projection\_map88.jpg,2,3

miller\_projection\_map74.jpg,0,2

slide\_38.jpg,3,2

225px-Wagner-VII\_world\_map\_projection.jpg,0,4

equirectangular\_projection\_map62.jpg,1,0

225px-Eckert\_II\_projection\_SW.jpg,0,4

equirectangular\_projection\_map65.jpg,1,0

SVM

Polynomial Kernel

sets of experiments0

train size:1000 test size:250

Polynomial kernel: value of c is: 2 value of alpha is: 0.0625 value of r is: 128 Training acc:100.0 Testing acc:**89.2**

Precise: 0.7924528301886793,0.9069767441860465,0.9298245614035088,0.8372093023255814,0.9814814814814815,

Recall: 0.8076923076923077,0.9285714285714286,0.8548387096774194,0.9473684210526315,0.9464285714285714,

F1 Score:0.8,0.9176470588235293,0.8907563025210083,0.8888888888888888,0.9636363636363636, train\_time:18.61988067626953 test\_time:13.943323850631714

mercator\_projection\_map93.jpg,2,0.0

mercator\_projection\_map50.jpg,2,0.0

robinson\_projection\_map62.jpg,4,0.0

miller\_projection\_map96.jpg,0,2.0

miller\_projection\_map91.jpg,0,3.0

map1498.png,2,3.0

map1490.png,2,0.0

miller\_projection\_map72.jpg,0,1.0

Augmented\_620px-Oceans\_base\_map.svg - Copy.png,3,2.0

equirectangular\_projection\_map65.jpg,1,0.0

map-projection-4-728.jpg,3,4.0

miller\_projection\_map74.jpg,0,2.0

mercator\_projection\_map41.jpg,2,3.0

equirectangular\_projection\_map94.jpg,1,3.0

mercator\_projection\_map76.jpg,2,0.0

miller\_projection\_map16.jpg,0,1.0

108271\_1.jpg,0,3.0

robinson\_projection\_map1.jpg,4,0.0

mercator\_projection\_map92.jpg,2,0.0

miller\_projection\_map53.jpg,0,3.0

mercator\_projection\_map99.jpg,2,0.0

miller\_projection\_map34.jpg,0,1.0

robinson\_projection\_map74.jpg,4,0.0

purple\_world\_map\_silhouette\_lds\_church\_membership.jpeg,0,1.0

mercator\_projection\_map81.jpg,2,0.0

equirectangular\_projection\_map59.jpg,1,3.0

miller\_projection\_map14.jpg,0,2.0train size:1000 test size:250sets of experiments0

CNN (from scratch)

128-256-512-1024

Sets of experiments0 optimizer=keras.optimizers.SGD(lr=0.01) epochs=100, batch\_size=20 train\_time:28917.634518384933 test\_time:29.41834783554077 Test loss:0.6782221093177795 Test accuracy:**0.9120000004768372**

Precise: 0.8913043478260869,0.9411764705882353,0.8983050847457628,0.9230769230769231,0.9090909090909091,

Recall: 0.8367346938775511,0.8888888888888888,0.9464285714285714,0.9230769230769231,0.9615384615384616,

F1 Score: 0.863157894736842,0.9142857142857143,0.9217391304347825,0.9230769230769231,0.9345794392523364,

miller\_projection\_map89.jpg,0,2

robinson\_projection\_map99.jpg,4,0

equirectangular\_projection\_map9.jpg,1,4

unnamed (2).jpg,3,4

miller\_projection\_map5.jpg,0,2

world-map-countries-geography-vector-9920386.jpg,0,1

robinson\_projection\_map88.jpg,4,1

equirectangular\_projection\_map19.jpg,1,4

equirectangular\_projection\_map28.jpg,1,2

map1490.png,2,0

images (4).jpg,3,4

miller\_projection\_map16.jpg,0,1

mercator\_projection\_map9.jpg,2,0

equirectangular\_projection\_map43.jpg,1,3

miller\_projection\_map7.jpg,0,2

miller\_projection\_map74.jpg,0,3

mercator\_projection\_map49.jpg,2,3

equirectangular\_projection\_map52.jpg,1,0

outbreak-coronavirus-world.png,0,2

108271\_1.jpg,0,2

equirectangular\_projection\_map73.jpg,1,4

behrmann-cylindrical-equal-area-l.jpg,3,0

Transfer Learning (VGG16)

Precise: 0.8478260869565217,0.9411764705882353,1.0,0.9743589743589743,0.9333333333333333,

Recall: 0.8478260869565217,0.96,0.9642857142857143,0.95,0.9655172413793104,

F1 Score: 0.8478260869565217,0.9504950495049503,0.9818181818181817,0.9620253164556962,0.9491525423728815,

layer\_inx: -10

Batch\_size: 32 epochs: 50

[INFO] loss=1.4959, accuracy: 94.0000%

Training time: 237.5680947303772

robinson\_projection\_map63.jpg,4,0

miller\_projection\_map66.jpg,0,1

eckert-3.jpg,0,4

equirectangular\_projection\_map15.jpg,1,0

robinson\_projection\_map1.jpg,4,0

map1490.png,2,0

225px-Nicolosi\_globular\_projections\_SW.jpg,0,4

miller\_projection\_map74.jpg,0,1

miller\_projection\_map10.jpg,0,1

equirectangular\_projection\_map51.jpg,1,0

hqdefault.jpg,0,4

lambert-cylindrical-equal-area-projection-6-638.jpg,3,4

unnamed (1).jpg,3,0

image-20170322-31187-12ez00u.jpg,0,3

map1470.png,2,0

|  |  |  |
| --- | --- | --- |
| **Image** | **Desired Label** | **Desired Label** |
|  | **0** | **4** |
|  | 0 | 4 |
|  | 1 | 0 |
|  | 1 | 0 |
|  | 0 | 4 |
|  | 0 | 3 |
|  | 3 | 4 |
|  | 2 | 0 |
|  | 0 | 1 |
|  | 0 | 1 |
|  | 0 | 1 |
|  | 0 | 1 |
|  | 0 | 4 |
|  | 4 | 0 |
|  | 3 | 0 |

