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PROJECT-Lending Club Loan Data Analysis

OBJECTIVE-

For companies like Lending Club correctly predicting whether or not a loan will be a default is very important. In this project, using the historical data from 2007 to 2015, you have to build a deep learning model to predict the chance of default for future loans.

In [1]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")
```

In [2]:
```python
df=pd.read_csv("loan_data.csv")
df.head()
```

Out[2]:

	credit.policy	purpose	int.rate	installment	log.annual.inc	dti	fico	days.with.cr.line	revol.bal	revol.util	inq.last.6mths	delinq.2yrs	pub.rec	not.fully.paid
0	1	debt_consolidation	0.1189	829.10	11.350407	19.48	737	5639.958333	28854	52.1	0	0	0	0
1	1	credit_card	0.1071	228.22	11.082143	14.29	707	2760.000000	33623	76.7	0	0	0	0
2	1	debt_consolidation	0.1357	366.86	10.373491	11.63	682	4710.000000	3511	25.6	1	0	0	0
3	1	debt_consolidation	0.1008	162.34	11.350407	8.10	712	2699.958333	33667	73.2	1	0	0	0
4	1	credit_card	0.1426	102.92	11.299732	14.97	667	4066.000000	4740	39.5	0	1	0	0

In [3]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9578 entries, 0 to 9577
Data columns (total 14 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   credit.policy      9578 non-null   int64  
 1   purpose            9578 non-null   object 
 2   int.rate           9578 non-null   float64
 3   installment        9578 non-null   float64
 4   log.annual.inc     9578 non-null   float64
 5   dti                9578 non-null   float64
 6   fico               9578 non-null   int64  
 7   days.with.cr.line  9578 non-null   float64
 8   revol.bal          9578 non-null   int64  
 9   revol.util         9578 non-null   float64
 10  inq.last.6mths     9578 non-null   int64  
 11  delinq.2yrs        9578 non-null   int64  
 12  pub.rec            9578 non-null   int64  
 13  not.fully.paid     9578 non-null   int64  
dtypes: float64(6), int64(7), object(1)
memory usage: 1.0+ MB
```

In [4]:
```python
df.describe()
```

Out[4]:

	credit.policy	int.rate	installment	log.annual.inc	dti	fico	days.with.cr.line	revol.bal	revol.util	inq.last.6mths	delinq.2yrs	pub.rec	not.fully.paid
count	9578.000000	9578.000000	9578.000000	9578.000000	9578.000000	9578.000000	9578.000000	9.578000e+03	9578.000000	9578.000000	9578.000000	9578.000000	9578.000000
mean	0.804970	0.122640	319.089413	10.932117	12.606679	710.846314	4560.767197	1.691396e+04	46.799236	1.577469	0.163708	0.062122	0.160054
std	0.396245	0.026847	207.071301	0.614813	6.883970	37.970537	2496.930377	3.375619e+04	29.014417	2.200245	0.546215	0.262126	0.366676
min	0.000000	0.060000	15.670000	7.547502	0.000000	612.000000	178.958333	0.000000e+00	0.000000	0.000000	0.000000	0.000000	0.000000
25%	1.000000	0.103900	163.770000	10.558414	7.212500	682.000000	2820.000000	3.187000e+03	22.600000	0.000000	0.000000	0.000000	0.000000
50%	1.000000	0.122100	268.950000	10.928884	12.665000	707.000000	4139.958333	8.596000e+03	46.300000	1.000000	0.000000	0.000000	0.000000
75%	1.000000	0.140700	432.762500	11.291293	17.950000	737.000000	5730.000000	1.824950e+04	70.900000	2.000000	0.000000	0.000000	0.000000
max	1.000000	0.216400	940.140000	14.528354	29.960000	827.000000	17639.958330	1.207359e+06	119.000000	33.000000	13.000000	5.000000	1.000000

In [5]:
```python
df.isna().sum()
```

Out[5]:
```
credit.policy        0
purpose              0
int.rate             0
installment          0
log.annual.inc       0
dti                  0
fico                 0
days.with.cr.line    0
revol.bal            0
revol.util           0
inq.last.6mths       0
delinq.2yrs          0
pub.rec              0
not.fully.paid       0
dtype: int64
```

In [6]:
```python
df["purpose"].unique()
```

Out[6]:
```
array(['debt_consolidation', 'credit_card', 'all_other',
       'home_improvement', 'small_business', 'major_purchase',
       'educational'], dtype=object)
```

In [7]:
```python
from sklearn.preprocessing import LabelEncoder
```

In [8]:
```python
le=LabelEncoder()
df["purpose"]=le.fit_transform(df["purpose"])
df.head()
```

Out[8]:

	credit.policy	purpose	int.rate	installment	log.annual.inc	dti	fico	days.with.cr.line	revol.bal	revol.util	inq.last.6mths	delinq.2yrs	pub.rec	not.fully.paid
0	1	2	0.1189	829.10	11.350407	19.48	737	5639.958333	28854	52.1	0	0	0	0
1	1	1	0.1071	228.22	11.082143	14.29	707	2760.000000	33623	76.7	0	0	0	0
2	1	2	0.1357	366.86	10.373491	11.63	682	4710.000000	3511	25.6	1	0	0	0
3	1	2	0.1008	162.34	11.350407	8.10	712	2699.958333	33667	73.2	1	0	0	0
4	1	1	0.1426	102.92	11.299732	14.97	667	4066.000000	4740	39.5	0	1	0	0

