```
0.1765 - val_loss: 0.0473 - val_mae: 0.1663
Epoch 72/75
0.1826 - val_loss: 0.0475 - val_mae: 0.1668
Epoch 73/75
48/48 [=============== ] - 0s 880us/step - loss: 0.0524 - mae:
0.1799 - val_loss: 0.0484 - val_mae: 0.1685
Epoch 74/75
0.1820 - val loss: 0.0492 - val mae: 0.1698
Epoch 75/75
0.1809 - val loss: 0.0475 - val mae: 0.1668
0.1697
loss 0.04936393350362778
mae 0.16969530284404755
```

## 8. Dense + Dropout + Batch Normalization

Experiment 1: A single Dense Hidden Layer

```
In [ ]: dataset_1 = data.drop(columns=["StudentID", "Gender", "Ethnicity", "Extracurric")
        X_1 = dataset_1.drop(columns=['GPA'])
        y_1 = dataset_1['GPA'].values
        X1_train, X1_test, y1_train, y1_test = train_test_split(X_1, y_1, test_size=
        scaler = StandardScaler()
        X3_train = scaler.fit_transform(X1_train)
        X3 test = scaler.transform(X1 test)
        model 1 = Sequential([
            Dense(64, activation='relu', input_dim=X1_train.shape[1]),
            Dense(32, activation='relu'),
            Dense(1)
        ])
        model_1.compile(
            optimizer='adam',
            loss='mse',
            metrics=['mae']
        history_1 = model_1.fit(X1_train, y1_train, epochs=75, batch_size=10, validate)
        loss1, mae1 = model_1.evaluate(X1_test, y1_test)
```

print("loss", loss1)

```
print("mae", mae1)
Epoch 1/75
0.3841 - val_loss: 0.1394 - val_mae: 0.2972
Epoch 2/75
e: 0.2689 - val_loss: 0.1180 - val_mae: 0.2787
Epoch 3/75
e: 0.2478 - val_loss: 0.1178 - val_mae: 0.2760
Epoch 4/75
e: 0.2414 - val_loss: 0.0948 - val_mae: 0.2479
Epoch 5/75
e: 0.2379 - val loss: 0.1160 - val mae: 0.2749
Epoch 6/75
e: 0.2447 - val_loss: 0.1059 - val_mae: 0.2599
Epoch 7/75
e: 0.2430 - val_loss: 0.0975 - val_mae: 0.2535
Epoch 8/75
e: 0.2372 - val_loss: 0.0940 - val_mae: 0.2483
Epoch 9/75
e: 0.2527 - val_loss: 0.0950 - val_mae: 0.2464
Epoch 10/75
e: 0.2247 - val loss: 0.0871 - val mae: 0.2356
Epoch 11/75
e: 0.2254 - val_loss: 0.0921 - val_mae: 0.2437
Epoch 12/75
e: 0.2252 - val_loss: 0.0907 - val mae: 0.2443
Epoch 13/75
e: 0.2426 - val_loss: 0.0842 - val_mae: 0.2341
Epoch 14/75
e: 0.2195 - val_loss: 0.0767 - val_mae: 0.2222
Epoch 15/75
e: 0.2279 - val_loss: 0.0827 - val_mae: 0.2328
Epoch 16/75
```

```
e: 0.2168 - val_loss: 0.0826 - val_mae: 0.2314
Epoch 17/75
e: 0.2219 - val_loss: 0.0785 - val_mae: 0.2259
Epoch 18/75
e: 0.2168 - val_loss: 0.0814 - val_mae: 0.2313
Epoch 19/75
e: 0.2217 - val loss: 0.0763 - val mae: 0.2236
Epoch 20/75
e: 0.2132 - val loss: 0.0995 - val mae: 0.2509
Epoch 21/75
e: 0.2121 - val loss: 0.0746 - val mae: 0.2197
Epoch 22/75
e: 0.2110 - val_loss: 0.0749 - val_mae: 0.2185
Epoch 23/75
e: 0.2105 - val_loss: 0.0842 - val_mae: 0.2333
Epoch 24/75
e: 0.2199 - val_loss: 0.0711 - val_mae: 0.2124
Epoch 25/75
e: 0.2037 - val_loss: 0.0876 - val_mae: 0.2367
Epoch 26/75
e: 0.2112 - val loss: 0.0700 - val mae: 0.2111
Epoch 27/75
e: 0.2096 - val_loss: 0.0866 - val_mae: 0.2347
