

# Import neccessery libraries

```
In [25]: from keras.models import Sequential
from scipy import stats
import numpy as np
import warnings
warnings.filterwarnings('ignore')
import matplotlib.pyplot as plt
import pandas as pd
from sklearn.preprocessing import StandardScaler
import seaborn as sns
from datetime import datetime
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix
from keras.models import Sequential
from keras.layers import Dense, Flatten, Activation, Layer, Lambda
from keras.layers.normalization import batch_normalization_v1
import seaborn as sns
from sklearn import preprocessing
from keras.layers import Dropout
from keras import regularizers
from sklearn.model_selection import train_test_split
from matplotlib import pyplot as plt
from sklearn.decomposition import PCA
from mlxtend.plotting import plot_decision_regions
from tensorflow import keras
```

## Problem

**predicting turbine energy yield (TEY) using ambient variables as features.**

## Import data

```
In [2]: turbine_data = pd.read_csv('turbines.csv')
turbine_data
```

```
Out[2]:
```

	AT	AP	AH	AFDP	GTEP	TIT	TAT	TEY	CDP	CO	NOX
0	6.8594	1007.9	96.799	3.5000	19.663	1059.2	550.00	114.70	10.605	3.1547	82.722
1	6.7850	1008.4	97.118	3.4998	19.728	1059.3	550.00	114.72	10.598	3.2363	82.776
2	6.8977	1008.8	95.939	3.4824	19.779	1059.4	549.87	114.71	10.601	3.2012	82.468
3	7.0569	1009.2	95.249	3.4805	19.792	1059.6	549.99	114.72	10.606	3.1923	82.670
4	7.3978	1009.7	95.150	3.4976	19.765	1059.7	549.98	114.72	10.612	3.2484	82.311
...	...	...	...	...	...	...	...	...	...	...	...
1334	14.4370	1015.1	65.684	4.6007	24.389	1085.3	550.00	132.73	11.930	1.3280	75.591
1335	13.3520	1014.8	69.204	4.6293	24.733	1087.2	549.91	134.53	12.033	1.0722	76.679
1336	12.5340	1014.5	71.264	4.4290	23.485	1078.9	549.43	128.98	11.531	1.4281	80.377
1337	11.0070	1014.2	75.717	3.8417	19.570	1047.7	544.29	111.22	10.472	3.2378	79.306
1338	10.8940	1013.5	76.652	3.8635	19.635	1045.2	542.60	110.15	10.480	5.2465	86.022

1339 rows × 11 columns

```
In [94]: df1=turbine_data.copy()
```

```
In [95]: df1.head()
```

```
Out[95]:
```

	AT	AP	AH	AFDP	GTEP	TIT	TAT	TEY	CDP	CO	NOX
0	6.8594	1007.9	96.799	3.5000	19.663	1059.2	550.00	114.70	10.605	3.1547	82.722
1	6.7850	1008.4	97.118	3.4998	19.728	1059.3	550.00	114.72	10.598	3.2363	82.776
2	6.8977	1008.8	95.939	3.4824	19.779	1059.4	549.87	114.71	10.601	3.2012	82.468
3	7.0569	1009.2	95.249	3.4805	19.792	1059.6	549.99	114.72	10.606	3.1923	82.670
4	7.3978	1009.7	95.150	3.4976	19.765	1059.7	549.98	114.72	10.612	3.2484	82.311

## Data understanding

```
In [96]: df1.shape
```

```
Out[96]: (1339, 11)
```

```
In [97]: df1.dtypes
```

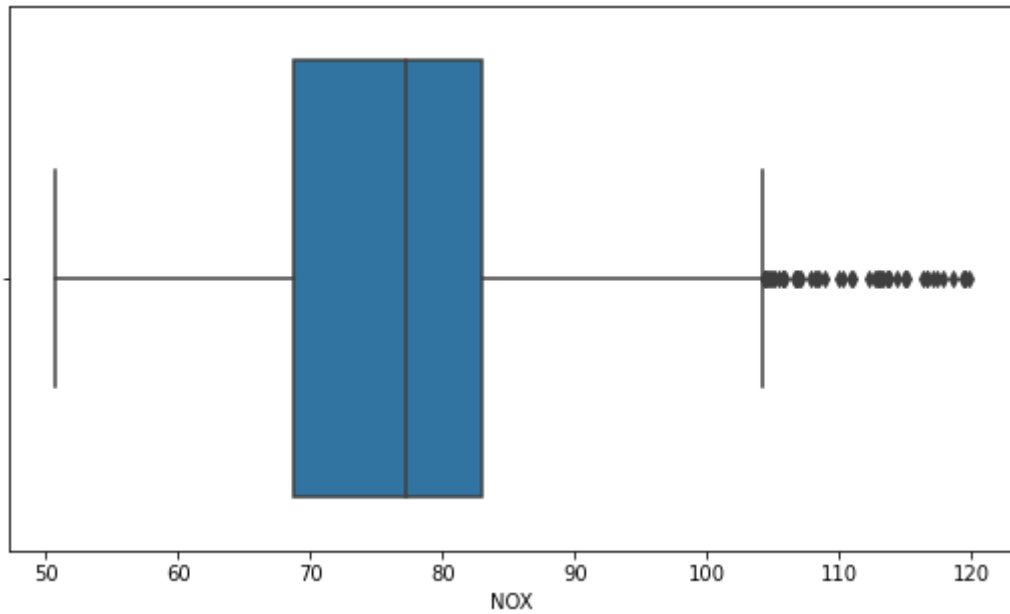
```
Out[97]: AT      float64
AP      float64
AH      float64
AFDP    float64
GTEP    float64
TIT     float64
TAT     float64
TEY     float64
CDP     float64
CO      float64
NOX     float64
dtype: object
```

```
In [98]: df1.isna().sum()
```

```
Out[98]: AT      0
AP      0
AH      0
AFDP    0
GTEP    0
TIT     0
TAT     0
TEY     0
CDP     0
CO      0
NOX     0
dtype: int64
```

## Outlier Check

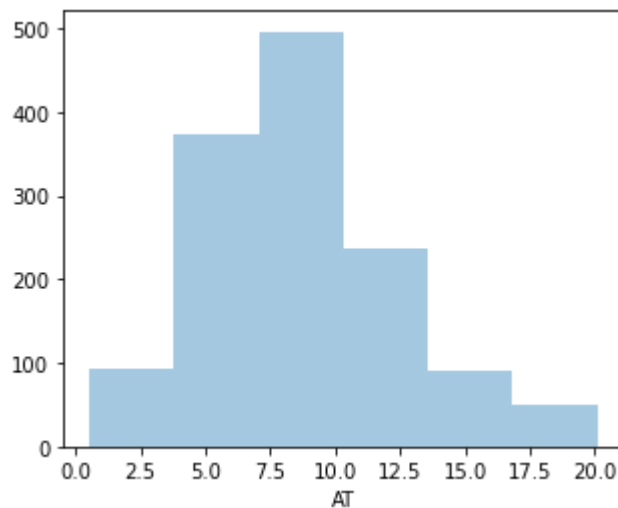
```
In [99]: ax = sns.boxplot(df1['NOX'])
```

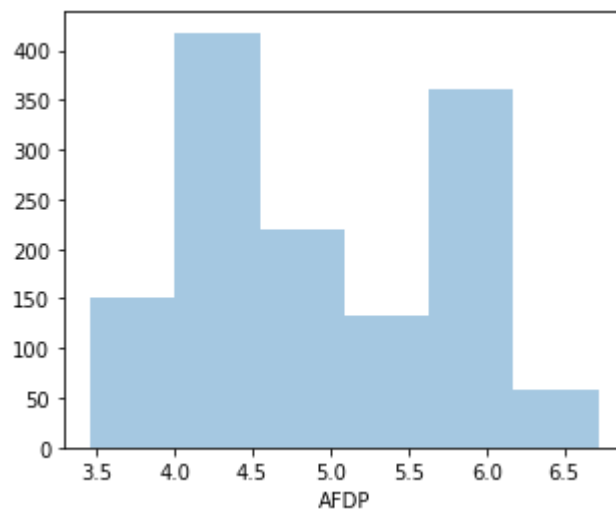
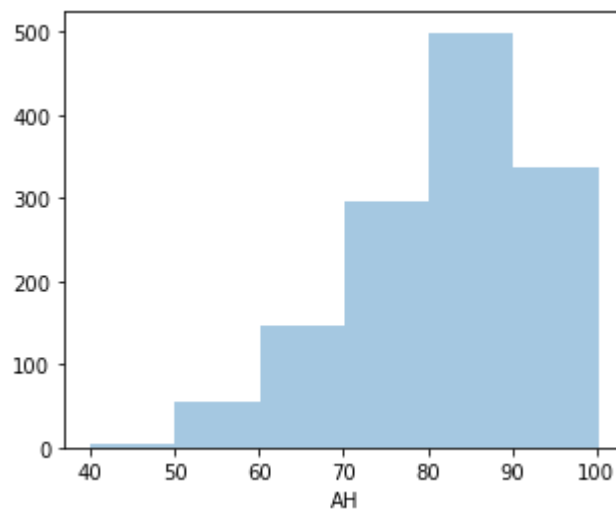
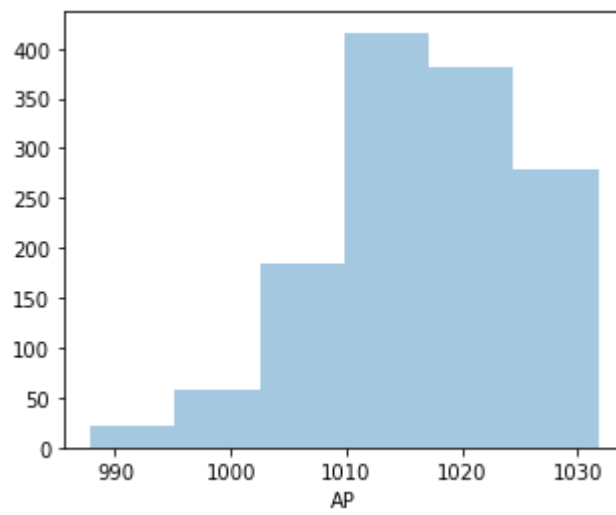