In [9]:
```python
#Drop duplicated values
df=df.drop_duplicates()
df.head()
```

Out[9]:

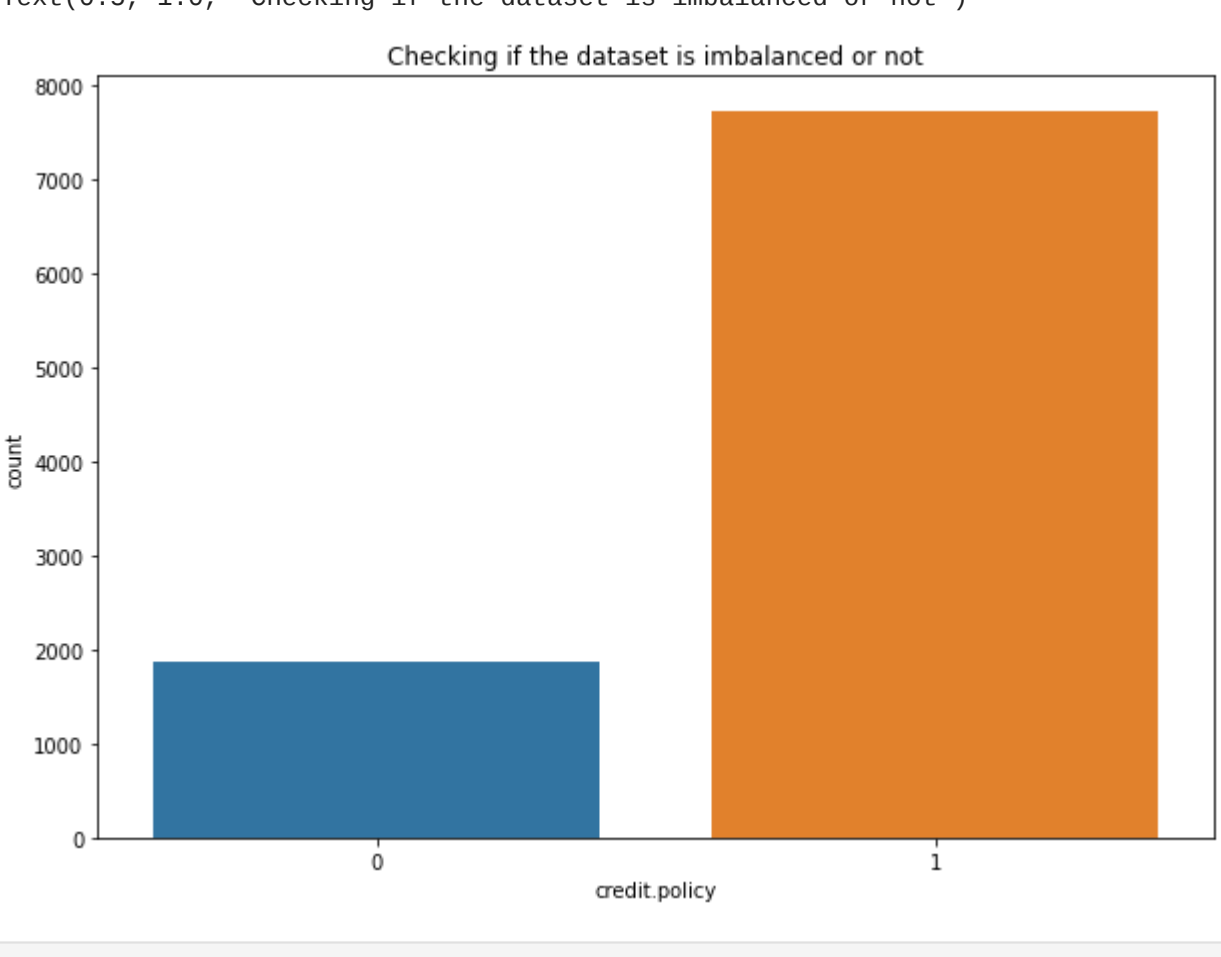
	credit.policy	purpose	int.rate	installment	log.annual.inc	dti	fico	days.with.cr.line	revol.bal	revol.util	inq.last.6mths	delinq.2yrs	pub.rec	not.fully.paid
0	1	2	0.1189	829.10	11.350407	19.48	737	5639.958333	28854	52.1	0	0	0	0
1	1	1	0.1071	228.22	11.082143	14.29	707	2760.000000	33623	76.7	0	0	0	0
2	1	2	0.1357	366.86	10.373491	11.63	682	4710.000000	3511	25.6	1	0	0	0
3	1	2	0.1008	162.34	11.350407	8.10	712	2699.958333	33667	73.2	1	0	0	0
4	1	1	0.1426	102.92	11.299732	14.97	667	4066.000000	4740	39.5	0	1	0	0

