

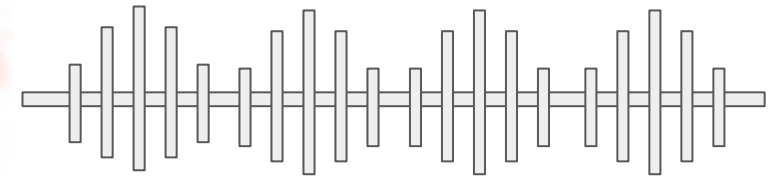
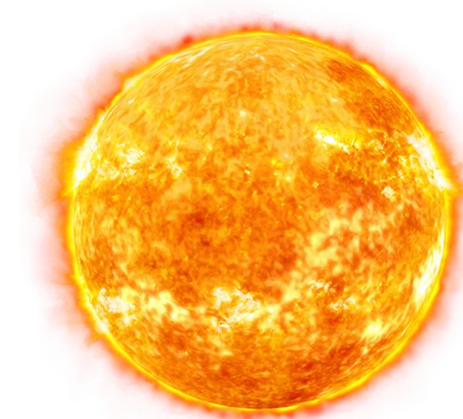


MEF/MAIE

**Advanced Techniques in Data Analysis**

Professor José Ricardo Gonalo

# Small Separations in Red Giants Stars: quest for late-evolution signatures using Asteroseismology

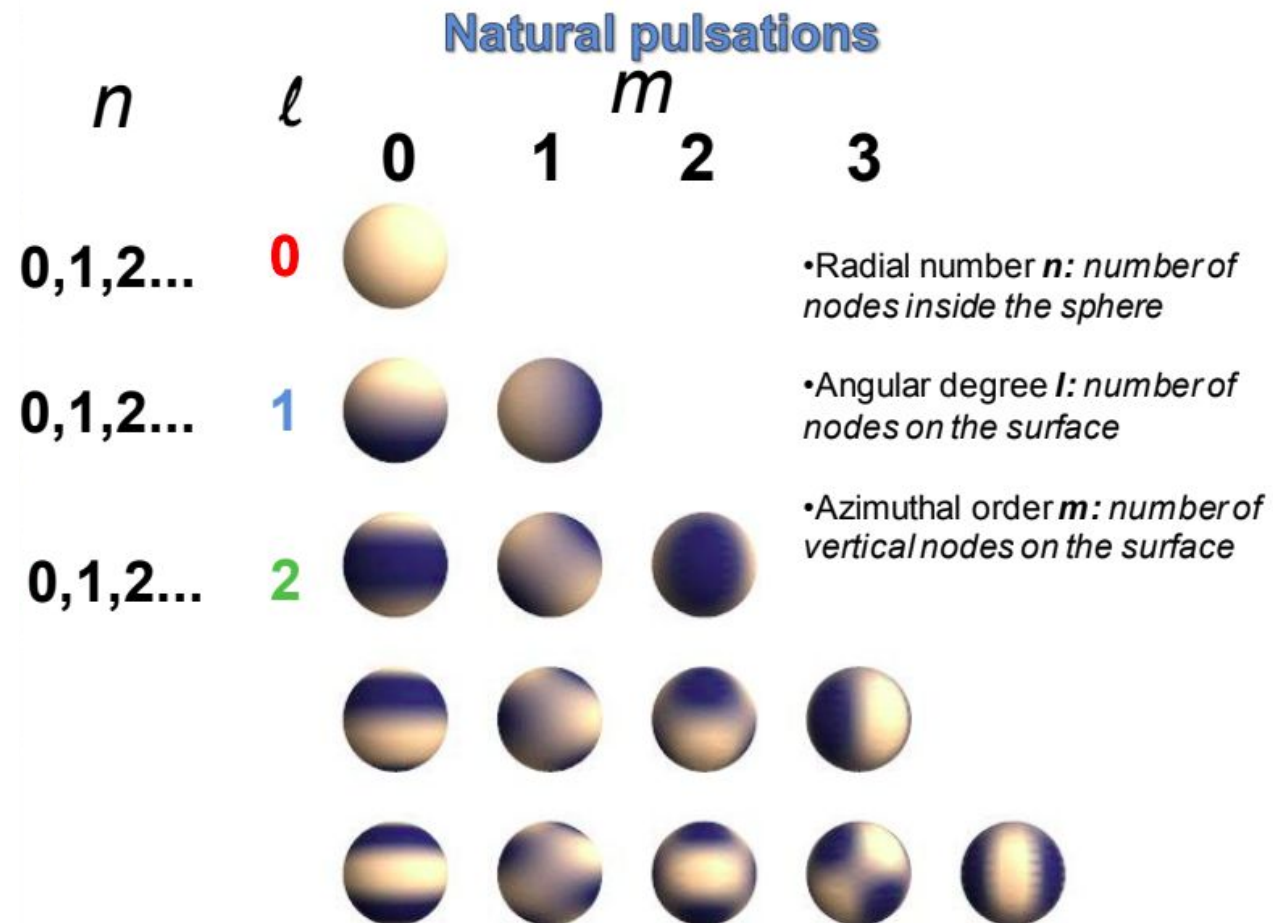