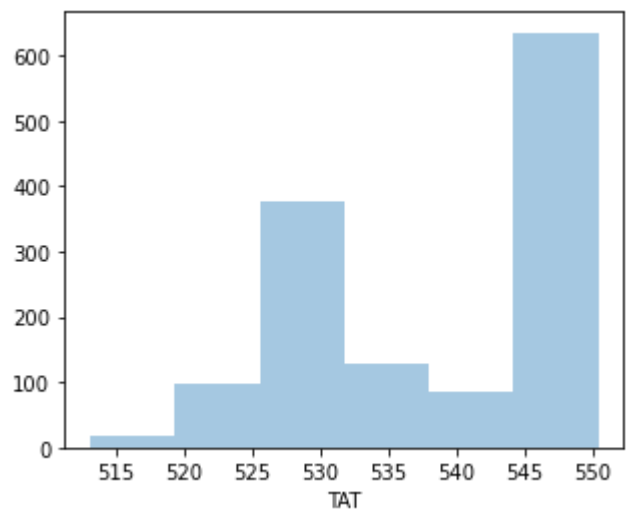
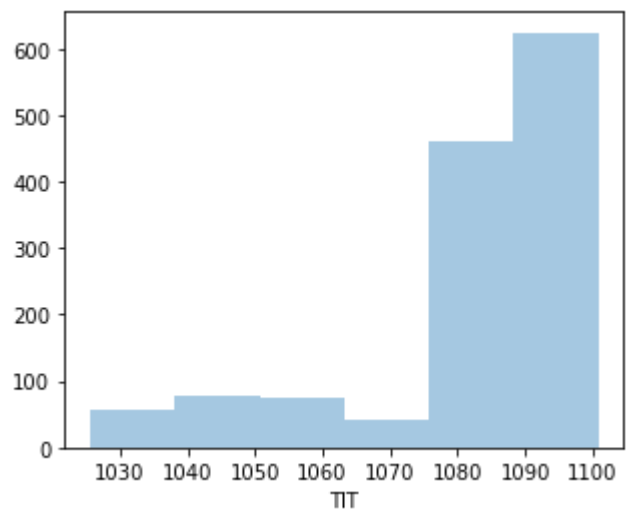
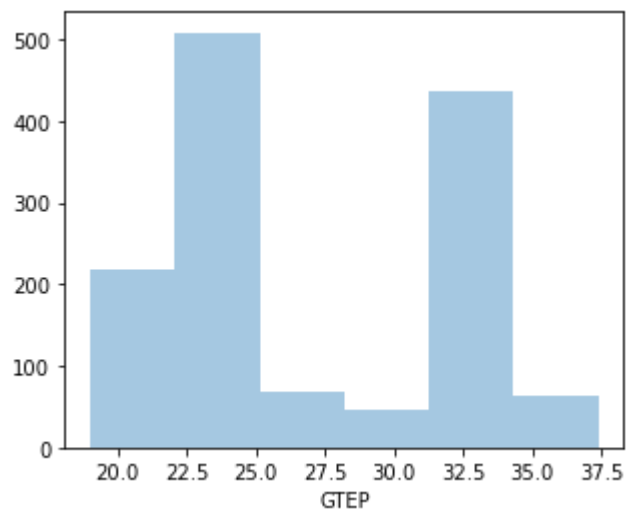
```
In [100]: A = sns.palplot(sns.color_palette("Blues"))
```

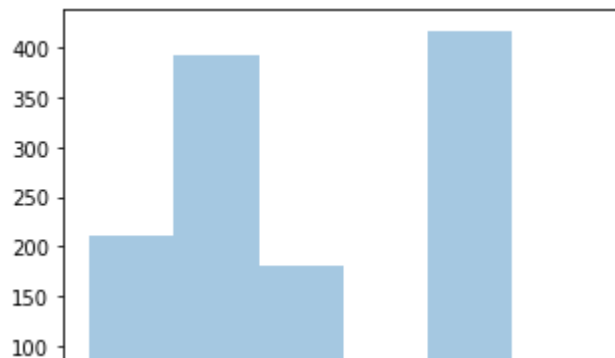
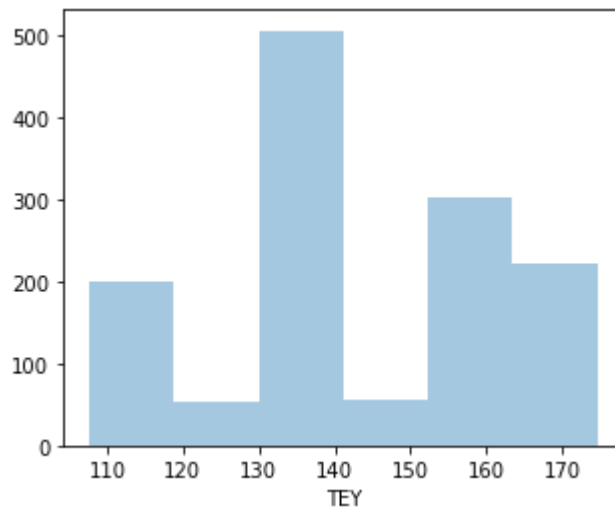


```
In [101]: for column in turbine_data.columns[0:]:
plt.figure(figsize=(5, 4))
plt.ticklabel_format(style='plain', axis='y')
sns.distplot(df1[column], color = A, kde=False, bins=6, hist_kws={'alp
```





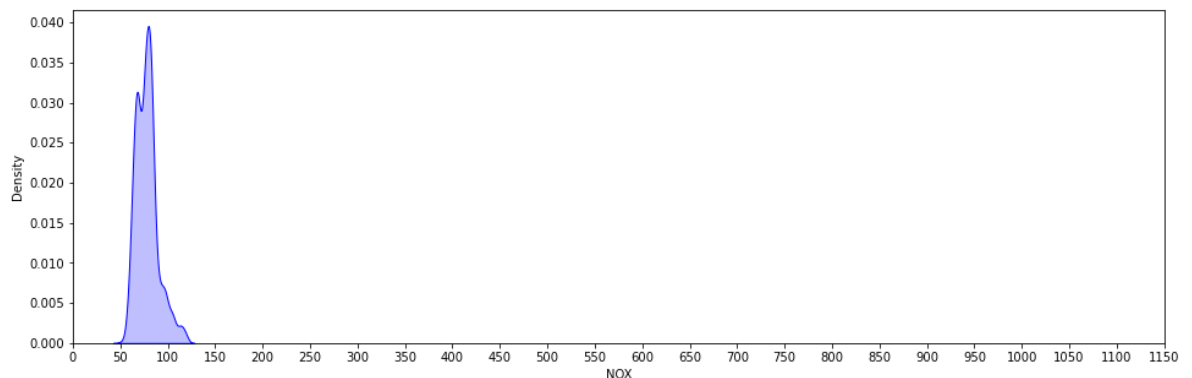




```
In [9]: plt.rcParams["figure.figsize"] = 9,5
```

```
In [102... plt.figure(figsize=(16,5))
print("Skew: {}".format(df1['NOX'].skew()))
print("Kurtosis: {}".format(df1['NOX'].kurtosis()))
ax = sns.kdeplot(df1['NOX'], shade=True, color='b')
plt.xticks([i for i in range(0,1200,50)])
plt.show()
```