In [10]:
```python
df["credit.policy"].value_counts()
```

Out[10]:
```
1    7710
0    1868
Name: credit.policy, dtype: int64
```

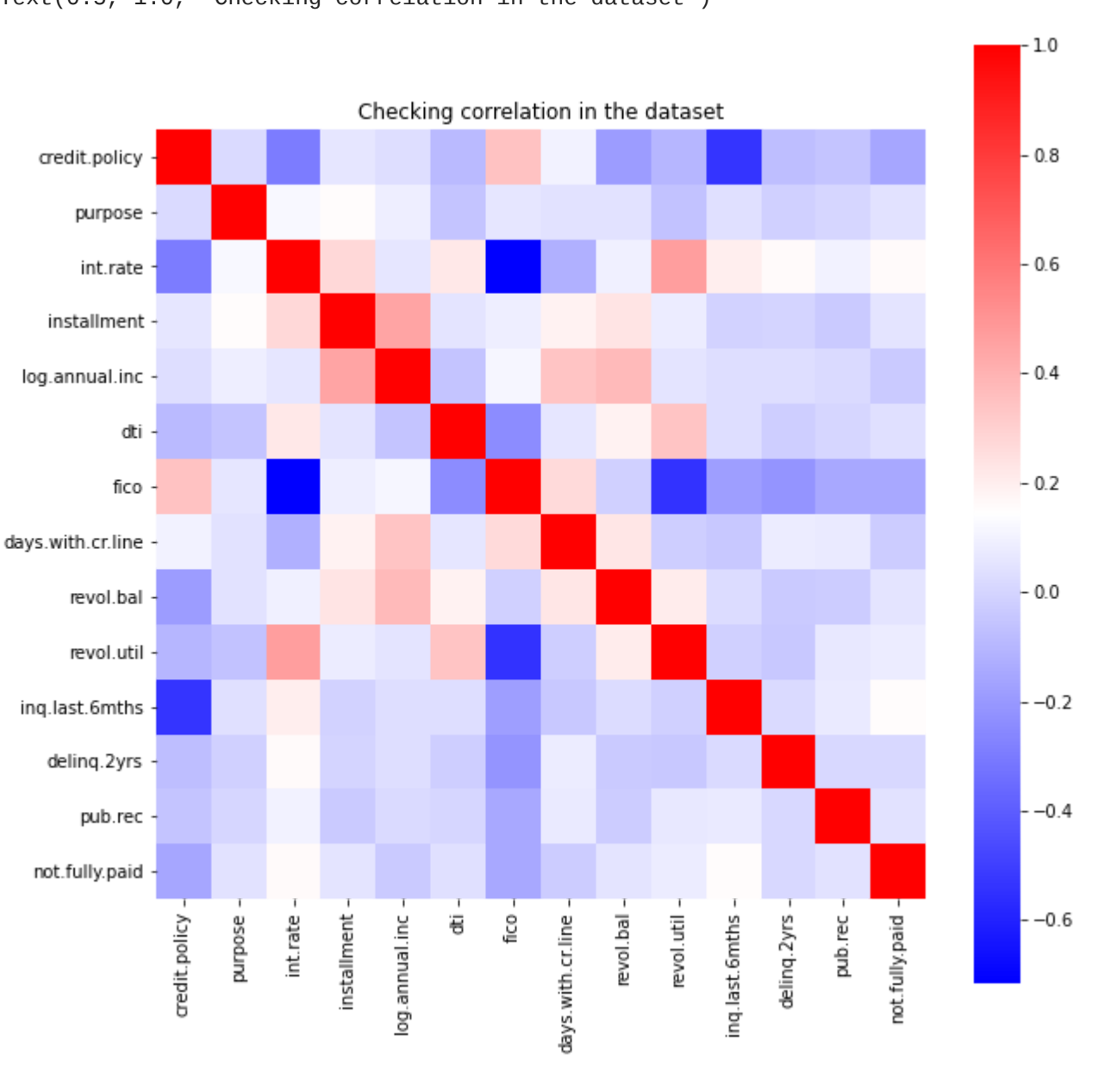
In [11]:
```python
plt.figure(figsize=(10,7))
sns.countplot(df["credit.policy"])
plt.title("Checking if the dataset is imbalanced or not")
```

Out[11]:
```
Text(0.5, 1.0, 'Checking if the dataset is imbalanced or not')
```



In [12]:
```python
plt.figure(figsize=(10,10))
sns.heatmap(data=df.corr(),cmap="bwr",square=True)
plt.title("Checking correlation in the dataset")
```

Out[12]:
```
Text(0.5, 1.0, 'Checking correlation in the dataset')
```



Since,no features have strong correlation.so, all the features are highly relevent and consider for model.

In [13]:
```python
df.head()
```

Out[13]:

	credit.policy	purpose	int.rate	installment	log.annual.inc	dti	fico	days.with.cr.line	revol.bal	revol.util	inq.last.6mths	delinq.2yrs	pub.rec	not.fully.paid
0	1	2	0.1189	829.10	11.350407	19.48	737	5639.958333	28854	52.1	0	0	0	0
1	1	1	0.1071	228.22	11.082143	14.29	707	2760.000000	33623	76.7	0	0	0	0
2	1	2	0.1357	366.86	10.373491	11.63	682	4710.000000	3511	25.6	1	0	0	0
3	1	2	0.1008	162.34	11.350407	8.10	712	2699.958333	33667	73.2	1	0	0	0
4	1	1	0.1426	102.92	11.299732	14.97	667	4066.000000	4740	39.5	0	1	0	0

