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Problem Statement

You are a data scientist working for a school

You are asked to predict the GPA of the current students based on the following provided data:

0 StudentID int64
1 Age int64
2 Gender int64
3 Ethnicity int64
4 ParentalEducation int64
5 StudyTimeWeekly float64 6 Absences int64
7 Tutoring int64
8 ParentalSupport int64
9 Extracurricular int64
10 Sports int64
11 Music int64
12 Volunteering int64
13 GPA float64 14 GradeClass float64

The GPA is the Grade Point Average, typically ranges from 0.0 to 4.0 in most educational systems, with 4.0 representing an 'A' or excellent performance.

The minimum passing GPA can vary by institution, but it's often around 2.0. This usually corresponds to a 'C' grade, which is considered satisfactory.

You need to create a Deep Learning model capable to predict the GPA of a Student based on a set of provided features. The data provided represents 2,392 students.

In this excersice you will be requested to create a total of three models and select the most performant one.

1) Import Libraries

First let's import the following libraries, if there is any library that you need and is not in the list bellow feel free to include it

```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.layers import Dropout
from tensorflow.keras.layers import Conv1D, MaxPooling1D, Flatten
from tensorflow.keras.regularizers import l2
```

```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
```

2) Load Data

- You will be provided with a cvs (comma separated value) file.
- You will need to add that file into a pandas dataframe, you can use the following code as reference
- The file will be available in canvas

```
data = pd.read_csv("Student_performance_data _.csv")
data

      StudentID  Age  Gender  Ethnicity  ParentalEducation
StudyTimeWeekly  \
0          1001   17       1          0                  2
19.833723
1          1002   18       0          0                  1
15.408756
2          1003   15       0          2                  3
4.210570
3          1004   17       1          0                  3
10.028829
4          1005   17       1          0                  2
4.672495
...         ...  ...     ...        ...                ...
...
2387       3388   18       1          0                  3
10.680555
2388       3389   17       0          0                  1
7.583217
2389       3390   16       1          0                  2
6.805500
2390       3391   16       1          1                  0
12.416653
2391       3392   16       1          0                  2
17.819907

      Absences  Tutoring  ParentalSupport  Extracurricular  Sports
Music  \
0            7         1                2                0       0
1
1            0         0                1                0       0
0
2           26         0                2                0       0
0
3           14         0                3                1       0
0
4           17         1                3                0       0
0
```

```
...         ...       ...              ...              ...     ...
...
2387          2         0                4                1       0
0
2388          4         1                4                0       1
0
2389         20         0                2                0       0
0
2390         17         0                2                0       1
1
2391         13         0                2                0       0
0

      Volunteering       GPA  GradeClass
0                0  2.929196         2.0
1                0  3.042915         1.0
2                0  0.112602         4.0
3                0  2.054218         3.0
4                0  1.288061         4.0
...            ...       ...         ...
2387             0  3.455509         0.0
2388             0  3.279150         4.0
2389             1  1.142333         2.0
2390             0  1.803297         1.0
2391             1  2.140014         1.0

[2392 rows x 15 columns]
```

3) Review you data:

Make sure you review your data. Place special attention of null or empty values.

```
data.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2392 entries, 0 to 2391
Data columns (total 15 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   StudentID          2392 non-null   int64
 1   Age                2392 non-null   int64
 2   Gender             2392 non-null   int64
 3   Ethnicity          2392 non-null   int64
 4   ParentalEducation  2392 non-null   int64
 5   StudyTimeWeekly    2392 non-null   float64
 6   Absences           2392 non-null   int64
 7   Tutoring           2392 non-null   int64
 8   ParentalSupport    2392 non-null   int64
 9   Extracurricular    2392 non-null   int64
```

```
 10  Sports             2392 non-null   int64
 11  Music              2392 non-null   int64
 12  Volunteering       2392 non-null   int64
 13  GPA                2392 non-null   float64
 14  GradeClass         2392 non-null   float64
dtypes: float64(3), int64(12)
memory usage: 280.4 KB
```

4. Based on what you learn in this course, create a model capabable to predict student GPA result.

- Deliverables of this activity:
- Explain the model architecture and why you choose such architecture.
- Show your Loss Function result during model evaluation. (Graph and Value)
- Show your Metric result (Graph and value)
- Use your test dataset to predict 5 random students. An show your resutls.

Note: Add as many Code and Markdown cells as you need.

Model architecture

First of all, we will select our columns, where we will drop gender, ethnicity and studentid, since we dont think they provide relevant information to our model.

```
dataset = data.drop(columns = ['Gender', 'Ethnicity', 'StudentID'])
X = dataset.drop(columns = 'GPA')
scaler = StandardScaler()
X = scaler.fit_transform(X) # we scale our input data
y = dataset['GPA']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size =
0.15, random_state = 42) # we split with a 85/15 rule with a random
state (42)
```

NN architecture

For this problem, a feed forward will be enough to obtain adequate results. Our plan is to use different types of techniques and layers so that we achieve this. Thus, we will incorporate dense layers, giving units to our nn, leakyReLU, so that the model can understand complex relations between our weights and data, batchnorm with the objective of normalizing our data for each minibatch input, and dropout, so that the model can 'turn off' certain neurons when computing and prevent overfitting.

```
from tensorflow.keras.layers import LeakyReLU, BatchNormalization
```

```
# NN architecture
model = Sequential()
model.add(Dense(32, input_shape=(X_train.shape[1],)))
model.add(BatchNormalization())
model.add(LeakyReLU(alpha=0.1))
model.add(Dropout(0.3))

model.add(Dense(16))
model.add(BatchNormalization())
model.add(LeakyReLU(alpha=0.1))
model.add(Dropout(0.2))

model.add(Dense(8, activation='relu'))
model.add(Dropout(0.1))

model.add(Dense(1, activation='linear'))
```