Epoch 28/75
e: 0.2021 - val_loss: 0.0843 - val_mae: 0.2334
Epoch 29/75
e: 0.2171 - val_loss: 0.0823 - val_mae: 0.2296
Epoch 30/75
e: 0.2024 - val_loss: 0.0824 - val_mae: 0.2307
Epoch 31/75
e: 0.2051 - val loss: 0.0692 - val mae: 0.2103
Epoch 32/75
e: 0.1977 - val_loss: 0.0712 - val_mae: 0.2146
Epoch 33/75
```

```
e: 0.1983 - val_loss: 0.0699 - val_mae: 0.2124
Epoch 34/75
e: 0.2013 - val_loss: 0.0695 - val_mae: 0.2095
Epoch 35/75
e: 0.1958 - val loss: 0.0652 - val mae: 0.2041
Epoch 36/75
e: 0.1953 - val_loss: 0.0757 - val_mae: 0.2188
Epoch 37/75
e: 0.1956 - val loss: 0.0755 - val mae: 0.2223
Epoch 38/75
e: 0.1887 - val_loss: 0.0866 - val_mae: 0.2397
Epoch 39/75
e: 0.1880 - val_loss: 0.0611 - val_mae: 0.1993
Epoch 40/75
e: 0.1932 - val loss: 0.0656 - val mae: 0.2036
Epoch 41/75
e: 0.1904 - val_loss: 0.0592 - val_mae: 0.1929
Epoch 42/75
e: 0.1901 - val_loss: 0.0659 - val_mae: 0.2058
Epoch 43/75
e: 0.1882 - val_loss: 0.0640 - val_mae: 0.2034
Epoch 44/75
e: 0.1884 - val_loss: 0.0588 - val_mae: 0.1957
Epoch 45/75
e: 0.2031 - val_loss: 0.0589 - val_mae: 0.1953
Epoch 46/75
e: 0.1840 - val_loss: 0.0661 - val_mae: 0.2012
Epoch 47/75
e: 0.1820 - val loss: 0.0600 - val mae: 0.1927
Epoch 48/75
e: 0.1874 - val_loss: 0.0570 - val_mae: 0.1893
Epoch 49/75
e: 0.1855 - val_loss: 0.0575 - val_mae: 0.1904
```

```
Epoch 50/75
e: 0.1945 - val_loss: 0.0574 - val_mae: 0.1898
Epoch 51/75
e: 0.1821 - val loss: 0.0565 - val mae: 0.1875
Epoch 52/75
e: 0.1791 - val_loss: 0.0696 - val_mae: 0.2140
Epoch 53/75
e: 0.1806 - val_loss: 0.0549 - val_mae: 0.1863
Epoch 54/75
e: 0.1794 - val_loss: 0.0598 - val_mae: 0.1902
Epoch 55/75
e: 0.1859 - val_loss: 0.0711 - val_mae: 0.2187
Epoch 56/75
e: 0.1808 - val_loss: 0.0605 - val_mae: 0.1914
Epoch 57/75
e: 0.1715 - val_loss: 0.0557 - val_mae: 0.1862
Epoch 58/75
e: 0.1694 - val loss: 0.0546 - val mae: 0.1877
Epoch 59/75
e: 0.1740 - val_loss: 0.0643 - val_mae: 0.2009
Epoch 60/75
e: 0.1729 - val_loss: 0.0512 - val_mae: 0.1776
Epoch 61/75
e: 0.1734 - val_loss: 0.0659 - val_mae: 0.1999
Epoch 62/75
e: 0.1795 - val_loss: 0.0629 - val_mae: 0.1953
Epoch 63/75
e: 0.1739 - val_loss: 0.0667 - val_mae: 0.2003
Epoch 64/75
e: 0.1772 - val_loss: 0.0557 - val_mae: 0.1881
Epoch 65/75
e: 0.1745 - val loss: 0.0641 - val mae: 0.2031
Epoch 66/75
```

```
e: 0.1725 - val_loss: 0.0917 - val_mae: 0.2472
Epoch 67/75
e: 0.1741 - val_loss: 0.0515 - val_mae: 0.1770
Epoch 68/75
e: 0.1720 - val_loss: 0.0552 - val_mae: 0.1808
Epoch 69/75
e: 0.1693 - val loss: 0.0473 - val mae: 0.1698
Epoch 70/75
e: 0.1686 - val loss: 0.0697 - val mae: 0.2061
Epoch 71/75
e: 0.1699 - val loss: 0.0582 - val mae: 0.1957
Epoch 72/75
e: 0.1683 - val_loss: 0.0533 - val_mae: 0.1806
Epoch 73/75
e: 0.1639 - val_loss: 0.0487 - val_mae: 0.1718
Epoch 74/75
e: 0.1636 - val_loss: 0.0549 - val_mae: 0.1799
Epoch 75/75
e: 0.1668 - val_loss: 0.0563 - val_mae: 0.1825
0.1851
loss 0.059342652559280396
mae 0.1851426661014557
```

Experiment 2: A set of three Dense Hidden Layers