Skew: 0.9425348708035359  
Kurtosis: 1.169825110704103

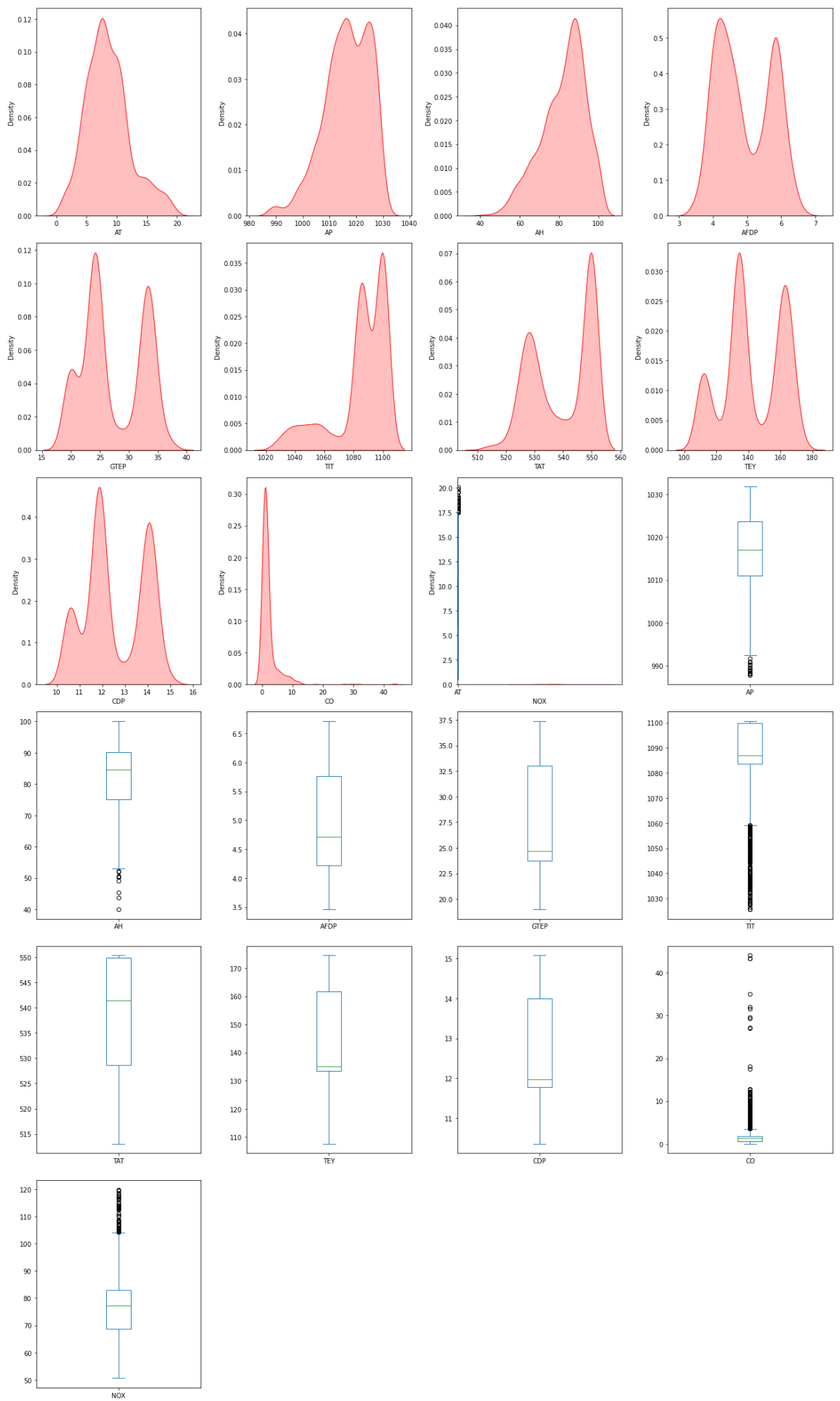


The Data is highly skewed and has large kurtosis value.

```
In [103... num_columns = df1.select_dtypes(exclude='object').columns.tolist()
```

In [104...

```
plt.figure(figsize=(18,40))
for i,col in enumerate(num_columns,1):
    plt.subplot(8,4,i)
    sns.kdeplot(df1[col],color='r',shade=True)
    plt.subplot(8,4,i+10)
    df1[col].plot.box()
plt.tight_layout()
plt.show()
num_data = df1[num_columns]
pd.DataFrame(data=[num_data.skew(),num_data.kurtosis()],index=['skewness',
```



Out[104...

AT

AP

AH

AFDP

GTEP

TIT

TAT

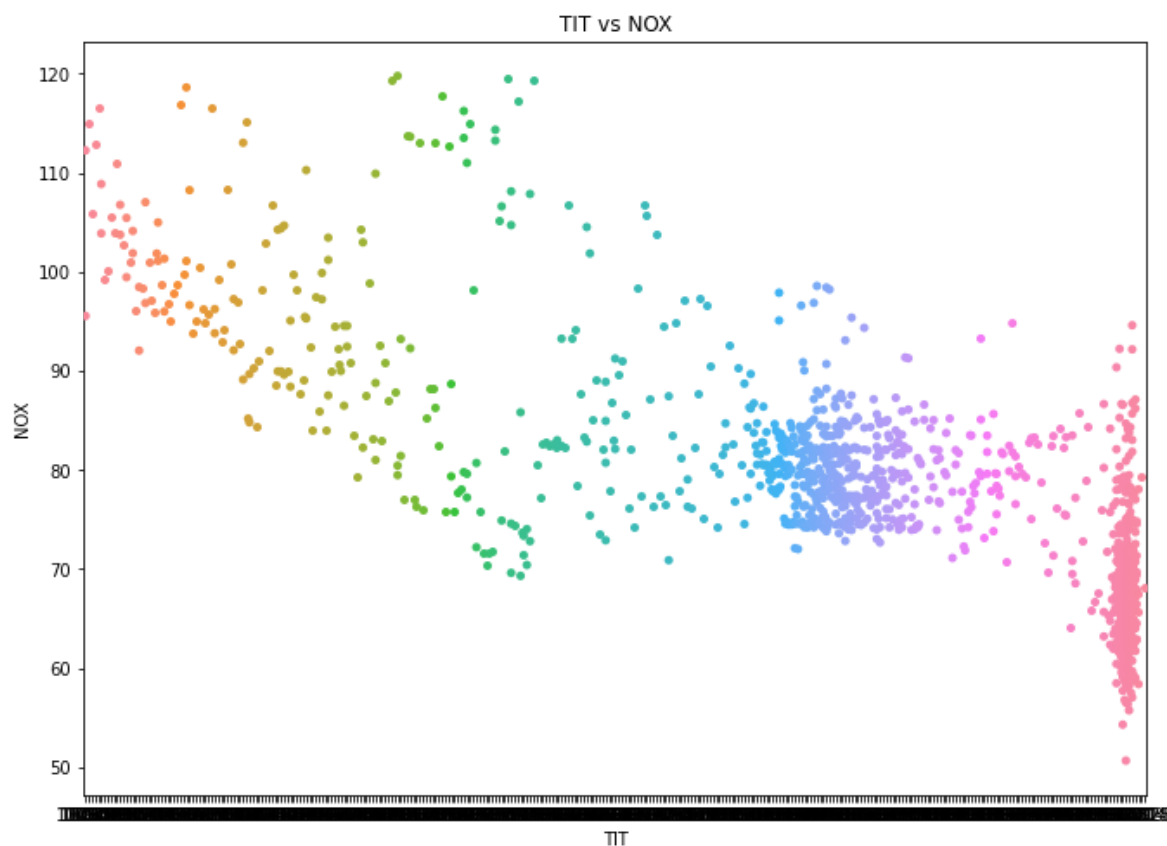
TEY



	AT	AP	AH	AFDP	GTEP	TIT	TAT	TEY	
<b>skewness</b>	0.630017	-0.647498	-0.659149	0.204136	0.173703	-1.430709	-0.279163	-0.137519	(

In [156...

```
plt.figure(figsize=(11,8))
plt.title('TIT vs NOX')
sns.swarmplot(x='TIT',y='NOX',data=df1,size=5)
plt.show()
```



## correlation

In [105...

```
corr = df1[turbine_data.columns[0:11]].corr()
```

In [106...

```
plt.figure(figsize=(10,10))
sns.heatmap(corr,annot=True)
```

Out[106...

