Credit Card Fraud Detection using CNN

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```
#!pip install tensorflow-gpu==2.0.0-rc0
# Keep your eyes for update: https://www.tensorflow.org/

import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import Sequential
from tensorflow.keras.layers import Flatten, Dense, Dropout,
BatchNormalization
from tensorflow.keras.layers import Conv1D, MaxPool1D
from tensorflow.keras.optimizers import Adam
print(tf.__version__)
```

```
2.0.0-rc0
```

```
import pandas as pd
import numpy as np
import  seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

data = pd.read_csv('creditcard.csv')
data.head()
```

```
   Time        V1        V2        V3        V4        V5        V6
V7  \
0   0.0 -1.359807 -0.072781  2.536347  1.378155 -0.338321  0.462388
0.239599
1   0.0  1.191857  0.266151  0.166480  0.448154  0.060018 -0.082361 -
0.078803
2   1.0 -1.358354 -1.340163  1.773209  0.379780 -0.503198  1.800499
0.791461
3   1.0 -0.966272 -0.185226  1.792993 -0.863291 -0.010309  1.247203
0.237609
4   2.0 -1.158233  0.877737  1.548718  0.403034 -0.407193  0.095921
0.592941

         V8        V9  ...       V21       V22       V23       V24
V25  \
0  0.098698  0.363787  ... -0.018307  0.277838 -0.110474  0.066928
0.128539
1  0.085102 -0.255425  ... -0.225775 -0.638672  0.101288 -0.339846
0.167170
2  0.247676 -1.514654  ...  0.247998  0.771679  0.909412 -0.689281 -
0.327642
3  0.377436 -1.387024  ... -0.108300  0.005274 -0.190321 -1.175575
```

```
0.647376
4 -0.270533  0.817739  ... -0.009431  0.798278 -0.137458  0.141267 -
0.206010

         V26       V27       V28  Amount  Class
0 -0.189115  0.133558 -0.021053  149.62      0
1  0.125895 -0.008983  0.014724    2.69      0
2 -0.139097 -0.055353 -0.059752  378.66      0
3 -0.221929  0.062723  0.061458  123.50      0
4  0.502292  0.219422  0.215153   69.99      0

[5 rows x 31 columns]
```

```
data.shape
```

```
(284807, 31)
```

```
data.isnull().sum()
```

```
Time      0
V1        0
V2        0
V3        0
V4        0
V5        0
V6        0
V7        0
V8        0
V9        0
V10       0
V11       0
V12       0
V13       0
V14       0
V15       0
V16       0
V17       0
V18       0
V19       0
V20       0
V21       0
V22       0
V23       0
V24       0
V25       0
V26       0
V27       0
V28       0
Amount    0
```

```
Class     0
dtype: int64
```

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 284807 entries, 0 to 284806
Data columns (total 31 columns):
Time      284807 non-null float64
V1        284807 non-null float64
V2        284807 non-null float64
V3        284807 non-null float64
V4        284807 non-null float64
V5        284807 non-null float64
V6        284807 non-null float64
V7        284807 non-null float64
V8        284807 non-null float64
V9        284807 non-null float64
V10       284807 non-null float64
V11       284807 non-null float64
V12       284807 non-null float64
V13       284807 non-null float64
V14       284807 non-null float64
V15       284807 non-null float64
V16       284807 non-null float64
V17       284807 non-null float64
V18       284807 non-null float64
V19       284807 non-null float64
V20       284807 non-null float64
V21       284807 non-null float64
V22       284807 non-null float64
V23       284807 non-null float64
V24       284807 non-null float64
V25       284807 non-null float64
V26       284807 non-null float64
V27       284807 non-null float64
V28       284807 non-null float64
Amount    284807 non-null float64
Class     284807 non-null int64
dtypes: float64(30), int64(1)
memory usage: 67.4 MB
```

```
data['Class'].value_counts()
```

```
0    284315
1       492
Name: Class, dtype: int64
```