CEA test

MLP

sets of experiments2 SGD(lr=0.0001, decay=1e-6, momentum=0.9, nesterov=True)

epochs=100, batch\_size=20 train\_time:497.5138647556305 test\_time:0.39394688606262207 Test loss:0.09025936245918274 Test accuracy:0.9760000109672546

Precise: 0.9850746268656716,0.9387755102040817, Recall: 0.9850746268656716,0.9387755102040817, F1 Score: 0.9850746268656717,0.9387755102040818,

stock-vector-world-map-globe-in-lambert-cylindrical-equal-area-projection-with-graticule-lines-style-outline-1376205200.jpg,1,0

low-poly-world-map-set-cylindrical-equal-area-projection-collection-maps-geometric-style-vector-illustration-1741838773.jpg,1,0

map108.png,1,0

miller\_projection\_map53.jpg,0,1

mercator\_projection\_map91.jpg,0,1

equirectangular\_projection\_map68.jpg,0,1

SVM

Polynomial kernel: value of c is: 0.125 value of alpha is: 0.0625 value of r is: 256 Training acc:100.0 Testing acc:96.39999999999999 Precise: 0.9637305699481865,0.9649122807017544, Recall: 0.9893617021276596,0.8870967741935484, F1 Score:0.9763779527559056,0.9243697478991597, train\_time:7.678511381149292 test\_time:12.477734565734863

images (2).jpg,1,0.0

225px-Gall朠eters\_projection\_SW.jpg,0,1.0

Augmented\_cylindrical-equal-area-300x177.png,1,0.0

unnamed (2).jpg,1,0.0

cylindrical-equal-area-300x177.png,1,0.0

image-20170322-31187-12ez00u.jpg,0,1.0

lambert.jpg,1,0.0

images (4).jpg,1,0.0

lambert-cylindrical-equal-area-projection-6-638.jpg,1,0.0

CNN

16-128

Sets of experiments0 optimizer=keras.optimizers.SGD(lr=0.01) epochs=100, batch\_size=20 train\_time:1783.9087927341461 test\_time:0.655247688293457 Test loss:0.07766578005254268 Test accuracy:0.9879999756813049

Precise: 0.9857142857142858,1.0, Recall: 1.0,0.9302325581395349, F1 Score: 0.9928057553956834,0.9638554216867469,

maxresdefault.jpg,1,0

map.jpg,1,0

map-projection-4-728.jpg,1,0

Transfer learning

VGG16

Precise: 0.9952153110047847,1.0, Recall: 1.0,0.9761904761904762, F1 Score: 0.9976019184652277,0.9879518072289156,layer\_inx: -9

Batch\_size: 32 epochs: 30

[INFO] loss=0.0656, accuracy: 99.6000%

Training time: 130.95020508766174

GMT\_general\_cyl.png,1,0

VGG19

Precise: 1.0,1.0, Recall: 1.0,1.0, F1 Score: 1.0,1.0,layer\_inx: -7

Batch\_size: 32 epochs: 30

[INFO] loss=0.0000, accuracy: 100.0000%

Training time: 297.63326954841614

In summary, we develop machine learning methods identify and classify maps to learn the basic information such as geographic region and projection, test the effects of hyper-parameters in the methods, and explore the abilities of the methods to identify features in different positions of images and with distortions in shape. The experiment results indicate that machine learning methods are able to identify and classify maps correctly based on region and projection. Among the methods, CNN models can obtain the best results in general. The CNN models using pretrained architectures are able to get the highest accuracy rate, while the CNN models trained from scratch are more efficient in applications. It is also found that using more training images will output more accurate predictions in our developed models, while batch size cannot influence the accuracy significantly but can affect the training time. For the ability of the methods to discover the same features in different positions of images, MLPs and CNNs perform well, while the performance of SVMs is poor. As for the ability to detect features with some degree of distortions in shape, SVMs are the best, and CNNs can also get high accuracy, while MLPs show a clear trend of decreasing accuracy as the distortion degree increases.

There are also some limitations in our research. For example, the images for projection classification are not totally from online resources. Because it is difficult to find enough world map images using the same projection, some images are generated for projection classification. We tried our best to make the generated images realistic. In the future, if we got more image data, the models will be updated. What’s more, the models to identify maps based on geographic region and projection are trained using only four or five categories. For example, our model can only tell the geographic region of a map as one of China, South Korea, the United States, and the world. If the models are to be used in practice, more image data is needed.

As introduced, our research is the beginning work to understand the contents on maps. There are many directions to be explored in the future. For example, the map elements such as map titles and legends can be detected, and semantic analysis should be extracted based on the elements. After the map title area extracted from a map, optical character recognition (OCR) techniques can be used to obtain title texts, then we can know the topic of the map with semantic analysis of the title texts. The detected legend area can give us the information about attribute values and legend symbols for each of the categories, and then we can know the corresponding attribute value of each unit on map area. In future research, text and voice can be generated on the basis of the information obtained from map understanding. The outcome of the research can be meaningful in practice. A system can be built to help blind or vision-impaired users to understand the contents of maps. Besides, map understanding is useful in image retrieval and update in a large image database based on content of the image map. For example, if database managers want to add new map images into a large database for images of various categories, automatically recognizing map information (e.g. geographical region) will facilitate the process, saving a considerable amount of manually labeling costs.