<AxesSubplot:>



## Neural Network Model

In [107...

```
df1.columns
```

Out[107...

```
Index(['AT', 'AP', 'AH', 'AFDP', 'GTEP', 'TIT', 'TAT', 'TEY', 'CDP', 'CO',
      'NOX'],
      dtype='object')
```

In [114...

```
dataset = df1.values
```

In [115...

```
dataset
```

Out[115...

```
array([[ 6.8594, 1007.9 , 96.799 , ..., 10.605 , 3.1547,
        82.722 ],
       [ 6.785 , 1008.4 , 97.118 , ..., 10.598 , 3.2363,
        82.776 ],
       [ 6.8977, 1008.8 , 95.939 , ..., 10.601 , 3.2012,
        82.468 ],
       ...,
       [ 12.534 , 1014.5 , 71.264 , ..., 11.531 , 1.4281,
        80.377 ],
       [ 11.007 , 1014.2 , 75.717 , ..., 10.472 , 3.2378,
        79.306 ],
       [ 10.894 , 1013.5 , 76.652 , ..., 10.48 , 5.2465,
        86.022 ]])
```

In [116...

```
min_max_scaler = preprocessing.MinMaxScaler()
X_scale = min_max_scaler.fit_transform(X)
```

In [117...

```
X_scale
```

Out[117...

```
array([[0.32383858, 0.45632393, 0.94382695, ..., 0.1058209 , 0.05249788,
        0.07118405],
       [0.32003659, 0.46769791, 0.94912692, ..., 0.1061194 , 0.05101609,
```

```

0.07303496],
[0.32579579, 0.47679709, 0.92953862, ..., 0.10597015, 0.05165114,
 0.0722388 ],
...,
[0.61382207, 0.60646042, 0.51957999, ..., 0.31895522, 0.2485182 ,
 0.03202019],
[0.5357893 , 0.59963603, 0.59356361, ..., 0.0538806 , 0.02434378,
 0.07306898],
[0.53001477, 0.58371247, 0.60909801, ..., 0.03791045, 0.02603726,

```

```
In [139... X_train, X_val_and_test, Y_train, Y_val_and_test = train_test_split(X_scaled,
```

```
In [140... X_val, X_test, Y_val, Y_test = train_test_split(X_val_and_test, Y_val_and_t
print(X_train.shape, X_val.shape, X_test.shape, Y_train.shape, Y_val.shape,
(937, 10) (201, 10) (201, 10) (937,) (201,) (201,)
```

```
In [141... model = Sequential([
    Dense(32, activation='relu', input_shape=(10,)),
    Dense(32, activation='relu'),
    Dense(1, activation='sigmoid'),
])
```

```
In [121... model.compile(optimizer='sgd',
                loss='binary_crossentropy',
                metrics=['accuracy'])
```

```
In [122... hist = model.fit(X_train, Y_train,
                  batch_size=32, epochs=100,
                  validation_data=(X_val, Y_val))
```

```

Epoch 1/100
30/30 [=====] - 0s 4ms/step - loss: nan - accuracy: 0.0000e+00 - val_loss: nan - val_accuracy: 0.0000e+00
Epoch 2/100
30/30 [=====] - 0s 1ms/step - loss: nan - accuracy: 0.0000e+00 - val_loss: nan - val_accuracy: 0.0000e+00
Epoch 3/100
30/30 [=====] - 0s 2ms/step - loss: nan - accuracy: 0.0000e+00 - val_loss: nan - val_accuracy: 0.0000e+00
Epoch 4/100
30/30 [=====] - 0s 1ms/step - loss: nan - accuracy: 0.0000e+00 - val_loss: nan - val_accuracy: 0.0000e+00
Epoch 5/100
30/30 [=====] - 0s 1ms/step - loss: nan - accuracy: 0.0000e+00 - val_loss: nan - val_accuracy: 0.0000e+00
Epoch 6/100
30/30 [=====] - 0s 2ms/step - loss: nan - accuracy: 0.0000e+00 - val_loss: nan - val_accuracy: 0.0000e+00
Epoch 7/100
30/30 [=====] - 0s 1ms/step - loss: nan - accuracy: 0.0000e+00 - val_loss: nan - val_accuracy: 0.0000e+00
Epoch 8/100
30/30 [=====] - 0s 1ms/step - loss: nan - accuracy: 0.0000e+00 - val_loss: nan - val_accuracy: 0.0000e+00
Epoch 9/100
30/30 [=====] - 0s 1ms/step - loss: nan - accuracy: 0.0000e+00 - val_loss: nan - val_accuracy: 0.0000e+00

```

[illegible]

[illegible]

[illegible]

[illegible]

```

Epoch 94/100
30/30 [=====] - 0s 1ms/step - loss: nan - accuracy: 0.0000e+00 - val_loss: nan - val_accuracy: 0.0000e+00
Epoch 95/100
30/30 [=====] - 0s 1ms/step - loss: nan - accuracy: 0.0000e+00 - val_loss: nan - val_accuracy: 0.0000e+00
Epoch 96/100
30/30 [=====] - 0s 1ms/step - loss: nan - accuracy: 0.0000e+00 - val_loss: nan - val_accuracy: 0.0000e+00
Epoch 97/100
30/30 [=====] - 0s 2ms/step - loss: nan - accuracy: 0.0000e+00 - val_loss: nan - val_accuracy: 0.0000e+00
Epoch 98/100
30/30 [=====] - 0s 1ms/step - loss: nan - accuracy: 0.0000e+00 - val_loss: nan - val_accuracy: 0.0000e+00
Epoch 99/100
30/30 [=====] - 0s 1ms/step - loss: nan - accuracy: 0.0000e+00 - val_loss: nan - val_accuracy: 0.0000e+00
Epoch 100/100
30/30 [=====] - 0s 1ms/step - loss: nan - accuracy: 0.0000e+00 - val_loss: nan - val_accuracy: 0.0000e+00

```

In [123...

```
model.evaluate(X_test, Y_test)[1]
```

```

7/7 [=====] - 0s 0s/step - loss: nan - accuracy: 0.0000e+00
0.0

```

Out[123...

