

Лабораторная работа №6. Применение сверточных нейронных сетей (многоклассовая классификация)

Данные: Набор данных для распознавания языка жестов, который состоит из изображений размерности 28x28 в оттенках серого (значение пикселя от 0 до 255). Каждое из изображений обозначает букву латинского алфавита, обозначенную с помощью жеста, как показано на рисунке ниже (рисунок цветной, а изображения в наборе данных в оттенках серого). Обучающая выборка включает в себя 27,455 изображений, а контрольная выборка содержит 7172 изображения. Данные в виде csv-файлов можно скачать на сайте Kaggle ->

<https://www.kaggle.com/datamunge/sign-language-mnist>

(<https://www.kaggle.com/datamunge/sign-language-mnist>)

```
In [0]: 1 # !pip install tensorflow==1.14.0
2 import pandas as pd
3 import tensorflow as tf
4 from keras.utils import np_utils
5 from sklearn.model_selection import train_test_split
6 from tensorflow.keras import layers, models, Sequential
7 from sklearn.metrics import roc_auc_score
8 from keras.layers import Conv2D, MaxPooling2D, GlobalAveragePooling2D
9 from keras.preprocessing.image import ImageDataGenerator
10 from keras.models import Model
11 from tensorflow.keras.layers import InputLayer
12 from keras.layers import Concatenate
```

Задание 1. Загрузите данные. Разделите исходный набор данных на обучающую и валидационную выборки.

```
In [0]: 1 df = pd.read_csv('/content/drive/My Drive/kaggle/sign_mnist_train.csv')
2 print(df)
3
4 testDF = pd.read_csv('/content/drive/My Drive/kaggle/sign_mnist_test.csv')
5 print(testDF)
```

	label	pixel1	pixel2	pixel3	...	pixel781	pixel782	pixel783	pixel784
0	3	107	118	127	...	206	204		
203	202								
1	6	155	157	156	...	175	103		
135	149								
2	2	187	188	188	...	198	195		
194	195								
3	2	211	211	212	...	225	222		

229	163						
4	13	164	167	170	...	157	163
164	179						
...
...	...						
27450	13	189	189	190	...	234	200
222	225						
27451	23	151	154	157	...	195	195
195	194						
27452	18	174	174	174	...	203	202
200	200						
27453	17	177	181	184	...	47	64
87	93						
27454	23	179	180	180	...	197	205
209	215						

[27455 rows x 785 columns]

	label	pixel1	pixel2	pixel3	...	pixel781	pixel782	pixel784
0	6	149	149	150	...	106	112	
120	107							
1	5	126	128	131	...	184	184	
182	180							
2	10	85	88	92	...	226	225	
224	222							
3	0	203	205	207	...	230	240	
253	255							
4	3	188	191	193	...	49	46	
46	53							
...
...	...							
7167	1	135	119	108	...	184	176	
167	163							
7168	12	157	159	161	...	210	210	
209	208							
7169	2	190	191	190	...	210	211	
209	208							
7170	4	201	205	208	...	91	67	
70	63							
7171	2	173	174	173	...	195	195	
193	192							

[7172 rows x 785 columns]

```
In [0]: 1 def getXandY(df):
2         y = df["label"].values.reshape((df.shape[0], 1))
3         x = df.drop(columns="label").values.reshape((df.shape[0], 28,
4         print(y.shape, x.shape)
5         return x, y
6
7 x, y = getXandY(df)
8 tX, tY = getXandY(testDF)
```

```
(27455, 1) (27455, 28, 28, 1)
(7172, 1) (7172, 28, 28, 1)
```

```
In [0]: 1 trainX, testX, trainY, testY = train_test_split(x, y, test_size
```

Задание 2. Реализуйте глубокую нейронную сеть со сверточными слоями. Какое качество классификации получено? Какая архитектура сети была использована?

```
In [0]: 1 model = Sequential([
2         layers.Conv2D(64, kernel_size=3, activation='relu', input_s
3         layers.Conv2D(32, kernel_size=5, activation='relu'),
4         layers.MaxPooling2D((2, 2)),
5         layers.Conv2D(64, (3, 3), activation='relu', padding='same'
6         layers.MaxPooling2D((2, 2)),
7         layers.Conv2D(128, (3, 3), activation='relu', padding='same
8         layers.MaxPooling2D((2, 2)),
9         layers.Flatten(),
10        layers.Dense(25, activation='softmax')
11    ])
12
13 model.compile(optimizer='adam', loss='sparse_categorical_crossentropy')
14
15 model.fit(trainX, trainY, validation_data=(testX, testY), epochs=15)
16
```