```
In []: dataset_2 = data.drop(columns=["StudentID","Gender","Ethnicity","Extracurric

X_2 = dataset_2.drop(columns=['GPA'])
y_2 = dataset_2['GPA'].values

X2_train, X2_test, y2_train, y2_test = train_test_split(X_2, y_2, test_size=
scaler = StandardScaler()
X2_train = scaler.fit_transform(X2_train)
X2_test = scaler.transform(X2_test)

model_2 = Sequential([
    Dense(64, activation='relu', input_dim=X2_train.shape[1]),
    Dense(32, activation='relu'),
    Dense(16, activation='relu'),
```

```
Dense(8, activation='relu'),
  Dense(1)
])
model_2.compile(
  optimizer='adam',
  loss='mse',
  metrics=['mae']
history_2 = model_2.fit(X2_train, y2_train, epochs=75, batch_size=10, validate
loss2, mae2 = model_2.evaluate(X2_test, y2_test)
print("loss", loss2)
print("mae", mae2)
Epoch 1/75
0.7012 - val_loss: 0.1659 - val_mae: 0.3262
Epoch 2/75
e: 0.2737 - val_loss: 0.1128 - val_mae: 0.2701
Epoch 3/75
e: 0.2368 - val loss: 0.0862 - val mae: 0.2317
Epoch 4/75
e: 0.2170 - val_loss: 0.0929 - val_mae: 0.2441
Epoch 5/75
e: 0.2021 - val_loss: 0.0697 - val_mae: 0.2102
Epoch 6/75
e: 0.1926 - val_loss: 0.0627 - val_mae: 0.1979
Epoch 7/75
e: 0.1803 - val_loss: 0.0601 - val_mae: 0.1941
Epoch 8/75
e: 0.1757 - val_loss: 0.0558 - val_mae: 0.1846
Epoch 9/75
e: 0.1685 - val_loss: 0.0578 - val_mae: 0.1886
Epoch 10/75
e: 0.1671 - val loss: 0.0607 - val mae: 0.1954
Epoch 11/75
e: 0.1670 - val_loss: 0.0613 - val_mae: 0.1952
Epoch 12/75
```

```
e: 0.1611 - val_loss: 0.0542 - val_mae: 0.1829
Epoch 13/75
e: 0.1589 - val_loss: 0.0548 - val_mae: 0.1826
Epoch 14/75
e: 0.1578 - val loss: 0.0567 - val mae: 0.1866
Epoch 15/75
e: 0.1563 - val_loss: 0.0589 - val_mae: 0.1910
Epoch 16/75
e: 0.1584 - val loss: 0.0534 - val mae: 0.1809
Epoch 17/75
e: 0.1552 - val_loss: 0.0539 - val_mae: 0.1794
Epoch 18/75
e: 0.1555 - val_loss: 0.0546 - val_mae: 0.1840
Epoch 19/75
e: 0.1543 - val loss: 0.0565 - val mae: 0.1844
Epoch 20/75
e: 0.1501 - val_loss: 0.0606 - val_mae: 0.1924
Epoch 21/75
e: 0.1501 - val loss: 0.0607 - val mae: 0.1895
Epoch 22/75
e: 0.1496 - val_loss: 0.0546 - val_mae: 0.1807
Epoch 23/75
e: 0.1488 - val_loss: 0.0568 - val_mae: 0.1862
Epoch 24/75
e: 0.1494 - val loss: 0.0625 - val mae: 0.1949
Epoch 25/75
e: 0.1497 - val_loss: 0.0564 - val_mae: 0.1814
Epoch 26/75
e: 0.1449 - val loss: 0.0590 - val mae: 0.1869
Epoch 27/75
e: 0.1468 - val_loss: 0.0549 - val_mae: 0.1795
Epoch 28/75
e: 0.1454 - val_loss: 0.0601 - val_mae: 0.1895
```

```
Epoch 29/75
e: 0.1449 - val_loss: 0.0533 - val_mae: 0.1776
Epoch 30/75
e: 0.1425 - val loss: 0.0574 - val mae: 0.1853
Epoch 31/75
e: 0.1427 - val_loss: 0.0601 - val_mae: 0.1856
Epoch 32/75
e: 0.1432 - val_loss: 0.0568 - val_mae: 0.1824
Epoch 33/75
e: 0.1423 - val_loss: 0.0597 - val_mae: 0.1915
Epoch 34/75
e: 0.1425 - val_loss: 0.0610 - val_mae: 0.1937
Epoch 35/75
e: 0.1429 - val_loss: 0.0591 - val_mae: 0.1902
Epoch 36/75
e: 0.1405 - val_loss: 0.0549 - val_mae: 0.1799
Epoch 37/75