As we can see, we created a layer of 32 units with our input data, with batch norm, leaky relu as activation and dropout of 0.3. Then, we added a layer of 16 units with a batch norm layer, a leaky relu as activation and a dropout of 0.2. Afterwards, we decided to add 8 units and create a new layer with relu as activation function, adding solely a dropout of 0.1. Finally, we added a dense layer of linear activation so that we obtain our final output data

Compilation and other things

Now, we will compile our model, using adam as our optimizer, mse as our loss function and we will also want to compare our mse with mae. Thus, we fit our model with our train data, using a batch size of 64 on 200 epochs and a train valid split of 0.2, preserving an 80/20 proportion.

```
model.compile(optimizer = 'adam', loss ='mse', metrics = ['mae'])
history = model.fit(X_train, y_train, batch_size = 64, epochs = 200,
validation_split = 0.2)
```

```
Epoch 1/200
26/26 [==============================] - 1s 5ms/step - loss: 5.7158 -
mae: 2.1504 - val_loss: 4.0332 - val_mae: 1.7880
Epoch 2/200
26/26 [==============================] - 0s 4ms/step - loss: 3.8431 -
mae: 1.7397 - val_loss: 3.2696 - val_mae: 1.5904
Epoch 3/200
26/26 [==============================] - 0s 3ms/step - loss: 2.8338 -
mae: 1.4608 - val_loss: 2.4136 - val_mae: 1.3484
Epoch 4/200
26/26 [==============================] - 0s 2ms/step - loss: 1.9944 -
mae: 1.2015 - val_loss: 1.5991 - val_mae: 1.0858
Epoch 5/200
26/26 [==============================] - 0s 2ms/step - loss: 1.3736 -
mae: 0.9673 - val_loss: 1.0464 - val_mae: 0.8753
```

```
Epoch 6/200
26/26 [==============================] - 0s 2ms/step - loss: 1.1316 -
mae: 0.8614 - val_loss: 0.7835 - val_mae: 0.7583
Epoch 7/200
26/26 [==============================] - 0s 2ms/step - loss: 0.9066 -
mae: 0.7571 - val_loss: 0.6586 - val_mae: 0.6969
Epoch 8/200
26/26 [==============================] - 0s 2ms/step - loss: 0.8180 -
mae: 0.7129 - val_loss: 0.6285 - val_mae: 0.6819
Epoch 9/200
26/26 [==============================] - 0s 2ms/step - loss: 0.7418 -
mae: 0.6854 - val_loss: 0.5080 - val_mae: 0.6115
Epoch 10/200
26/26 [==============================] - 0s 2ms/step - loss: 0.7196 -
mae: 0.6627 - val_loss: 0.4259 - val_mae: 0.5584
Epoch 11/200
26/26 [==============================] - 0s 2ms/step - loss: 0.6485 -
mae: 0.6217 - val_loss: 0.4035 - val_mae: 0.5472
Epoch 12/200
26/26 [==============================] - 0s 2ms/step - loss: 0.5983 -
mae: 0.6067 - val_loss: 0.3988 - val_mae: 0.5465
Epoch 13/200
26/26 [==============================] - 0s 2ms/step - loss: 0.6312 -
mae: 0.6186 - val_loss: 0.3720 - val_mae: 0.5278
Epoch 14/200
26/26 [==============================] - 0s 2ms/step - loss: 0.5631 -
mae: 0.5785 - val_loss: 0.3010 - val_mae: 0.4710
Epoch 15/200
26/26 [==============================] - 0s 2ms/step - loss: 0.5539 -
mae: 0.5751 - val_loss: 0.3355 - val_mae: 0.5034
Epoch 16/200
26/26 [==============================] - 0s 2ms/step - loss: 0.5252 -
mae: 0.5609 - val_loss: 0.2974 - val_mae: 0.4740
Epoch 17/200
26/26 [==============================] - 0s 2ms/step - loss: 0.4855 -
mae: 0.5391 - val_loss: 0.2471 - val_mae: 0.4288
Epoch 18/200
26/26 [==============================] - 0s 2ms/step - loss: 0.4587 -
mae: 0.5280 - val_loss: 0.2605 - val_mae: 0.4435
Epoch 19/200
26/26 [==============================] - 0s 2ms/step - loss: 0.4806 -
mae: 0.5360 - val_loss: 0.2484 - val_mae: 0.4323
Epoch 20/200
26/26 [==============================] - 0s 2ms/step - loss: 0.4577 -
mae: 0.5272 - val_loss: 0.2305 - val_mae: 0.4139
Epoch 21/200
26/26 [==============================] - 0s 2ms/step - loss: 0.4779 -
mae: 0.5333 - val_loss: 0.2476 - val_mae: 0.4319
Epoch 22/200
```

```
26/26 [==============================] - 0s 4ms/step - loss: 0.3874 -
mae: 0.4883 - val_loss: 0.2351 - val_mae: 0.4211
Epoch 23/200
26/26 [==============================] - 0s 2ms/step - loss: 0.4021 -
mae: 0.4955 - val_loss: 0.1861 - val_mae: 0.3708
Epoch 24/200
26/26 [==============================] - 0s 2ms/step - loss: 0.4139 -
mae: 0.4898 - val_loss: 0.1838 - val_mae: 0.3694
Epoch 25/200
26/26 [==============================] - 0s 2ms/step - loss: 0.4006 -
mae: 0.4897 - val_loss: 0.1640 - val_mae: 0.3459
Epoch 26/200
26/26 [==============================] - 0s 2ms/step - loss: 0.3890 -