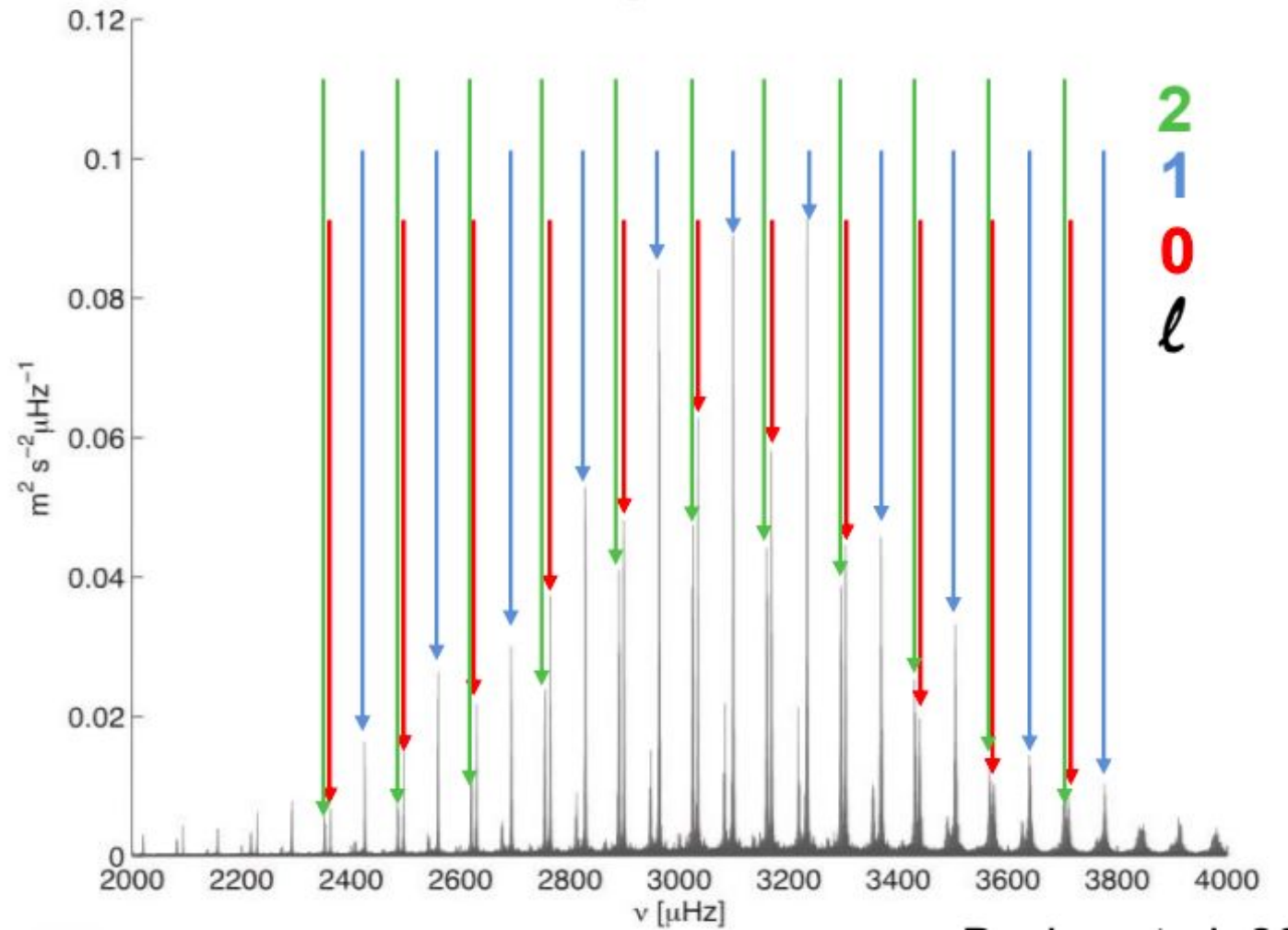
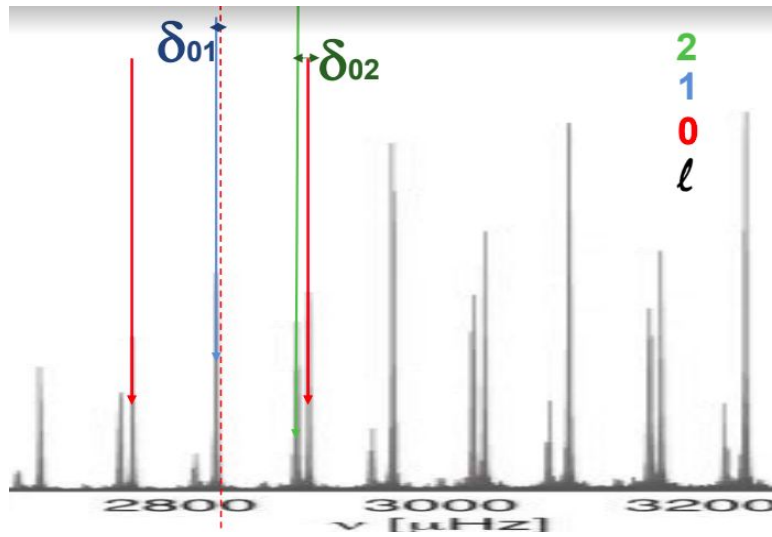
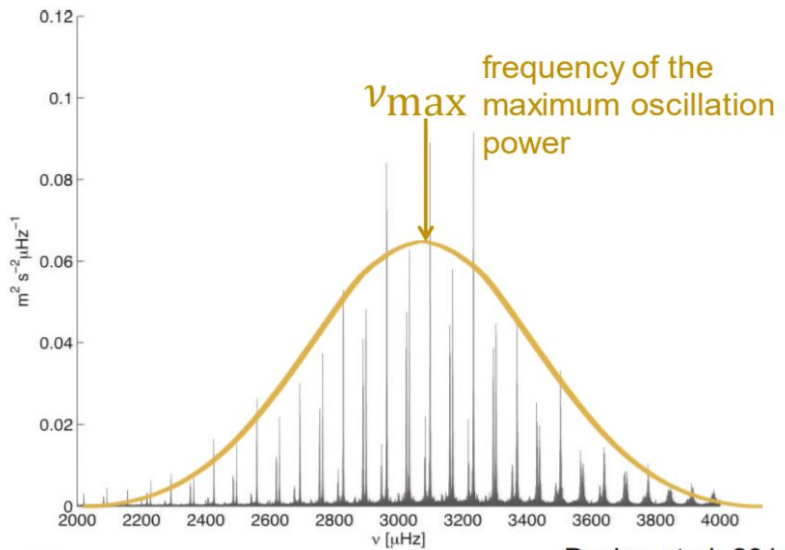
Maria Inês Ferreira, 2018296679