e: 0.1380 - val loss: 0.0589 - val mae: 0.1859
Epoch 38/75
e: 0.1407 - val_loss: 0.0576 - val_mae: 0.1830
Epoch 39/75
e: 0.1434 - val_loss: 0.0592 - val_mae: 0.1889
Epoch 40/75
e: 0.1405 - val_loss: 0.0584 - val_mae: 0.1842
Epoch 41/75
e: 0.1400 - val_loss: 0.0583 - val_mae: 0.1873
Epoch 42/75
e: 0.1418 - val_loss: 0.0563 - val_mae: 0.1821
Epoch 43/75
e: 0.1389 - val_loss: 0.0569 - val_mae: 0.1830
Epoch 44/75
e: 0.1412 - val loss: 0.0595 - val mae: 0.1882
Epoch 45/75
```

```
e: 0.1339 - val_loss: 0.0567 - val_mae: 0.1826
Epoch 46/75
e: 0.1388 - val_loss: 0.0623 - val_mae: 0.1924
Epoch 47/75
e: 0.1343 - val_loss: 0.0568 - val_mae: 0.1801
Epoch 48/75
e: 0.1392 - val_loss: 0.0593 - val_mae: 0.1891
Epoch 49/75
e: 0.1340 - val loss: 0.0591 - val mae: 0.1876
Epoch 50/75
e: 0.1334 - val loss: 0.0584 - val mae: 0.1823
Epoch 51/75
e: 0.1342 - val_loss: 0.0578 - val_mae: 0.1822
Epoch 52/75
e: 0.1348 - val_loss: 0.0582 - val_mae: 0.1856
Epoch 53/75
e: 0.1295 - val_loss: 0.0615 - val_mae: 0.1885
Epoch 54/75
e: 0.1317 - val_loss: 0.0600 - val_mae: 0.1861
Epoch 55/75
e: 0.1317 - val loss: 0.0599 - val mae: 0.1890
Epoch 56/75
e: 0.1319 - val_loss: 0.0580 - val_mae: 0.1844
Epoch 57/75
e: 0.1320 - val_loss: 0.0594 - val_mae: 0.1864
Epoch 58/75
e: 0.1288 - val_loss: 0.0611 - val_mae: 0.1897
Epoch 59/75
e: 0.1307 - val_loss: 0.0600 - val_mae: 0.1870
Epoch 60/75
e: 0.1256 - val loss: 0.0713 - val mae: 0.2097
Epoch 61/75
e: 0.1304 - val_loss: 0.0586 - val_mae: 0.1845
Epoch 62/75
```

```
e: 0.1297 - val_loss: 0.0599 - val_mae: 0.1882
Epoch 63/75
e: 0.1279 - val_loss: 0.0611 - val_mae: 0.1879
Epoch 64/75
e: 0.1301 - val loss: 0.0619 - val mae: 0.1905
Epoch 65/75
e: 0.1248 - val_loss: 0.0597 - val_mae: 0.1875
Epoch 66/75
e: 0.1236 - val loss: 0.0655 - val mae: 0.1962
Epoch 67/75
e: 0.1272 - val_loss: 0.0610 - val_mae: 0.1882
Epoch 68/75
e: 0.1247 - val_loss: 0.0634 - val_mae: 0.1949
Epoch 69/75
e: 0.1260 - val loss: 0.0591 - val mae: 0.1847
Epoch 70/75
0.1225 - val_loss: 0.0613 - val_mae: 0.1895
Epoch 71/75
e: 0.1274 - val loss: 0.0623 - val mae: 0.1929
Epoch 72/75
e: 0.1207 - val_loss: 0.0607 - val_mae: 0.1892
Epoch 73/75
e: 0.1236 - val_loss: 0.0658 - val_mae: 0.1956
Epoch 74/75
e: 0.1229 - val loss: 0.0653 - val mae: 0.1974
Epoch 75/75
e: 0.1220 - val_loss: 0.0618 - val_mae: 0.1896
15/15 [============= ] - 0s 497us/step - loss: 0.0630 - mae:
0.1903
loss 0.0629812628030777
mae 0.19033977389335632
```

Experiment 3: Add a dropout layer after each Dense Hidden Layer

```
In [ ]: dataset_3 = data.drop(columns=["StudentID", "Gender", "Ethnicity", "Extracurric
```

```
X 3 = dataset 3.drop(columns=['GPA'])
y_3 = dataset_3['GPA'].values
X3_train, X3_test, y3_train, y3_test = train_test_split(X_3, y_3, test_size=
scaler = StandardScaler()
X3 train = scaler.fit transform(X3 train)
X3 test = scaler.transform(X3 test)
model_3 = Sequential([
   Dense(64, activation='relu', input_dim=X3_train.shape[1]),
   Dropout(0.25).