mae: 0.4776 - val_loss: 0.1678 - val_mae: 0.3505
Epoch 27/200
26/26 [==============================] - 0s 2ms/step - loss: 0.3975 -
mae: 0.4849 - val_loss: 0.1732 - val_mae: 0.3579
Epoch 28/200
26/26 [==============================] - 0s 2ms/step - loss: 0.3599 -
mae: 0.4568 - val_loss: 0.1648 - val_mae: 0.3489
Epoch 29/200
26/26 [==============================] - 0s 2ms/step - loss: 0.3606 -
mae: 0.4570 - val_loss: 0.1517 - val_mae: 0.3339
Epoch 30/200
26/26 [==============================] - 0s 2ms/step - loss: 0.3502 -
mae: 0.4588 - val_loss: 0.1372 - val_mae: 0.3149
Epoch 31/200
26/26 [==============================] - 0s 2ms/step - loss: 0.3415 -
mae: 0.4537 - val_loss: 0.1222 - val_mae: 0.2946
Epoch 32/200
26/26 [==============================] - 0s 2ms/step - loss: 0.3487 -
mae: 0.4560 - val_loss: 0.1268 - val_mae: 0.3022
Epoch 33/200
26/26 [==============================] - 0s 2ms/step - loss: 0.3385 -
mae: 0.4434 - val_loss: 0.1114 - val_mae: 0.2804
Epoch 34/200
26/26 [==============================] - 0s 2ms/step - loss: 0.3443 -
mae: 0.4456 - val_loss: 0.1184 - val_mae: 0.2917
Epoch 35/200
26/26 [==============================] - 0s 2ms/step - loss: 0.3259 -
mae: 0.4324 - val_loss: 0.1073 - val_mae: 0.2743
Epoch 36/200
26/26 [==============================] - 0s 2ms/step - loss: 0.3275 -
mae: 0.4405 - val_loss: 0.1104 - val_mae: 0.2794
Epoch 37/200
26/26 [==============================] - 0s 2ms/step - loss: 0.3190 -
mae: 0.4344 - val_loss: 0.0992 - val_mae: 0.2608
Epoch 38/200
26/26 [==============================] - 0s 2ms/step - loss: 0.2987 -
```

```
mae: 0.4170 - val_loss: 0.1001 - val_mae: 0.2628
Epoch 39/200
26/26 [==============================] - 0s 2ms/step - loss: 0.2915 -
mae: 0.4172 - val_loss: 0.1006 - val_mae: 0.2636
Epoch 40/200
26/26 [==============================] - 0s 2ms/step - loss: 0.3107 -
mae: 0.4268 - val_loss: 0.1015 - val_mae: 0.2663
Epoch 41/200
26/26 [==============================] - 0s 2ms/step - loss: 0.3018 -
mae: 0.4189 - val_loss: 0.0941 - val_mae: 0.2547
Epoch 42/200
26/26 [==============================] - 0s 2ms/step - loss: 0.2956 -
mae: 0.4197 - val_loss: 0.1001 - val_mae: 0.2640
Epoch 43/200
26/26 [==============================] - 0s 2ms/step - loss: 0.2828 -
mae: 0.4044 - val_loss: 0.0864 - val_mae: 0.2425
Epoch 44/200
26/26 [==============================] - 0s 2ms/step - loss: 0.2703 -
mae: 0.3999 - val_loss: 0.0971 - val_mae: 0.2609
Epoch 45/200
26/26 [==============================] - 0s 2ms/step - loss: 0.2687 -
mae: 0.3988 - val_loss: 0.1017 - val_mae: 0.2676
Epoch 46/200
26/26 [==============================] - 0s 2ms/step - loss: 0.2652 -
mae: 0.3886 - val_loss: 0.0930 - val_mae: 0.2538
Epoch 47/200
26/26 [==============================] - 0s 4ms/step - loss: 0.2603 -
mae: 0.3931 - val_loss: 0.0938 - val_mae: 0.2555
Epoch 48/200
26/26 [==============================] - 0s 2ms/step - loss: 0.2819 -
mae: 0.4058 - val_loss: 0.0820 - val_mae: 0.2361
Epoch 49/200
26/26 [==============================] - 0s 2ms/step - loss: 0.2557 -
mae: 0.3853 - val_loss: 0.0807 - val_mae: 0.2344
Epoch 50/200
26/26 [==============================] - 0s 2ms/step - loss: 0.2777 -
mae: 0.4057 - val_loss: 0.0748 - val_mae: 0.2243
Epoch 51/200
26/26 [==============================] - 0s 2ms/step - loss: 0.2727 -
mae: 0.3962 - val_loss: 0.0755 - val_mae: 0.2246
Epoch 52/200
26/26 [==============================] - 0s 2ms/step - loss: 0.2452 -
mae: 0.3720 - val_loss: 0.0705 - val_mae: 0.2155
Epoch 53/200
26/26 [==============================] - 0s 2ms/step - loss: 0.2487 -
mae: 0.3874 - val_loss: 0.0723 - val_mae: 0.2196
Epoch 54/200
26/26 [==============================] - 0s 2ms/step - loss: 0.2439 -
mae: 0.3787 - val_loss: 0.0702 - val_mae: 0.2159
```

```
Epoch 55/200
26/26 [==============================] - 0s 2ms/step - loss: 0.2641 -
mae: 0.3895 - val_loss: 0.0655 - val_mae: 0.2076
Epoch 56/200
26/26 [==============================] - 0s 2ms/step - loss: 0.2371 -
mae: 0.3809 - val_loss: 0.0618 - val_mae: 0.2004
Epoch 57/200
26/26 [==============================] - 0s 2ms/step - loss: 0.2552 -
mae: 0.3842 - val_loss: 0.0650 - val_mae: 0.2075
Epoch 58/200
26/26 [==============================] - 0s 2ms/step - loss: 0.2362 -
mae: 0.3716 - val_loss: 0.0642 - val_mae: 0.2059
Epoch 59/200