Balance Dataset

```
non_fraud = data[data['Class']==0]
fraud = data[data['Class']==1]

non_fraud.shape, fraud.shape
```

```
((284315, 31), (492, 31))
```

```
non_fraud = non_fraud.sample(fraud.shape[0])
non_fraud.shape
```

```
(492, 31)
```

```
data = fraud.append(non_fraud, ignore_index=True)
data
```

```
          Time         V1        V2          V3        V4         V5
V6  \
0       406.0 -2.312227  1.951992  -1.609851  3.997906 -0.522188 -
1.426545
1       472.0 -3.043541 -3.157307   1.088463  2.288644  1.359805 -
1.064823
2      4462.0 -2.303350  1.759247  -0.359745  2.330243 -0.821628 -
0.075788
3      6986.0 -4.397974  1.358367  -2.592844  2.679787 -1.128131 -
1.706536
4      7519.0  1.234235  3.019740  -4.304597  4.732795  3.624201 -
1.357746
5      7526.0  0.008430  4.137837  -6.240697  6.675732  0.768307 -
3.353060
6      7535.0  0.026779  4.132464  -6.560600  6.348557  1.329666 -
2.513479
7      7543.0  0.329594  3.712889  -5.775935  6.078266  1.667359 -
2.420168
8      7551.0  0.316459  3.809076  -5.615159  6.047445  1.554026 -
2.651353
9      7610.0  0.725646  2.300894  -5.329976  4.007683 -1.730411 -
1.732193
10     7672.0  0.702710  2.426433  -5.234513  4.416661 -2.170806 -
2.667554
11     7740.0  1.023874  2.001485  -4.769752  3.819195 -1.271754 -
1.734662
12     7891.0 -1.585505  3.261585  -4.137422  2.357096 -1.405043 -
1.879437
13     8090.0 -1.783229  3.402794  -3.822742  2.625368 -1.976415 -
2.731689
14     8169.0  0.857321  4.093912  -7.423894  7.380245  0.973366 -
2.730762
15     8408.0 -1.813280  4.917851  -5.926130  5.701500  1.204393 -
3.035138
```

```
16     8415.0 -0.251471  4.313523  -6.891438  6.796797  0.616297 -
2.966327
17     8451.0  0.314597  2.660670  -5.920037  4.522500 -2.315027 -
2.278352
18     8528.0  0.447396  2.481954  -5.660814  4.455923 -2.443780 -
2.185040
19     8614.0 -2.169929  3.639654  -4.508498  2.730668 -2.122693 -
2.341017
20     8757.0 -1.863756  3.442644  -4.468260  2.805336 -2.118412 -
2.332285
21     8808.0 -4.617217  1.695694  -3.114372  4.328199 -1.873257 -
0.989908
22     8878.0 -2.661802  5.856393  -7.653616  6.379742 -0.060712 -
3.131550
23     8886.0 -2.535852  5.793644  -7.618463  6.395830 -0.065210 -
3.136372
24     9064.0 -3.499108  0.258555  -4.489558  4.853894 -6.974522
3.628382
25    11080.0 -2.125490  5.973556 -11.034727  9.007147 -1.689451 -
2.854415
26    11092.0  0.378275  3.914797  -5.726872  6.094141  1.698875 -
2.807314
27    11131.0 -1.426623  4.141986  -9.804103  6.666273 -4.749527 -
2.073129
28    11629.0 -3.891192  7.098916 -11.426467  8.607557 -2.065706 -
2.985288
29    11635.0  0.919137  4.199633  -7.535607  7.426940  1.118215 -
2.886722
..        ...       ...       ...        ...       ...       ...
...
954   51632.0 -0.910542 -0.207061  -0.238652 -1.620610  1.068202
4.117210
955   40914.0 -0.915835  1.317547   0.993125 -0.236196  0.197397 -
0.666025
956  157688.0 -0.497431  0.678159  -1.520938 -1.000571 -0.741602 -
0.888050
957  139800.0 -0.927206 -0.725931   0.818936 -0.552991  0.558724 -
0.535803
958  135483.0 -5.770397 -5.696525  -1.220788  0.991614  2.852955 -
2.299697
959   49684.0 -1.065596  0.842987   0.172065 -0.436670  2.653078
3.806699
960   70867.0 -0.682535  1.058084   0.664150 -0.030638 -0.183924 -
0.772025
961  125113.0 -0.550393  0.606198   1.732814 -0.477593  0.063260 -
0.080612
962   57642.0  1.296055  0.307048  -0.340150  0.931280  0.572522
0.236900
963   67905.0  1.124166 -0.245039  -1.243372  0.323470  2.115415
```

```
3.632770
964   12443.0  1.105762 -0.616627   0.816607  0.339242 -0.900344
0.138514
965   45034.0  1.195644 -1.696748   0.772249 -1.386388 -2.002641 -
0.146342
966   65436.0 -3.877934  2.831185  -0.682614  1.295636 -2.063089
1.283378
967  146776.0  1.970169 -0.596364  -1.733929 -0.680361  1.818093
3.778353
968   74968.0  0.969108 -1.810261  -0.070629 -1.054164 -1.634434 -
0.743319
969  152001.0 -1.414994  2.236620   1.378835  4.262823 -0.478623
0.823817
970   56322.0  0.179097  1.945647  -3.804657  0.395820  3.220904
2.333843
971  157194.0  0.014710  1.232299  -0.961770 -0.669596  1.595960 -
1.128452
972   38007.0 -0.596652  0.606731   2.035640 -1.216988 -0.220961 -
0.898262
973   44791.0 -2.014166  2.057500   0.800515 -0.046729  0.237468
1.924049
974   79383.0  0.268050  0.012069   1.282745 -1.201270 -0.622377 -
0.405405
975   63925.0  1.139142 -0.574897   0.176115 -0.812239 -0.809421 -
0.568300
976    8449.0  1.192691  1.243546  -1.373662  1.799776  0.713990 -
1.618146
977  162993.0 -0.562449  1.665333  -0.789924 -0.246244  1.866147 -
0.912833
978   36002.0  1.318495 -0.229179   0.307091  0.254830 -0.444094 -
0.059009
979  153538.0  0.134416  0.743800  -1.984022 -1.295774  3.151207
3.155450
980   79156.0  0.886793 -0.890167   0.956626  0.388763 -1.369543 -
0.334280
981   48642.0 -1.713619  1.357466  -0.138878  0.260421  0.880219
0.228354
982   89988.0  1.819294 -0.098211  -1.190861  2.760301  2.164190
4.772675
983   97710.0  1.559744  0.590840  -1.936930  1.116909  0.397621 -
0.747927

            V7        V8        V9  ...       V21       V22       V23
\
0    -2.537387  1.391657 -2.770089  ...  0.517232 -0.035049 -0.465211

1     0.325574 -0.067794 -0.270953  ...  0.661696  0.435477  1.375966

2     0.562320 -0.399147 -0.238253  ... -0.294166 -0.932391  0.172726
```

```
3    -3.496197 -0.248778 -0.247768  ...  0.573574  0.176968 -0.436207