   Dense(32, activation='relu'),
   Dropout (0.25),
   Dense(16, activation='relu'),
   Dropout(0.25),
   Dense(8, activation='relu'),
   Dropout(0.25),
   Dense(1)
])
model_3.compile(
   optimizer='adam',
   loss='mse',
   metrics=['mae']
history_3 = model_3.fit(X3_train, y3_train, epochs=75, batch_size=10, validate
loss3, mae3 = model_3.evaluate(X3_test, y3_test)
print("loss", loss3)
print("mae", mae3)
Epoch 1/75
1.2490 - val_loss: 0.6574 - val_mae: 0.7082
Epoch 2/75
e: 0.8357 - val loss: 0.4883 - val mae: 0.6086
Epoch 3/75
e: 0.7459 - val_loss: 0.4672 - val_mae: 0.5940
Epoch 4/75
e: 0.6821 - val_loss: 0.3154 - val_mae: 0.4891
Epoch 5/75
e: 0.6157 - val_loss: 0.1695 - val_mae: 0.3496
Epoch 6/75
```

```
e: 0.5605 - val_loss: 0.2324 - val_mae: 0.4183
Epoch 7/75
e: 0.5357 - val_loss: 0.1978 - val_mae: 0.3796
Epoch 8/75
e: 0.5222 - val_loss: 0.1825 - val_mae: 0.3617
e: 0.5112 - val_loss: 0.1543 - val_mae: 0.3308
Epoch 10/75
e: 0.4869 - val loss: 0.1517 - val mae: 0.3268
Epoch 11/75
e: 0.4587 - val loss: 0.1921 - val mae: 0.3647
Epoch 12/75
e: 0.4325 - val_loss: 0.1474 - val_mae: 0.3177
Epoch 13/75
e: 0.4366 - val_loss: 0.1542 - val_mae: 0.3234
Epoch 14/75
e: 0.4093 - val_loss: 0.1439 - val_mae: 0.3145
Epoch 15/75
e: 0.4042 - val_loss: 0.1078 - val_mae: 0.2701
Epoch 16/75
e: 0.3909 - val loss: 0.1466 - val mae: 0.3174
Epoch 17/75
e: 0.4077 - val_loss: 0.1150 - val_mae: 0.2769
Epoch 18/75
e: 0.3741 - val_loss: 0.1436 - val_mae: 0.3128
Epoch 19/75
e: 0.3774 - val_loss: 0.1295 - val_mae: 0.2981
Epoch 20/75
e: 0.3658 - val_loss: 0.1463 - val_mae: 0.3128
Epoch 21/75
e: 0.3595 - val loss: 0.1162 - val mae: 0.2758
Epoch 22/75
e: 0.3614 - val_loss: 0.1380 - val_mae: 0.3073
Epoch 23/75
```

```
e: 0.3616 - val_loss: 0.1192 - val_mae: 0.2830
Epoch 24/75
e: 0.3515 - val_loss: 0.1179 - val_mae: 0.2777
Epoch 25/75
e: 0.3454 - val loss: 0.1317 - val mae: 0.2955
Epoch 26/75
e: 0.3355 - val_loss: 0.1270 - val_mae: 0.2888
Epoch 27/75
e: 0.3426 - val loss: 0.1046 - val mae: 0.2599
Epoch 28/75
e: 0.3345 - val_loss: 0.1365 - val_mae: 0.3016
Epoch 29/75
e: 0.3137 - val_loss: 0.0996 - val_mae: 0.2478
Epoch 30/75
e: 0.3296 - val_loss: 0.1051 - val_mae: 0.2596
Epoch 31/75
e: 0.3297 - val_loss: 0.0940 - val_mae: 0.2444
Epoch 32/75
e: 0.3334 - val_loss: 0.1281 - val_mae: 0.2886
Epoch 33/75
e: 0.3251 - val_loss: 0.1106 - val_mae: 0.2660
Epoch 34/75
