Credit Card Fraud Detection using CNN

```
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
_________________________________________________________________
```

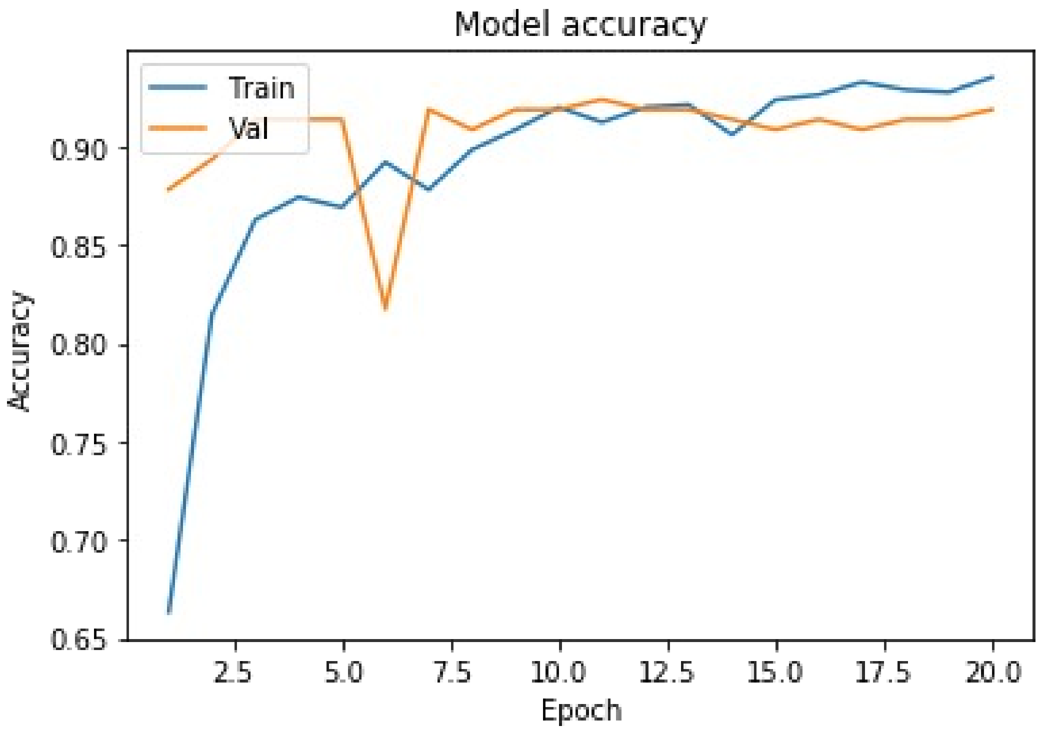
```
model.compile(optimizer=Adam(lr=0.0001), loss = 'binary_crossentropy',
metrics=['accuracy'])
```

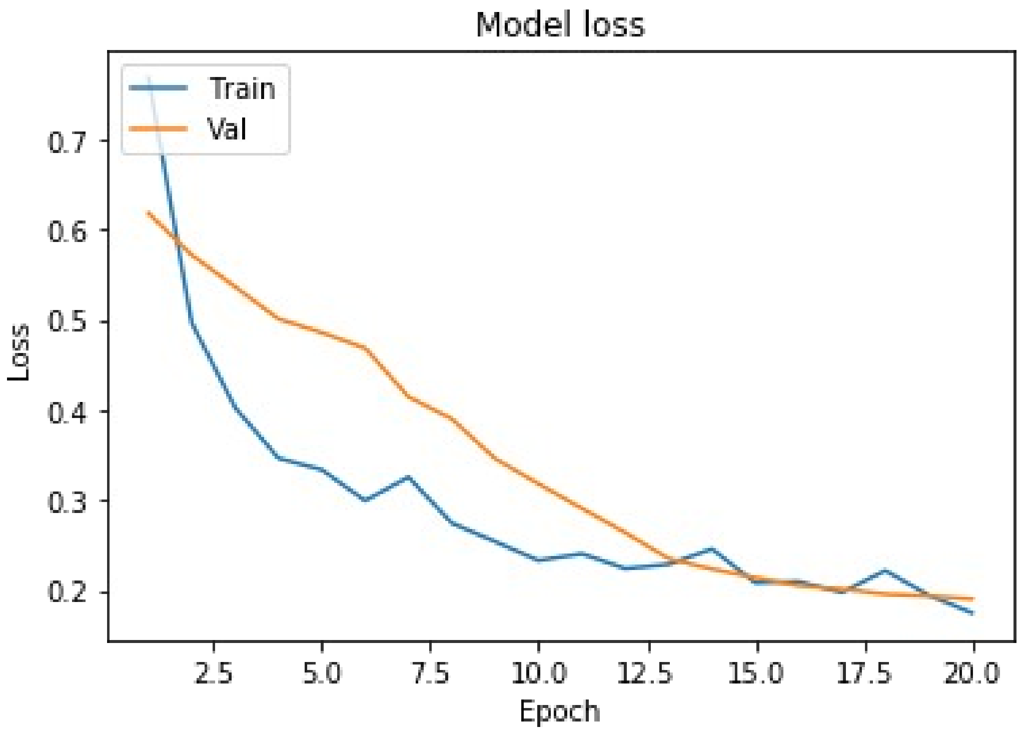
```
history = model.fit(X_train, y_train, epochs=epochs,
validation_data=(X_test, y_test), verbose=1)
```

```
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,
```