4     1.713445 -0.496358 -1.282858  ... -0.379068 -0.704181 -0.656805
5    -1.631735  0.154612 -2.795892  ...  0.364514 -0.608057 -0.539528
6    -1.689102  0.303253 -3.139409  ...  0.370509 -0.576752 -0.669605
7    -0.812891  0.133080 -2.214311  ...  0.156617 -0.652450 -0.551572
8    -0.746579  0.055586 -2.678679  ...  0.208828 -0.511747 -0.583813
9    -3.968593  1.063728 -0.486097  ...  0.589669  0.109541  0.601045
10   -3.878088  0.911337 -0.166199  ...  0.551180 -0.009802  0.721698
11   -3.059245  0.889805  0.415382  ...  0.343283 -0.054196  0.709654
12   -3.513687  1.515607 -1.207166  ...  0.501543 -0.546869 -0.076584
13   -3.430559  1.413204 -0.776941  ...  0.454032 -0.577526  0.045967
14   -1.496497  0.543015 -2.351190  ...  0.375026  0.145400  0.240603
15   -1.713402  0.561257 -3.796354  ...  0.615642 -0.406427 -0.737018
16   -2.436653  0.489328 -3.371639  ...  0.536892 -0.546126 -0.605240
17   -4.684054  1.202270 -0.694696  ...  0.743314  0.064038  0.677842
18   -4.716143  1.249803 -0.718326  ...  0.756053  0.140168  0.665411
19   -4.235253  1.703538 -1.305279  ...  0.645103 -0.503529 -0.000523
20   -4.261237  1.701682 -1.439396  ...  0.667927 -0.516242 -0.012218
21   -4.577265  0.472216  0.472017  ...  0.481830  0.146023  0.117039
22   -3.103570  1.778492 -3.831154  ...  0.734775 -0.435901 -0.384766
23   -3.104557  1.823233 -3.878658  ...  0.716720 -0.448060 -0.402407
24    5.431271 -1.946734 -0.775680  ... -1.052368  0.204817 -2.119007
25   -7.810441  2.030870 -5.902828  ...  1.646518 -0.278485 -0.664841
26   -0.591118 -0.123496 -2.530713  ...  0.149896 -0.601967 -0.613724
27  -10.089931  2.791345 -3.249516  ...  1.865679  0.407809  0.605809
28   -8.138589  2.973928 -6.272790  ...  1.757085 -0.189709 -0.508629
```

```
29   -1.341036  0.363933 -2.203224  ...  0.316094  0.055179  0.210692
..         ...       ...       ...  ...       ...       ...       ...
954  -0.141094  1.477371  0.350114  ...  0.020076 -0.350732  0.552200
955   0.757835 -0.116348  0.023059  ... -0.001425  0.379368 -0.239480
956   0.653594  0.429176 -2.047518  ... -0.004812  0.276263  0.064681
957   0.086743  0.137233  0.323443  ... -0.228540 -0.427330  1.049918
958   0.548609  0.190603  0.285034  ... -0.567495  0.116072  5.485748
959   0.304196  0.812782 -0.368669  ... -0.108110 -0.390159 -0.408153
960   0.625303  0.359726 -0.987842  ...  0.176234  0.250496 -0.000062
961   0.392867 -0.053336  0.414040  ...  0.329778  1.366743 -0.392367
962   0.201531 -0.020137 -0.161151  ... -0.069141 -0.045908 -0.325746
963  -0.343524  0.830462  0.163974  ... -0.139787 -0.518830 -0.190092
964  -0.719458  0.063580  2.698915  ... -0.399295 -0.884769 -0.075285
965  -1.411495  0.114976 -1.577998  ... -0.040671 -0.113978 -0.075130
966  -2.270468  3.243956  0.390027  ... -0.289132 -0.746505  0.111810
967  -1.102810  1.027472  1.120832  ... -0.181881 -0.489404  0.411581
968  -0.432448 -0.247401 -2.120424  ...  0.013725 -0.070490 -0.302346
969  -0.247187  0.504294 -0.490021  ...  0.104418  0.861802 -0.109472
970   0.195374  0.950539 -0.113631  ... -0.269630 -0.504177  0.088089
971   1.593136 -0.342923 -0.832564  ...  0.044372  0.104575 -0.330069
972   0.699627 -0.109285  0.237855  ... -0.081429 -0.028667 -0.001075
973  -1.105882 -3.077766 -0.190878  ... -0.813233 -0.423911 -0.088260
974  -0.237844  0.162505  1.565277  ...  0.113336  0.589706  0.079297
975  -0.259045  0.085214  1.617206  ... -0.212520 -0.587116 -0.081918
976   0.466555 -0.234287  0.828311  ... -0.316004 -0.683985 -0.162753
977   1.595264 -0.138339 -1.304623  ... -0.015247 -0.024051 -0.683411
```

```
978  -0.384156 -0.014430 -0.971022  ... -0.595372 -1.235881  0.141314
979   0.410317  0.842173 -0.140472  ...  0.267528  0.876781 -0.120359
980  -0.428430  0.008812  1.185911  ... -0.131964 -0.499977 -0.067951
981  -0.138277  1.160096 -1.090570  ...  0.180030  0.336668 -0.134927
982  -1.163118  1.219110 -0.411377  ...  0.236633  0.655310  0.175033
983   0.543659 -0.423814  1.219402  ...  0.073917  0.519319  0.071452

          V24       V25       V26       V27       V28   Amount  Class
0    0.320198  0.044519  0.177840  0.261145 -0.143276     0.00      1
1   -0.293803  0.279798 -0.145362 -0.252773  0.035764   529.00      1
2   -0.087330 -0.156114 -0.542628  0.039566 -0.153029   239.93      1
3   -0.053502  0.252405 -0.657488 -0.827136  0.849573    59.00      1
4   -1.632653  1.488901  0.566797 -0.010016  0.146793     1.00      1
5    0.128940  1.488481  0.507963  0.735822  0.513574     1.00      1
6   -0.759908  1.605056  0.540675  0.737040  0.496699     1.00      1
7   -0.716522  1.415717  0.555265  0.530507  0.404474     1.00      1
8   -0.219845  1.474753  0.491192  0.518868  0.402528     1.00      1
9   -0.364700 -1.843078  0.351909  0.594550  0.099372     1.00      1
10   0.473246 -1.959304  0.319476  0.600485  0.129305     1.00      1
11  -0.372216 -2.032068  0.366778  0.395171  0.020206     1.00      1
12  -0.425550  0.123644  0.321985  0.264028  0.132817     1.00      1
13   0.461700  0.044146  0.305704  0.530981  0.243746     1.00      1
14  -0.234649 -1.004881  0.435832  0.618324  0.148469     1.00      1
15  -0.279642  1.106766  0.323885  0.894767  0.569519     1.00      1
16  -0.263743  1.539916  0.523574  0.891025  0.572741     1.00      1
17   0.083008 -1.911034  0.322188  0.620867  0.185030     1.00      1
18   0.131464 -1.908217  0.334808  0.748534  0.175414     1.00      1
```