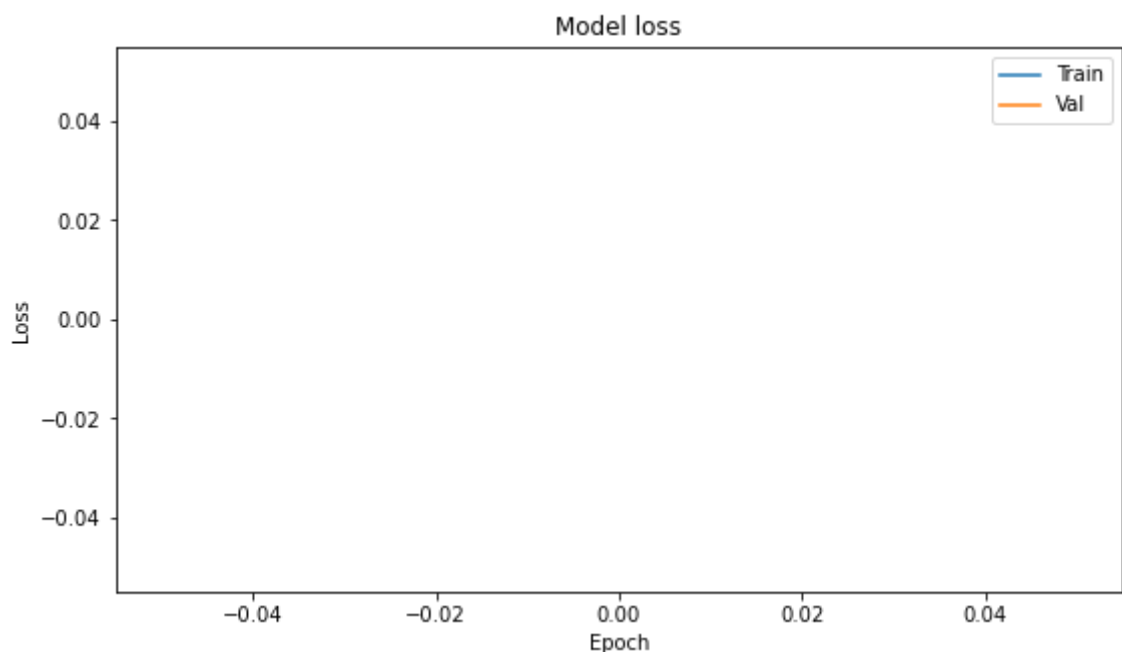
## Visualizing Loss and Accuracy

In [124...

```

plt.plot(hist.history['loss'])
plt.plot(hist.history['val_loss'])
plt.title('Model loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Val'], loc='upper right')
plt.show()

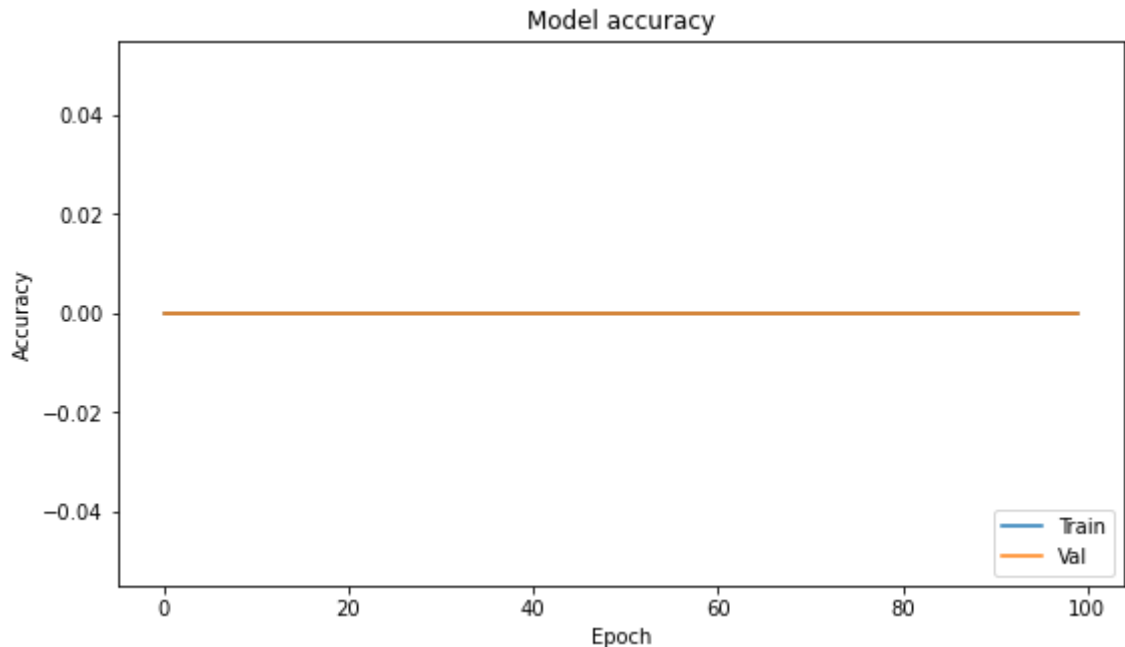
```





In [125...

```
plt.plot(hist.history['accuracy'])
plt.plot(hist.history['val_accuracy'])
plt.title('Model accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train', 'Val'], loc='lower right')
plt.show()
```



## Adding Regularization to our Neural Network

In [126...

```
model_2 = Sequential([
    Dense(1000, activation='relu', input_shape=(10,)),
    Dense(1000, activation='relu'),
    Dense(1000, activation='relu'),
    Dense(1000, activation='relu'),
    Dense(1, activation='sigmoid'),
])

model_2.compile(optimizer='adam',
                loss='binary_crossentropy',
                metrics=['accuracy'])

hist_2 = model_2.fit(X_train, Y_train,
                    batch_size=32, epochs=100,
                    validation_data=(X_val, Y_val))
```

```
Epoch 1/100
30/30 [=====] - 1s 24ms/step - loss: -294721.4062
- accuracy: 0.0000e+00 - val_loss: -2317941.7500 - val_accuracy: 0.0000e+00
Epoch 2/100
30/30 [=====] - 1s 23ms/step - loss: -35800740.000
0 - accuracy: 0.0000e+00 - val_loss: -150233904.0000 - val_accuracy: 0.0000
e+00
Epoch 3/100
30/30 [=====] - 1s 25ms/step - loss: -753909760.00
00 - accuracy: 0.0000e+00 - val_loss: -2201394432.0000 - val_accuracy: 0.00
00e+00
Epoch 4/100
```

30/30 [=====] - 1s 23ms/step - loss: -6600784896.0000 - accuracy: 0.0000e+00 - val\_loss: -15202729984.0000 - val\_accuracy: 0.0000e+00  
Epoch 5/100  
30/30 [=====] - 1s 25ms/step - loss: -34207166464.0000 - accuracy: 0.0000e+00 - val\_loss: -67042340864.0000 - val\_accuracy: 0.0000e+00  
Epoch 6/100  
30/30 [=====] - 1s 24ms/step - loss: -126131355648.0000 - accuracy: 0.0000e+00 - val\_loss: -220411002880.0000 - val\_accuracy: 0.0000e+00  
Epoch 7/100  
30/30 [=====] - 1s 24ms/step - loss: -368241213440.0000 - accuracy: 0.0000e+00 - val\_loss: -590872444928.0000 - val\_accuracy: 0.0000e+00  
Epoch 8/100  
30/30 [=====] - 1s 22ms/step - loss: -906788012032.0000 - accuracy: 0.0000e+00 - val\_loss: -1365430894592.0000 - val\_accuracy: 0.0000e+00  
Epoch 9/100  
30/30 [=====] - 1s 21ms/step - loss: -1968472457216.0000 - accuracy: 0.0000e+00 - val\_loss: -2818406350848.0000 - val\_accuracy: 0.0000e+00  
Epoch 10/100  
30/30 [=====] - 1s 22ms/step - loss: -3869497098240.0000 - accuracy: 0.0000e+00 - val\_loss: -5323555864576.0000 - val\_accuracy: 0.0000e+00  
Epoch 11/100  
30/30 [=====] - 1s 22ms/step - loss: -7039625461760.0000 - accuracy: 0.0000e+00 - val\_loss: -9379433676800.0000 - val\_accuracy: 0.0000e+00  
Epoch 12/100  
30/30 [=====] - 1s 22ms/step - loss: -12037892603904.0000 - accuracy: 0.0000e+00 - val\_loss: -15601166712832.0000 - val\_accuracy: 0.0000e+00  
Epoch 13/100  
30/30 [=====] - 1s 22ms/step - loss: -19539270041600.0000 - accuracy: 0.0000e+00 - val\_loss: -24780193398784.0000 - val\_accuracy: 0.0000e+00  
Epoch 14/100  
30/30 [=====] - 1s 22ms/step - loss: -30375315243008.0000 - accuracy: 0.0000e+00 - val\_loss: -37769011265536.0000 - val\_accuracy: 0.0000e+00  
Epoch 15/100  
30/30 [=====] - 1s 22ms/step - loss: -45523104956416.0000 - accuracy: 0.0000e+00 - val\_loss: -55696770990080.0000 - val\_accuracy: 0.0000e+00  
Epoch 16/100  
30/30 [=====] - 1s 23ms/step - loss: -66105922027520.0000 - accuracy: 0.0000e+00 - val\_loss: -79749372182528.0000 - val\_accuracy: 0.0000e+00  
Epoch 17/100  
30/30 [=====] - 1s 22ms/step - loss: -93405338140672.0000 - accuracy: 0.0000e+00 - val\_loss: -111288214618112.0000 - val\_accuracy: 0.0000e+00  
Epoch 18/100  
30/30 [=====] - 1s 23ms/step - loss: -128898746548224.0000 - accuracy: 0.0000e+00 - val\_loss: -151915191074816.0000 - val\_accuracy: 0.0000e+00  
Epoch 19/100  
30/30 [=====] - 1s 22ms/step - loss: -17428381696000.0000 - accuracy: 0.0000e+00 - val\_loss: -203289576603648.0000 - val\_accuracy: 0.0000e+00