Simão Pedro Neto Sousa, 2017253022

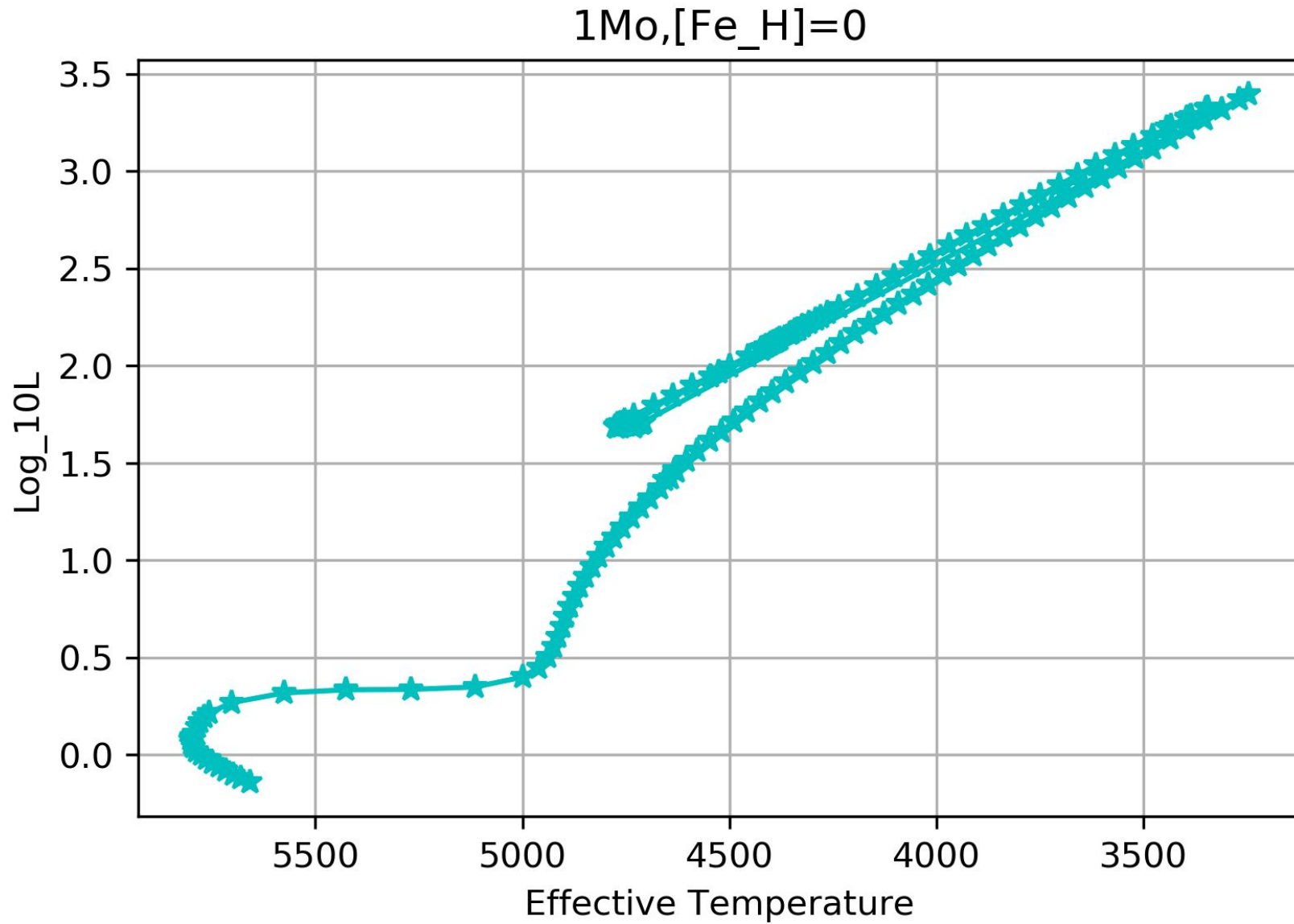
# Introduction

## Asteroseismology





# Hertzprung-Russell Diagram



## Data used

A library of frequencies, amplitudes, and lifetimes of more than 250,000 individual  $l=0$  to 3 oscillations modes of 6,179 red giants from APOKASC sample ([Pinsonneault et al. 2018](#)) - KALLINGER SAMPLE

- *f<sub>max</sub>*: The frequency of the maximum oscillation power in microHz;
- *dnu*, *dnu02*: The large and small frequency separation determined in the central three radial orders around *f<sub>max</sub>*. All parameters are in microHz;
- *dnu<sub>cor</sub>*: Curvature-corrected large separation in microHz;
- *evo*: Evolutionary stage of the star determined from the phase shift of the central radial mode ([Kallinger et al. 2012](#)) with the following code: 0 - RGB star, 1 - RC star, 2 - secondary clump star, and 3 - AGB star.



### KEPLER SAMPLE:

- *TEFF*: effective temperature of the star (in Kelvin);
- *M<sub>H</sub>*: metallicity of the star;
- *M/M<sub>sun</sub>*: stellar mass in solar units.