In [14]:
```python
from sklearn.model_selection import train_test_split
```

In [15]:
```python
x=df.drop("credit.policy",axis=1)
y=df[["credit.policy"]]
```

In [16]:
```python
x.head()
```

Out[16]:

	purpose	int.rate	installment	log.annual.inc	dti	fico	days.with.cr.line	revol.bal	revol.util	inq.last.6mths	delinq.2yrs	pub.rec	not.fully.paid
0	2	0.1189	829.10	11.350407	19.48	737	5639.958333	28854	52.1	0	0	0	0
1	1	0.1071	228.22	11.082143	14.29	707	2760.000000	33623	76.7	0	0	0	0
2	2	0.1357	366.86	10.373491	11.63	682	4710.000000	3511	25.6	1	0	0	0
3	2	0.1008	162.34	11.350407	8.10	712	2699.958333	33667	73.2	1	0	0	0
4	1	0.1426	102.92	11.299732	14.97	667	4066.000000	4740	39.5	0	1	0	0

In [17]:
```python
y.head()
```

Out[17]:

	credit.policy
0	1
1	1
2	1
3	1
4	1

In [18]:
```python
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.25,random_state=25)
```

In [19]:
```python
x_train.shape,x_test.shape
```

Out[19]:
```
((7183, 13), (2395, 13))
```

In [20]:
```python
y_train.shape,y_test.shape
```

Out[20]:
```
((7183, 1), (2395, 1))
```

In [21]:
```python
from sklearn.preprocessing import StandardScaler
```

In [22]:
```python
scaler=StandardScaler()
x_train=scaler.fit_transform(x_train)
x_test=scaler.transform(x_test)
```

Architect the model

In [23]:
```python
import tensorflow
```

In [24]:
```python
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
```

In [25]:
```python
x_train.shape[1],
```

Out[25]:
```
(13,)
```

In [26]:
```python
model=Sequential()
model.add(Dense(64,activation="relu",input_shape=(x_train.shape[1],)))
model.add(Dense(32,activation="relu"))
model.add(Dense(16,activation="relu"))
model.add(Dense(1,activation="sigmoid"))
```

In [27]:
```python
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 dense (Dense)               (None, 64)                896       
                                                                 
 dense_1 (Dense)             (None, 32)                2080      
                                                                 
 dense_2 (Dense)             (None, 16)                528       
                                                                 
 dense_3 (Dense)             (None, 1)                 17        
                                                                 
=================================================================
Total params: 3,521
Trainable params: 3,521
Non-trainable params: 0
_________________________________________________________________
```

In [28]:
```python
model.compile(optimizer="adam",loss="binary_crossentropy",metrics=["accuracy"])
```