e: 0.3215 - val_loss: 0.1121 - val_mae: 0.2703
Epoch 35/75
e: 0.3173 - val_loss: 0.0931 - val_mae: 0.2422
Epoch 36/75
e: 0.3126 - val_loss: 0.1373 - val_mae: 0.3007
Epoch 37/75
e: 0.3061 - val loss: 0.1182 - val mae: 0.2772
Epoch 38/75
e: 0.3041 - val_loss: 0.0938 - val_mae: 0.2448
Epoch 39/75
e: 0.3035 - val_loss: 0.1055 - val_mae: 0.2556
```

```
Epoch 40/75
e: 0.3139 - val_loss: 0.1127 - val_mae: 0.2681
Epoch 41/75
e: 0.3117 - val loss: 0.1088 - val mae: 0.2649
Epoch 42/75
e: 0.3081 - val_loss: 0.1063 - val_mae: 0.2632
Epoch 43/75
e: 0.3093 - val_loss: 0.1124 - val_mae: 0.2708
Epoch 44/75
e: 0.2968 - val_loss: 0.0841 - val_mae: 0.2329
Epoch 45/75
e: 0.2991 - val_loss: 0.1161 - val_mae: 0.2731
Epoch 46/75
e: 0.3079 - val_loss: 0.1087 - val_mae: 0.2650
Epoch 47/75
e: 0.2954 - val_loss: 0.0994 - val_mae: 0.2556
Epoch 48/75
e: 0.2952 - val loss: 0.1085 - val mae: 0.2669
Epoch 49/75
e: 0.2970 - val_loss: 0.1100 - val_mae: 0.2639
Epoch 50/75
e: 0.2934 - val_loss: 0.1097 - val_mae: 0.2671
Epoch 51/75
e: 0.2975 - val_loss: 0.0905 - val_mae: 0.2397
Epoch 52/75
e: 0.2956 - val_loss: 0.1030 - val_mae: 0.2563
Epoch 53/75
e: 0.2959 - val_loss: 0.1026 - val_mae: 0.2560
Epoch 54/75
e: 0.3073 - val_loss: 0.1190 - val_mae: 0.2796
Epoch 55/75
e: 0.2918 - val loss: 0.1023 - val mae: 0.2625
Epoch 56/75
```

```
e: 0.2936 - val_loss: 0.0808 - val_mae: 0.2260
Epoch 57/75
e: 0.2879 - val_loss: 0.1122 - val_mae: 0.2684
Epoch 58/75
e: 0.3055 - val_loss: 0.1128 - val_mae: 0.2718
Epoch 59/75
e: 0.2886 - val loss: 0.0822 - val mae: 0.2228
Epoch 60/75
e: 0.2901 - val loss: 0.1065 - val mae: 0.2633
Epoch 61/75
e: 0.2841 - val loss: 0.0984 - val mae: 0.2459
Epoch 62/75
e: 0.2899 - val_loss: 0.0964 - val_mae: 0.2485
Epoch 63/75
e: 0.2940 - val_loss: 0.0851 - val_mae: 0.2303
Epoch 64/75
e: 0.2916 - val_loss: 0.0954 - val_mae: 0.2481
Epoch 65/75
e: 0.2927 - val_loss: 0.0921 - val_mae: 0.2426
Epoch 66/75
e: 0.2845 - val loss: 0.1019 - val mae: 0.2582
Epoch 67/75
e: 0.2929 - val_loss: 0.1225 - val_mae: 0.2781
Epoch 68/75
e: 0.2914 - val_loss: 0.1047 - val_mae: 0.2525
Epoch 69/75
e: 0.2876 - val_loss: 0.1050 - val_mae: 0.2612
Epoch 70/75
e: 0.2791 - val_loss: 0.0874 - val_mae: 0.2301
Epoch 71/75
e: 0.2860 - val loss: 0.0972 - val mae: 0.2448
Epoch 72/75
e: 0.2863 - val_loss: 0.1060 - val_mae: 0.2569
Epoch 73/75
```

Experiment 4: Add a Batch Normalization Layer after each Dropout Layer.