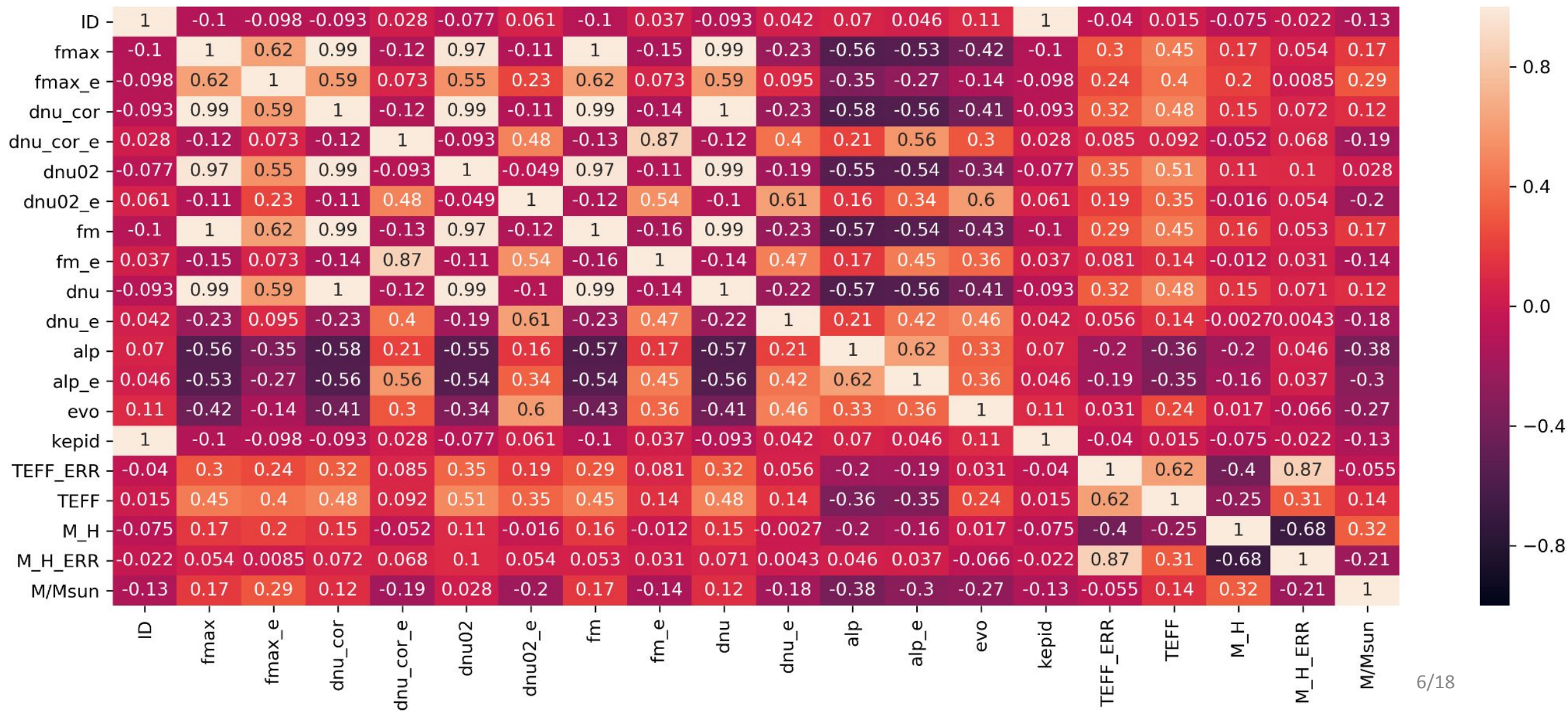


Crossmatch: Sample with 6152 stars.