19	0.071696	0.092007	0.308498	0.552591	0.298954	1.00	1
20	0.070614	0.058504	0.304883	0.418012	0.208858	1.00	1
21	-0.217565	-0.138776	-0.424453	-1.002041	0.890780	1.10	1
22	-0.286016	1.007934	0.413196	0.280284	0.303937	1.00	1
23	-0.288835	1.011752	0.425965	0.413140	0.308205	1.00	1
24	0.170279	-0.393844	0.296367	1.985913	-0.900452	1809.68	1
25	-1.164555	1.701796	0.690806	2.119749	1.108933	1.00	1
26	-0.403114	1.568445	0.521884	0.527938	0.411910	1.00	1
27	-0.769348	-1.746337	0.502040	1.977258	0.711607	1.00	1
28	-1.189308	1.188536	0.605242	1.881529	0.875260	1.00	1
29	-0.417918	-0.911188	0.466524	0.627393	0.157851	1.00	1
..	...	...	...	...	...	...	...
954	1.034758	-0.700922	0.648581	-0.057502	0.127988	202.31	0
955	-0.081333	-0.074885	0.330273	-0.149884	-0.253422	2.29	0
956	0.051060	-0.429060	0.750027	-0.282959	-0.101003	126.00	0
957	-0.458899	-0.679002	0.191879	0.037741	-0.076710	28.98	0
958	0.470629	0.552619	0.352217	1.019398	-0.462908	298.33	0
959	1.012433	0.773454	-0.328314	-0.307860	0.062356	27.42	0
960	0.334310	-0.346491	0.240723	-0.052977	0.076273	42.81	0
961	0.066650	-0.089823	-0.114947	0.135096	-0.019503	7.50	0
962	-0.968079	0.998955	-0.196661	0.006097	-0.009609	1.00	0
963	1.013573	0.866757	-0.334311	0.011730	0.024999	80.43	0
964	-0.466664	0.157056	0.950496	-0.084727	0.012128	94.85	0
965	-0.031352	0.100761	-0.228967	0.027680	0.042448	149.92	0
966	-0.859272	0.411489	-0.300106	0.226980	0.054999	8.52	0
967	0.657254	-0.390779	-0.601500	0.054462	-0.037135	7.49	0

```
968  0.571201  0.525534 -0.122198 -0.036533  0.046692   275.00      0
969 -0.025219 -0.504606  0.437847  0.504577  0.209921    10.00      0
970  0.646476 -0.201730 -0.402726  0.180500 -0.156480     1.79      0
971  0.457462  0.330857  0.584320 -0.057324  0.033154     8.67      0
972  0.613370 -0.545931  0.690521  0.104853 -0.048594     5.30      0
973 -1.321815  0.279711  0.549207  0.263836  0.262827    25.00      0
974  0.086910 -0.469945 -0.799564  0.093064 -0.051164     1.00      0
975 -0.034412  0.545794 -0.839016  0.040610  0.018029    59.90      0
976  0.101930  0.718241 -0.357059 -0.001664  0.078659     0.76      0
977  0.522385  1.049123  0.872576 -0.046526  0.081082     0.76      0
978 -0.545857  0.253408 -0.567055  0.064468  0.027141    12.32      0
979  0.631436 -0.284440 -0.118500  0.401493  0.185501    20.80      0
980  0.468261  0.074170  0.924785 -0.065359  0.043538   176.42      0
981 -0.735988 -0.324900  0.418468 -0.177558 -0.104505     0.76      0
982  0.689492 -0.154773  0.106330  0.032736 -0.035525    22.66      0
983 -0.503598 -0.355496  0.497140 -0.499752 -0.388871    27.31      0

[984 rows x 31 columns]
```

```
data['Class'].value_counts()
```

```
1    492
0    492
Name: Class, dtype: int64
```

```
X = data.drop('Class', axis = 1)
y = data['Class']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size =
0.2, random_state = 0, stratify = y)

X_train.shape, X_test.shape
```

```
((787, 30), (197, 30))
```

```
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

y_train = y_train.to_numpy()
y_test = y_test.to_numpy()

X_train.shape
```

```
(787, 30)
```

```
X_train = X_train.reshape(X_train.shape[0], X_train.shape[1], 1)
X_test = X_test.reshape(X_test.shape[0], X_test.shape[1], 1)

X_train.shape, X_test.shape
```

```
((787, 30, 1), (197, 30, 1))
```