Epoch 20/100  
30/30 [=====] - 1s 22ms/step - loss: -231256289705  
984.0000 - accuracy: 0.0000e+00 - val\_loss: -267588491804672.0000 - val\_acc  
uracy: 0.0000e+00  
Epoch 21/100  
30/30 [=====] - 1s 23ms/step - loss: -301944153309  
184.0000 - accuracy: 0.0000e+00 - val\_loss: -346491587657728.0000 - val\_acc  
uracy: 0.0000e+00  
Epoch 22/100  
30/30 [=====] - 1s 22ms/step - loss: -388292692410  
368.0000 - accuracy: 0.0000e+00 - val\_loss: -442610606931968.0000 - val\_acc  
uracy: 0.0000e+00  
Epoch 23/100  
30/30 [=====] - 1s 22ms/step - loss: -492965877252  
096.0000 - accuracy: 0.0000e+00 - val\_loss: -558215624392704.0000 - val\_acc  
uracy: 0.0000e+00  
Epoch 24/100  
30/30 [=====] - 1s 23ms/step - loss: -618010091978  
752.0000 - accuracy: 0.0000e+00 - val\_loss: -695941132713984.0000 - val\_acc  
uracy: 0.0000e+00  
Epoch 25/100  
30/30 [=====] - 1s 23ms/step - loss: -766476977963  
008.0000 - accuracy: 0.0000e+00 - val\_loss: -858514704564224.0000 - val\_acc  
uracy: 0.0000e+00  
Epoch 26/100  
30/30 [=====] - 1s 23ms/step - loss: -941129004482  
560.0000 - accuracy: 0.0000e+00 - val\_loss: -1049328223256576.0000 - val\_ac  
curacy: 0.0000e+00  
Epoch 27/100  
30/30 [=====] - 1s 22ms/step - loss: -114500821634  
2528.0000 - accuracy: 0.0000e+00 - val\_loss: -1270932630929408.0000 - val\_a  
ccuracy: 0.0000e+00  
Epoch 28/100  
30/30 [=====] - 1s 21ms/step - loss: -138161366971  
1872.0000 - accuracy: 0.0000e+00 - val\_loss: -1527369827352576.0000 - val\_a  
ccuracy: 0.0000e+00  
Epoch 29/100  
30/30 [=====] - 1s 21ms/step - loss: -165409310585  
6512.0000 - accuracy: 0.0000e+00 - val\_loss: -1821197398441984.0000 - val\_a  
ccuracy: 0.0000e+00  
Epoch 30/100  
30/30 [=====] - 1s 21ms/step - loss: -196549434094  
3872.0000 - accuracy: 0.0000e+00 - val\_loss: -2157035252613120.0000 - val\_a  
ccuracy: 0.0000e+00  
Epoch 31/100  
30/30 [=====] - 1s 21ms/step - loss: -232041567433  
5232.0000 - accuracy: 0.0000e+00 - val\_loss: -2537612707364864.0000 - val\_a  
ccuracy: 0.0000e+00  
Epoch 32/100  
30/30 [=====] - 1s 22ms/step - loss: -272236904710  
1440.0000 - accuracy: 0.0000e+00 - val\_loss: -2968374304833536.0000 - val\_a  
ccuracy: 0.0000e+00  
Epoch 33/100  
30/30 [=====] - 1s 21ms/step - loss: -317555735317  
7088.0000 - accuracy: 0.0000e+00 - val\_loss: -3451648588382208.0000 - val\_a  
ccuracy: 0.0000e+00  
Epoch 34/100  
30/30 [=====] - 1s 21ms/step - loss: -368353253051  
5968.0000 - accuracy: 0.0000e+00 - val\_loss: -3994606811217920.0000 - val\_a  
ccuracy: 0.0000e+00  
Epoch 35/100  
30/30 [=====] - 1s 20ms/step - loss: -425187239945  
8304.0000 - accuracy: 0.0000e+00 - val\_loss: -4597935362801664.0000 - val\_a

```
ccuracy: 0.0000e+00
Epoch 36/100
30/30 [=====] - 1s 21ms/step - loss: -488383469269
8112.0000 - accuracy: 0.0000e+00 - val_loss: -5270418793431040.0000 - val_a
ccuracy: 0.0000e+00
Epoch 37/100
30/30 [=====] - 1s 21ms/step - loss: -558595071331
5328.0000 - accuracy: 0.0000e+00 - val_loss: -6014716224733184.0000 - val_a
ccuracy: 0.0000e+00
Epoch 38/100
30/30 [=====] - 1s 23ms/step - loss: -636162502819
8400.0000 - accuracy: 0.0000e+00 - val_loss: -6834514349260800.0000 - val_a
ccuracy: 0.0000e+00
Epoch 39/100
30/30 [=====] - 1s 22ms/step - loss: -721583443070
1568.0000 - accuracy: 0.0000e+00 - val_loss: -7737028175200256.0000 - val_a
ccuracy: 0.0000e+00
Epoch 40/100
30/30 [=====] - 1s 22ms/step - loss: -815440880205
8240.0000 - accuracy: 0.0000e+00 - val_loss: -8727006862639104.0000 - val_a
ccuracy: 0.0000e+00
Epoch 41/100
30/30 [=====] - 1s 22ms/step - loss: -918254988453
4784.0000 - accuracy: 0.0000e+00 - val_loss: -9809462638411776.0000 - val_a
ccuracy: 0.0000e+00
Epoch 42/100
30/30 [=====] - 1s 22ms/step - loss: -103042933367
76704.0000 - accuracy: 0.0000e+00 - val_loss: -10990478786822144.0000 - val
_accuracy: 0.0000e+00
Epoch 43/100
30/30 [=====] - 1s 22ms/step - loss: -115268139016
51968.0000 - accuracy: 0.0000e+00 - val_loss: -12273867628216320.0000 - val
_accuracy: 0.0000e+00
Epoch 44/100
30/30 [=====] - 1s 22ms/step - loss: -128545311005
08160.0000 - accuracy: 0.0000e+00 - val_loss: -13667263466962944.0000 - val
_accuracy: 0.0000e+00
Epoch 45/100
30/30 [=====] - 1s 21ms/step - loss: -142929993998
00832.0000 - accuracy: 0.0000e+00 - val_loss: -15175930859225088.0000 - val
_accuracy: 0.0000e+00
Epoch 46/100
30/30 [=====] - 1s 21ms/step - loss: -158515410260
45952.0000 - accuracy: 0.0000e+00 - val_loss: -16804242081710080.0000 - val
_accuracy: 0.0000e+00
Epoch 47/100
30/30 [=====] - 1s 22ms/step - loss: -175319544967
98720.0000 - accuracy: 0.0000e+00 - val_loss: -18565286047252480.0000 - val
_accuracy: 0.0000e+00
Epoch 48/100
30/30 [=====] - 1s 21ms/step - loss: -193433472902
10304.0000 - accuracy: 0.0000e+00 - val_loss: -20455657920528384.0000 - val
_accuracy: 0.0000e+00
Epoch 49/100
30/30 [=====] - 1s 22ms/step - loss: -212924249239
71584.0000 - accuracy: 0.0000e+00 - val_loss: -22490267680505856.0000 - val
_accuracy: 0.0000e+00
Epoch 50/100
30/30 [=====] - 1s 21ms/step - loss: -233849480229
68320.0000 - accuracy: 0.0000e+00 - val_loss: -24672061674749952.0000 - val
_accuracy: 0.0000e+00
Epoch 51/100
30/30 [=====] - 1s 21ms/step - loss: -256240390284
```

24704.0000 - accuracy: 0.0000e+00 - val\_loss: -27007293375643648.0000 - val  
\_accuracy: 0.0000e+00  
Epoch 52/100  
30/30 [=====] - 1s 21ms/step - loss: -280218183380  
50048.0000 - accuracy: 0.0000e+00 - val\_loss: -29498105971867648.0000 - val  
\_accuracy: 0.0000e+00  
Epoch 53/100  
30/30 [=====] - 1s 22ms/step - loss: -305808844070  
58432.0000 - accuracy: 0.0000e+00 - val\_loss: -3215993557942272.0000 - val  
\_accuracy: 0.0000e+00  
Epoch 54/100  
30/30 [=====] - 1s 21ms/step - loss: -333103661884  
37504.0000 - accuracy: 0.0000e+00 - val\_loss: -34995337693233152.0000 - val  
\_accuracy: 0.0000e+00  
Epoch 55/100  
30/30 [=====] - 1s 21ms/step - loss: -362140346634  
73152.0000 - accuracy: 0.0000e+00 - val\_loss: -38020175785623552.0000 - val  
\_accuracy: 0.0000e+00  
Epoch 56/100  
30/30 [=====] - 1s 21ms/step - loss: -393074547936  
46080.0000 - accuracy: 0.0000e+00 - val\_loss: -41224105424322560.0000 - val  
\_accuracy: 0.0000e+00  
Epoch 57/100  
30/30 [=====] - 1s 21ms/step - loss: -425882987066  
81856.0000 - accuracy: 0.0000e+00 - val\_loss: -44619350086254592.0000 - val  
\_accuracy: 0.0000e+00  
Epoch 58/100  
30/30 [=====] - 1s 21ms/step - loss: -460654398050  
14016.0000 - accuracy: 0.0000e+00 - val\_loss: -48223068165767168.0000 - val  
\_accuracy: 0.0000e+00  
Epoch 59/100  
30/30 [=====] - 1s 21ms/step - loss: -497528281424  
19968.0000 - accuracy: 0.0000e+00 - val\_loss: -52041152357990400.0000 - val  
\_accuracy: 0.0000e+00  
Epoch 60/100  
30/30 [=====] - 1s 22ms/step - loss: -536509275753  
67680.0000 - accuracy: 0.0000e+00 - val\_loss: -56085250614231040.0000 - val  
\_accuracy: 0.0000e+00  
Epoch 61/100  
30/30 [=====] - 1s 21ms/step - loss: -577779272903  
55712.0000 - accuracy: 0.0000e+00 - val\_loss: -60342336298680320.0000 - val  
\_accuracy: 0.0000e+00  
Epoch 62/100  
30/30 [=====] - 1s 21ms/step - loss: -621245673378  
93888.0000 - accuracy: 0.0000e+00 - val\_loss: -64844982443311104.0000 - val  
\_accuracy: 0.0000e+00  
Epoch 63/100  
30/30 [=====] - 1s 21ms/step - loss: -667120949211  
95520.0000 - accuracy: 0.0000e+00 - val\_loss: -69579054310752256.0000 - val  
\_accuracy: 0.0000e+00  
Epoch 64/100  
30/30 [=====] - 1s 22ms/step - loss: -715403811912  
41728.0000 - accuracy: 0.0000e+00 - val\_loss: -74566310205325312.0000 - val  
\_accuracy: 0.0000e+00  
Epoch 65/100  
30/30 [=====] - 1s 21ms/step - loss: -766256525344  
76800.0000 - accuracy: 0.0000e+00 - val\_loss: -79807965602775040.0000 - val  
\_accuracy: 0.0000e+00  
Epoch 66/100  
30/30 [=====] - 1s 24ms/step - loss: -819619604211  
95776.0000 - accuracy: 0.0000e+00 - val\_loss: -85325048662982656.0000 - val  
\_accuracy: 0.0000e+00  
Epoch 67/100