26/26 [==============================] - 0s 2ms/step - loss: 0.2352 -
mae: 0.3708 - val_loss: 0.0675 - val_mae: 0.2122
Epoch 60/200
26/26 [==============================] - 0s 2ms/step - loss: 0.2209 -
mae: 0.3572 - val_loss: 0.0564 - val_mae: 0.1911
Epoch 61/200
26/26 [==============================] - 0s 2ms/step - loss: 0.2275 -
mae: 0.3672 - val_loss: 0.0662 - val_mae: 0.2100
Epoch 62/200
26/26 [==============================] - 0s 2ms/step - loss: 0.2228 -
mae: 0.3582 - val_loss: 0.0633 - val_mae: 0.2048
Epoch 63/200
26/26 [==============================] - 0s 2ms/step - loss: 0.2123 -
mae: 0.3445 - val_loss: 0.0627 - val_mae: 0.2039
Epoch 64/200
26/26 [==============================] - 0s 2ms/step - loss: 0.2132 -
mae: 0.3496 - val_loss: 0.0556 - val_mae: 0.1898
Epoch 65/200
26/26 [==============================] - 0s 2ms/step - loss: 0.2429 -
mae: 0.3750 - val_loss: 0.0602 - val_mae: 0.2002
Epoch 66/200
26/26 [==============================] - 0s 2ms/step - loss: 0.2364 -
mae: 0.3659 - val_loss: 0.0544 - val_mae: 0.1883
Epoch 67/200
26/26 [==============================] - 0s 2ms/step - loss: 0.2020 -
mae: 0.3413 - val_loss: 0.0602 - val_mae: 0.2005
Epoch 68/200
26/26 [==============================] - 0s 2ms/step - loss: 0.2245 -
mae: 0.3548 - val_loss: 0.0605 - val_mae: 0.2008
Epoch 69/200
26/26 [==============================] - 0s 2ms/step - loss: 0.2171 -
mae: 0.3524 - val_loss: 0.0599 - val_mae: 0.1991
Epoch 70/200
26/26 [==============================] - 0s 2ms/step - loss: 0.2330 -
mae: 0.3649 - val_loss: 0.0522 - val_mae: 0.1834
Epoch 71/200
```

```
26/26 [==============================] - 0s 3ms/step - loss: 0.2094 -
mae: 0.3470 - val_loss: 0.0661 - val_mae: 0.2111
Epoch 72/200
26/26 [==============================] - 0s 2ms/step - loss: 0.2005 -
mae: 0.3398 - val_loss: 0.0596 - val_mae: 0.1992
Epoch 73/200
26/26 [==============================] - 0s 2ms/step - loss: 0.2183 -
mae: 0.3485 - val_loss: 0.0561 - val_mae: 0.1934
Epoch 74/200
26/26 [==============================] - 0s 2ms/step - loss: 0.2081 -
mae: 0.3441 - val_loss: 0.0514 - val_mae: 0.1830
Epoch 75/200
26/26 [==============================] - 0s 2ms/step - loss: 0.2036 -
mae: 0.3470 - val_loss: 0.0585 - val_mae: 0.1973
Epoch 76/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1822 -
mae: 0.3277 - val_loss: 0.0550 - val_mae: 0.1904
Epoch 77/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1868 -
mae: 0.3242 - val_loss: 0.0528 - val_mae: 0.1862
Epoch 78/200
26/26 [==============================] - 0s 2ms/step - loss: 0.2114 -
mae: 0.3475 - val_loss: 0.0474 - val_mae: 0.1756
Epoch 79/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1974 -
mae: 0.3358 - val_loss: 0.0514 - val_mae: 0.1844
Epoch 80/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1846 -
mae: 0.3321 - val_loss: 0.0505 - val_mae: 0.1828
Epoch 81/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1891 -
mae: 0.3292 - val_loss: 0.0498 - val_mae: 0.1825
Epoch 82/200
26/26 [==============================] - 0s 2ms/step - loss: 0.2098 -
mae: 0.3477 - val_loss: 0.0535 - val_mae: 0.1899
Epoch 83/200
26/26 [==============================] - 0s 2ms/step - loss: 0.2012 -
mae: 0.3428 - val_loss: 0.0473 - val_mae: 0.1765
Epoch 84/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1968 -
mae: 0.3371 - val_loss: 0.0566 - val_mae: 0.1955
Epoch 85/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1854 -
mae: 0.3291 - val_loss: 0.0493 - val_mae: 0.1809
Epoch 86/200
26/26 [==============================] - 0s 2ms/step - loss: 0.2019 -
mae: 0.3436 - val_loss: 0.0503 - val_mae: 0.1825
Epoch 87/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1821 -
```

```
mae: 0.3260 - val_loss: 0.0593 - val_mae: 0.2007
Epoch 88/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1923 -
mae: 0.3308 - val_loss: 0.0451 - val_mae: 0.1721
Epoch 89/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1958 -
mae: 0.3324 - val_loss: 0.0495 - val_mae: 0.1818
Epoch 90/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1991 -
mae: 0.3329 - val_loss: 0.0455 - val_mae: 0.1734
Epoch 91/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1828 -
mae: 0.3285 - val_loss: 0.0464 - val_mae: 0.1755
Epoch 92/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1873 -
mae: 0.3246 - val_loss: 0.0476 - val_mae: 0.1778