```
In [ ]: dataset_4 = data.drop(columns=["StudentID", "Gender", "Ethnicity", "Extracurric
        X_4 = dataset_4.drop(columns=['GPA'])
        y 4 = dataset 4['GPA'].values
        X4_train, X4_test, y4_train, y4_test = train_test_split(X_4, y_4, test_size=
        scaler = StandardScaler()
        X4_train = scaler.fit_transform(X4_train)
        X4_test = scaler.transform(X4_test)
        model_4 = Sequential([
            Dense(64, activation='relu', input_dim=X4_train.shape[1]),
            BatchNormalization(),
            Dropout(0.25).
            Dense(32, activation='relu'),
            BatchNormalization(),
            Dropout (0.25),
            Dense(16, activation='relu'),
            BatchNormalization(),
            Dropout (0.25),
            Dense(8, activation='relu'),
            BatchNormalization(),
            Dropout(0.25),
            Dense(1)
        1)
        model 4.compile(
            optimizer='adam',
            loss='mse',
            metrics=['mae']
        )
        history_4 = model_4.fit(X4_train, y4_train, epochs=75, batch_size=10, valida
```

```
print("loss", loss4)
print("mae", mae4)
Epoch 1/75
1.7957 - val_loss: 3.4301 - val_mae: 1.7099
Epoch 2/75
1.3585 - val loss: 1.7462 - val mae: 1.1938
Epoch 3/75
1.0029 - val_loss: 0.7968 - val_mae: 0.7834
Epoch 4/75
0.8040 - val loss: 0.4334 - val mae: 0.5546
Epoch 5/75
0.7236 - val_loss: 0.2706 - val_mae: 0.4302
Epoch 6/75
0.6700 - val_loss: 0.2428 - val_mae: 0.4067
Epoch 7/75
0.6383 - val loss: 0.1929 - val mae: 0.3588
Epoch 8/75
0.5900 - val_loss: 0.1878 - val_mae: 0.3564
Epoch 9/75
0.5577 - val loss: 0.1616 - val mae: 0.3287
Epoch 10/75
0.5345 - val_loss: 0.1387 - val_mae: 0.3022
Epoch 11/75
0.5381 - val_loss: 0.1398 - val_mae: 0.3066
Epoch 12/75
0.5155 - val_loss: 0.1189 - val_mae: 0.2793
Epoch 13/75
0.4797 - val_loss: 0.1090 - val_mae: 0.2677
Epoch 14/75
0.5036 - val loss: 0.1056 - val mae: 0.2630
Epoch 15/75
0.4774 - val_loss: 0.0995 - val_mae: 0.2549
Epoch 16/75
```

loss4, mae4 = model\_4.evaluate(X4\_test, y4\_test)

```
0.4695 - val_loss: 0.1000 - val_mae: 0.2553
Epoch 17/75
0.4631 - val_loss: 0.0845 - val_mae: 0.2328
Epoch 18/75
0.4614 - val loss: 0.1001 - val mae: 0.2569
Epoch 19/75
0.4538 - val_loss: 0.0879 - val_mae: 0.2402
Epoch 20/75
0.4394 - val loss: 0.0950 - val mae: 0.2516
Epoch 21/75
0.4482 - val_loss: 0.0800 - val_mae: 0.2280
Epoch 22/75
0.4370 - val_loss: 0.0741 - val_mae: 0.2172
Epoch 23/75
0.4411 - val loss: 0.0824 - val mae: 0.2316
Epoch 24/75
0.4397 - val_loss: 0.0820 - val_mae: 0.2306
Epoch 25/75
0.4448 - val loss: 0.0785 - val mae: 0.2247
Epoch 26/75
0.4258 - val_loss: 0.0740 - val_mae: 0.2182
Epoch 27/75
0.4145 - val_loss: 0.0827 - val_mae: 0.2324
Epoch 28/75
0.4240 - val loss: 0.0807 - val mae: 0.2301
Epoch 29/75
0.4152 - val_loss: 0.0805 - val_mae: 0.2306
Epoch 30/75
0.4097 - val loss: 0.0807 - val mae: 0.2308
Epoch 31/75
0.4130 - val_loss: 0.0771 - val_mae: 0.2253
Epoch 32/75
0.4136 - val_loss: 0.0757 - val_mae: 0.2229
```

```
Epoch 33/75
0.4070 - val_loss: 0.0781 - val_mae: 0.2247
Epoch 34/75