# Correlation Heatmap

Correlation Heatmap



# Machine Learning Code

```
1 from numpy import loadtxt
2 from keras.models import Sequential
3 from keras.layers import Dense
4 from matplotlib import pyplot
5 import pandas as pd
6 from sklearn.model_selection import train_test_split
7 import time
8 import seaborn as sns
9 import matplotlib.pyplot as plt
10
```

```
11 # get the start time-----#
12 st = time.time()
13
14 # load the dataset-----#
15 df = pd.read_csv('Summ+KeplerM')
16 #print(df)
17
18 #Choose the RGB and RC stars-----#
19 stars = df.loc[(df['evo']==0) | (df['evo']==1) ]
20 model_name = 'Stars_Classifier'
```



```
22
23 #Split in input 'X' and in output 'Y'-----#
24 X = stars[['fmax', 'dnu_cor', 'dnu02', 'dnu', 'TEFF', 'M_H', 'M/Msun']]
25 y = stars[['evo']]
26
27 #print(X)
28 #print(y)
29
30
31 #Correlation heatmap-----#
32 sns.heatmap(stars.corr())
33 plt.figure(figsize=(16, 6))
34 heatmap = sns.heatmap(stars.corr(), vmin=-1, vmax=1, annot=True)
35 heatmap.set_title('Correlation Heatmap', fontdict={'fontsize':12}, pad=12)
36
37
```

```
39 # split into train, test sets-----#
40 train_ratio = 0.80
41 validation_ratio = 0.10
42 test_ratio = 0.10
43 trainX, testX, trainY, testY = train_test_split(X, y, test_size= 1 - train_ratio)
44 valX, testX, valY, testY = train_test_split(testX, testY, test_size=test_ratio/(test_ratio + validation_ratio))
45
```

```
50 #Model-----#
51     #define the keras model-----#
52 model = Sequential()
53 model.add(Dense(10, input_dim=(7), kernel_initializer='uniform', activation='relu'))
54 model.add(Dense(6, kernel_initializer='uniform', activation='relu'))
55 model.add(Dense(1, kernel_initializer='uniform', activation='sigmoid'))
56
57 model.summary()
58
59     #compile the keras model-----#
60 model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
61
62     #fit the keras model on the dataset-----#
63 history=model.fit(trainX, trainY, epochs=900, batch_size=50, validation_data=(valX, valY))
64
```

```
67 #Obtaining the best model values-----#
68 hist_stars=pd.DataFrame(history.history)
69 hist_stars['epoch'] = hist_stars.index + 1
70 cols = list(hist_stars.columns)
71 cols = [cols[-1]] + cols[:-1]
72 hist_stars= hist_stars[cols]
73 #hist_stars.to_csv('/') + 'history_stars_' + model_name + '.csv')
74 hist_stars.head()
75
76 values_of_best_model = hist_stars[hist_stars.val_loss == hist_stars.val_loss.min()]
77 print('Best model', values_of_best_model)
```



```
80
81 #Validation-----#
82 acc = history.history['accuracy']
83 val_acc = history.history['val_accuracy']
84 loss = history.history['loss']
85 val_loss = history.history['val_loss']
86
87 epochs = range(1, len(acc) + 1)
88
89 plt.plot(epochs, acc, 'ro', label='Training acc')
90 plt.plot(epochs, val_acc, 'b', label='Validation acc')
91 plt.title('Training and validation accuracy')
92 plt.legend()
93 plt.show()
94
95
96 plt.plot(epochs, loss, 'go', label='Training loss')
97 plt.plot(epochs, val_loss, 'b', label='Validation loss')
98 plt.title('Training and validation loss')
99 plt.legend()
00
01 plt.show()
02
```

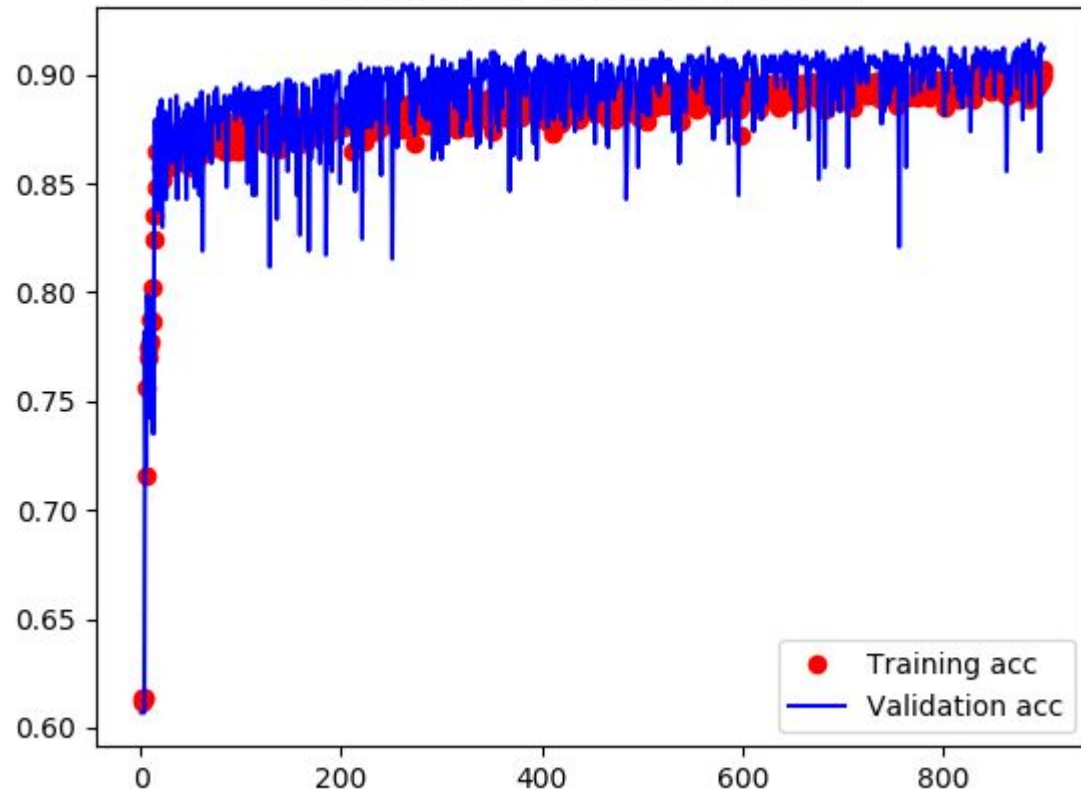


```
103
104 #Model testing-----#
105 test_loss, test_acc = model.evaluate(testX, testY)
106 print()
107 print('Test Accuracy:', test_acc)
108
```