Epoch 93/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1672 -
mae: 0.3131 - val_loss: 0.0500 - val_mae: 0.1825
Epoch 94/200
26/26 [==============================] - 0s 4ms/step - loss: 0.1633 -
mae: 0.3088 - val_loss: 0.0451 - val_mae: 0.1729
Epoch 95/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1531 -
mae: 0.2986 - val_loss: 0.0430 - val_mae: 0.1679
Epoch 96/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1705 -
mae: 0.3192 - val_loss: 0.0458 - val_mae: 0.1741
Epoch 97/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1842 -
mae: 0.3235 - val_loss: 0.0438 - val_mae: 0.1696
Epoch 98/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1797 -
mae: 0.3212 - val_loss: 0.0452 - val_mae: 0.1727
Epoch 99/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1942 -
mae: 0.3320 - val_loss: 0.0436 - val_mae: 0.1686
Epoch 100/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1778 -
mae: 0.3174 - val_loss: 0.0502 - val_mae: 0.1828
Epoch 101/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1543 -
mae: 0.2969 - val_loss: 0.0475 - val_mae: 0.1775
Epoch 102/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1606 -
mae: 0.3079 - val_loss: 0.0454 - val_mae: 0.1734
Epoch 103/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1744 -
mae: 0.3183 - val_loss: 0.0433 - val_mae: 0.1682
```

```
Epoch 104/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1741 -
mae: 0.3095 - val_loss: 0.0445 - val_mae: 0.1704
Epoch 105/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1640 -
mae: 0.3037 - val_loss: 0.0495 - val_mae: 0.1809
Epoch 106/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1613 -
mae: 0.3089 - val_loss: 0.0445 - val_mae: 0.1703
Epoch 107/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1596 -
mae: 0.3017 - val_loss: 0.0466 - val_mae: 0.1750
Epoch 108/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1670 -
mae: 0.3102 - val_loss: 0.0465 - val_mae: 0.1744
Epoch 109/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1608 -
mae: 0.3081 - val_loss: 0.0476 - val_mae: 0.1756
Epoch 110/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1504 -
mae: 0.3010 - val_loss: 0.0489 - val_mae: 0.1792
Epoch 111/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1736 -
mae: 0.3083 - val_loss: 0.0423 - val_mae: 0.1640
Epoch 112/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1724 -
mae: 0.3101 - val_loss: 0.0451 - val_mae: 0.1709
Epoch 113/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1645 -
mae: 0.3020 - val_loss: 0.0463 - val_mae: 0.1732
Epoch 114/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1758 -
mae: 0.3110 - val_loss: 0.0498 - val_mae: 0.1809
Epoch 115/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1561 -
mae: 0.3000 - val_loss: 0.0443 - val_mae: 0.1682
Epoch 116/200
26/26 [==============================] - 0s 3ms/step - loss: 0.1655 -
mae: 0.3127 - val_loss: 0.0455 - val_mae: 0.1702
Epoch 117/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1555 -
mae: 0.3025 - val_loss: 0.0485 - val_mae: 0.1767
Epoch 118/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1621 -
mae: 0.2985 - val_loss: 0.0435 - val_mae: 0.1661
Epoch 119/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1638 -
mae: 0.3069 - val_loss: 0.0441 - val_mae: 0.1677
Epoch 120/200
```

```
26/26 [==============================] - 0s 2ms/step - loss: 0.1711 -
mae: 0.3156 - val_loss: 0.0482 - val_mae: 0.1766
Epoch 121/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1558 -
mae: 0.2973 - val_loss: 0.0455 - val_mae: 0.1692
Epoch 122/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1647 -
mae: 0.3038 - val_loss: 0.0497 - val_mae: 0.1790
Epoch 123/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1533 -
mae: 0.2970 - val_loss: 0.0457 - val_mae: 0.1704
Epoch 124/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1494 -
mae: 0.2925 - val_loss: 0.0443 - val_mae: 0.1664
Epoch 125/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1439 -
mae: 0.2936 - val_loss: 0.0517 - val_mae: 0.1832
Epoch 126/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1715 -
mae: 0.3162 - val_loss: 0.0495 - val_mae: 0.1778
Epoch 127/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1454 -
mae: 0.2904 - val_loss: 0.0464 - val_mae: 0.1722
Epoch 128/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1457 -
mae: 0.2919 - val_loss: 0.0459 - val_mae: 0.1711