Train on 20591 samples, validate on 6864 samples

Epoch 1/15

20591/20591 [=====] - 144s 7ms/sample - loss: 1.0571 - acc: 0.7136 - val_loss: 0.0424 - val_acc: 0.9850

Epoch 2/15

20591/20591 [=====] - 145s 7ms/sample - loss: 0.0364 - acc: 0.9891 - val_loss: 0.0588 - val_acc: 0.9768

Epoch 3/15

20591/20591 [=====] - 146s 7ms/sample - loss: 0.0436 - acc: 0.9884 - val_loss: 0.0113 - val_acc: 0.9969

Epoch 4/15

20591/20591 [=====] - 146s 7ms/sample - loss: 0.0436 - acc: 0.9884 - val_loss: 0.0113 - val_acc: 0.9969

```

oss: 0.0145 - acc: 0.9957 - val_loss: 7.3109e-04 - val_acc: 0.9999
Epoch 5/15
20591/20591 [=====] - 147s 7ms/sample - l
oss: 8.1862e-05 - acc: 1.0000 - val_loss: 6.7947e-04 - val_acc: 0.
9999
Epoch 6/15
20591/20591 [=====] - 145s 7ms/sample - l
oss: 3.6115e-05 - acc: 1.0000 - val_loss: 6.0458e-04 - val_acc: 0.
9999
Epoch 7/15
20591/20591 [=====] - 144s 7ms/sample - l
oss: 2.1497e-05 - acc: 1.0000 - val_loss: 6.1721e-04 - val_acc: 0.
9999
Epoch 8/15
20591/20591 [=====] - 144s 7ms/sample - l
oss: 1.3678e-05 - acc: 1.0000 - val_loss: 5.6933e-04 - val_acc: 0.
9999
Epoch 9/15
20591/20591 [=====] - 142s 7ms/sample - l
oss: 9.1778e-06 - acc: 1.0000 - val_loss: 5.2476e-04 - val_acc: 0.
9999
Epoch 10/15
20591/20591 [=====] - 142s 7ms/sample - l
oss: 6.2680e-06 - acc: 1.0000 - val_loss: 5.4921e-04 - val_acc: 0.
9999
Epoch 11/15
20591/20591 [=====] - 141s 7ms/sample - l
oss: 4.3298e-06 - acc: 1.0000 - val_loss: 5.2253e-04 - val_acc: 0.
9999
Epoch 12/15
20591/20591 [=====] - 141s 7ms/sample - l
oss: 3.0284e-06 - acc: 1.0000 - val_loss: 5.1974e-04 - val_acc: 0.
9999
Epoch 13/15
20591/20591 [=====] - 141s 7ms/sample - l
oss: 2.1118e-06 - acc: 1.0000 - val_loss: 4.9742e-04 - val_acc: 0.
9999
Epoch 14/15
20591/20591 [=====] - 141s 7ms/sample - l
oss: 1.4905e-06 - acc: 1.0000 - val_loss: 5.0703e-04 - val_acc: 0.
9999
Epoch 15/15
20591/20591 [=====] - 142s 7ms/sample - l
oss: 1.0459e-06 - acc: 1.0000 - val_loss: 5.2003e-04 - val_acc: 0.
9999

```

Out [32]: <tensorflow.python.keras.callbacks.History at 0x7f59071aa400>

```
In [0]: 1 test_loss, test_acc = model.evaluate(tX, tY, verbose=2)
        2
```

```
7172/7172 - 10s - loss: 0.9118 - acc: 0.8938
```