In [29]:
```python
result=model.fit(x_train,y_train,validation_data=(x_test,y_test),epochs=100)
result
```

```
Epoch 1/100
225/225 [==============================] - 1s 3ms/step - loss: 0.3691 - accuracy: 0.8412 - val_loss: 0.2719 - val_accuracy: 0.8935
Epoch 2/100
225/225 [==============================] - 0s 2ms/step - loss: 0.2366 - accuracy: 0.9070 - val_loss: 0.2523 - val_accuracy: 0.9044
Epoch 3/100
225/225 [==============================] - 0s 2ms/step - loss: 0.2144 - accuracy: 0.9123 - val_loss: 0.2342 - val_accuracy: 0.9094
Epoch 4/100
225/225 [==============================] - 0s 2ms/step - loss: 0.1957 - accuracy: 0.9238 - val_loss: 0.2264 - val_accuracy: 0.9094
Epoch 5/100
225/225 [==============================] - 0s 2ms/step - loss: 0.1794 - accuracy: 0.9304 - val_loss: 0.2131 - val_accuracy: 0.9194
Epoch 6/100
225/225 [==============================] - 0s 2ms/step - loss: 0.1676 - accuracy: 0.9362 - val_loss: 0.1975 - val_accuracy: 0.9269
Epoch 7/100
225/225 [==============================] - 0s 2ms/step - loss: 0.1563 - accuracy: 0.9424 - val_loss: 0.1897 - val_accuracy: 0.9299
Epoch 8/100
225/225 [==============================] - 0s 2ms/step - loss: 0.1446 - accuracy: 0.9460 - val_loss: 0.2002 - val_accuracy: 0.9203
Epoch 9/100
225/225 [==============================] - 1s 2ms/step - loss: 0.1361 - accuracy: 0.9504 - val_loss: 0.1805 - val_accuracy: 0.9299
Epoch 10/100
225/225 [==============================] - 0s 2ms/step - loss: 0.1275 - accuracy: 0.9550 - val_loss: 0.1773 - val_accuracy: 0.9382
Epoch 11/100
225/225 [==============================] - 0s 2ms/step - loss: 0.1216 - accuracy: 0.9559 - val_loss: 0.1691 - val_accuracy: 0.9407
Epoch 12/100
225/225 [==============================] - 0s 2ms/step - loss: 0.1113 - accuracy: 0.9598 - val_loss: 0.1627 - val_accuracy: 0.9441
Epoch 13/100
225/225 [==============================] - 0s 2ms/step - loss: 0.1055 - accuracy: 0.9627 - val_loss: 0.1814 - val_accuracy: 0.9403
Epoch 14/100
225/225 [==============================] - 0s 2ms/step - loss: 0.0990 - accuracy: 0.9667 - val_loss: 0.1623 - val_accuracy: 0.9491
Epoch 15/100
225/225 [==============================] - 1s 2ms/step - loss: 0.0927 - accuracy: 0.9669 - val_loss: 0.1551 - val_accuracy: 0.9474
Epoch 16/100
225/225 [==============================] - 0s 2ms/step - loss: 0.0903 - accuracy: 0.9681 - val_loss: 0.1508 - val_accuracy: 0.9503
Epoch 17/100
225/225 [==============================] - 0s 2ms/step - loss: 0.0841 - accuracy: 0.9733 - val_loss: 0.1547 - val_accuracy: 0.9491
Epoch 18/100
225/225 [==============================] - 1s 2ms/step - loss: 0.0803 - accuracy: 0.9756 - val_loss: 0.1428 - val_accuracy: 0.9532
Epoch 19/100
225/225 [==============================] - 0s 2ms/step - loss: 0.0780 - accuracy: 0.9745 - val_loss: 0.1464 - val_accuracy: 0.9495
Epoch 20/100
225/225 [==============================] - 1s 3ms/step - loss: 0.0711 - accuracy: 0.9780 - val_loss: 0.1528 - val_accuracy: 0.9457
Epoch 21/100
225/225 [==============================] - 1s 2ms/step - loss: 0.0684 - accuracy: 0.9798 - val_loss: 0.1429 - val_accuracy: 0.9528
Epoch 22/100
225/225 [==============================] - 1s 2ms/step - loss: 0.0661 - accuracy: 0.9780 - val_loss: 0.1618 - val_accuracy: 0.9503
Epoch 23/100
225/225 [==============================] - 0s 2ms/step - loss: 0.0655 - accuracy: 0.9777 - val_loss: 0.1430 - val_accuracy: 0.9532
Epoch 24/100
225/225 [==============================] - 0s 2ms/step - loss: 0.0610 - accuracy: 0.9811 - val_loss: 0.1539 - val_accuracy: 0.9466
Epoch 25/100
225/225 [==============================] - 0s 2ms/step - loss: 0.0601 - accuracy: 0.9805 - val_loss: 0.1769 - val_accuracy: 0.9453
Epoch 26/100
225/225 [==============================] - 1s 2ms/step - loss: 0.0616 - accuracy: 0.9801 - val_loss: 0.1552 - val_accuracy: 0.9441
Epoch 27/100
225/225 [==============================] - 1s 2ms/step - loss: 0.0542 - accuracy: 0.9830 - val_loss: 0.1449 - val_accuracy: 0.9549
Epoch 28/100
225/225 [==============================] - 1s 2ms/step - loss: 0.0509 - accuracy: 0.9847 - val_loss: 0.1500 - val_accuracy: 0.9557
Epoch 29/100
225/225 [==============================] - 0s 2ms/step - loss: 0.0503 - accuracy: 0.9861 - val_loss: 0.1550 - val_accuracy: 0.9553
Epoch 30/100
225/225 [==============================] - 0s 2ms/step - loss: 0.0521 - accuracy: 0.9826 - val_loss: 0.1497 - val_accuracy: 0.9557
Epoch 31/100
225/225 [==============================] - 0s 2ms/step - loss: 0.0459 - accuracy: 0.9869 - val_loss: 0.1553 - val_accuracy: 0.9532
Epoch 32/100
225/225 [==============================] - 0s 2ms/step - loss: 0.0498 - accuracy: 0.9850 - val_loss: 0.1742 - val_accuracy: 0.9461
Epoch 33/100
225/225 [==============================] - 0s 2ms/step - loss: 0.0454 - accuracy: 0.9862 - val_loss: 0.1591 - val_accuracy: 0.9566