Epoch 129/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1573 -
mae: 0.3006 - val_loss: 0.0421 - val_mae: 0.1613
Epoch 130/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1492 -
mae: 0.2935 - val_loss: 0.0424 - val_mae: 0.1626
Epoch 131/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1529 -
mae: 0.3040 - val_loss: 0.0459 - val_mae: 0.1708
Epoch 132/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1351 -
mae: 0.2782 - val_loss: 0.0463 - val_mae: 0.1714
Epoch 133/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1499 -
mae: 0.2942 - val_loss: 0.0428 - val_mae: 0.1637
Epoch 134/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1492 -
mae: 0.2945 - val_loss: 0.0451 - val_mae: 0.1691
Epoch 135/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1455 -
mae: 0.2901 - val_loss: 0.0458 - val_mae: 0.1698
Epoch 136/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1484 -
```

```
mae: 0.2923 - val_loss: 0.0413 - val_mae: 0.1598
Epoch 137/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1546 -
mae: 0.2984 - val_loss: 0.0429 - val_mae: 0.1636
Epoch 138/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1433 -
mae: 0.2891 - val_loss: 0.0445 - val_mae: 0.1673
Epoch 139/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1434 -
mae: 0.2854 - val_loss: 0.0455 - val_mae: 0.1700
Epoch 140/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1440 -
mae: 0.2868 - val_loss: 0.0459 - val_mae: 0.1711
Epoch 141/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1442 -
mae: 0.2886 - val_loss: 0.0501 - val_mae: 0.1798
Epoch 142/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1461 -
mae: 0.2911 - val_loss: 0.0465 - val_mae: 0.1711
Epoch 143/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1411 -
mae: 0.2870 - val_loss: 0.0526 - val_mae: 0.1852
Epoch 144/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1620 -
mae: 0.3058 - val_loss: 0.0467 - val_mae: 0.1713
Epoch 145/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1432 -
mae: 0.2893 - val_loss: 0.0457 - val_mae: 0.1691
Epoch 146/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1405 -
mae: 0.2836 - val_loss: 0.0434 - val_mae: 0.1636
Epoch 147/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1469 -
mae: 0.2893 - val_loss: 0.0467 - val_mae: 0.1711
Epoch 148/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1405 -
mae: 0.2864 - val_loss: 0.0478 - val_mae: 0.1734
Epoch 149/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1313 -
mae: 0.2743 - val_loss: 0.0479 - val_mae: 0.1737
Epoch 150/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1469 -
mae: 0.2865 - val_loss: 0.0456 - val_mae: 0.1684
Epoch 151/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1336 -
mae: 0.2788 - val_loss: 0.0463 - val_mae: 0.1697
Epoch 152/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1329 -
mae: 0.2761 - val_loss: 0.0451 - val_mae: 0.1673
```

```
Epoch 153/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1370 -
mae: 0.2831 - val_loss: 0.0451 - val_mae: 0.1665
Epoch 154/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1326 -
mae: 0.2758 - val_loss: 0.0455 - val_mae: 0.1679
Epoch 155/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1330 -
mae: 0.2829 - val_loss: 0.0483 - val_mae: 0.1752
Epoch 156/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1290 -
mae: 0.2704 - val_loss: 0.0439 - val_mae: 0.1644
Epoch 157/200
26/26 [==============================] - 0s 3ms/step - loss: 0.1378 -
mae: 0.2790 - val_loss: 0.0435 - val_mae: 0.1630
Epoch 158/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1336 -
mae: 0.2747 - val_loss: 0.0438 - val_mae: 0.1639
Epoch 159/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1300 -
mae: 0.2749 - val_loss: 0.0454 - val_mae: 0.1682
Epoch 160/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1305 -
mae: 0.2767 - val_loss: 0.0463 - val_mae: 0.1697
Epoch 161/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1366 -
mae: 0.2765 - val_loss: 0.0444 - val_mae: 0.1651
Epoch 162/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1289 -
mae: 0.2750 - val_loss: 0.0455 - val_mae: 0.1673
Epoch 163/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1356 -
mae: 0.2844 - val_loss: 0.0492 - val_mae: 0.1755
Epoch 164/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1332 -
mae: 0.2826 - val_loss: 0.0464 - val_mae: 0.1694