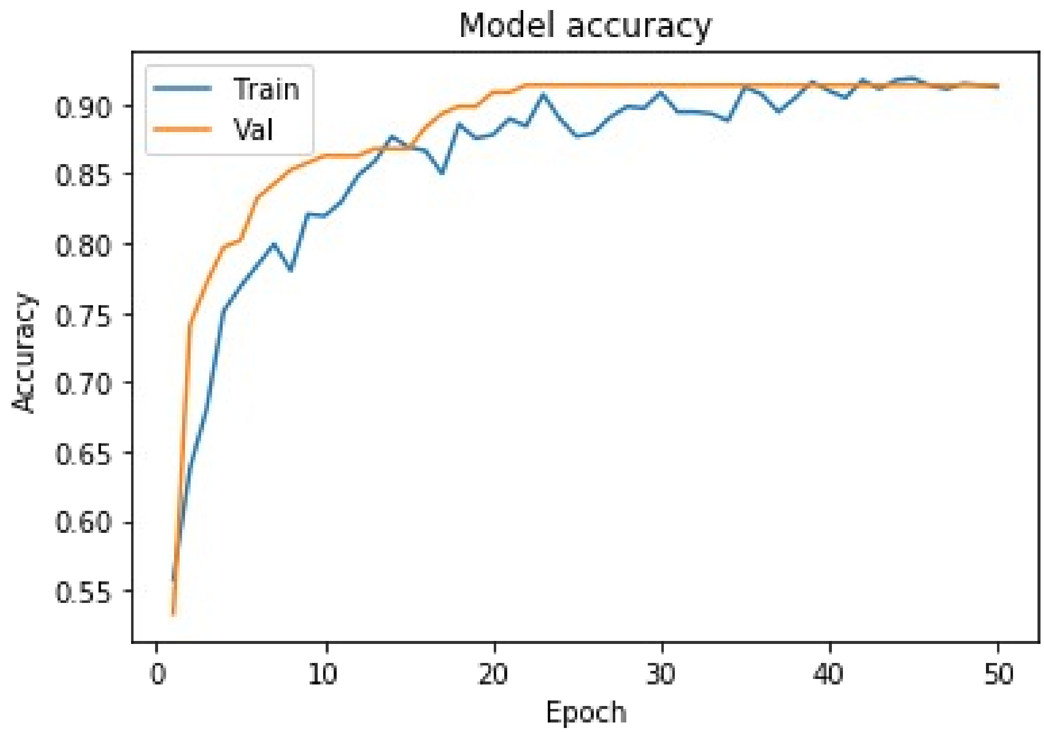
```
validation_data=(X_test, y_test), verbose=1)
plot_learningCurve(history, epochs)
```

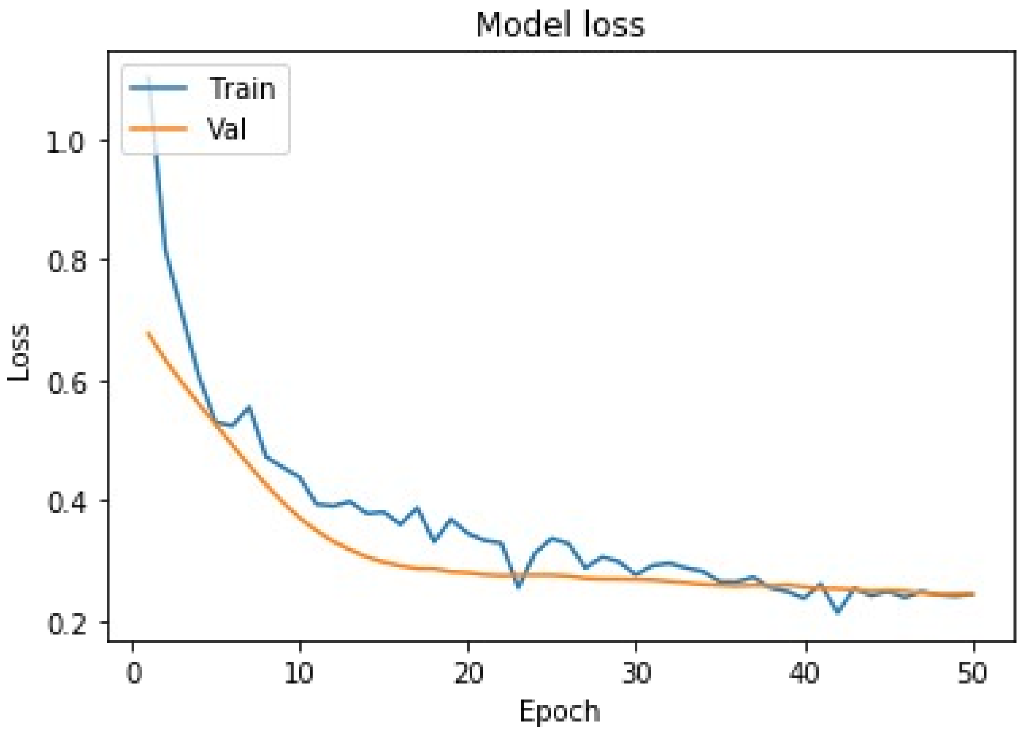
```
Train on 787 samples, validate on 197 samples
Epoch 1/50
787/787 [==============================] - 2s 2ms/sample - loss:
1.1020 - accuracy: 0.5578 - val_loss: 0.6766 - val_accuracy: 0.5330
Epoch 2/50
787/787 [==============================] - 0s 203us/sample - loss:
0.8175 - accuracy: 0.6379 - val_loss: 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