Build CNN

```
epochs = 20
model = Sequential()
model.add(Conv1D(32, 2, activation='relu', input_shape =
X_train[0].shape))
model.add(BatchNormalization())
model.add(Dropout(0.2))

model.add(Conv1D(64, 2, activation='relu'))
model.add(BatchNormalization())
model.add(Dropout(0.5))

model.add(Flatten())
model.add(Dense(64, activation='relu'))
model.add(Dropout(0.5))

model.add(Dense(1, activation='sigmoid'))

model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv1d (Conv1D)              (None, 29, 32)            96
_________________________________________________________________
batch_normalization (BatchNo (None, 29, 32)            128
_________________________________________________________________
dropout (Dropout)            (None, 29, 32)            0
_________________________________________________________________
conv1d_1 (Conv1D)            (None, 28, 64)            4160
_________________________________________________________________
```

```
batch_normalization_1 (Batch (None, 28, 64)            256
_________________________________________________________________
dropout_1 (Dropout)          (None, 28, 64)            0
_________________________________________________________________
flatten (Flatten)            (None, 1792)              0
_________________________________________________________________
dense (Dense)                (None, 64)                114752
_________________________________________________________________
dropout_2 (Dropout)          (None, 64)                0
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 65
=================================================================
Total params: 119,457
Trainable params: 119,265
Non-trainable params: 192
_________________________________________________________________
```

```
model.compile(optimizer=Adam(lr=0.0001), loss = 'binary_crossentropy',
metrics=['accuracy'])
```

```
history = model.fit(X_train, y_train, epochs=epochs,
validation_data=(X_test, y_test), verbose=1)
```

```
WARNING: Logging before flag parsing goes to stderr.
W0904 18:49:33.834567  8812 deprecation.py:323] From C:\ProgramData\
Anaconda3\lib\site-packages\tensorflow_core\python\ops\nn_impl.py:183:
where (from tensorflow.python.ops.array_ops) is deprecated and will be
removed in a future version.
Instructions for updating:
Use tf.where in 2.0, which has the same broadcast rule as np.where

Train on 787 samples, validate on 197 samples
Epoch 1/20
787/787 [==============================] - 2s 2ms/sample - loss:
0.7682 - accuracy: 0.6633 - val_loss: 0.6181 - val_accuracy: 0.8782
Epoch 2/20
787/787 [==============================] - 0s 243us/sample - loss:
0.4962 - accuracy: 0.8145 - val_loss: 0.5716 - val_accuracy: 0.8934
Epoch 3/20
787/787 [==============================] - 0s 250us/sample - loss:
0.4026 - accuracy: 0.8628 - val_loss: 0.5365 - val_accuracy: 0.9137
Epoch 4/20
787/787 [==============================] - 0s 244us/sample - loss:
0.3464 - accuracy: 0.8742 - val_loss: 0.5008 - val_accuracy: 0.9137
Epoch 5/20
787/787 [==============================] - 0s 239us/sample - loss:
0.3336 - accuracy: 0.8691 - val_loss: 0.4857 - val_accuracy: 0.9137
Epoch 6/20
787/787 [==============================] - 0s 227us/sample - loss:
0.2994 - accuracy: 0.8920 - val_loss: 0.4685 - val_accuracy: 0.8173
```