0.4229 - val loss: 0.0742 - val mae: 0.2163
Epoch 35/75
0.4059 - val_loss: 0.0686 - val_mae: 0.2070
Epoch 36/75
0.3918 - val_loss: 0.0706 - val_mae: 0.2111
Epoch 37/75
0.4110 - val_loss: 0.0641 - val_mae: 0.1995
Epoch 38/75
0.3952 - val_loss: 0.0741 - val_mae: 0.2182
Epoch 39/75
0.4017 - val_loss: 0.0712 - val_mae: 0.2133
Epoch 40/75
0.4086 - val_loss: 0.0708 - val_mae: 0.2136
Epoch 41/75
0.4042 - val loss: 0.0653 - val mae: 0.2030
Epoch 42/75
0.4061 - val_loss: 0.0647 - val_mae: 0.2016
Epoch 43/75
0.4020 - val_loss: 0.0766 - val_mae: 0.2232
Epoch 44/75
0.3995 - val_loss: 0.0713 - val_mae: 0.2128
Epoch 45/75
0.4049 - val_loss: 0.0714 - val_mae: 0.2124
Epoch 46/75
0.3926 - val_loss: 0.0601 - val_mae: 0.1915
Epoch 47/75
0.4005 - val_loss: 0.0692 - val_mae: 0.2076
Epoch 48/75
0.3867 - val loss: 0.0686 - val mae: 0.2071
Epoch 49/75
```

```
0.3907 - val_loss: 0.0711 - val_mae: 0.2116
Epoch 50/75
0.3958 - val_loss: 0.0657 - val_mae: 0.2020
Epoch 51/75
0.3805 - val_loss: 0.0732 - val_mae: 0.2169
Epoch 52/75
0.3927 - val loss: 0.0640 - val mae: 0.2003
Epoch 53/75
0.3727 - val loss: 0.0660 - val mae: 0.2027
Epoch 54/75
0.3793 - val loss: 0.0722 - val mae: 0.2143
Epoch 55/75
0.3746 - val_loss: 0.0733 - val_mae: 0.2172
Epoch 56/75
0.3785 - val_loss: 0.0628 - val_mae: 0.1985
Epoch 57/75
0.3780 - val_loss: 0.0685 - val_mae: 0.2078
Epoch 58/75
0.3982 - val_loss: 0.0684 - val_mae: 0.2079
Epoch 59/75
0.3829 - val loss: 0.0685 - val mae: 0.2062
Epoch 60/75
0.3736 - val_loss: 0.0710 - val_mae: 0.2107
Epoch 61/75
0.4014 - val_loss: 0.0618 - val_mae: 0.1933
Epoch 62/75
0.3579 - val_loss: 0.0672 - val_mae: 0.2051
Epoch 63/75
0.3839 - val_loss: 0.0703 - val_mae: 0.2111
Epoch 64/75
0.3863 - val loss: 0.0646 - val mae: 0.2009
Epoch 65/75
0.3542 - val_loss: 0.0667 - val_mae: 0.2030
Epoch 66/75
```

```
0.3911 - val_loss: 0.0653 - val_mae: 0.2018
Epoch 67/75
0.3653 - val_loss: 0.0645 - val_mae: 0.1992
Epoch 68/75
0.3839 - val loss: 0.0634 - val mae: 0.1968
Epoch 69/75
0.3720 - val_loss: 0.0655 - val_mae: 0.2001
Epoch 70/75
0.3601 - val loss: 0.0574 - val mae: 0.1850
Epoch 71/75
0.3646 - val_loss: 0.0591 - val_mae: 0.1893
Epoch 72/75
0.3871 - val_loss: 0.0659 - val_mae: 0.2026
Epoch 73/75
0.3602 - val loss: 0.0630 - val mae: 0.1966
Epoch 74/75
0.3488 - val_loss: 0.0649 - val_mae: 0.2008
Epoch 75/75
0.3882 - val loss: 0.0619 - val mae: 0.1954
0.1904
loss 0.06040399521589279
mae 0.1904185265302658
```

## Comparative Table

```
In []: data = {
    'MAE': [mae1, mae2, mae3, mae4],
    'Loss': [loss1, loss2, loss3, loss4]
}
df = pd.DataFrame(data, index=['Modelo 1', 'Modelo 2', 'Modelo 3', 'Modelo 4'
# Mostramos la tabla
print(df)
```

```
MAE Loss
Modelo 1 0.185143 0.059343
Modelo 2 0.190340 0.062981
Modelo 3 0.249870 0.100768
Modelo 4 0.190419 0.060404
```

Los modelos tienen una arquitectura similar, con 64 de input, 32, 16 y 8 layers en dense, con una ultima de 1, el dropout tendra un valor del 25%, y dentro del ultimo modelo se usa Batchnormalization.

El mejor modelo es el primero, ya que tiene el valor mas pequeño de MAE con 0.185143 y un Loss de 0.059343.