Epoch 34/100
225/225 [==============================] - 0s 2ms/step - loss: 0.0446 - accuracy: 0.9877 - val_loss: 0.1597 - val_accuracy: 0.9562
Epoch 35/100
225/225 [==============================] - 1s 2ms/step - loss: 0.0455 - accuracy: 0.9858 - val_loss: 0.1555 - val_accuracy: 0.9562
Epoch 36/100
225/225 [==============================] - 1s 2ms/step - loss: 0.0436 - accuracy: 0.9865 - val_loss: 0.1588 - val_accuracy: 0.9549
Epoch 37/100
225/225 [==============================] - 1s 3ms/step - loss: 0.0392 - accuracy: 0.9883 - val_loss: 0.1526 - val_accuracy: 0.9570
Epoch 38/100
225/225 [==============================] - 1s 2ms/step - loss: 0.0376 - accuracy: 0.9884 - val_loss: 0.1635 - val_accuracy: 0.9553
Epoch 39/100
225/225 [==============================] - 1s 2ms/step - loss: 0.0372 - accuracy: 0.9901 - val_loss: 0.1558 - val_accuracy: 0.9545
Epoch 40/100
225/225 [==============================] - 1s 2ms/step - loss: 0.0378 - accuracy: 0.9891 - val_loss: 0.1547 - val_accuracy: 0.9587
Epoch 41/100
225/225 [==============================] - 1s 2ms/step - loss: 0.0362 - accuracy: 0.9890 - val_loss: 0.1867 - val_accuracy: 0.9511
Epoch 42/100
225/225 [==============================] - 1s 2ms/step - loss: 0.0354 - accuracy: 0.9891 - val_loss: 0.1765 - val_accuracy: 0.9578
Epoch 43/100
225/225 [==============================] - 1s 2ms/step - loss: 0.0365 - accuracy: 0.9882 - val_loss: 0.1700 - val_accuracy: 0.9537
Epoch 44/100
225/225 [==============================] - 0s 2ms/step - loss: 0.0320 - accuracy: 0.9904 - val_loss: 0.1676 - val_accuracy: 0.9591
Epoch 45/100
225/225 [==============================] - 1s 2ms/step - loss: 0.0360 - accuracy: 0.9883 - val_loss: 0.1687 - val_accuracy: 0.9549
Epoch 46/100
225/225 [==============================] - 1s 2ms/step - loss: 0.0279 - accuracy: 0.9916 - val_loss: 0.1866 - val_accuracy: 0.9516
Epoch 47/100
225/225 [==============================] - 1s 2ms/step - loss: 0.0272 - accuracy: 0.9929 - val_loss: 0.1891 - val_accuracy: 0.9516
Epoch 48/100
225/225 [==============================] - 1s 3ms/step - loss: 0.0301 - accuracy: 0.9910 - val_loss: 0.2027 - val_accuracy: 0.9453
Epoch 49/100
225/225 [==============================] - 0s 2ms/step - loss: 0.0333 - accuracy: 0.9905 - val_loss: 0.2032 - val_accuracy: 0.9461
Epoch 50/100
225/225 [==============================] - 1s 2ms/step - loss: 0.0299 - accuracy: 0.9911 - val_loss: 0.1847 - val_accuracy: 0.9507
Epoch 51/100
225/225 [==============================] - 1s 2ms/step - loss: 0.0278 - accuracy: 0.9929 - val_loss: 0.1878 - val_accuracy: 0.9516
Epoch 52/100
225/225 [==============================] - 1s 2ms/step - loss: 0.0271 - accuracy: 0.9926 - val_loss: 0.1987 - val_accuracy: 0.9503
Epoch 53/100
225/225 [==============================] - 1s 3ms/step - loss: 0.0263 - accuracy: 0.9916 - val_loss: 0.1898 - val_accuracy: 0.9553
Epoch 54/100
225/225 [==============================] - 1s 2ms/step - loss: 0.0269 - accuracy: 0.9914 - val_loss: 0.1877 - val_accuracy: 0.9582
Epoch 55/100
225/225 [==============================] - 1s 2ms/step - loss: 0.0241 - accuracy: 0.9929 - val_loss: 0.1908 - val_accuracy: 0.9541
Epoch 56/100
225/225 [==============================] - 0s 2ms/step - loss: 0.0269 - accuracy: 0.9921 - val_loss: 0.2042 - val_accuracy: 0.9574
Epoch 57/100
225/225 [==============================] - 1s 2ms/step - loss: 0.0207 - accuracy: 0.9951 - val_loss: 0.2082 - val_accuracy: 0.9578
Epoch 58/100
225/225 [==============================] - 0s 2ms/step - loss: 0.0210 - accuracy: 0.9936 - val_loss: 0.2302 - val_accuracy: 0.9474
Epoch 59/100
225/225 [==============================] - 1s 2ms/step - loss: 0.0277 - accuracy: 0.9914 - val_loss: 0.1946 - val_accuracy: 0.9478
Epoch 60/100
225/225 [==============================] - 1s 2ms/step - loss: 0.0222 - accuracy: 0.9932 - val_loss: 0.2126 - val_accuracy: 0.9557
Epoch 61/100
225/225 [==============================] - 1s 2ms/step - loss: 0.0239 - accuracy: 0.9925 - val_loss: 0.2076 - val_accuracy: 0.9524
Epoch 62/100
225/225 [==============================] - 0s 2ms/step - loss: 0.0262 - accuracy: 0.9908 - val_loss: 0.2178 - val_accuracy: 0.9562
Epoch 63/100
225/225 [==============================] - 1s 2ms/step - loss: 0.0269 - accuracy: 0.9916 - val_loss: 0.2072 - val_accuracy: 0.9541
Epoch 64/100
225/225 [==============================] - 0s 2ms/step - loss: 0.0196 - accuracy: 0.9947 - val_loss: 0.2126 - val_accuracy: 0.9570
Epoch 65/100
225/225 [==============================] - 1s 2ms/step - loss: 0.0167 - accuracy: 0.9965 - val_loss: 0.2114 - val_accuracy: 0.9566
Epoch 66/100
225/225 [==============================] - 0s 2ms/step - loss: 0.0181 - accuracy: 0.9957 - val_loss: 0.2153 - val_accuracy: 0.9537
Epoch 67/100