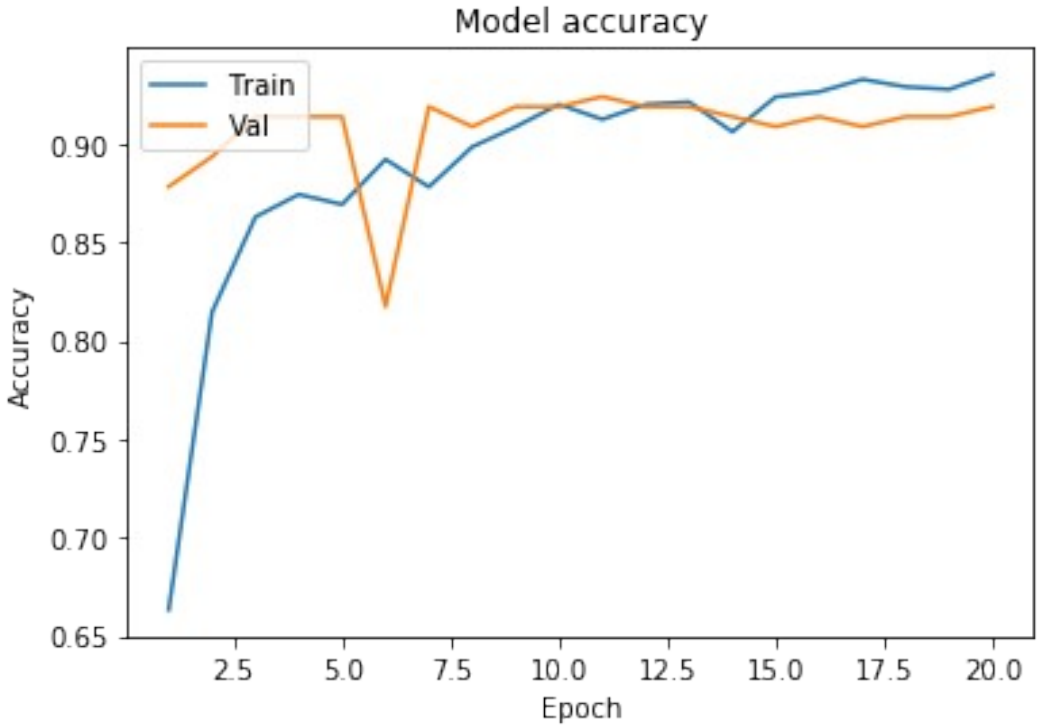
```
Epoch 7/20
787/787 [==============================] - 0s 250us/sample - loss:
0.3255 - accuracy: 0.8780 - val_loss: 0.4145 - val_accuracy: 0.9188
Epoch 8/20
787/787 [==============================] - 0s 230us/sample - loss:
0.2744 - accuracy: 0.8983 - val_loss: 0.3900 - val_accuracy: 0.9086
Epoch 9/20
787/787 [==============================] - 0s 267us/sample - loss:
0.2540 - accuracy: 0.9085 - val_loss: 0.3458 - val_accuracy: 0.9188
Epoch 10/20
787/787 [==============================] - 0s 264us/sample - loss:
0.2330 - accuracy: 0.9199 - val_loss: 0.3180 - val_accuracy: 0.9188
Epoch 11/20
787/787 [==============================] - 0s 226us/sample - loss:
0.2405 - accuracy: 0.9123 - val_loss: 0.2908 - val_accuracy: 0.9239
Epoch 12/20
787/787 [==============================] - 0s 231us/sample - loss:
0.2241 - accuracy: 0.9199 - val_loss: 0.2639 - val_accuracy: 0.9188
Epoch 13/20
787/787 [==============================] - 0s 229us/sample - loss:
0.2288 - accuracy: 0.9212 - val_loss: 0.2350 - val_accuracy: 0.9188
Epoch 14/20
787/787 [==============================] - 0s 249us/sample - loss:
0.2457 - accuracy: 0.9060 - val_loss: 0.2236 - val_accuracy: 0.9137
Epoch 15/20
787/787 [==============================] - 0s 273us/sample - loss:
0.2084 - accuracy: 0.9238 - val_loss: 0.2141 - val_accuracy: 0.9086
Epoch 16/20
787/787 [==============================] - 0s 268us/sample - loss:
0.2096 - accuracy: 0.9263 - val_loss: 0.2050 - val_accuracy: 0.9137
Epoch 17/20
787/787 [==============================] - 0s 257us/sample - loss:
0.1976 - accuracy: 0.9327 - val_loss: 0.2014 - val_accuracy: 0.9086
Epoch 18/20
787/787 [==============================] - 0s 262us/sample - loss:
0.2219 - accuracy: 0.9288 - val_loss: 0.1957 - val_accuracy: 0.9137
Epoch 19/20
787/787 [==============================] - 0s 257us/sample - loss:
0.1945 - accuracy: 0.9276 - val_loss: 0.1937 - val_accuracy: 0.9137
Epoch 20/20
787/787 [==============================] - 0s 259us/sample - loss:
0.1750 - accuracy: 0.9352 - val_loss: 0.1904 - val_accuracy: 0.9188
```