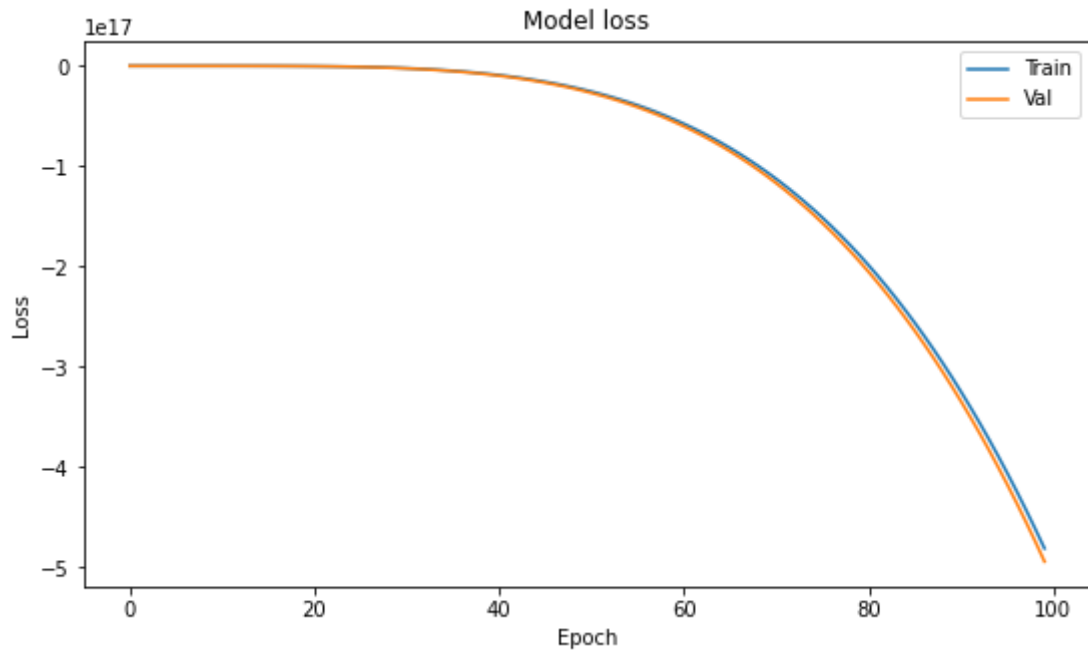
30/30 [=====] - 1s 21ms/step - loss: -875763330805  
92384.0000 - accuracy: 0.0000e+00 - val\_loss: -9110608323333248.0000 - val  
\_accuracy: 0.0000e+00  
Epoch 68/100  
30/30 [=====] - 1s 23ms/step - loss: -934628090980  
59776.0000 - accuracy: 0.0000e+00 - val\_loss: -97176641549107200.0000 - val  
\_accuracy: 0.0000e+00  
Epoch 69/100  
30/30 [=====] - 1s 22ms/step - loss: -996370908740  
32128.0000 - accuracy: 0.0000e+00 - val\_loss: -103531329131380736.0000 - va  
l\_accuracy: 0.0000e+00  
Epoch 70/100  
30/30 [=====] - 1s 22ms/step - loss: -106094934980  
820992.0000 - accuracy: 0.0000e+00 - val\_loss: -110187987274301440.0000 - v  
al\_accuracy: 0.0000e+00  
Epoch 71/100  
30/30 [=====] - 1s 23ms/step - loss: -112859087565  
225984.0000 - accuracy: 0.0000e+00 - val\_loss: -117149081289097216.0000 - v  
al\_accuracy: 0.0000e+00  
Epoch 72/100  
30/30 [=====] - 1s 21ms/step - loss: -119934350400  
684032.0000 - accuracy: 0.0000e+00 - val\_loss: -124427504667590656.0000 - v  
al\_accuracy: 0.0000e+00  
Epoch 73/100  
30/30 [=====] - 1s 23ms/step - loss: -127327045679  
054848.0000 - accuracy: 0.0000e+00 - val\_loss: -132038083636887552.0000 - v  
al\_accuracy: 0.0000e+00  
Epoch 74/100  
30/30 [=====] - 1s 23ms/step - loss: -135044225736  
638464.0000 - accuracy: 0.0000e+00 - val\_loss: -139954309658836992.0000 - v  
al\_accuracy: 0.0000e+00  
Epoch 75/100  
30/30 [=====] - 1s 24ms/step - loss: -143094016651  
558912.0000 - accuracy: 0.0000e+00 - val\_loss: -148225935634595840.0000 - v  
al\_accuracy: 0.0000e+00  
Epoch 76/100  
30/30 [=====] - 1s 22ms/step - loss: -151492258263  
203840.0000 - accuracy: 0.0000e+00 - val\_loss: -156867375474409472.0000 - v  
al\_accuracy: 0.0000e+00  
Epoch 77/100  
30/30 [=====] - 1s 22ms/step - loss: -160252514078  
294016.0000 - accuracy: 0.0000e+00 - val\_loss: -165870640539107328.0000 - v  
al\_accuracy: 0.0000e+00  
Epoch 78/100  
30/30 [=====] - 1s 23ms/step - loss: -169386260249  
444352.0000 - accuracy: 0.0000e+00 - val\_loss: -175235404411174912.0000 - v  
al\_accuracy: 0.0000e+00  
Epoch 79/100  
30/30 [=====] - 1s 22ms/step - loss: -178880543155  
290112.0000 - accuracy: 0.0000e+00 - val\_loss: -184995013216698368.0000 - v  
al\_accuracy: 0.0000e+00  
Epoch 80/100  
30/30 [=====] - 1s 21ms/step - loss: -188750068763  
852800.0000 - accuracy: 0.0000e+00 - val\_loss: -195121807366291456.0000 - v  
al\_accuracy: 0.0000e+00  
Epoch 81/100  
30/30 [=====] - 1s 21ms/step - loss: -199014542385  
086464.0000 - accuracy: 0.0000e+00 - val\_loss: -205649218885386240.0000 - v  
al\_accuracy: 0.0000e+00  
Epoch 82/100  
30/30 [=====] - 1s 22ms/step - loss: -209681609060  
777984.0000 - accuracy: 0.0000e+00 - val\_loss: -216590493453123584.0000 - v  
al\_accuracy: 0.0000e+00