Epoch 165/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1251 -
mae: 0.2696 - val_loss: 0.0481 - val_mae: 0.1721
Epoch 166/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1330 -
mae: 0.2757 - val_loss: 0.0458 - val_mae: 0.1671
Epoch 167/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1255 -
mae: 0.2719 - val_loss: 0.0441 - val_mae: 0.1627
Epoch 168/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1333 -
mae: 0.2784 - val_loss: 0.0433 - val_mae: 0.1619
Epoch 169/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1361 -
```

```
mae: 0.2777 - val_loss: 0.0462 - val_mae: 0.1684
Epoch 170/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1223 -
mae: 0.2677 - val_loss: 0.0461 - val_mae: 0.1673
Epoch 171/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1250 -
mae: 0.2682 - val_loss: 0.0472 - val_mae: 0.1700
Epoch 172/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1335 -
mae: 0.2740 - val_loss: 0.0433 - val_mae: 0.1610
Epoch 173/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1372 -
mae: 0.2823 - val_loss: 0.0469 - val_mae: 0.1691
Epoch 174/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1332 -
mae: 0.2797 - val_loss: 0.0455 - val_mae: 0.1643
Epoch 175/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1223 -
mae: 0.2668 - val_loss: 0.0458 - val_mae: 0.1664
Epoch 176/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1360 -
mae: 0.2761 - val_loss: 0.0465 - val_mae: 0.1697
Epoch 177/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1094 -
mae: 0.2549 - val_loss: 0.0442 - val_mae: 0.1649
Epoch 178/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1271 -
mae: 0.2665 - val_loss: 0.0432 - val_mae: 0.1629
Epoch 179/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1270 -
mae: 0.2702 - val_loss: 0.0463 - val_mae: 0.1684
Epoch 180/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1145 -
mae: 0.2596 - val_loss: 0.0441 - val_mae: 0.1641
Epoch 181/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1188 -
mae: 0.2655 - val_loss: 0.0459 - val_mae: 0.1682
Epoch 182/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1183 -
mae: 0.2623 - val_loss: 0.0439 - val_mae: 0.1633
Epoch 183/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1205 -
mae: 0.2670 - val_loss: 0.0431 - val_mae: 0.1611
Epoch 184/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1220 -
mae: 0.2688 - val_loss: 0.0478 - val_mae: 0.1712
Epoch 185/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1144 -
mae: 0.2606 - val_loss: 0.0477 - val_mae: 0.1712
```

```
Epoch 186/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1127 -
mae: 0.2545 - val_loss: 0.0434 - val_mae: 0.1612
Epoch 187/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1284 -
mae: 0.2703 - val_loss: 0.0471 - val_mae: 0.1698
Epoch 188/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1226 -
mae: 0.2638 - val_loss: 0.0437 - val_mae: 0.1621
Epoch 189/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1217 -
mae: 0.2650 - val_loss: 0.0427 - val_mae: 0.1603
Epoch 190/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1164 -
mae: 0.2597 - val_loss: 0.0435 - val_mae: 0.1621
Epoch 191/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1170 -
mae: 0.2602 - val_loss: 0.0475 - val_mae: 0.1712
Epoch 192/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1199 -
mae: 0.2677 - val_loss: 0.0451 - val_mae: 0.1662
Epoch 193/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1064 -
mae: 0.2484 - val_loss: 0.0418 - val_mae: 0.1582
Epoch 194/200
26/26 [==============================] - 0s 3ms/step - loss: 0.1219 -
mae: 0.2668 - val_loss: 0.0438 - val_mae: 0.1633
Epoch 195/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1150 -
mae: 0.2583 - val_loss: 0.0454 - val_mae: 0.1649
Epoch 196/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1305 -
mae: 0.2722 - val_loss: 0.0445 - val_mae: 0.1643
Epoch 197/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1159 -
mae: 0.2613 - val_loss: 0.0481 - val_mae: 0.1729
Epoch 198/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1315 -
mae: 0.2786 - val_loss: 0.0498 - val_mae: 0.1768
Epoch 199/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1197 -
mae: 0.2608 - val_loss: 0.0430 - val_mae: 0.1607
Epoch 200/200
26/26 [==============================] - 0s 2ms/step - loss: 0.1217 -
mae: 0.2681 - val_loss: 0.0449 - val_mae: 0.1651
```