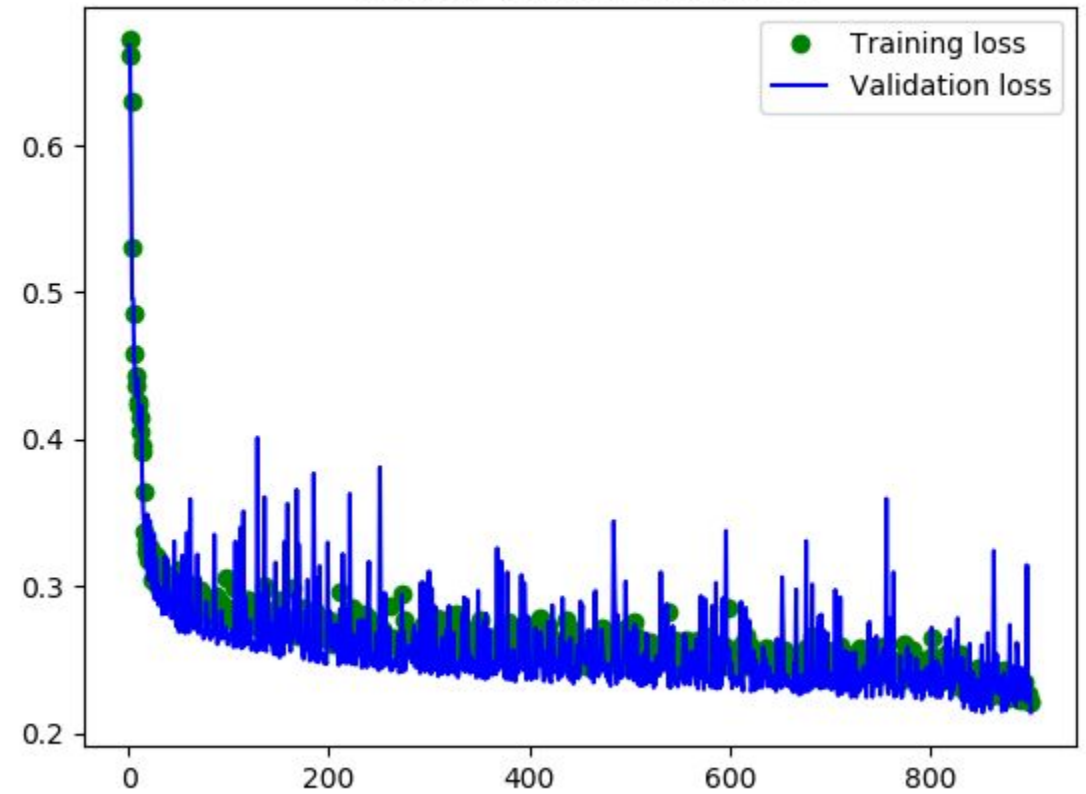
```
107
108 #Predictions-----#
109 y_pred = model.predict(X)
110 #print(y_pred)
111
112 plt.scatter(y,y_pred, c='k', s=1, alpha=0.3)
113 plt.title('Expected and Predicted RGB')
114 plt.show()
115
116
117 # get the end time-----#
118 et = time.time()
119
120 # get the execution time-----#
121 elapsed_time = et - st
122 print('Execution time:', elapsed_time, 'seconds')
```