Задание 3. Примените дополнение данных (data augmentation). Как это повлияло на качество классификатора?

```
In [0]: 1 datagen = ImageDataGenerator(zoom_range=[0.5,1.0], brightness_r
2 train_generator = datagen.flow(trainX, trainY, batch_size=1)
3 test_generator = datagen.flow(testX, testY, batch_size=1)
```

```
In [0]: 1 model.fit_generator(
2     train_generator,
3     epochs=15,
4     validation_data=test_generator)
```

```
Epoch 1/15
20591/20591 [=====] - 291s 14ms/step - loss: 3.1809 - acc: 0.0447 - val_loss: 3.1770 - val_acc: 0.0455
Epoch 2/15
20591/20591 [=====] - 283s 14ms/step - loss: 3.2048 - acc: 0.0444 - val_loss: 3.1705 - val_acc: 0.0447
Epoch 3/15
20591/20591 [=====] - 278s 13ms/step - loss: 3.1752 - acc: 0.0470 - val_loss: 3.1752 - val_acc: 0.0398
Epoch 4/15
20591/20591 [=====] - 282s 14ms/step - loss: 3.1747 - acc: 0.0459 - val_loss: 3.1761 - val_acc: 0.0455
Epoch 5/15
20591/20591 [=====] - 287s 14ms/step - loss: 3.1806 - acc: 0.0462 - val_loss: 3.1747 - val_acc: 0.0446
Epoch 6/15
20591/20591 [=====] - 282s 14ms/step - loss: 3.2386 - acc: 0.0478 - val_loss: 3.1763 - val_acc: 0.0453
Epoch 7/15
20591/20591 [=====] - 293s 14ms/step - loss: 3.1835 - acc: 0.0448 - val_loss: 3.1741 - val_acc: 0.0424
Epoch 8/15
20591/20591 [=====] - 279s 14ms/step - loss: 3.1763 - acc: 0.0440 - val_loss: 3.1778 - val_acc: 0.0455
Epoch 9/15
20591/20591 [=====] - 280s 14ms/step - loss: 3.1751 - acc: 0.0440 - val_loss: 3.1771 - val_acc: 0.0455
Epoch 10/15
20591/20591 [=====] - 283s 14ms/step - loss: 3.1761 - acc: 0.0436 - val_loss: 3.1768 - val_acc: 0.0455
Epoch 11/15
20591/20591 [=====] - 289s 14ms/step - loss: 3.1866 - acc: 0.0460 - val_loss: 3.1766 - val_acc: 0.0503
Epoch 12/15
20591/20591 [=====] - 287s 14ms/step - loss: 3.1774 - acc: 0.0453 - val_loss: 3.1745 - val_acc: 0.0510
Epoch 13/15
20591/20591 [=====] - 290s 14ms/step - loss: 3.1774 - acc: 0.0453 - val_loss: 3.1745 - val_acc: 0.0510
```

```
ss: 3.1773 - acc: 0.0464 - val_loss: 3.1788 - val_acc: 0.0514
Epoch 14/15
20591/20591 [=====] - 282s 14ms/step - lo
ss: 3.1792 - acc: 0.0450 - val_loss: 3.1771 - val_acc: 0.0433
Epoch 15/15
20591/20591 [=====] - 279s 14ms/step - lo
ss: 3.1765 - acc: 0.0456 - val_loss: 3.1749 - val_acc: 0.0440
```

Out [66]: <tensorflow.python.keras.callbacks.History at 0x7f5906ab69e8>

```
In [0]: 1 test_loss, test_acc = model.evaluate(tX, tY, verbose=2)
```

```
7172/7172 - 10s - loss: 3.2389 - acc: 0.0291
```

Задание 4. Поэкспериментируйте с готовыми нейронными сетями (например, AlexNet, VGG16, Inception и т.п.), применив передаточное обучение. Как это повлияло на качество классификатора? Можно ли было обойтись без него? Какой максимальный результат удалось получить на контрольной выборке?

```
In [92]: 1 from keras.applications import MobileNet
2
3 base_model=MobileNet(weights='imagenet',include_top=False)
4
5 x=base_model.output
6 x=GlobalAveragePooling2D()(x)
7 x=Dense(1024,activation='relu')(x)
8 x=Dense(1024,activation='relu')(x)
9 x=Dense(512,activation='relu')(x)
10 preds=Dense(25,activation='softmax')(x)
11 model=Model(inputs=base_model.input,outputs=preds)
12 model.summary()
```