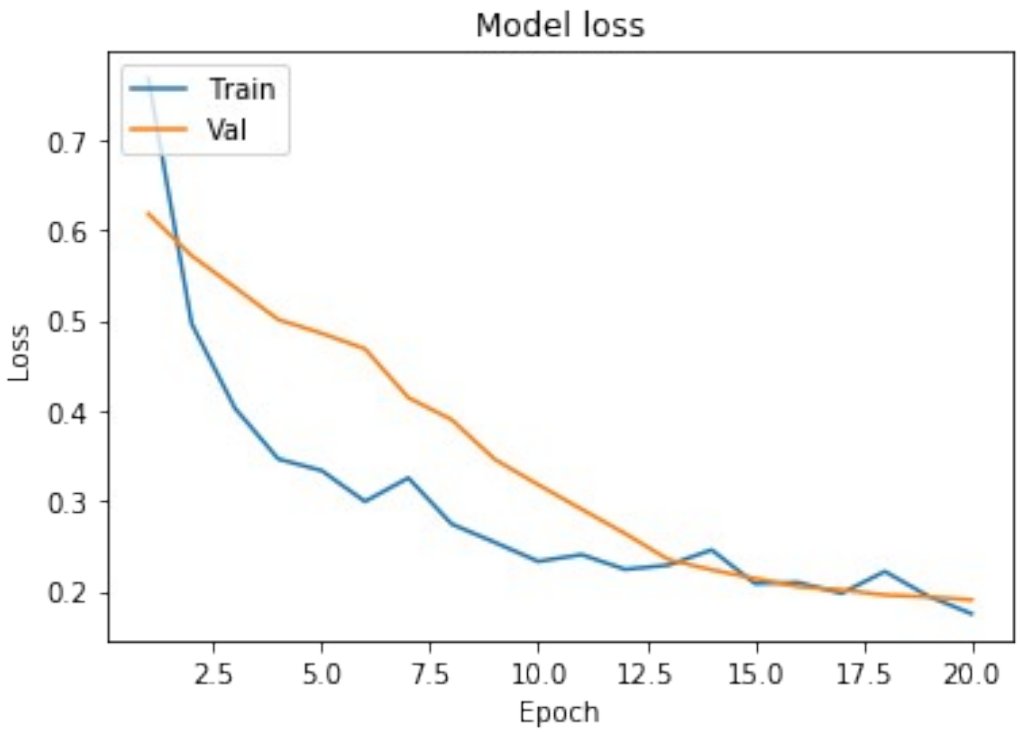
```
def plot_learningCurve(history, epoch):
  # Plot training & validation accuracy values
  epoch_range = range(1, epoch+1)
  plt.plot(epoch_range, history.history['accuracy'])
  plt.plot(epoch_range, history.history['val_accuracy'])
  plt.title('Model accuracy')
  plt.ylabel('Accuracy')
```

```
  plt.xlabel('Epoch')
  plt.legend(['Train', 'Val'], loc='upper left')
  plt.show()

  # Plot training & validation loss values
  plt.plot(epoch_range, history.history['loss'])
  plt.plot(epoch_range, history.history['val_loss'])
  plt.title('Model loss')
  plt.ylabel('Loss')
  plt.xlabel('Epoch')
  plt.legend(['Train', 'Val'], loc='upper left')
  plt.show()

plot_learningCurve(history, epochs)
```





Adding MaxPool

```
epochs = 50
model = Sequential()
model.add(Conv1D(32, 2, activation='relu', input_shape =
X_train[0].shape))
model.add(BatchNormalization())
model.add(MaxPool1D(2))
model.add(Dropout(0.2))

model.add(Conv1D(64, 2, activation='relu'))
model.add(BatchNormalization())
model.add(MaxPool1D(2))
model.add(Dropout(0.5))

model.add(Flatten())
model.add(Dense(64, activation='relu'))
model.add(Dropout(0.5))

model.add(Dense(1, activation='sigmoid'))

model.compile(optimizer=Adam(lr=0.0001), loss = 'binary_crossentropy',
metrics=['accuracy'])
history = model.fit(X_train, y_train, epochs=epochs,
```

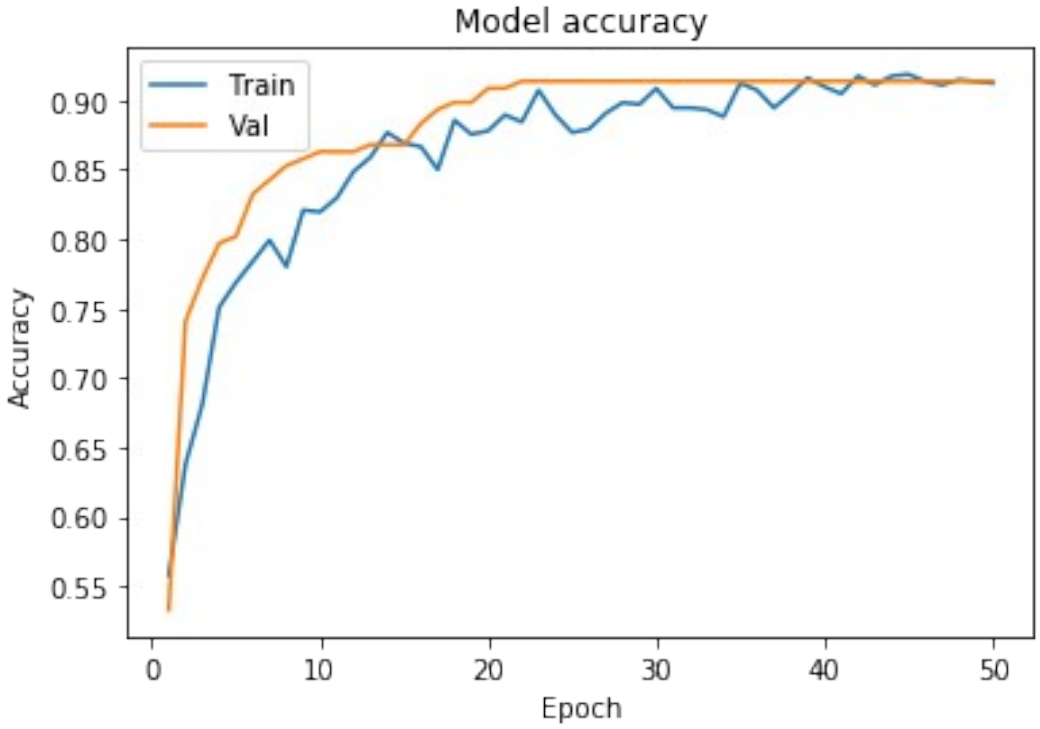
```
validation_data=(X_test, y_test), verbose=1)
plot_learningCurve(history, epochs)
```