225/225 [==============================] - 1s 2ms/step - loss: 0.0207 - accuracy: 0.9926 - val_loss: 0.2775 - val_accuracy: 0.9344
Epoch 68/100
225/225 [==============================] - 1s 3ms/step - loss: 0.0245 - accuracy: 0.9925 - val_loss: 0.2152 - val_accuracy: 0.9524
Epoch 69/100
225/225 [==============================] - 1s 2ms/step - loss: 0.0225 - accuracy: 0.9933 - val_loss: 0.2114 - val_accuracy: 0.9570
Epoch 70/100
225/225 [==============================] - 0s 2ms/step - loss: 0.0146 - accuracy: 0.9967 - val_loss: 0.2193 - val_accuracy: 0.9562
Epoch 71/100
225/225 [==============================] - 0s 2ms/step - loss: 0.0148 - accuracy: 0.9958 - val_loss: 0.2131 - val_accuracy: 0.9578
Epoch 72/100
225/225 [==============================] - 0s 2ms/step - loss: 0.0217 - accuracy: 0.9925 - val_loss: 0.3095 - val_accuracy: 0.9399
Epoch 73/100
225/225 [==============================] - 0s 2ms/step - loss: 0.0229 - accuracy: 0.9918 - val_loss: 0.2115 - val_accuracy: 0.9574
Epoch 74/100
225/225 [==============================] - 0s 2ms/step - loss: 0.0173 - accuracy: 0.9947 - val_loss: 0.2110 - val_accuracy: 0.9537
Epoch 75/100
225/225 [==============================] - 0s 2ms/step - loss: 0.0123 - accuracy: 0.9969 - val_loss: 0.2153 - val_accuracy: 0.9582
Epoch 76/100
225/225 [==============================] - 0s 2ms/step - loss: 0.0145 - accuracy: 0.9962 - val_loss: 0.2247 - val_accuracy: 0.9553
Epoch 77/100
225/225 [==============================] - 0s 2ms/step - loss: 0.0135 - accuracy: 0.9962 - val_loss: 0.2317 - val_accuracy: 0.9570
Epoch 78/100
225/225 [==============================] - 0s 2ms/step - loss: 0.0152 - accuracy: 0.9947 - val_loss: 0.2641 - val_accuracy: 0.9428
Epoch 79/100
225/225 [==============================] - 0s 2ms/step - loss: 0.0241 - accuracy: 0.9926 - val_loss: 0.2312 - val_accuracy: 0.9553
Epoch 80/100
225/225 [==============================] - 0s 2ms/step - loss: 0.0130 - accuracy: 0.9969 - val_loss: 0.2198 - val_accuracy: 0.9541
Epoch 81/100
225/225 [==============================] - 1s 3ms/step - loss: 0.0112 - accuracy: 0.9982 - val_loss: 0.2250 - val_accuracy: 0.9516
Epoch 82/100
225/225 [==============================] - 1s 2ms/step - loss: 0.0130 - accuracy: 0.9961 - val_loss: 0.2325 - val_accuracy: 0.9553
Epoch 83/100
225/225 [==============================] - 0s 2ms/step - loss: 0.0121 - accuracy: 0.9969 - val_loss: 0.2560 - val_accuracy: 0.9507
Epoch 84/100
225/225 [==============================] - 1s 2ms/step - loss: 0.0242 - accuracy: 0.9910 - val_loss: 0.2624 - val_accuracy: 0.9478
Epoch 85/100
225/225 [==============================] - 1s 3ms/step - loss: 0.0257 - accuracy: 0.9916 - val_loss: 0.2355 - val_accuracy: 0.9520
Epoch 86/100
225/225 [==============================] - 0s 2ms/step - loss: 0.0233 - accuracy: 0.9925 - val_loss: 0.2279 - val_accuracy: 0.9578
Epoch 87/100
225/225 [==============================] - 1s 2ms/step - loss: 0.0112 - accuracy: 0.9974 - val_loss: 0.2536 - val_accuracy: 0.9537
Epoch 88/100
225/225 [==============================] - 0s 2ms/step - loss: 0.0096 - accuracy: 0.9978 - val_loss: 0.2537 - val_accuracy: 0.9491
Epoch 89/100
225/225 [==============================] - 0s 2ms/step - loss: 0.0097 - accuracy: 0.9981 - val_loss: 0.2580 - val_accuracy: 0.9541
Epoch 90/100
225/225 [==============================] - 1s 2ms/step - loss: 0.0092 - accuracy: 0.9982 - val_loss: 0.2463 - val_accuracy: 0.9574
Epoch 91/100
225/225 [==============================] - 0s 2ms/step - loss: 0.0077 - accuracy: 0.9990 - val_loss: 0.2509 - val_accuracy: 0.9507
Epoch 92/100
225/225 [==============================] - 0s 2ms/step - loss: 0.0116 - accuracy: 0.9971 - val_loss: 0.2368 - val_accuracy: 0.9537
Epoch 93/100
225/225 [==============================] - 1s 2ms/step - loss: 0.0137 - accuracy: 0.9964 - val_loss: 0.2471 - val_accuracy: 0.9553
Epoch 94/100
225/225 [==============================] - 0s 2ms/step - loss: 0.0202 - accuracy: 0.9929 - val_loss: 0.2783 - val_accuracy: 0.9507
Epoch 95/100
225/225 [==============================] - 0s 2ms/step - loss: 0.0108 - accuracy: 0.9971 - val_loss: 0.2532 - val_accuracy: 0.9562
Epoch 96/100
225/225 [==============================] - 0s 2ms/step - loss: 0.0217 - accuracy: 0.9922 - val_loss: 0.2553 - val_accuracy: 0.9520
Epoch 97/100
225/225 [==============================] - 1s 2ms/step - loss: 0.0112 - accuracy: 0.9967 - val_loss: 0.2934 - val_accuracy: 0.9545
Epoch 98/100
225/225 [==============================] - 1s 2ms/step - loss: 0.0102 - accuracy: 0.9971 - val_loss: 0.2473 - val_accuracy: 0.9562
Epoch 99/100
225/225 [==============================] - 1s 3ms/step - loss: 0.0106 - accuracy: 0.9971 - val_loss: 0.2966 - val_accuracy: 0.9478
Epoch 100/100
225/225 [==============================] - 0s 2ms/step - loss: 0.0172 - accuracy: 0.9944 - val_loss: 0.2608 - val_accuracy: 0.9516
```