# Results/Conclusion

Training and validation accuracy



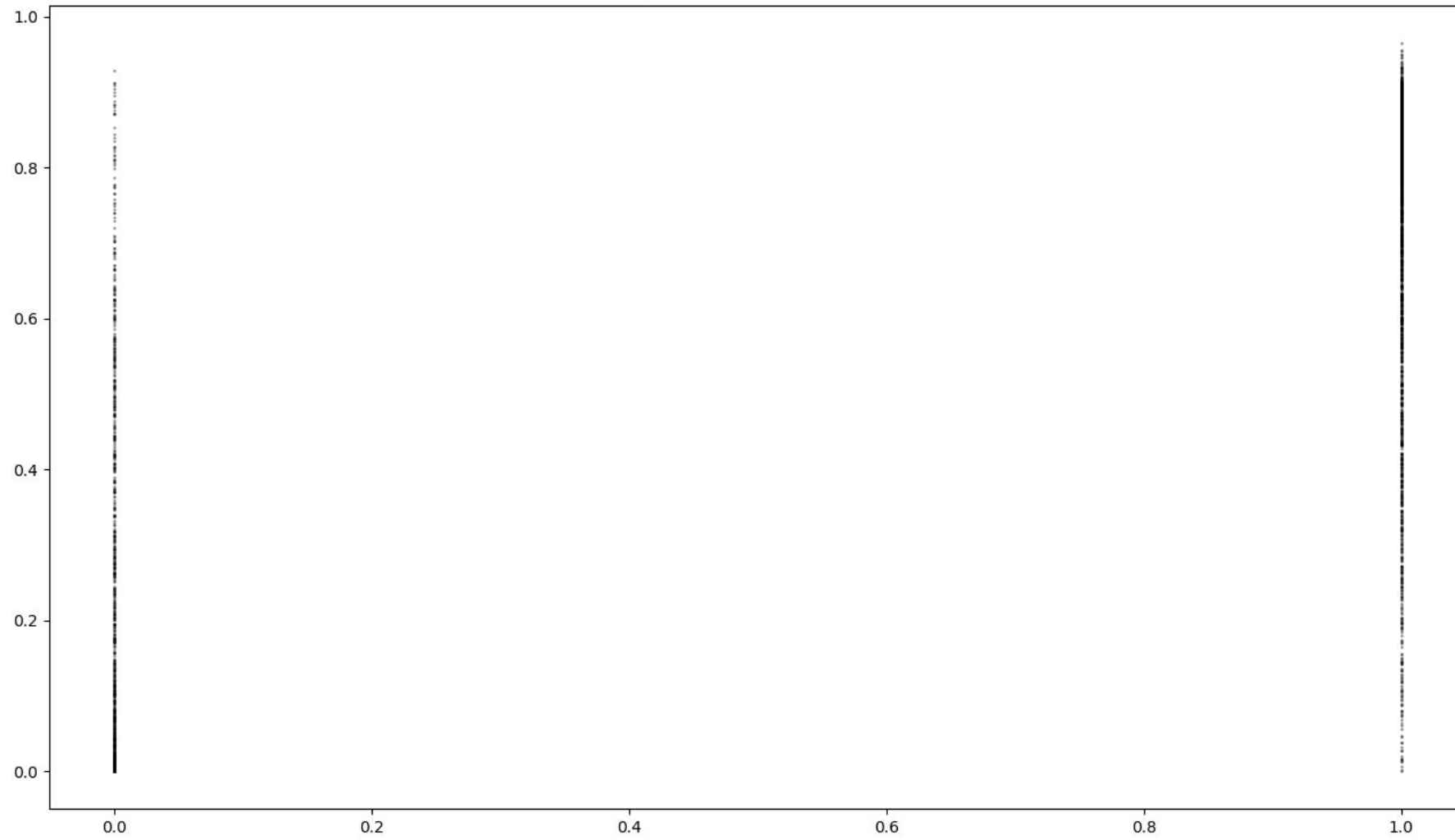
Training and validation loss



```
Epoch 900/900
88/88 [=====] - 0s 792us/step - loss: 0.2219 - accuracy: 0.8999 - val_loss: 0.2139 - val_accuracy: 0.9122
Best model      epoch      loss  accuracy  val_loss  val_accuracy
851      852  0.238022  0.89719  0.213854  0.91042
18/18 [=====] - 0s 794us/step - loss: 0.2108 - accuracy: 0.8996

Test Accuracy: 0.8996350169181824
18/18 [=====] - 0s 733us/step
Execution time: 259.887921333313 seconds
maria@maria-Creator-M16-A12UC:~/Documents/TAAD/Projeto$ █
```

Expected and Predicted RGB





# The End + Questions