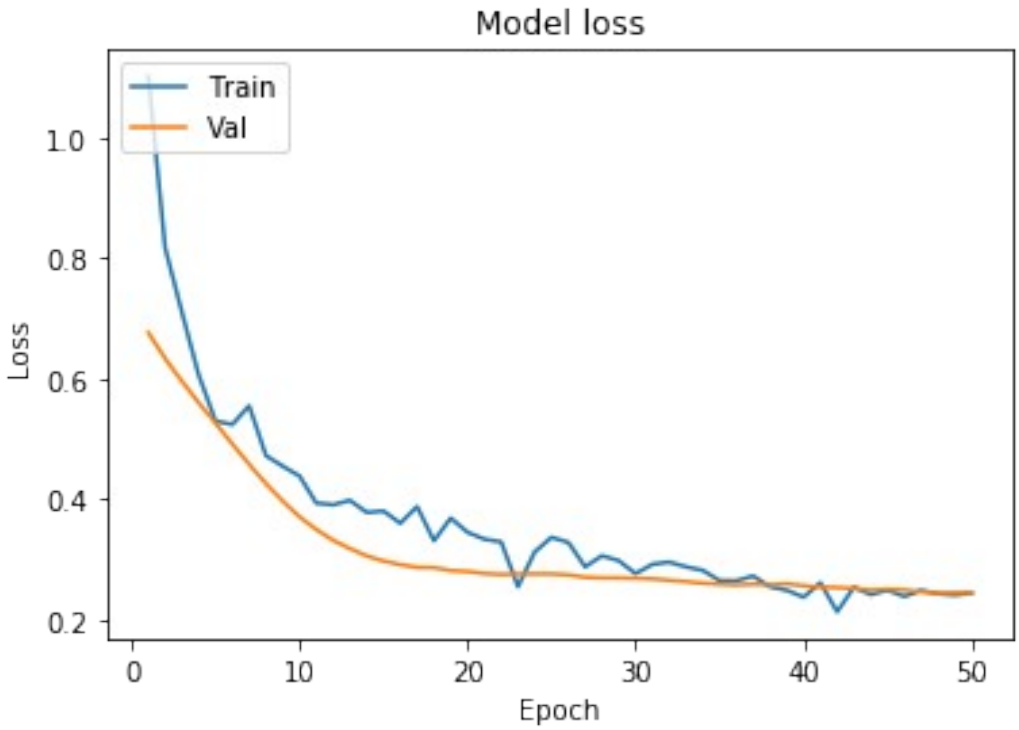
```
Train on 787 samples, validate on 197 samples
Epoch 1/50
787/787 [==============================] - 2s 2ms/sample - loss:
1.1020 - accuracy: 0.5578 - val_loss: 0.6766 - val_accuracy: 0.5330
Epoch 2/50
787/787 [==============================] - 0s 203us/sample - loss:
0.8175 - accuracy: 0.6379 - val_loss: 0.6338 - val_accuracy: 0.7411
Epoch 3/50
787/787 [==============================] - 0s 196us/sample - loss:
0.7102 - accuracy: 0.6811 - val_loss: 0.5959 - val_accuracy: 0.7716
Epoch 4/50
787/787 [==============================] - 0s 196us/sample - loss:
0.6062 - accuracy: 0.7510 - val_loss: 0.5602 - val_accuracy: 0.7970
Epoch 5/50
787/787 [==============================] - 0s 197us/sample - loss:
0.5300 - accuracy: 0.7687 - val_loss: 0.5268 - val_accuracy: 0.8020
Epoch 6/50
787/787 [==============================] - 0s 204us/sample - loss:
0.5243 - accuracy: 0.7840 - val_loss: 0.4918 - val_accuracy: 0.8325
Epoch 7/50
787/787 [==============================] - 0s 217us/sample - loss:
0.5553 - accuracy: 0.7992 - val_loss: 0.4584 - val_accuracy: 0.8426
Epoch 8/50
787/787 [==============================] - 0s 216us/sample - loss:
0.4727 - accuracy: 0.7802 - val_loss: 0.4261 - val_accuracy: 0.8528
Epoch 9/50
787/787 [==============================] - 0s 222us/sample - loss:
0.4551 - accuracy: 0.8208 - val_loss: 0.3972 - val_accuracy: 0.8579
Epoch 10/50
787/787 [==============================] - 0s 216us/sample - loss:
0.4387 - accuracy: 0.8196 - val_loss: 0.3710 - val_accuracy: 0.8629
Epoch 11/50
787/787 [==============================] - 0s 194us/sample - loss:
0.3938 - accuracy: 0.8297 - val_loss: 0.3500 - val_accuracy: 0.8629
Epoch 12/50
787/787 [==============================] - 0s 194us/sample - loss:
0.3911 - accuracy: 0.8488 - val_loss: 0.3322 - val_accuracy: 0.8629
Epoch 13/50
787/787 [==============================] - 0s 201us/sample - loss:
0.3984 - accuracy: 0.8590 - val_loss: 0.3183 - val_accuracy: 0.8680
Epoch 14/50
787/787 [==============================] - 0s 216us/sample - loss:
0.3784 - accuracy: 0.8767 - val_loss: 0.3063 - val_accuracy: 0.8680
Epoch 15/50
787/787 [==============================] - 0s 203us/sample - loss:
0.3806 - accuracy: 0.8691 - val_loss: 0.2976 - val_accuracy: 0.8680
Epoch 16/50
```

```
787/787 [==============================] - 0s 223us/sample - loss:
0.3605 - accuracy: 0.8666 - val_loss: 0.2918 - val_accuracy: 0.8832
Epoch 17/50
787/787 [==============================] - 0s 210us/sample - loss:
0.3881 - accuracy: 0.8501 - val_loss: 0.2870 - val_accuracy: 0.8934
Epoch 18/50
787/787 [==============================] - 0s 196us/sample - loss:
0.3314 - accuracy: 0.8856 - val_loss: 0.2868 - val_accuracy: 0.8985
Epoch 19/50
787/787 [==============================] - 0s 190us/sample - loss:
0.3690 - accuracy: 0.8755 - val_loss: 0.2820 - val_accuracy: 0.8985
Epoch 20/50
787/787 [==============================] - 0s 194us/sample - loss:
0.3454 - accuracy: 0.8780 - val_loss: 0.2805 - val_accuracy: 0.9086
Epoch 21/50
787/787 [==============================] - 0s 221us/sample - loss:
0.3340 - accuracy: 0.8895 - val_loss: 0.2770 - val_accuracy: 0.9086
Epoch 22/50
787/787 [==============================] - 0s 221us/sample - loss:
0.3296 - accuracy: 0.8844 - val_loss: 0.2755 - val_accuracy: 0.9137
Epoch 23/50
787/787 [==============================] - 0s 199us/sample - loss:
0.2552 - accuracy: 0.9072 - val_loss: 0.2762 - val_accuracy: 0.9137
Epoch 24/50
787/787 [==============================] - 0s 204us/sample - loss:
0.3131 - accuracy: 0.8895 - val_loss: 0.2765 - val_accuracy: 0.9137
Epoch 25/50
787/787 [==============================] - 0s 213us/sample - loss:
0.3371 - accuracy: 0.8767 - val_loss: 0.2763 - val_accuracy: 0.9137
Epoch 26/50
787/787 [==============================] - 0s 202us/sample - loss:
0.3286 - accuracy: 0.8793 - val_loss: 0.2748 - val_accuracy: 0.9137
Epoch 27/50
787/787 [==============================] - 0s 204us/sample - loss:
0.2882 - accuracy: 0.8907 - val_loss: 0.2708 - val_accuracy: 0.9137
Epoch 28/50
787/787 [==============================] - 0s 221us/sample - loss:
0.3065 - accuracy: 0.8983 - val_loss: 0.2697 - val_accuracy: 0.9137
Epoch 29/50
787/787 [==============================] - 0s 201us/sample - loss:
0.2984 - accuracy: 0.8971 - val_loss: 0.2696 - val_accuracy: 0.9137
Epoch 30/50
787/787 [==============================] - 0s 231us/sample - loss:
0.2769 - accuracy: 0.9085 - val_loss: 0.2691 - val_accuracy: 0.9137
Epoch 31/50
787/787 [==============================] - 0s 258us/sample - loss:
0.2923 - accuracy: 0.8945 - val_loss: 0.2683 - val_accuracy: 0.9137
Epoch 32/50
787/787 [==============================] - 0s 241us/sample - loss:
```

```
0.2961 - accuracy: 0.8945 - val_loss: 0.2658 - val_accuracy: 0.9137
Epoch 33/50
787/787 [==============================] - 0s 227us/sample - loss:
0.2881 - accuracy: 0.8933 - val_loss: 0.2636 - val_accuracy: 0.9137
Epoch 34/50
787/787 [==============================] - 0s 222us/sample - loss:
0.2823 - accuracy: 0.8882 - val_loss: 0.2611 - val_accuracy: 0.9137
Epoch 35/50
787/787 [==============================] - 0s 244us/sample - loss:
0.2652 - accuracy: 0.9123 - val_loss: 0.2592 - val_accuracy: 0.9137
Epoch 36/50
787/787 [==============================] - 0s 249us/sample - loss:
0.2650 - accuracy: 0.9072 - val_loss: 0.2581 - val_accuracy: 0.9137
Epoch 37/50
787/787 [==============================] - 0s 211us/sample - loss:
0.2729 - accuracy: 0.8945 - val_loss: 0.2594 - val_accuracy: 0.9137
Epoch 38/50
787/787 [==============================] - 0s 198us/sample - loss:
0.2550 - accuracy: 0.9047 - val_loss: 0.2584 - val_accuracy: 0.9137
Epoch 39/50
787/787 [==============================] - 0s 190us/sample - loss:
0.2493 - accuracy: 0.9161 - val_loss: 0.2599 - val_accuracy: 0.9137
Epoch 40/50
787/787 [==============================] - 0s 188us/sample - loss:
0.2378 - accuracy: 0.9098 - val_loss: 0.2568 - val_accuracy: 0.9137
Epoch 41/50
787/787 [==============================] - 0s 207us/sample - loss:
0.2616 - accuracy: 0.9047 - val_loss: 0.2544 - val_accuracy: 0.9137
Epoch 42/50
787/787 [==============================] - 0s 213us/sample - loss:
0.2136 - accuracy: 0.9174 - val_loss: 0.2537 - val_accuracy: 0.9137
Epoch 43/50
787/787 [==============================] - 0s 194us/sample - loss:
0.2545 - accuracy: 0.9111 - val_loss: 0.2522 - val_accuracy: 0.9137
Epoch 44/50
787/787 [==============================] - 0s 223us/sample - loss:
0.2420 - accuracy: 0.9174 - val_loss: 0.2494 - val_accuracy: 0.9137
Epoch 45/50
787/787 [==============================] - 0s 211us/sample - loss:
0.2494 - accuracy: 0.9187 - val_loss: 0.2509 - val_accuracy: 0.9137
Epoch 46/50
787/787 [==============================] - 0s 212us/sample - loss:
0.2390 - accuracy: 0.9136 - val_loss: 0.2498 - val_accuracy: 0.9137
Epoch 47/50
787/787 [==============================] - 0s 225us/sample - loss:
0.2490 - accuracy: 0.9111 - val_loss: 0.2466 - val_accuracy: 0.9137
Epoch 48/50
787/787 [==============================] - 0s 210us/sample - loss:
0.2435 - accuracy: 0.9149 - val_loss: 0.2443 - val_accuracy: 0.9137
```

```
Epoch 49/50
787/787 [==============================] - 0s 192us/sample - loss:
0.2413 - accuracy: 0.9136 - val_loss: 0.2453 - val_accuracy: 0.9137
Epoch 50/50
787/787 [==============================] - 0s 194us/sample - loss:
0.2445 - accuracy: 0.9123 - val_loss: 0.2449 - val_accuracy: 0.9137
```




Model loss
Train
Val
Loss
1.0
0.8
0.6
0.4
0.2
0
10
20
30
40
50
Epoch