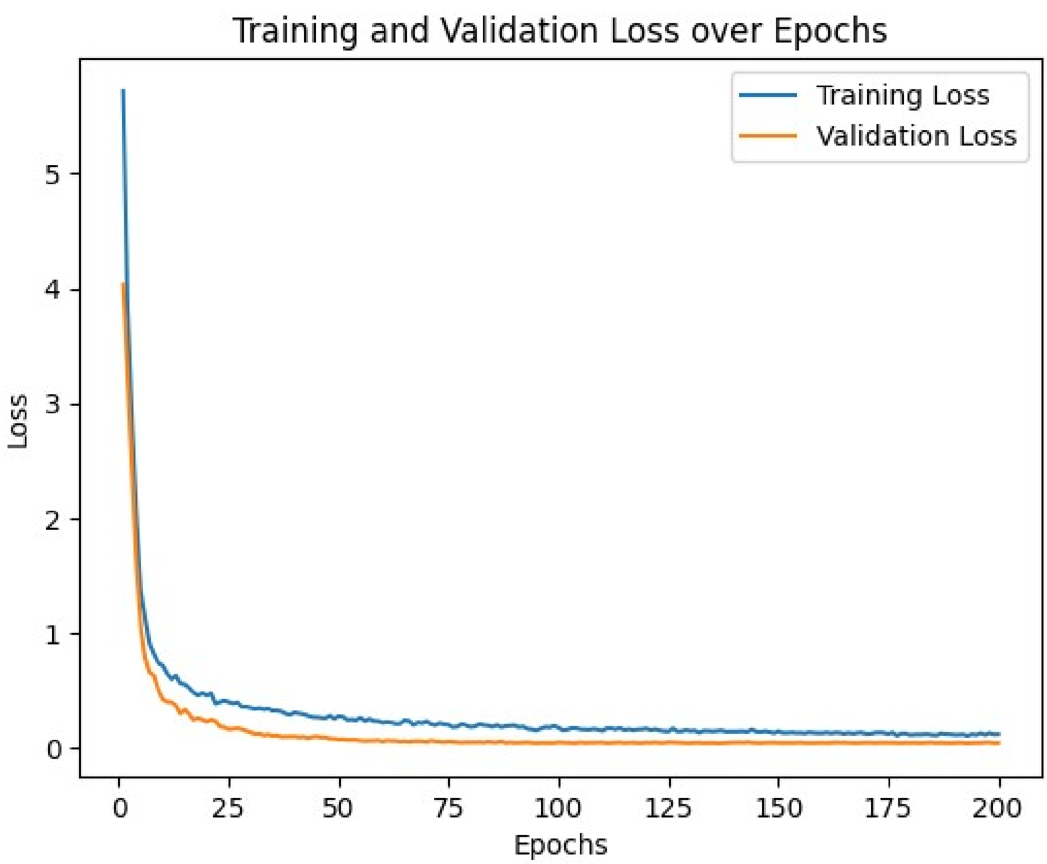
Plotting results

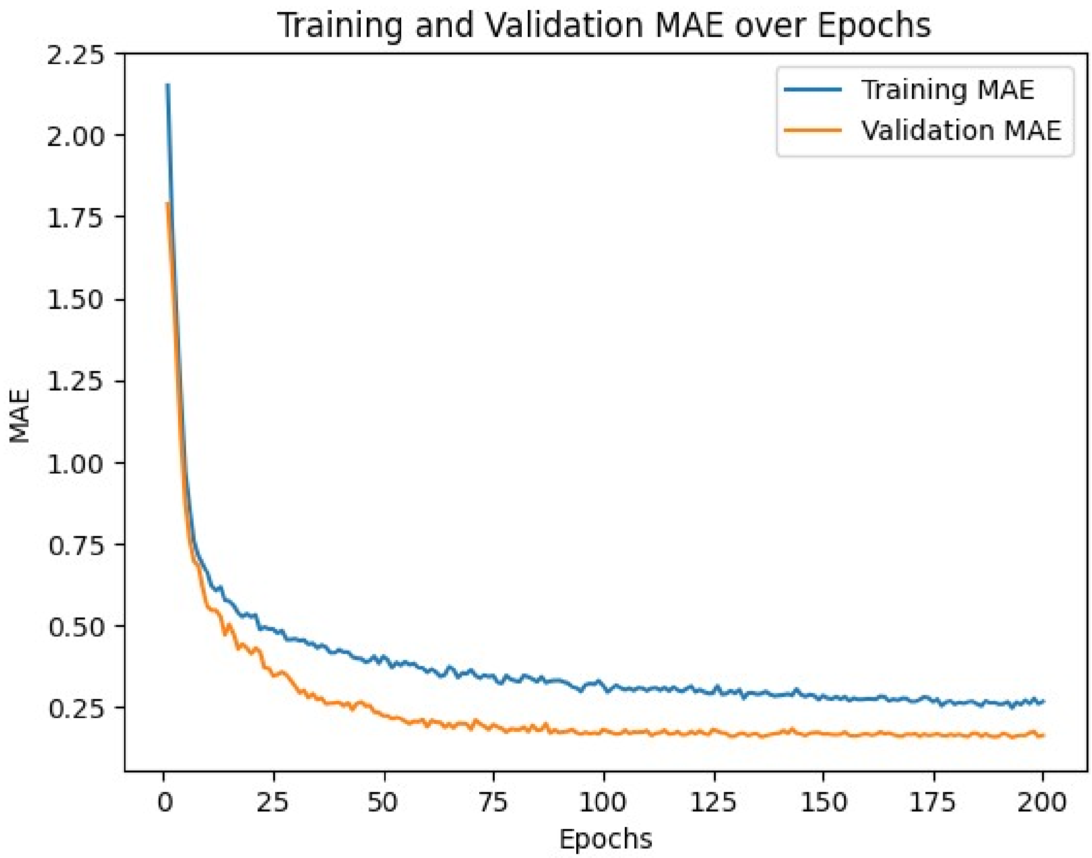
Now, we will plot our results, showing our loss function and MAE over epochs.

```
X_epochs = np.arange(1, 201)
y_loss = history.history['loss']
val_loss = history.history['val_loss']
mae_train = history.history['mae']
mae_val = history.history['val_mae']

plt.plot(X_epochs, y_loss, label = 'Training Loss')
plt.plot(X_epochs, val_loss, label = 'Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.title('Training and Validation Loss over Epochs')
plt.show()


plt.plot(X_epochs, mae_train, label = 'Training MAE')
plt.plot(X_epochs, mae_val, label = 'Validation MAE')
plt.xlabel('Epochs')
plt.ylabel('MAE')
plt.legend()
plt.title('Training and Validation MAE over Epochs')
plt.show()
```





As we can see, we achieved a very low loss value for both our training and validation dataset, obtaining adequate results. Also, we can see that the MAE metric obtained adequate results.

Finally, we will make predictions on 5 random students

```
random_indices = np.random.choice(X_test.shape[0], 5, replace=False)
X_random = X_test[random_indices]
y_random = model.predict(X_random)

y_random
y_true = y_test.iloc[random_indices]
for i in range(0, len(y_random)):
    print(y_random[i], y_true.iloc[i])

1/1 [==============================] - 0s 49ms/step
[2.60001] 2.583738162772638
[1.2797991] 1.0444999950877136
[1.2052262] 1.2714946229661936
[1.520498] 1.5165082679194366
[1.5186576] 1.6831172628416484
```

As we can see, our predicted data is not very far of the real labels, suggesting that our model works adequately and perfectly fitted (without neither overffiting, nor underfitting)