/usr/local/lib/python3.6/dist-packages/keras_applications/mobilenet.py:207: UserWarning: `input_shape` is undefined or non-square, or `rows` is not in [128, 160, 192, 224]. Weights for input shape (224, 224) will be loaded as the default.

warnings.warn("`input_shape` is undefined or non-square, '

Model: "model_5"

Layer (type)	Output Shape	Param #
input_6 (InputLayer)	(None, None, None, 3)	0
conv1_pad (ZeroPadding2D)	(None, None, None, 3)	0
conv1 (Conv2D)	(None, None, None, 32)	864
conv1_bn (BatchNormalization)	(None, None, None, 32)	128
conv1_relu (ReLU)	(None, None, None, 32)	0

```
In [0]: 1 for layer in model.layers:
2         layer.trainable=False
```

```
In [0]: 1 def transform(dataset):
2         newDataset = list()
3         for x in dataset:
4             x = np.repeat(x, 3, 2)
5             newDataset.append(x)
6         return np.array(newDataset)
7
8 newTrainX = transform(trainX)
9 newTestX = transform(testX)
```

```
In [90]: 1 print(newTrainX.shape, newTestX.shape)
(20591, 28, 28, 3) (6864, 28, 28, 3)
```



```
In [94]: 1 model.compile(optimizer='adam', loss='sparse_categorical_crossentropy',
2           model.fit(newTrainX, trainY, validation_data=(newTestX, testY),
3
```

Train on 20591 samples, validate on 6864 samples

Epoch 1/15

20591/20591 [=====] - 47s 2ms/step - loss : nan - acc: 0.0414 - val_loss: nan - val_acc: 0.0398

Epoch 2/15

20591/20591 [=====] - 44s 2ms/step - loss : nan - acc: 0.0414 - val_loss: nan - val_acc: 0.0398

Epoch 3/15

20591/20591 [=====] - 44s 2ms/step - loss : nan - acc: 0.0414 - val_loss: nan - val_acc: 0.0398

Epoch 4/15

20591/20591 [=====] - 44s 2ms/step - loss : nan - acc: 0.0414 - val_loss: nan - val_acc: 0.0398

Epoch 5/15

20591/20591 [=====] - 44s 2ms/step - loss : nan - acc: 0.0414 - val_loss: nan - val_acc: 0.0398

Epoch 6/15

20591/20591 [=====] - 44s 2ms/step - loss : nan - acc: 0.0414 - val_loss: nan - val_acc: 0.0398

Epoch 7/15

20591/20591 [=====] - 45s 2ms/step - loss : nan - acc: 0.0414 - val_loss: nan - val_acc: 0.0398

Epoch 8/15

20591/20591 [=====] - 45s 2ms/step - loss : nan - acc: 0.0414 - val_loss: nan - val_acc: 0.0398

Epoch 9/15

20591/20591 [=====] - 45s 2ms/step - loss : nan - acc: 0.0414 - val_loss: nan - val_acc: 0.0398

Epoch 10/15

20591/20591 [=====] - 45s 2ms/step - loss : nan - acc: 0.0414 - val_loss: nan - val_acc: 0.0398

Epoch 11/15

20591/20591 [=====] - 45s 2ms/step - loss : nan - acc: 0.0414 - val_loss: nan - val_acc: 0.0398

Epoch 12/15

20591/20591 [=====] - 46s 2ms/step - loss : nan - acc: 0.0414 - val_loss: nan - val_acc: 0.0398

Epoch 13/15

20591/20591 [=====] - 46s 2ms/step - loss : nan - acc: 0.0414 - val_loss: nan - val_acc: 0.0398

Epoch 14/15

20591/20591 [=====] - 46s 2ms/step - loss : nan - acc: 0.0414 - val_loss: nan - val_acc: 0.0398

Epoch 15/15

20591/20591 [=====] - 46s 2ms/step - loss : nan - acc: 0.0414 - val_loss: nan - val_acc: 0.0398

Out [94]: <keras.callbacks.History at 0x7f9abbce00b8>