Out[29]:
```
<keras.callbacks.History at 0x1c204ad8910>
```

In [30]:
```python
pred=(model.predict(x_test)>0.5)*1.0
pred
```

Out[30]:
```
array([[1.],
       [1.],
       [1.],
       ...,
       [1.],
       [1.],
       [1.]])
```

In [31]:
```python
from sklearn.metrics import confusion_matrix,classification_report
```

In [32]:
```python
print(confusion_matrix(pred,y_test))
```

```
[[ 406   56]
 [  60 1873]]
```

In [33]:
```python
print(classification_report(pred,y_test))
```

```
              precision    recall  f1-score   support

         0.0       0.87      0.88      0.88       462
         1.0       0.97      0.97      0.97      1933

    accuracy                           0.95      2395
   macro avg       0.92      0.92      0.92      2395
weighted avg       0.95      0.95      0.95      2395
```

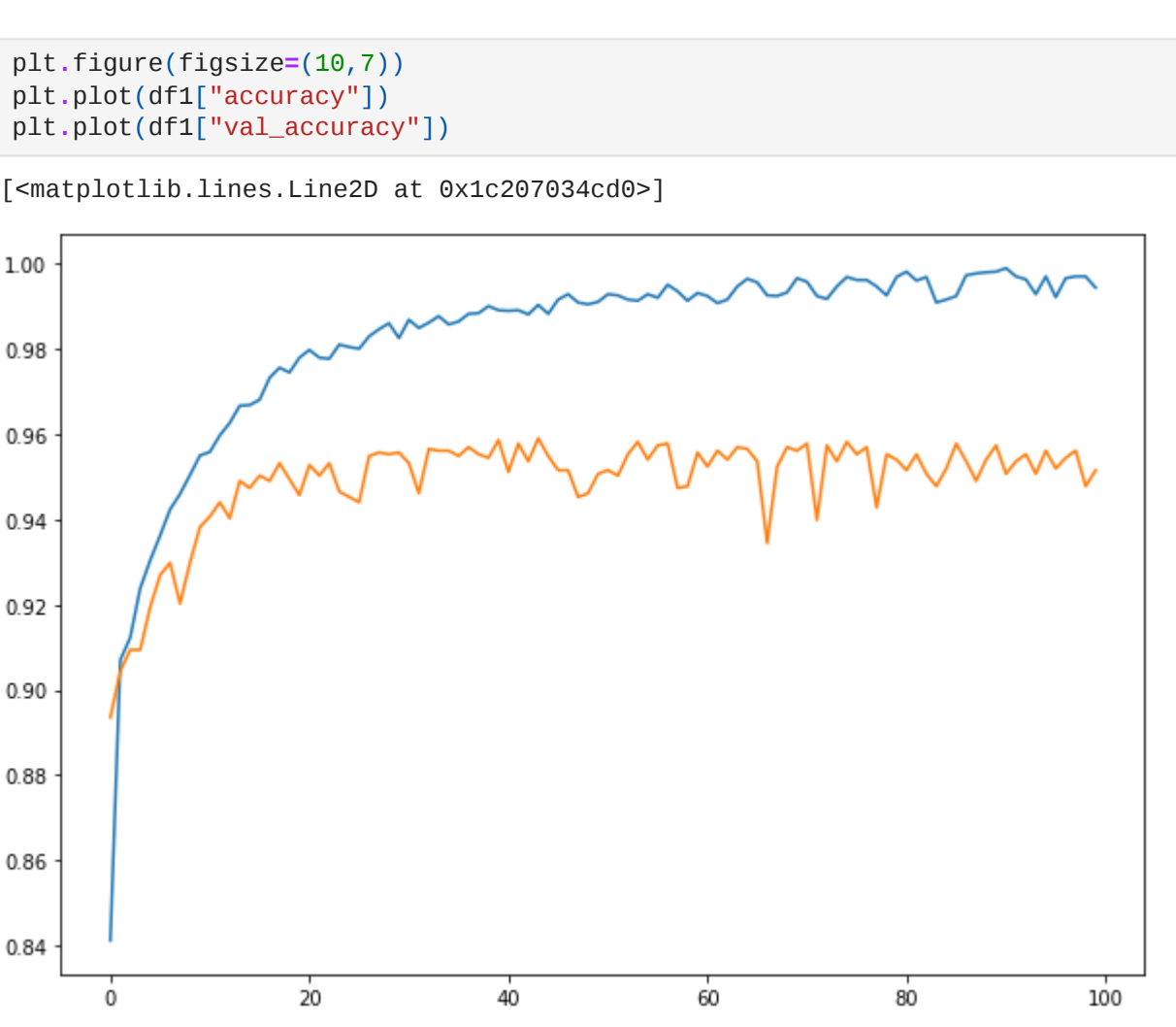
In [34]:
```python
df1=pd.DataFrame(result.history)
df1.head()
```

Out[34]:

	loss	accuracy	val_loss	val_accuracy
0	0.369062	0.841153	0.271902	0.893528
1	0.236558	0.907003	0.252330	0.904384
2	0.214423	0.912293	0.234218	0.909395
3	0.195716	0.923848	0.226374	0.909395
4	0.179404	0.930391	0.213123	0.919415

In [35]:
```python
plt.figure(figsize=(10,7))
plt.plot(df1["loss"])
plt.plot(df1["val_loss"])
```

Out[35]:
```
[<matplotlib.lines.Line2D at 0x1c206fe6040>]
```



In [36]:
```python
plt.figure(figsize=(10,7))
plt.plot(df1["accuracy"])
plt.plot(df1["val_accuracy"])
```

Out[36]:
```
[<matplotlib.lines.Line2D at 0x1c207034cd0>]
```

THANK YOU...!!!