Epoch 83/100  
30/30 [=====] - 1s 22ms/step - loss: -220757694062  
002176.0000 - accuracy: 0.0000e+00 - val\_loss: -227933656700682240.0000 - v  
al\_accuracy: 0.0000e+00  
Epoch 84/100  
30/30 [=====] - 1s 24ms/step - loss: -232249463178  
002432.0000 - accuracy: 0.0000e+00 - val\_loss: -239712329632055296.0000 - v  
al\_accuracy: 0.0000e+00  
Epoch 85/100  
30/30 [=====] - 1s 21ms/step - loss: -244164011694  
751744.0000 - accuracy: 0.0000e+00 - val\_loss: -251917544355528704.0000 - v  
al\_accuracy: 0.0000e+00  
Epoch 86/100  
30/30 [=====] - 1s 22ms/step - loss: -256499518546  
116608.0000 - accuracy: 0.0000e+00 - val\_loss: -264545469760274432.0000 - v  
al\_accuracy: 0.0000e+00  
Epoch 87/100  
30/30 [=====] - 1s 21ms/step - loss: -269291717859  
999744.0000 - accuracy: 0.0000e+00 - val\_loss: -277652026320486400.0000 - v  
al\_accuracy: 0.0000e+00  
Epoch 88/100  
30/30 [=====] - 1s 22ms/step - loss: -282549388549  
554176.0000 - accuracy: 0.0000e+00 - val\_loss: -291209812144816128.0000 - v  
al\_accuracy: 0.0000e+00  
Epoch 89/100  
30/30 [=====] - 1s 21ms/step - loss: -296270245692  
178432.0000 - accuracy: 0.0000e+00 - val\_loss: -305260436876427264.0000 - v  
al\_accuracy: 0.0000e+00  
Epoch 90/100  
30/30 [=====] - 1s 21ms/step - loss: -310464219252  
260864.0000 - accuracy: 0.0000e+00 - val\_loss: -319800069404491776.0000 - v  
al\_accuracy: 0.0000e+00  
Epoch 91/100  
30/30 [=====] - 1s 21ms/step - loss: -325154828470  
714368.0000 - accuracy: 0.0000e+00 - val\_loss: -334817714612731904.0000 - v  
al\_accuracy: 0.0000e+00  
Epoch 92/100  
30/30 [=====] - 1s 20ms/step - loss: -340335957314  
109440.0000 - accuracy: 0.0000e+00 - val\_loss: -350356837570183168.0000 - v  
al\_accuracy: 0.0000e+00  
Epoch 93/100  
30/30 [=====] - 1s 20ms/step - loss: -356021384037  
531648.0000 - accuracy: 0.0000e+00 - val\_loss: -366387923261587456.0000 - v  
al\_accuracy: 0.0000e+00  
Epoch 94/100  
30/30 [=====] - 1s 19ms/step - loss: -372235572774  
699008.0000 - accuracy: 0.0000e+00 - val\_loss: -382964160561938432.0000 - v  
al\_accuracy: 0.0000e+00  
Epoch 95/100  
30/30 [=====] - 1s 21ms/step - loss: -388964779630  
264320.0000 - accuracy: 0.0000e+00 - val\_loss: -400065174146383872.0000 - v  
al\_accuracy: 0.0000e+00  
Epoch 96/100  
30/30 [=====] - 1s 19ms/step - loss: -406225256760  
475648.0000 - accuracy: 0.0000e+00 - val\_loss: -417685088499662848.0000 - v  
al\_accuracy: 0.0000e+00  
Epoch 97/100  
30/30 [=====] - 1s 20ms/step - loss: -424020852456  
030208.0000 - accuracy: 0.0000e+00 - val\_loss: -435866063020752896.0000 - v  
al\_accuracy: 0.0000e+00  
Epoch 98/100  
30/30 [=====] - 1s 19ms/step - loss: -442387713161  
691136.0000 - accuracy: 0.0000e+00 - val\_loss: -454627167364448256.0000 - v

```
al_accuracy: 0.0000e+00
Epoch 99/100
30/30 [=====] - 1s 21ms/step - loss: -461322265464
668160.0000 - accuracy: 0.0000e+00 - val_loss: -473960258272755712.0000 - v
al_accuracy: 0.0000e+00
Epoch 100/100
```

In [127...

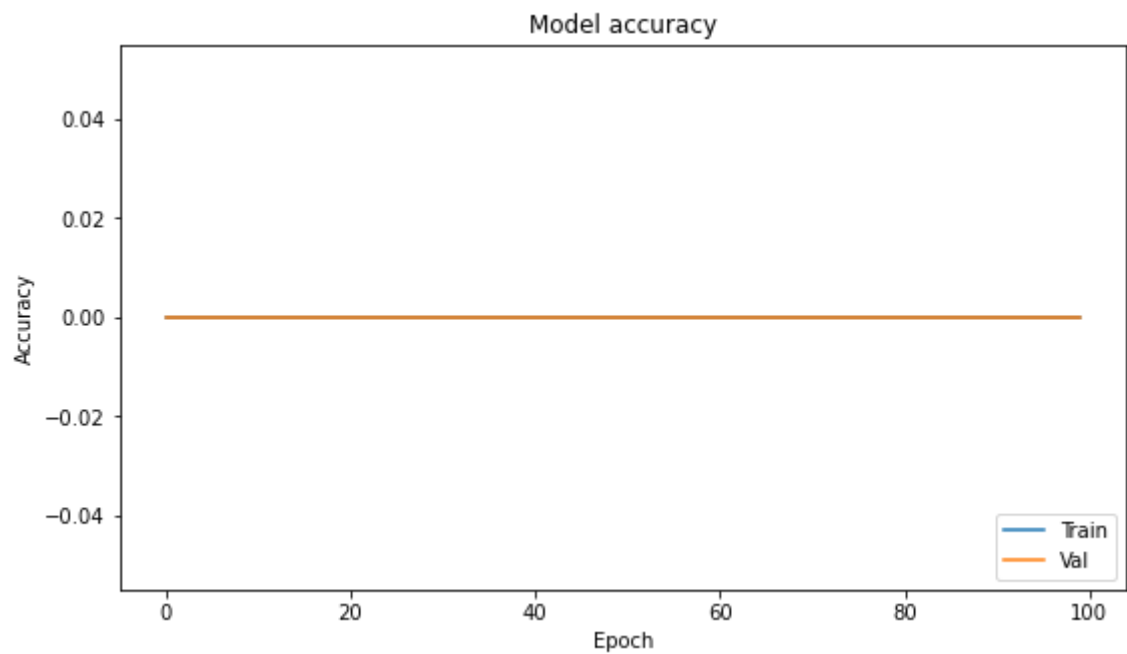
```
plt.plot(hist_2.history['loss'])
plt.plot(hist_2.history['val_loss'])
plt.title('Model loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Val'], loc='upper right')
plt.show()
```



In [41]:

```
plt.plot(hist_2.history['accuracy'])
plt.plot(hist_2.history['val_accuracy'])
plt.title('Model accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train', 'Val'], loc='lower right')
plt.show()
```





In [128...

```
_, accuracy = model.evaluate(X_train, Y_train)
print('Accuracy: %.2f' % (accuracy*100))
```

```
30/30 [=====] - 0s 538us/step - loss: nan - accuracy: 0.0000e+00
Accuracy: 0.00
```

In [137...

```
y_pred = model.predict(x_train)
pd.DataFrame(y_pred)
```

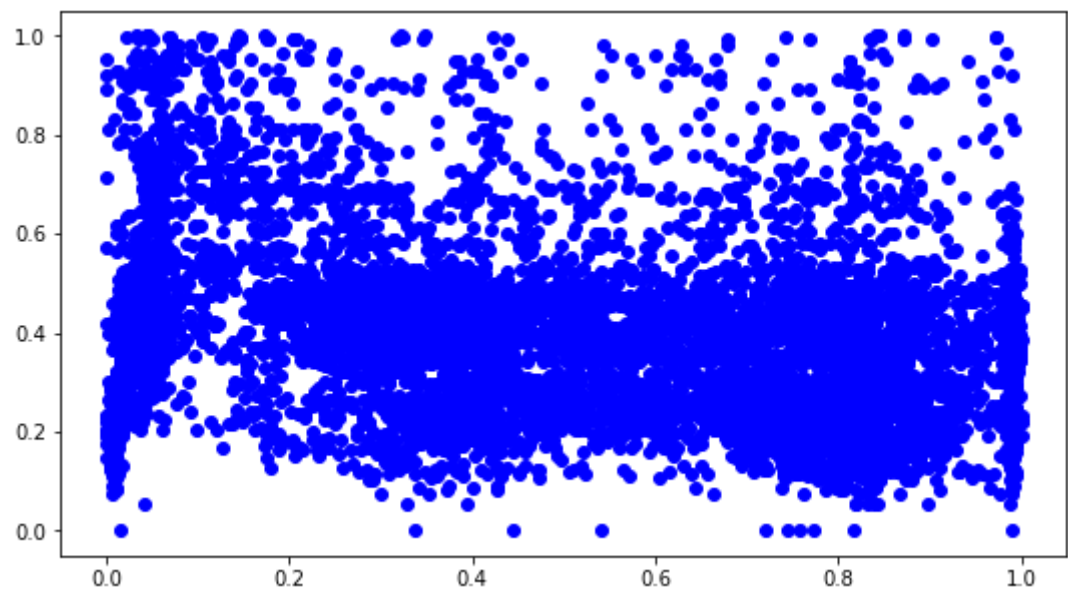
Out[137...

	0
0	NaN
1	NaN
2	NaN
3	NaN
4	NaN
...	...
932	NaN
933	NaN
934	NaN
935	NaN
936	NaN

937 rows × 1 columns

In [148...

```
plt.plot(x_train, y_train, "bo")
plt.show()
```



In [ ]:

In [ ]: