Predicting real exoplanets using machine learning techniques (Evaluator-OMID-BAGHCHEH-SARAEI)

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The idea is to create a machine learning model that can predict if an observation is a real exoplanet or not. The data was collected by the Kepler mission that revealed thousands of planets out of our Solar System. The purpose of this project is to build an algorithm to find planets out of the solar system in NASA Exoplanet Dataset stored in `exoplanets.zip`. I use classic machine learning algorithms and TensorFlow to identify real exoplanets.

[ ]:
```
#Import libraries
import numpy as np
import scipy.optimize as opt
import seaborn as sns
import pandas as pd
from sklearn.tree import DecisionTreeClassifier
import matplotlib.pyplot as plt
from sklearn import preprocessing
import tensorflow as tf
import cv2
from google.colab.patches import cv2_imshow
from sklearn.neighbors import KNeighborsClassifier
from sklearn import metrics
from sklearn.metrics import classification_report
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.ensemble import VotingClassifier
from sklearn.neural_network import MLPClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
%matplotlib inline
```

1 Read data using pandas

[ ]:
```
df = pd.read_csv("exoplanets.zip")
df.sample(5)
```

[ ]:

```
         kepid kepoi_name   kepler_name koi_disposition koi_pdisposition  \
3506   6347299  K00661.01  Kepler-204 b       CONFIRMED        CANDIDATE
3552   7368664  K00614.01  Kepler-434 b       CONFIRMED        CANDIDATE
202    7135852  K00875.01           NaN       CANDIDATE        CANDIDATE
9     10910878  K00757.01  Kepler-229 c       CONFIRMED        CANDIDATE
9285  10535991  K08024.01           NaN  FALSE POSITIVE   FALSE POSITIVE

      koi_score  koi_fpflag_nt  koi_fpflag_ss  koi_fpflag_co  koi_fpflag_ec  \
3506        1.0              0              0              0              0
3552        1.0              0              0              0              0
202         1.0              0              0              0              0
9           1.0              0              0              0              0
9285        0.0              0              0              1              1

      ...  koi_steff_err2  koi_slogg  koi_slogg_err1  koi_slogg_err2  \
3506  ...          -117.0      4.270           0.156          -0.104
3552  ...           -80.0      4.218           0.143          -0.117
202   ...          -259.0      4.747           0.105          -0.094
9     ...           -83.0      4.485           0.083          -0.028
9285  ...          -179.0      4.554           0.036          -0.192

      koi_srad  koi_srad_err1  koi_srad_err2         ra        dec  koi_kepmag
3506     1.198          0.178         -0.198  285.34720  41.761921      13.909
3552     1.424          0.249         -0.249  293.58636  42.928909      14.517
202      0.517          0.114         -0.114  296.69394  42.626110      15.692
9        0.848          0.033         -0.072  286.99948  48.375790      15.841
9285     0.846          0.235         -0.078  292.22760  47.746262      15.767

[5 rows x 49 columns]
```

2 Rename columns to make them easier to use

[ ]:

```
df = df.rename(columns={'kepid':'KepID',
'kepoi_name':'KOIName',
'kepler_name':'KeplerName',
'koi_disposition':'ExoplanetArchiveDisposition',
'koi_pdisposition':'DispositionUsingKeplerData',
'koi_score':'DispositionScore',
'koi_fpflag_nt':'NotTransit-LikeFalsePositiveFlag',
'koi_fpflag_ss':'koi_fpflag_ss',
'koi_fpflag_co':'CentroidOffsetFalsePositiveFlag',
'koi_fpflag_ec':'EphemerisMatchIndicatesContaminationFalsePositiveFlag',
'koi_period':'OrbitalPeriod_days',
'koi_period_err1':'OrbitalPeriodUpperUnc_days',
'koi_period_err2':'OrbitalPeriodLowerUnc_days',
'koi_time0bk':'TransitEpoch_BKJD',
```

```
'koi_time0bk_err1':'TransitEpochUpperUnc_BKJD',
'koi_time0bk_err2':'TransitEpochLowerUnc_BKJD',
'koi_impact':'ImpactParamete',
'koi_impact_err1':'ImpactParameterUpperUnc',
'koi_impact_err2':'ImpactParameterLowerUnc',
'koi_duration':'TransitDuration_hrs',
'koi_duration_err1':'TransitDurationUpperUnc_hrs',
'koi_duration_err2':'TransitDurationLowerUnc_hrs',
'koi_depth':'TransitDepth_ppm',
'koi_depth_err1':'TransitDepthUpperUnc_ppm',
'koi_depth_err2':'TransitDepthLowerUnc_ppm',
'koi_prad':'PlanetaryRadius_Earthradii',
'koi_prad_err1':'PlanetaryRadiusUpperUnc_Earthradii',
'koi_prad_err2':'PlanetaryRadiusLowerUnc_Earthradii',
'koi_teq':'EquilibriumTemperatureK',
'koi_teq_err1':'EquilibriumTemperatureUpperUncK',
'koi_teq_err2':'EquilibriumTemperatureLowerUncK',
'koi_insol':'InsolationFlux_Earthflux',
'koi_insol_err1':'InsolationFluxUpperUnc_Earthflux',
'koi_insol_err2':'InsolationFluxLowerUnc_Earthflux',
'koi_model_snr':'TransitSignal-to-Nois',
'koi_tce_plnt_num':'TCEPlanetNumbe',
'koi_tce_delivname':'TCEDeliver',
'koi_steff':'StellarEffectiveTemperatureK',
'koi_steff_err1':'StellarEffectiveTemperatureUpperUncK',
'koi_steff_err2':'StellarEffectiveTemperatureLowerUncK',
'koi_slogg':'StellarSurfaceGravity_log10(cm/s**2)',
'koi_slogg_err1':'StellarSurfaceGravityUpperUnc_log10(cm/s**2)',
'koi_slogg_err2':'StellarSurfaceGravityLowerUnc_log10(cm/s**2)',
'koi_srad':'StellarRadius_Solarradii',
'koi_srad_err1':'StellarRadiusUpperUnc_Solarradii',
'koi_srad_err2':'StellarRadiusLowerUnc_Solarradii',
'ra':'RA_decimaldegrees',
'dec':'Dec_decimaldegrees',
'koi_kepmag':'Kepler-band_mag'
})
df.head().T
```

[ ]:

```
                                                     0  \
KepID                                         10797460
KOIName                                      K00752.01
KeplerName                                Kepler-227 b
ExoplanetArchiveDisposition                  CONFIRMED
DispositionUsingKeplerData                   CANDIDATE
DispositionScore                                   1.0
NotTransit-LikeFalsePositiveFlag                     0
koi_fpflag_ss                                        0
```

CentroidOffsetFalsePositiveFlag	0
EphemerisMatchIndicatesContaminationFalsePositi...	0
OrbitalPeriod_days	9.488036
OrbitalPeriodUpperUnc_days	0.000028
OrbitalPeriodLowerUnc_days	-0.000028
TransitEpoch_BKJD	170.53875
TransitEpochUpperUnc_BKJD	0.00216
TransitEpochLowerUnc_BKJD	-0.00216
ImpactParamete	0.146
ImpactParameterUpperUnc	0.318
ImpactParameterLowerUnc	-0.146
TransitDuration_hrs	2.9575
TransitDurationUpperUnc_hrs	0.0819
TransitDurationLowerUnc_hrs	-0.0819
TransitDepth_ppm	616.0
TransitDepthUpperUnc_ppm	19.5
TransitDepthLowerUnc_ppm	-19.5
PlanetaryRadius_Earthradii	2.26
PlanetaryRadiusUpperUnc_Earthradii	0.26
PlanetaryRadiusLowerUnc_Earthradii	-0.15
EquilibriumTemperatureK	793.0
EquilibriumTemperatureUpperUncK	NaN
EquilibriumTemperatureLowerUncK	NaN
InsolationFlux_Earthflux	93.59
InsolationFluxUpperUnc_Earthflux	29.45
InsolationFluxLowerUnc_Earthflux	-16.65
TransitSignal-to-Nois	35.8
TCEPlanetNumbe	1.0
TCEDeliver	q1_q17_dr25_tce
StellarEffectiveTemperatureK	5455.0
StellarEffectiveTemperatureUpperUncK	81.0
StellarEffectiveTemperatureLowerUncK	-81.0
StellarSurfaceGravity_log10(cm/s**2)	4.467
StellarSurfaceGravityUpperUnc_log10(cm/s**2)	0.064
StellarSurfaceGravityLowerUnc_log10(cm/s**2)	-0.096
StellarRadius_Solarradii	0.927
StellarRadiusUpperUnc_Solarradii	0.105
StellarRadiusLowerUnc_Solarradii	-0.061
RA_decimaldegrees	291.93423
Dec_decimaldegrees	48.141651
Kepler-band_mag	15.347

	1 \
KepID	10797460
KOIName	K00752.02
KeplerName	Kepler-227 c
ExoplanetArchiveDisposition	CONFIRMED

DispositionUsingKeplerData	CANDIDATE
DispositionScore	0.969
NotTransit-LikeFalsePositiveFlag	0
koi_fpflag_ss	0
CentroidOffsetFalsePositiveFlag	0
EphemerisMatchIndicatesContaminationFalsePositi...	0
OrbitalPeriod_days	54.418383
OrbitalPeriodUpperUnc_days	0.000248
OrbitalPeriodLowerUnc_days	-0.000248
TransitEpoch_BKJD	162.51384
TransitEpochUpperUnc_BKJD	0.00352
TransitEpochLowerUnc_BKJD	-0.00352
ImpactParamete	0.586
ImpactParameterUpperUnc	0.059
ImpactParameterLowerUnc	-0.443
TransitDuration_hrs	4.507
TransitDurationUpperUnc_hrs	0.116
TransitDurationLowerUnc_hrs	-0.116
TransitDepth_ppm	875.0
TransitDepthUpperUnc_ppm	35.5
TransitDepthLowerUnc_ppm	-35.5
PlanetaryRadius_Earthradii	2.83
PlanetaryRadiusUpperUnc_Earthradii	0.32
PlanetaryRadiusLowerUnc_Earthradii	-0.19
EquilibriumTemperatureK	443.0
EquilibriumTemperatureUpperUncK	NaN
EquilibriumTemperatureLowerUncK	NaN
InsolationFlux_Earthflux	9.11
InsolationFluxUpperUnc_Earthflux	2.87
InsolationFluxLowerUnc_Earthflux	-1.62
TransitSignal-to-Nois	25.8
TCEPlanetNumbe	2.0
TCEDeliver	q1_q17_dr25_tce
StellarEffectiveTemperatureK	5455.0
StellarEffectiveTemperatureUpperUncK	81.0
StellarEffectiveTemperatureLowerUncK	-81.0
StellarSurfaceGravity_log10(cm/s**2)	4.467
StellarSurfaceGravityUpperUnc_log10(cm/s**2)	0.064
StellarSurfaceGravityLowerUnc_log10(cm/s**2)	-0.096
StellarRadius_Solarradii	0.927
StellarRadiusUpperUnc_Solarradii	0.105
StellarRadiusLowerUnc_Solarradii	-0.061
RA_decimaldegrees	291.93423
Dec_decimaldegrees	48.141651
Kepler-band_mag	15.347

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KepID	10811496
KOIName	K00753.01
KeplerName	NaN
ExoplanetArchiveDisposition	CANDIDATE
DispositionUsingKeplerData	CANDIDATE
DispositionScore	0.0
NotTransit-LikeFalsePositiveFlag	0
koi_fpflag_ss	0
CentroidOffsetFalsePositiveFlag	0
EphemerisMatchIndicatesContaminationFalsePositi...	0
OrbitalPeriod_days	19.89914
OrbitalPeriodUpperUnc_days	0.000015
OrbitalPeriodLowerUnc_days	-0.000015
TransitEpoch_BKJD	175.850252
TransitEpochUpperUnc_BKJD	0.000581
TransitEpochLowerUnc_BKJD	-0.000581
ImpactParamete	0.969
ImpactParameterUpperUnc	5.126
ImpactParameterLowerUnc	-0.077
TransitDuration_hrs	1.7822
TransitDurationUpperUnc_hrs	0.0341
TransitDurationLowerUnc_hrs	-0.0341
TransitDepth_ppm	10800.0
TransitDepthUpperUnc_ppm	171.0
TransitDepthLowerUnc_ppm	-171.0
PlanetaryRadius_Earthradii	14.6
PlanetaryRadiusUpperUnc_Earthradii	3.92
PlanetaryRadiusLowerUnc_Earthradii	-1.31
EquilibriumTemperatureK	638.0
EquilibriumTemperatureUpperUncK	NaN
EquilibriumTemperatureLowerUncK	NaN
InsolationFlux_Earthflux	39.3
InsolationFluxUpperUnc_Earthflux	31.04
InsolationFluxLowerUnc_Earthflux	-10.49
TransitSignal-to-Nois	76.3
TCEPlanetNumbe	1.0
TCEDeliver	q1_q17_dr25_tce
StellarEffectiveTemperatureK	5853.0
StellarEffectiveTemperatureUpperUncK	158.0
StellarEffectiveTemperatureLowerUncK	-176.0
StellarSurfaceGravity_log10(cm/s**2)	4.544
StellarSurfaceGravityUpperUnc_log10(cm/s**2)	0.044
StellarSurfaceGravityLowerUnc_log10(cm/s**2)	-0.176
StellarRadius_Solarradii	0.868
StellarRadiusUpperUnc_Solarradii	0.233
StellarRadiusLowerUnc_Solarradii	-0.078
RA_decimaldegrees	297.00482

Dec_decimaldegrees	48.134129
Kepler-band_mag	15.436

	3 \
KepID	10848459
KOIName	K00754.01
KeplerName	NaN
ExoplanetArchiveDisposition	FALSE POSITIVE
DispositionUsingKeplerData	FALSE POSITIVE
DispositionScore	0.0
NotTransit-LikeFalsePositiveFlag	0
koi_fpflag_ss	1
CentroidOffsetFalsePositiveFlag	0
EphemerisMatchIndicatesContaminationFalsePositi...	0
OrbitalPeriod_days	1.736952
OrbitalPeriodUpperUnc_days	0.0
OrbitalPeriodLowerUnc_days	-0.0
TransitEpoch_BKJD	170.307565
TransitEpochUpperUnc_BKJD	0.000115
TransitEpochLowerUnc_BKJD	-0.000115
ImpactParamete	1.276
ImpactParameterUpperUnc	0.115
ImpactParameterLowerUnc	-0.092
TransitDuration_hrs	2.40641
TransitDurationUpperUnc_hrs	0.00537
TransitDurationLowerUnc_hrs	-0.00537
TransitDepth_ppm	8080.0
TransitDepthUpperUnc_ppm	12.8
TransitDepthLowerUnc_ppm	-12.8
PlanetaryRadius_Earthradii	33.46
PlanetaryRadiusUpperUnc_Earthradii	8.5
PlanetaryRadiusLowerUnc_Earthradii	-2.83
EquilibriumTemperatureK	1395.0
EquilibriumTemperatureUpperUncK	NaN
EquilibriumTemperatureLowerUncK	NaN
InsolationFlux_Earthflux	891.96
InsolationFluxUpperUnc_Earthflux	668.95
InsolationFluxLowerUnc_Earthflux	-230.35
TransitSignal-to-Nois	505.6
TCEPlanetNumbe	1.0
TCEDeliver	q1_q17_dr25_tce
StellarEffectiveTemperatureK	5805.0
StellarEffectiveTemperatureUpperUncK	157.0
StellarEffectiveTemperatureLowerUncK	-174.0
StellarSurfaceGravity_log10(cm/s**2)	4.564
StellarSurfaceGravityUpperUnc_log10(cm/s**2)	0.053
StellarSurfaceGravityLowerUnc_log10(cm/s**2)	-0.168

StellarRadius_Solarradii	0.791
StellarRadiusUpperUnc_Solarradii	0.201
StellarRadiusLowerUnc_Solarradii	-0.067
RA_decimaldegrees	285.53461
Dec_decimaldegrees	48.28521
Kepler-band_mag	15.597

	4
KepID	10854555
KOIName	K00755.01
KeplerName	Kepler-664 b
ExoplanetArchiveDisposition	CONFIRMED
DispositionUsingKeplerData	CANDIDATE
DispositionScore	1.0
NotTransit-LikeFalsePositiveFlag	0
koi_fpflag_ss	0
CentroidOffsetFalsePositiveFlag	0
EphemerisMatchIndicatesContaminationFalsePositi...	0
OrbitalPeriod_days	2.525592
OrbitalPeriodUpperUnc_days	0.000004
OrbitalPeriodLowerUnc_days	-0.000004
TransitEpoch_BKJD	171.59555
TransitEpochUpperUnc_BKJD	0.00113
TransitEpochLowerUnc_BKJD	-0.00113
ImpactParamete	0.701
ImpactParameterUpperUnc	0.235
ImpactParameterLowerUnc	-0.478
TransitDuration_hrs	1.6545
TransitDurationUpperUnc_hrs	0.042
TransitDurationLowerUnc_hrs	-0.042
TransitDepth_ppm	603.0
TransitDepthUpperUnc_ppm	16.9
TransitDepthLowerUnc_ppm	-16.9
PlanetaryRadius_Earthradii	2.75
PlanetaryRadiusUpperUnc_Earthradii	0.88
PlanetaryRadiusLowerUnc_Earthradii	-0.35
EquilibriumTemperatureK	1406.0
EquilibriumTemperatureUpperUncK	NaN
EquilibriumTemperatureLowerUncK	NaN
InsolationFlux_Earthflux	926.16
InsolationFluxUpperUnc_Earthflux	874.33
InsolationFluxLowerUnc_Earthflux	-314.24
TransitSignal-to-Nois	40.9
TCEPlanetNumbe	1.0
TCEDeliver	q1_q17_dr25_tce
StellarEffectiveTemperatureK	6031.0
StellarEffectiveTemperatureUpperUncK	169.0

```
StellarEffectiveTemperatureLowerUncK                      -211.0
StellarSurfaceGravity_log10(cm/s**2)                       4.438
StellarSurfaceGravityUpperUnc_log10(cm/s**2)                0.07
StellarSurfaceGravityLowerUnc_log10(cm/s**2)               -0.21
StellarRadius_Solarradii                                   1.046
StellarRadiusUpperUnc_Solarradii                           0.334
StellarRadiusLowerUnc_Solarradii                          -0.133
RA_decimaldegrees                                      288.75488
Dec_decimaldegrees                                       48.2262
Kepler-band_mag                                           15.509
```

The dataset contains some columns that are not numeric. To work with these columns, they must be encoded into numeric forms. To do this, I use a map().

[ ]:
```
df.DispositionUsingKeplerData = df.DispositionUsingKeplerData.map({'FALSE␣
↪POSITIVE': 0, 'CANDIDATE': 1})
df.ExoplanetArchiveDisposition = df.ExoplanetArchiveDisposition.
↪map({'CONFIRMED': 2, 'CANDIDATE': 1, 'FALSE POSITIVE': 0})
df.TCEDeliver = df.TCEDeliver.map({'q1_q17_dr25_tce': 0, 'q1_q16_tce': 1,␣
↪'q1_q17_dr24_tce': 2})
```

3 Rename targets

[ ]:
```
df = df.rename(columns={'DispositionUsingKeplerData': 'ExoplanetCandidate',␣
↪'ExoplanetArchiveDisposition': 'ExoplanetConfirmed'})
```

4 Remove extra columns

[ ]:
```
df = df.drop(columns=['KeplerName', 'KOIName',␣
↪'EquilibriumTemperatureUpperUncK', 'KepID',␣
↪'EquilibriumTemperatureLowerUncK'])
```

5 Replace NaN values with a specified value

[ ]:
```
df = df.fillna(method="ffill")
```

6 I need to know what type of data I am working with before I can work with dataframe, so I check it using the `dtypes`.

[ ]:
```
df.dtypes
```

[ ]:
```
ExoplanetConfirmed                                  int64
ExoplanetCandidate                                  int64
```

```
DispositionScore                                          float64
NotTransit-LikeFalsePositiveFlag                            int64
koi_fpflag_ss                                               int64
CentroidOffsetFalsePositiveFlag                             int64
EphemerisMatchIndicatesContaminationFalsePositiveFlag       int64
OrbitalPeriod_days                                        float64
OrbitalPeriodUpperUnc_days                                float64
OrbitalPeriodLowerUnc_days                                float64
TransitEpoch_BKJD                                         float64
TransitEpochUpperUnc_BKJD                                 float64
TransitEpochLowerUnc_BKJD                                 float64
ImpactParamete                                            float64
ImpactParameterUpperUnc                                   float64
ImpactParameterLowerUnc                                   float64
TransitDuration_hrs                                       float64
TransitDurationUpperUnc_hrs                               float64
TransitDurationLowerUnc_hrs                               float64
TransitDepth_ppm                                          float64
TransitDepthUpperUnc_ppm                                  float64
TransitDepthLowerUnc_ppm                                  float64
PlanetaryRadius_Earthradii                                float64
PlanetaryRadiusUpperUnc_Earthradii                        float64
PlanetaryRadiusLowerUnc_Earthradii                        float64
EquilibriumTemperatureK                                   float64
InsolationFlux_Earthflux                                  float64
InsolationFluxUpperUnc_Earthflux                          float64
InsolationFluxLowerUnc_Earthflux                          float64
TransitSignal-to-Nois                                     float64
TCEPlanetNumbe                                            float64
TCEDeliver                                                float64
StellarEffectiveTemperatureK                              float64
StellarEffectiveTemperatureUpperUncK                      float64
StellarEffectiveTemperatureLowerUncK                      float64
StellarSurfaceGravity_log10(cm/s**2)                      float64
StellarSurfaceGravityUpperUnc_log10(cm/s**2)              float64
StellarSurfaceGravityLowerUnc_log10(cm/s**2)              float64
StellarRadius_Solarradii                                  float64
StellarRadiusUpperUnc_Solarradii                          float64
StellarRadiusLowerUnc_Solarradii                          float64
RA_decimaldegrees                                         float64
Dec_decimaldegrees                                        float64
Kepler-band_mag                                           float64
dtype: object
```

In the dataframe, there are 9564 records with 44 columns.

[ ]:
```
df.shape
```

[ ]:
```
(9564, 44)
```

I am going to test if there are NaN values in dataframe

[ ]:
```
df.isnull().any().any()
```

[ ]: `False`

There are no NaN values

7 The next step is to examine classic machine learning algorithms and TensorFlow.

7.1 I first split the DataFrame into X (data) and Y (labels), where:

Target(label): `ExoplanetConfirmed`, with three class:

- CONFIRMED: 2
- CANDIDATE: 1
- FALSE POSITIVE: 0

[ ]:
```
X = df.drop(['ExoplanetConfirmed'], axis=1)
y = df['ExoplanetConfirmed']
```

7.2 Using a train-test split, I split X and Y into train and test data to evaluate the machine learning algorithm's performance.

- Train Dataset: Used to fit the machine learning model.
- Test Dataset: Used to evaluate the fit machine learning model.

[ ]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25,␣
 ↪random_state=42)
# Normalization
scaler = MinMaxScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

7.3 1. Classic machine learning algorithms

7.3.1 KNeighborsClassifier

Using X_train and y_train, train a KNeighborsClassifier with default parameters and `n_neighbors=12`.

[ ]:
```
KNClf = KNeighborsClassifier(n_neighbors = 12)  # KNClf= KNeighborsClassifier
KNClf.fit(X_train_scaled, y_train)
```

[ ]: `KNeighborsClassifier(n_neighbors=12)`

Model prediction

[ ]:
```
Model_Prediction_knn = KNClf.predict(X_test_scaled)
Model_Prediction_knn
```

[ ]:
```
array([1, 1, 2, ..., 0, 2, 2])
```

Model Accuracy

[ ]:
```
print('Accuracy of KNeighborsClassifier on train set: {:.3f}' .format(KNClf.
 ↪score(X_train_scaled, y_train)))
print('Accuracy of KNeighborsClassifier on test set: {:.3f}' .format(KNClf.
 ↪score(X_test_scaled, y_test)))
```

```
Accuracy of KNeighborsClassifier on train set: 0.885
Accuracy of KNeighborsClassifier on test set: 0.860
```

I predicted the correct class on 86% of the samples in X_test.
Is n_neighbors = 12 the best value? Yes, because:

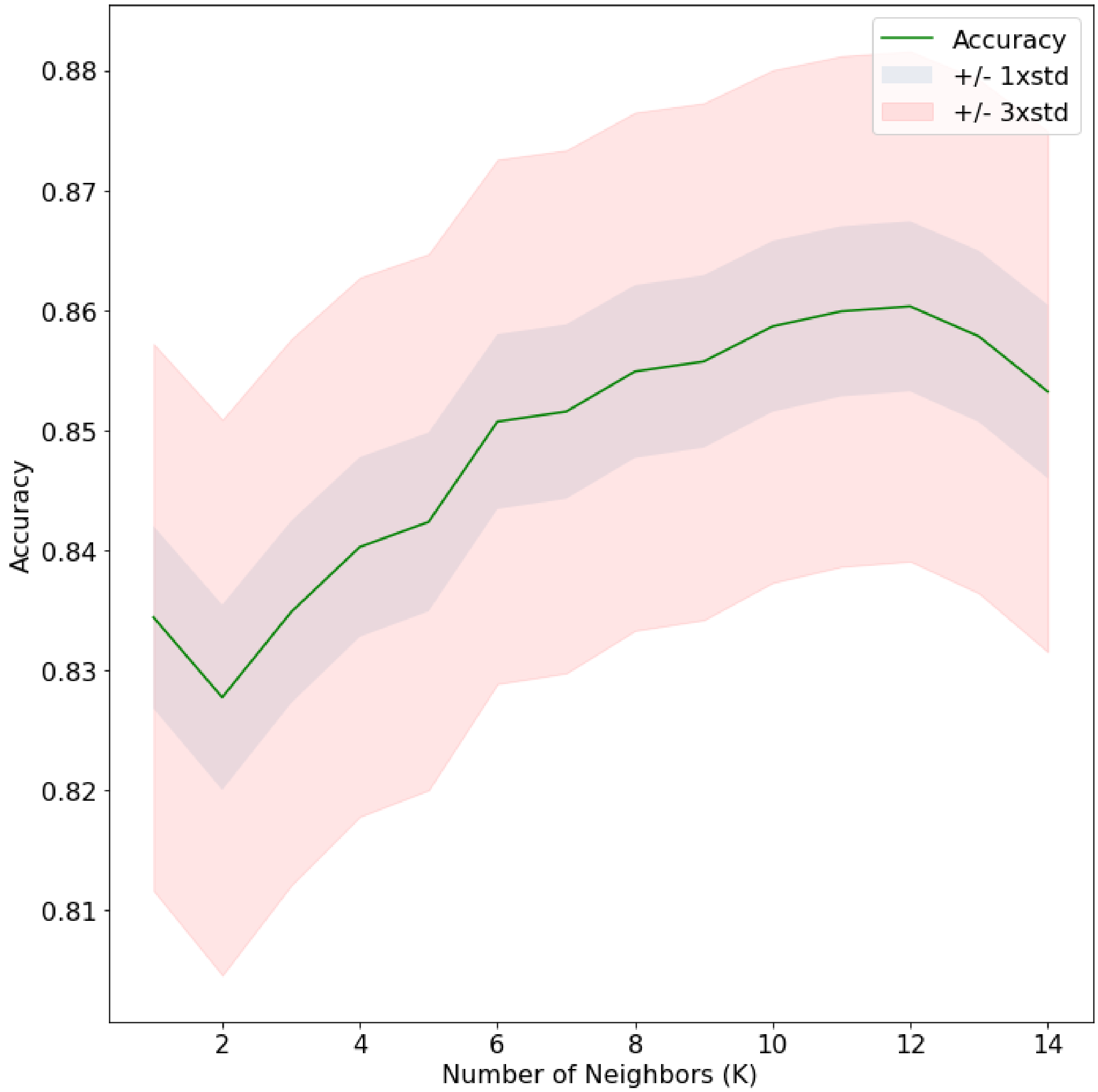
[ ]:
```
Ks = 15
mean_acc = np.zeros((Ks-1))
std_acc = np.zeros((Ks-1))

for n in range(1,Ks):

    #Train Model and Predict
    neigh = KNeighborsClassifier(n_neighbors = n).fit(X_train_scaled, y_train)
    yhat = neigh.predict(X_test_scaled)
    mean_acc[n-1] = metrics.accuracy_score(y_test, yhat)

    std_acc[n-1]=np.std(yhat==y_test)/np.sqrt(yhat.shape[0])

mean_acc
```

[ ]:
```
array([0.83437892, 0.82768716, 0.83479716, 0.84023421, 0.84232539,
       0.85069009, 0.85152656, 0.85487244, 0.85570891, 0.85863655,
       0.85989126, 0.86030949, 0.85780008, 0.8531995 ])
```

To better understand, I visualize previous cell to see better the relationship between Accuracy and Number of Neighbors(K).

[ ]:
```
plt.figure(figsize=(10,10))
plt.rcParams.update({'font.size': 16})
plt.plot(range(1,Ks), mean_acc, 'g')
plt.fill_between(range(1,Ks), mean_acc - 1 * std_acc, mean_acc + 1 * std_acc,␣
 ↪alpha=0.10)
plt.fill_between(range(1,Ks), mean_acc - 3 * std_acc, mean_acc + 3 * std_acc,␣
 ↪alpha=0.10, color='red')
plt.legend(('Accuracy', '+/- 1xstd', '+/- 3xstd'))
plt.ylabel('Accuracy')
plt.xlabel('Number of Neighbors (K)')
plt.tight_layout()
```

```
plt.show()
```




```
[ ]: print("The best accuracy is {:.3f}" .format(mean_acc.max()), "with k =",␣
     ↪mean_acc.argmax()+ 1)
```

```
The best accuracy is 0.860 with k = 12
```

```
[ ]: print(classification_report(y_test, Model_Prediction_knn))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      1190
```

```
           1       0.77      0.64      0.70       601
           2       0.69      0.80      0.74       600

    accuracy                           0.86      2391
   macro avg       0.82      0.81      0.81      2391
weighted avg       0.86      0.86      0.86      2391
```

7.3.2 DecisionTreeClassifier

Using X_train and y_train, train a DecisionTreeClassifier with `default parameters` and `random_state=0`.

[ ]:
```
DTClf = DecisionTreeClassifier(random_state = 0)  #DTClf = Decision Tree␣
↪Classifier
DTClf.fit(X_train, y_train)
```

[ ]:
```
DecisionTreeClassifier(random_state=0)
```

[ ]:
```
Model_Prediction = DTClf.predict(X_test)
```

In order to show easily the differences between `model-based prediction` and `real values`, I create a dataframe.

[ ]:
```
d = {'real or true values(y_test)': y_test, 'Model_Prediction':␣
↪Model_Prediction}
dfC = pd.DataFrame(data=d)
dfC.head(10)
```

[ ]:

	real or true values(y_test)	Model_Prediction
9004	1	1
5028	1	1
1142	2	1
1355	0	0
8740	0	0
1432	2	2
1770	2	2
3465	0	0
3999	0	0
5418	0	0

Model Accuracy

[ ]:
```
print('Accuracy of Decision Tree classifier on train set: {:.3f}' .format(DTClf.
↪score(X_train, y_train)))
print('Accuracy of Decision Tree classifier on test set: {:.3f}' .format(DTClf.
↪score(X_test, y_test)))
```

```
Accuracy of Decision Tree classifier on train set: 1.000
Accuracy of Decision Tree classifier on test set: 0.875
```

I predicted the correct class on `87.5%` of the samples in X_test.

7.3.3 RandomForestClassifier

A random forest is a meta estimator that fits a number of decision tree classifiers on various sub-samples of the dataset and uses averaging to improve the predictive accuracy and control over-fitting.

[ ]:
```
RFClf = RandomForestClassifier(n_estimators=300, criterion='entropy',␣
 ↪min_samples_leaf=2, random_state=0) # RFClf = RandomForestClassifier
RFClf.fit(X_train, y_train)
```

[ ]:
```
RandomForestClassifier(criterion='entropy', min_samples_leaf=2,
                       n_estimators=300, random_state=0)
```

Model Accuracy

[ ]:
```
print('Accuracy of RandomForestClassifier on train set: {:.3f}' .format(RFClf.
 ↪score(X_train, y_train)))
print('Accuracy of RandomForestClassifier on test set: {:.3f}' .format(RFClf.
 ↪score(X_test, y_test)))
```

```
Accuracy of RandomForestClassifier on train set: 0.998
Accuracy of RandomForestClassifier on test set: 0.920
```

I predicted the correct class on 92% of the samples in X_test.

7.3.4 GradientBoostingClassifier

[ ]:
```
GBClf = GradientBoostingClassifier(n_estimators=300, learning_rate=1.0,
     max_depth=1, random_state=0) # ABClf = AdaBoostClassifier
GBClf.fit(X_train, y_train)
```

[ ]:
```
GradientBoostingClassifier(learning_rate=1.0, max_depth=1, n_estimators=300,
                           random_state=0)
```

Model Accuracy

[ ]:
```
print('Accuracy of GradientBoostingClassifier on train set: {:.3f}' .
 ↪format(GBClf.score(X_train, y_train)))
print('Accuracy of GradientBoostingClassifier on test set: {:.3f}' .
 ↪format(GBClf.score(X_test, y_test)))
```

```
Accuracy of GradientBoostingClassifier on train set: 0.944
Accuracy of GradientBoostingClassifier on test set: 0.918
```

I predicted the correct class on 91.8% of the samples in X_test.

7.3.5 Neural_Network.MLPClassifier

[ ]:
```
NNClf = MLPClassifier(hidden_layer_sizes=(300,), activation='relu',␣
 ↪random_state=0, max_iter=300)
NNClf.fit(X_train_scaled, y_train)
```

[ ]:
```
MLPClassifier(hidden_layer_sizes=(300,), max_iter=300, random_state=0)
```

Model Accuracy

[ ]:
```
print('Accuracy of MLPClassifier on train set: {:.3f}' .format(NNClf.
 ↪score(X_train_scaled, y_train)))
print('Accuracy of MLPClassifier on test set: {:.3f}' .format(NNClf.
 ↪score(X_test_scaled, y_test)))
```

```
Accuracy of MLPClassifier on train set: 0.909
Accuracy of MLPClassifier on test set: 0.902
```

I predicted the correct class on `90.2%` of the samples in X_test.

7.3.6 VotingClassifier

Combining three algorithms, Random Forest Classifier, GradientBoostingClassifier, and MLP-Classifier, I achieve high accuracy. For this, I use `VotingClassifier`.

[ ]:
```
eclf1 = VotingClassifier(estimators=[
        ('gb', GBClf), ('rf', RFClf), ('nn', NNClf)], voting='hard')
eclf1.fit(X_train_scaled, y_train)
```

[ ]:
```
VotingClassifier(estimators=[('gb',
                              GradientBoostingClassifier(learning_rate=1.0,
                                                         max_depth=1,
                                                         n_estimators=300,
                                                         random_state=0)),
                             ('rf',
                              RandomForestClassifier(criterion='entropy',
                                                     min_samples_leaf=2,
                                                     n_estimators=300,
                                                     random_state=0)),
                             ('nn',
                              MLPClassifier(hidden_layer_sizes=(300,),
                                            max_iter=300, random_state=0))])
```

Model Accuracy

[ ]:
```
print('Accuracy of VotingClassifier on train set: {:.3f}' .format(eclf1.
 ↪score(X_train_scaled, y_train)))
print('Accuracy of VotingClassifier on test set: {:.3f}' .format(eclf1.
 ↪score(X_test_scaled, y_test)))
```

```
Accuracy of VotingClassifier on train set: 0.957
Accuracy of VotingClassifier on test set: 0.924
```

On 92.4% of the samples in X_test, I correctly predicted the class.

7.3.7 As a data frame, model accuracies are as follows:

```
[ ]: d = {'Model': ['VotingClassifier', 'RandomForestClassifier',␣
      ↪'GradientBoostingClassifier', 'Neural_Network.MLPClassifier',
                  'DecisionTreeClassifier', 'KNeighborsClassifier'], 'Accuracy':␣
      ↪[92.4, 92, 91.8, 90.2, 87.5, 86]}
     dfC = pd.DataFrame(data=d)
     dfC
```

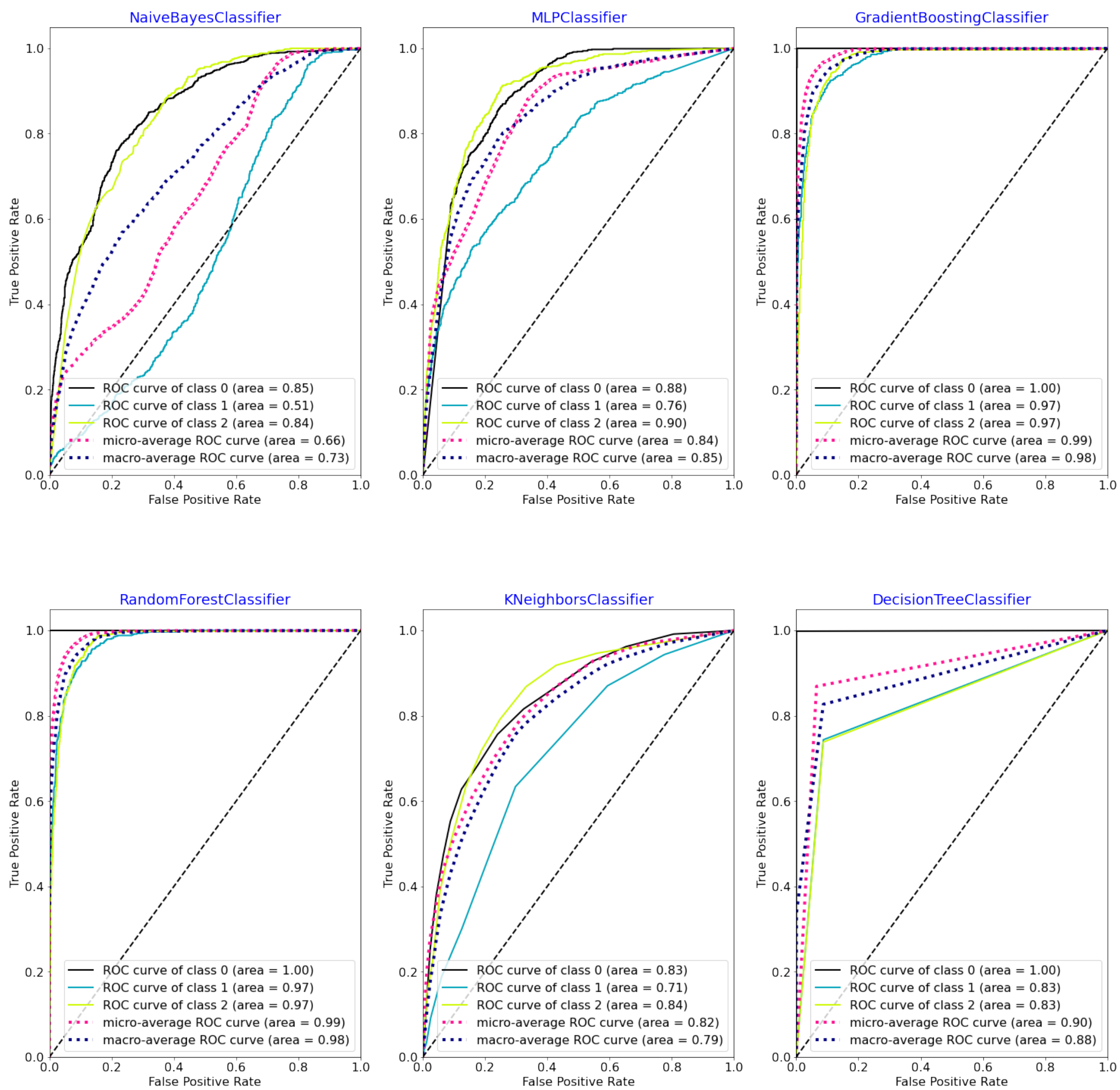
[ ]:

	Model	Accuracy
0	VotingClassifier	92.4
1	RandomForestClassifier	92.0
2	GradientBoostingClassifier	91.8
3	Neural_Network.MLPClassifier	90.2
4	DecisionTreeClassifier	87.5
5	KNeighborsClassifier	86.0

For the ROC Curve, the ideal curve is close to the top left: I want a classifier that produces a high recall while keeping a low false positive rate. Also, for Precision_Recall, the closer a curve stays to the upper right corner, the better the classifier. A point at the upper right means high precision and high recall for the same threshold. Here I plot ROC Curves that reflect ROC scores in comparison charts. This provides us with a better understanding of which algorithm works best for our dataset.

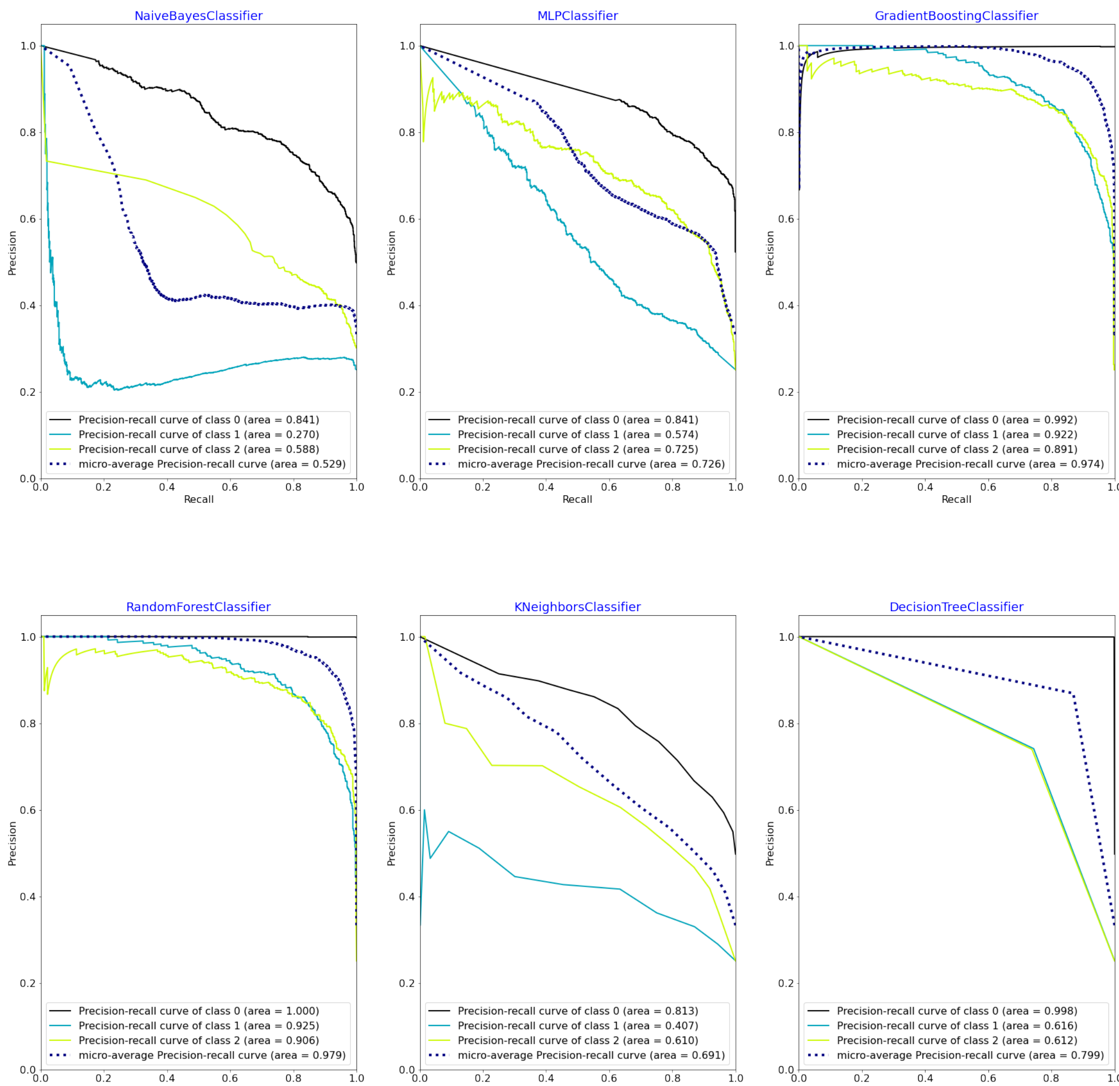
```
[ ]: import scikitplot as skplt
     NBC = GaussianNB()
     NNC = MLPClassifier(hidden_layer_sizes=(300,), activation='relu',␣
      ↪random_state=0, max_iter=300)
     GBC = GradientBoostingClassifier(n_estimators=300, learning_rate=1.0,␣
      ↪max_depth=1, random_state=0)
     RFC = RandomForestClassifier(n_estimators=300, criterion='entropy',␣
      ↪min_samples_leaf=2, random_state=0)
     KNC = KNeighborsClassifier(n_neighbors = 12)
     DTC = DecisionTreeClassifier()

     classifiers = [NBC, NNC, GBC, RFC, KNC, DTC]
     title =␣
      ↪['NaiveBayesClassifier','MLPClassifier','GradientBoostingClassifier','RandomForestClassifie
               'KNeighborsClassifier', 'DecisionTreeClassifier']

     for cls in classifiers:
         cls.fit(X_train, y_train)

     plt.figure(figsize=(25,25))
```

```
grid = plt.GridSpec(2, 3, wspace=0.2, hspace=0.3)

for i in range(6):

    col, row = i%3,i//3
    ax = plt.subplot(grid[row,col])
    ax.title.set_color('blue')

    model = classifiers[i]
    skplt.metrics.plot_roc(y_test, model.predict_proba(X_test), ax=ax, title=title[i])

plt.show()
```



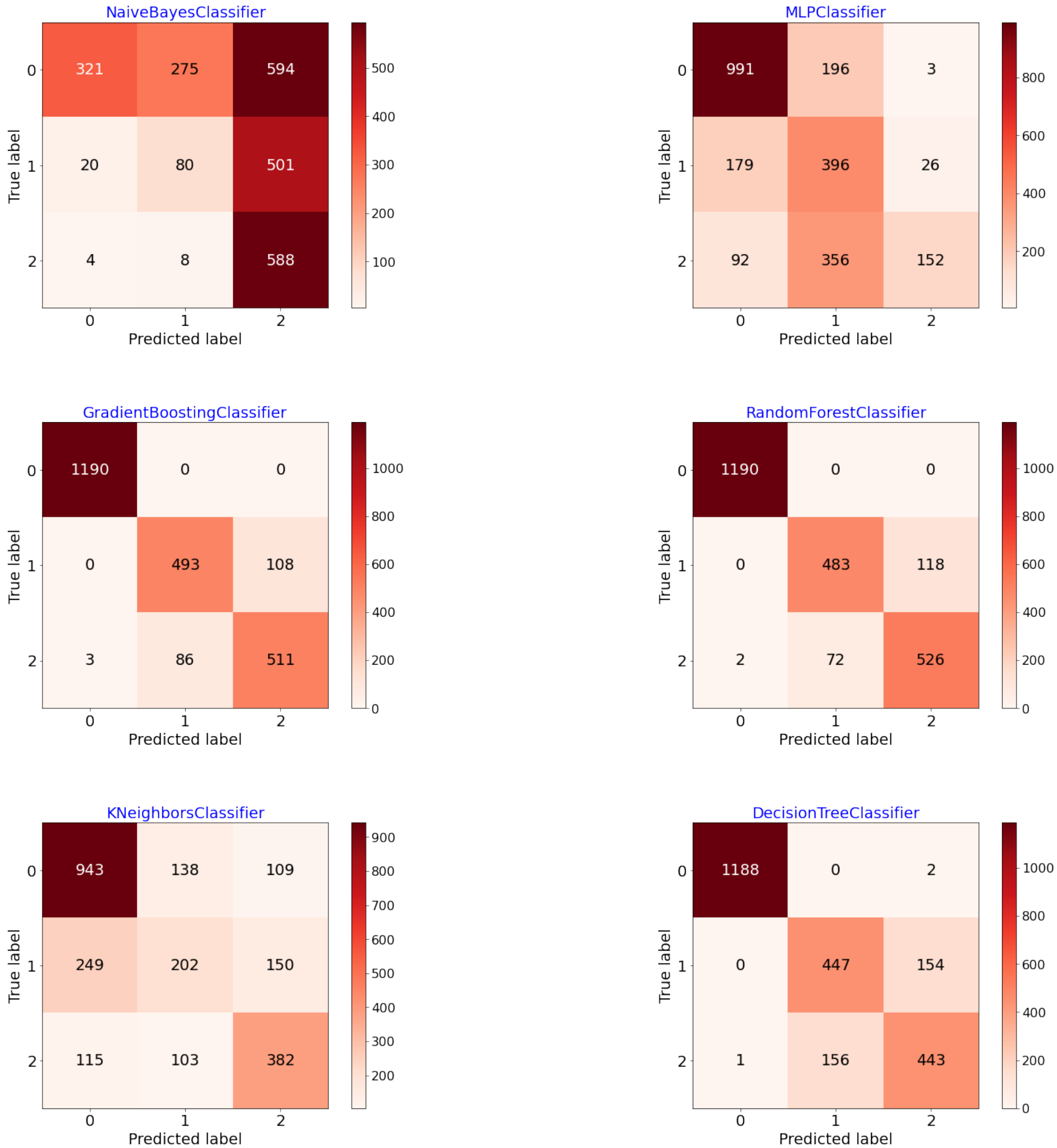
Additionally, I plot the `Precision-Recall Curve` and `Confusion Matrix` to determine which algorithms are best for this dataset in general.

[ ]:
```python
plt.figure(figsize=(30,30))
grid = plt.GridSpec(2, 3, wspace=0.2, hspace=0.3)

for i in range(6):

    col, row = i%3,i//3
    ax = plt.subplot(grid[row,col])
    ax.title.set_color('blue')

    model = classifiers[i]
    skplt.metrics.plot_precision_recall(y_test, model.predict_proba(X_test), ax=ax, title=title[i])

plt.show()
```



Confusion Matrix

[ ]:
```
plt.figure(figsize=(25, 25))
grid = plt.GridSpec(3, 2, wspace=0.4, hspace=0.4)


for i in range(6):

    col, row = i%2,i//2
    ax = plt.subplot(grid[row,col])
    ax.title.set_color('blue')

    model = classifiers[i]
    skplt.metrics.plot_confusion_matrix(y_test, model.predict(X_test), ax=ax,␣
 ↪cmap='Reds', title=title[i], text_fontsize='large')

plt.show()
```


NaiveBayesClassifier
321 275 594
20 80 501
4 8 588
MLPClassifier
991 196 3
179 396 26
92 356 152
GradientBoostingClassifier
1190 0 0
0 493 108
3 86 511
RandomForestClassifier
1190 0 0
0 483 118
2 72 526
KNeighborsClassifier
943 138 109
249 202 150
115 103 382
DecisionTreeClassifier
1188 0 2
0 447 154
1 156 443
True label
Predicted label

2. TensorFlow

June 27, 2022

The first thing I do is train a simple Neural Network using TensorFlow, and then plot accuracy and loss graphs on the training and validation datasets to find a balance between the model that is underfitting and one that is overfitting, resulting in a model with a good fit. I first need to convert the train and test data into a TensorFlow tensor.

0.0.1 To convert DataFrame to a tensor, I use `tf.convert_to_tensor`

[ ]:
```
tf.convert_to_tensor(X_train)
```

[ ]:
```
<tf.Tensor: shape=(7173, 43), dtype=float64, numpy=
array([[1.0000000e+00, 1.0000000e+00, 0.0000000e+00, ..., 3.0041751e+02,
        4.5605518e+01, 1.5017000e+01],
       [0.0000000e+00, 0.0000000e+00, 0.0000000e+00, ..., 2.9441245e+02,
        4.5130852e+01, 1.3794000e+01],
       [1.0000000e+00, 9.8500000e-01, 0.0000000e+00, ..., 2.9024103e+02,
        3.9968010e+01, 1.5614000e+01],
       ...,
       [0.0000000e+00, 0.0000000e+00, 0.0000000e+00, ..., 2.9754337e+02,
        4.1947979e+01, 1.3998000e+01],
       [1.0000000e+00, 1.0000000e+00, 0.0000000e+00, ..., 2.8420966e+02,
        4.5258080e+01, 1.5977000e+01],
       [0.0000000e+00, 2.2800000e-01, 1.0000000e+00, ..., 2.9532828e+02,
        3.8847500e+01, 1.0924000e+01]])>
```

[ ]:
```
tf.convert_to_tensor(X_test)
```

[ ]:
```
<tf.Tensor: shape=(2391, 43), dtype=float64, numpy=
array([[  1.       ,   1.       ,   0.       , ..., 294.6015   ,  43.159935,
         13.583   ],
       [  1.       ,   1.       ,   0.       , ..., 286.54041  ,  38.3326  ,
         14.634   ],
       [  1.       ,   1.       ,   0.       , ..., 298.60788  ,  46.453678,
         14.548   ],
       ...,
       [  0.       ,   0.       ,   0.       , ..., 289.5249   ,  51.172005,
         13.181   ],
       [  1.       ,   1.       ,   0.       , ..., 284.73904  ,  49.5984  ,
         12.324   ],
       [  1.       ,   0.996    ,   0.       , ..., 293.08447  ,  48.57539  ,
```

```
        15.451    ]])>
```

0.0.2 Normalize X_train

```
[ ]: X_train_scaled = tf.keras.layers.Normalization(axis=-1)
     X_train_scaled.adapt(X_train)
```

0.0.3 Building a simple neural network model

The compile function takes three arguments: optimizer, loss, and metrics.

- **Optimizer**: These are certain algorithms that are used to change the attributes of the neural network to decrease the loss rate.
- **Loss**: This is used to compute the quantity that a model should seek to minimize during training.
- **Metrics**: This is used to judge the performance of the model.

In order to find the best result, I start with simple models and then gradually make them more complex.

Test models with 10, 16, 32, 64 neurons, with 50, 100, and 200 batch sizes

0.1 Model 1: one hidden layer with 10 neurons

```
[ ]: def get_basic_model():
       model = tf.keras.Sequential([
         X_train_scaled,
         tf.keras.layers.Dense(10, activation='relu'),
         tf.keras.layers.Dense(3, activation=tf.nn.softmax)
       ])

       model.compile(optimizer='adam',
                     loss='sparse_categorical_crossentropy',
                     metrics=['accuracy'])
       return model
     model = get_basic_model()
     history = model.fit(X_train, y_train, epochs=500, validation_data=(X_test,␣
      ↪y_test))
```

0.1.1 Evaluate the model

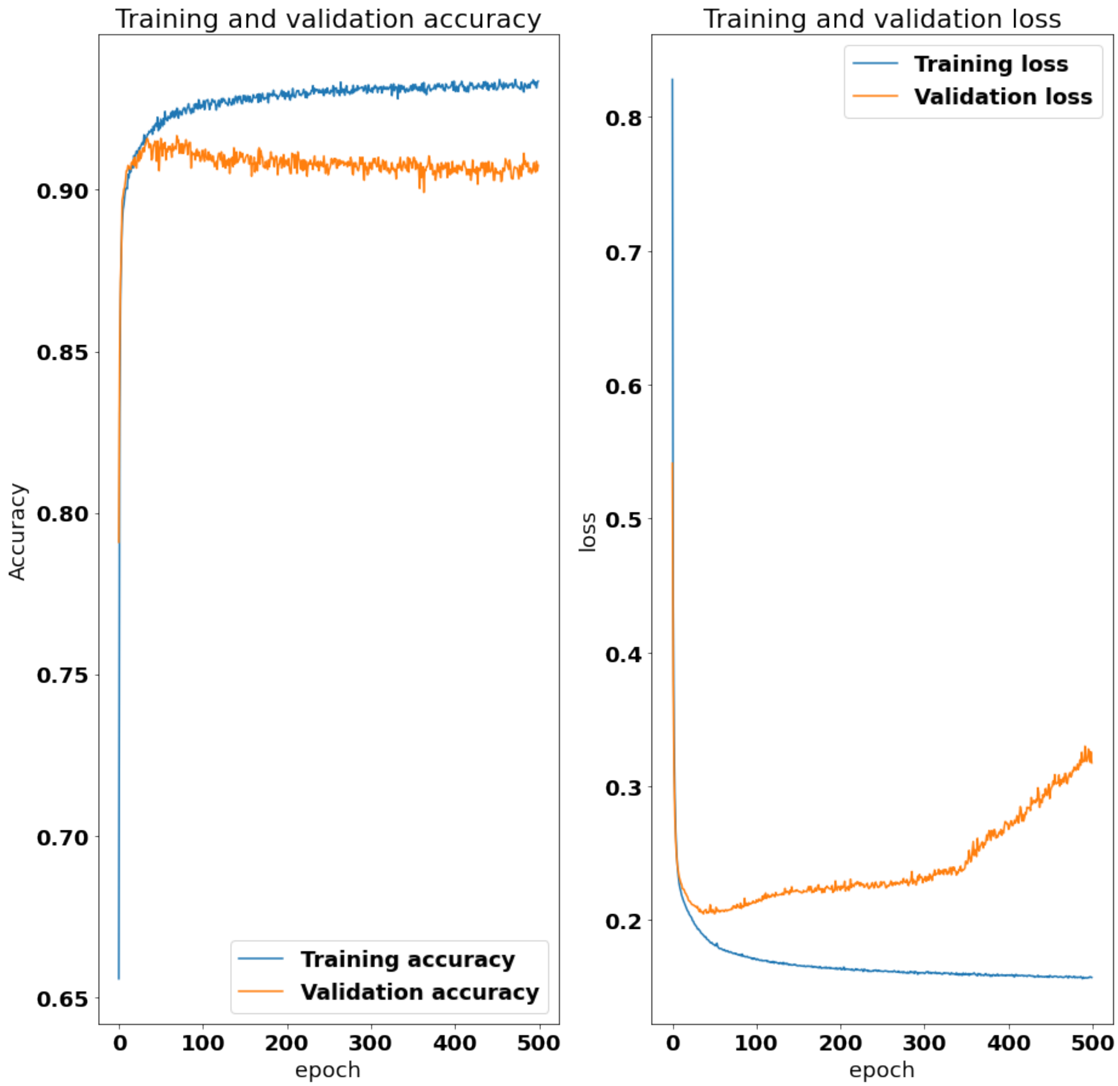
I create plots from the collected history data.

- A plot of accuracy on the training and validation datasets over training epochs.
- A plot of loss on the training and validation datasets over training epochs.

[ ]:

```
font = {'family' : 'normal',
        'weight' : 'bold',
        'size'   : 18}

plt.rc('font', **font)

plt.figure(figsize=(15,15))

ax1 = plt.subplot(121)
ax2 = plt.subplot(122)

ax1.plot(history.history['accuracy'], label='Training accuracy')
ax1.plot(history.history['val_accuracy'], label = 'Validation accuracy')
ax1.set_title("Training and validation accuracy")
ax1.set(xlabel='epoch', ylabel='Accuracy')
ax1.legend(loc='lower right')

ax2.plot(history.history['loss'], label='Training loss')
ax2.plot(history.history['val_loss'], label='Validation loss')
ax2.set_title("Training and validation loss")
ax2.set(xlabel='epoch', ylabel='loss')
ax2.legend(loc='upper right')
#To check the network accuracy on test data
test_loss, test_acc = model.evaluate(X_test,  y_test, verbose=2)
```

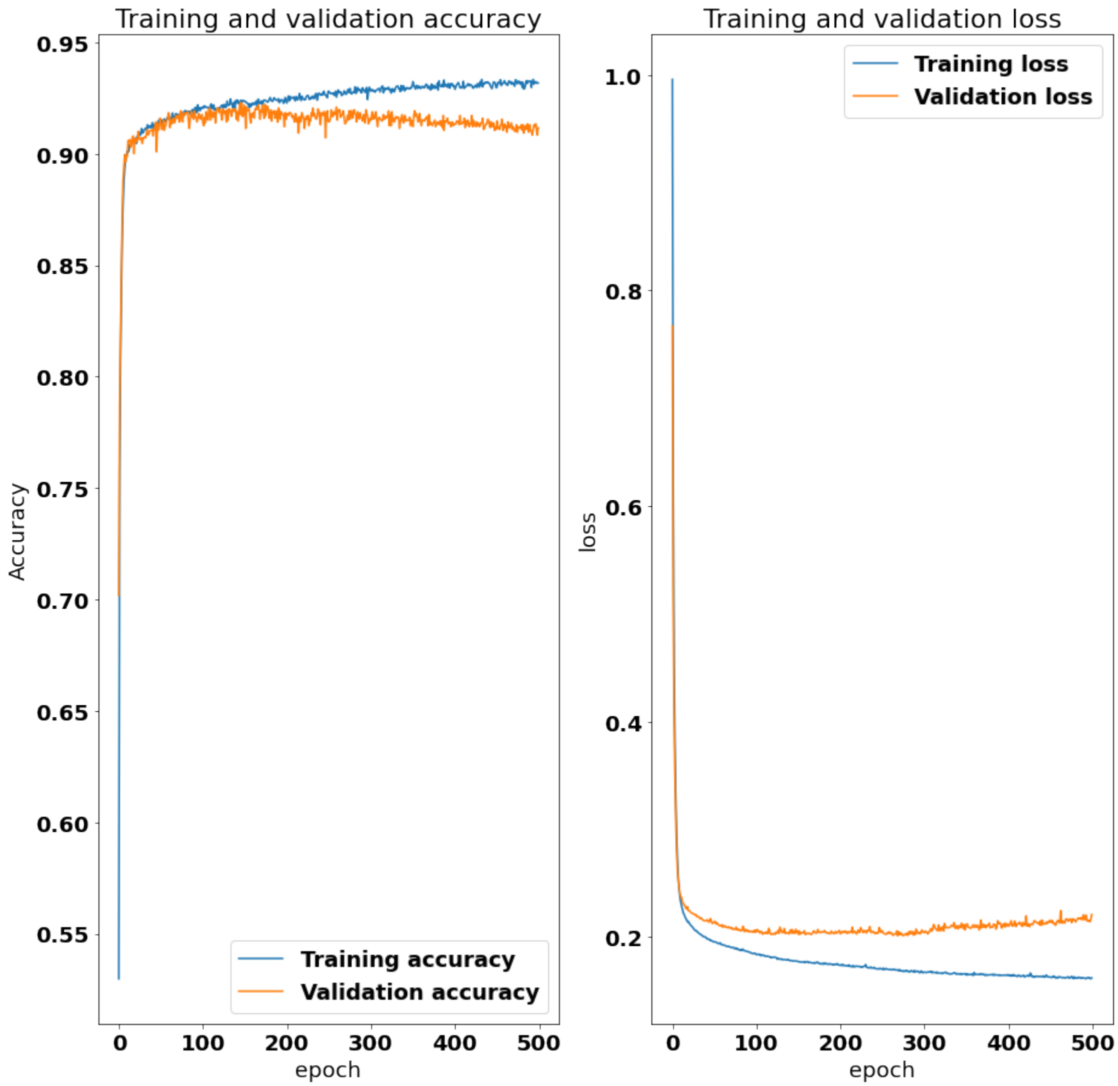
```
75/75 - 0s - loss: 0.3175 - accuracy: 0.9076 - 97ms/epoch - 1ms/step

findfont: Font family ['normal'] not found. Falling back to DejaVu Sans.
findfont: Font family ['normal'] not found. Falling back to DejaVu Sans.
findfont: Font family ['normal'] not found. Falling back to DejaVu Sans.
```



According to the plot of loss, validation loss is decreasing before the 50th epoch, so the model is underfitting. However, after the 50th epoch, validation loss is increasing, meaning the model is overfitting. Around the 50th epoch, when the model is either perfectly fitted or in a local minimum, the neural network model achieved an accuracy of 91%. The goal of Deep Learning training is to find a balance between a model that is underfitting and one that is overfitting, resulting in a model with a good fit. I found an optimum where the change in the slope of loss is around the 50th epoch, as shown above. At that point, the training process can be stopped. Since the codes for other models are the same, I just show the results.

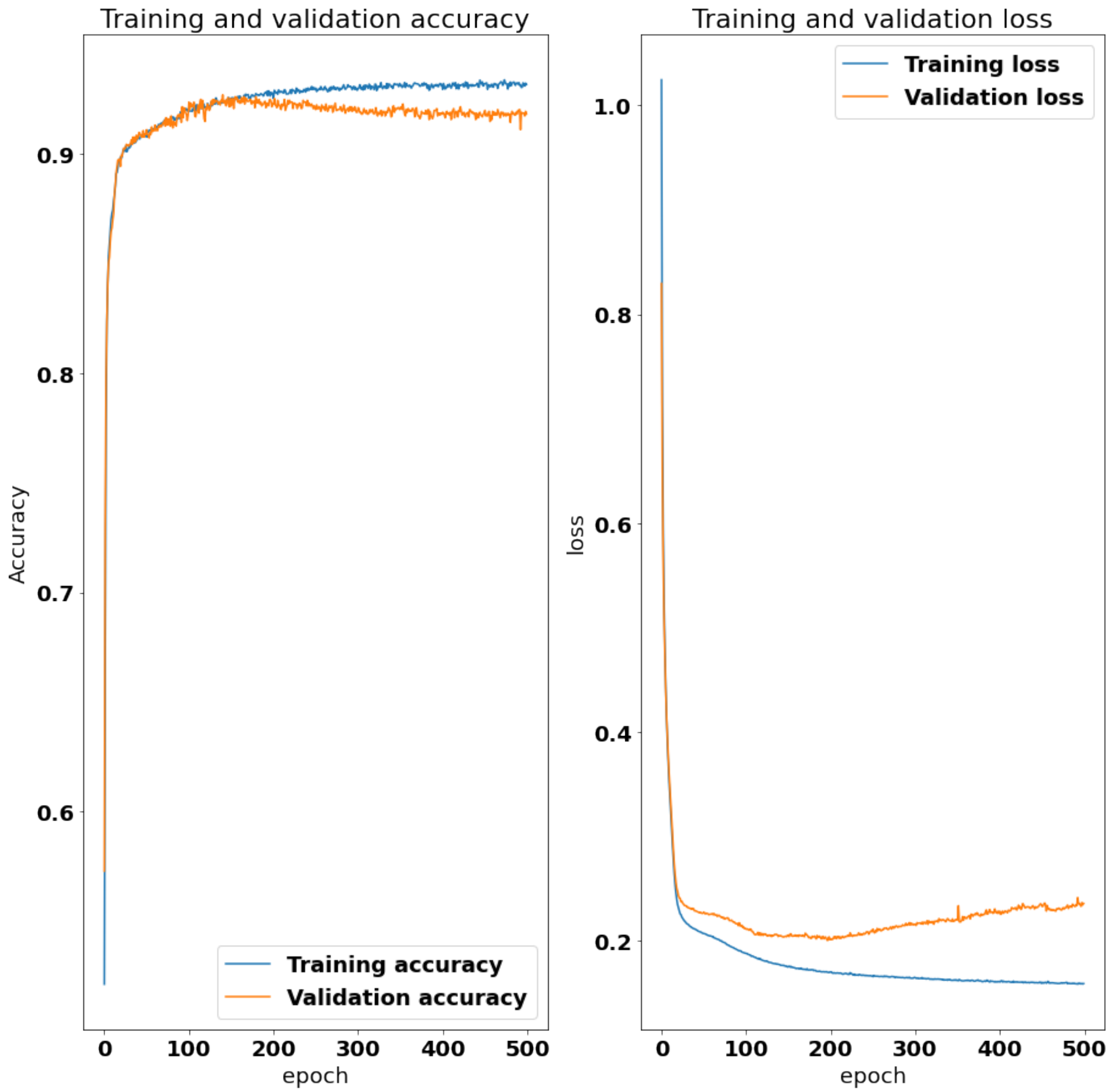
0.2 Model 2: one hidden layer with 10 neurons and batch_size=50

[ ]:
```
image = cv2.imread('1.png',  cv2.IMREAD_UNCHANGED)
cv2_imshow(image)
```



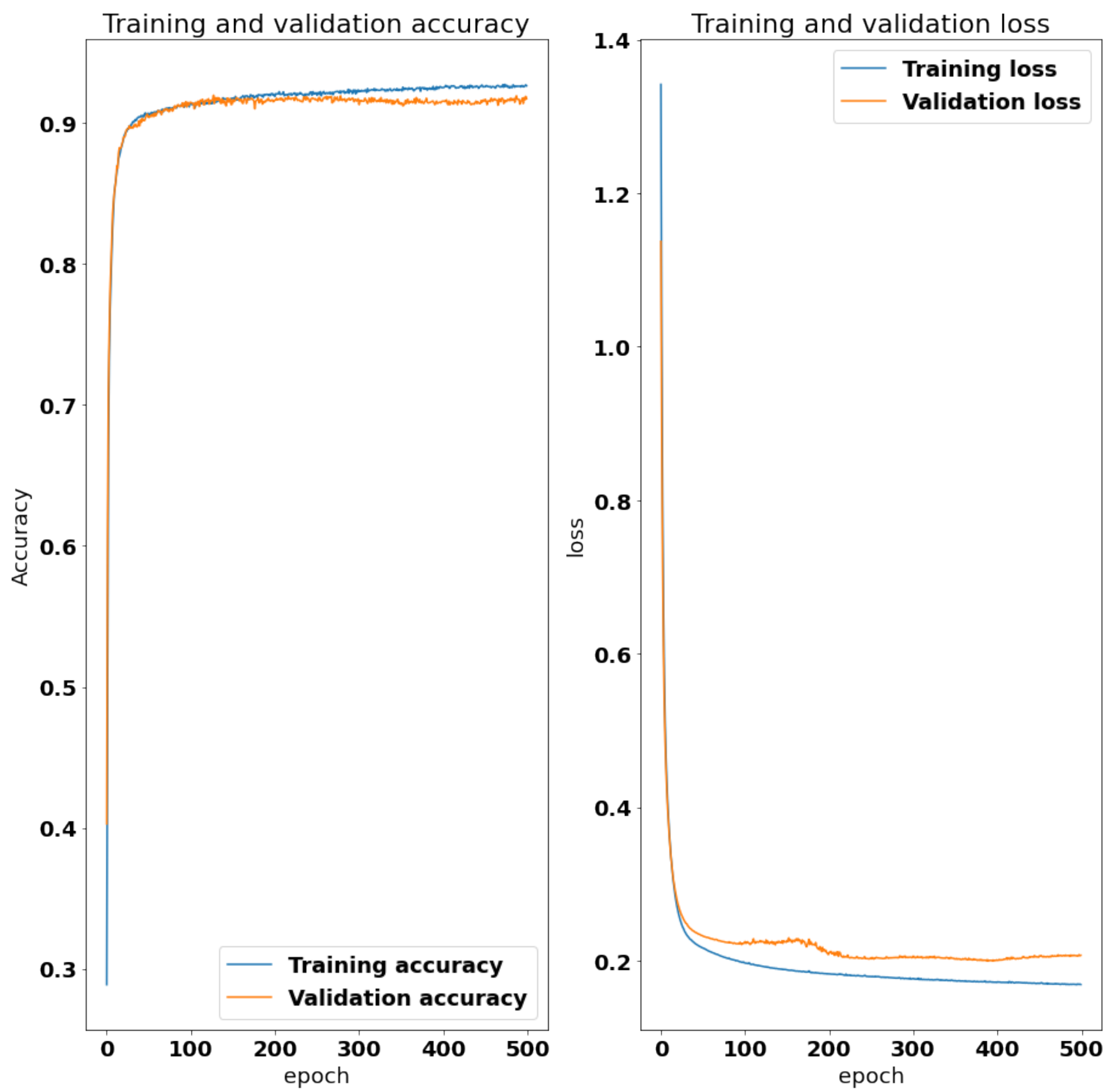
0.3 Model 3: one hidden layer with 10 neurons and batch_size=100

[ ]:
```
image = cv2.imread('2.png',  cv2.IMREAD_UNCHANGED)
cv2_imshow(image)
```



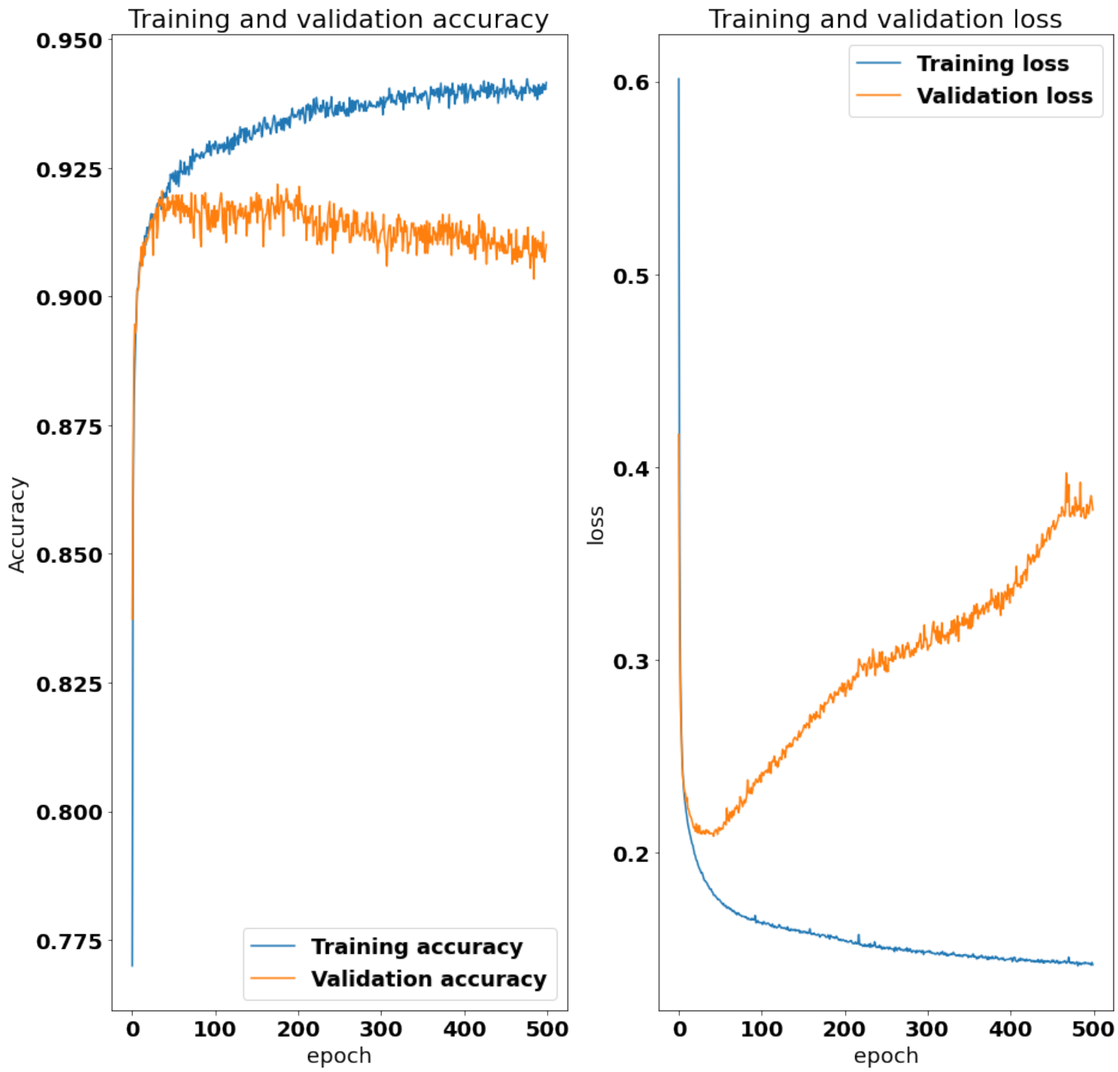
0.4 Model 4: one hidden layer with 10 neurons and batch_size=200

[ ]:
```
image = cv2.imread('3.png',  cv2.IMREAD_UNCHANGED)
cv2_imshow(image)
```



0.5 Model 5: one hidden layer with 16 neurons

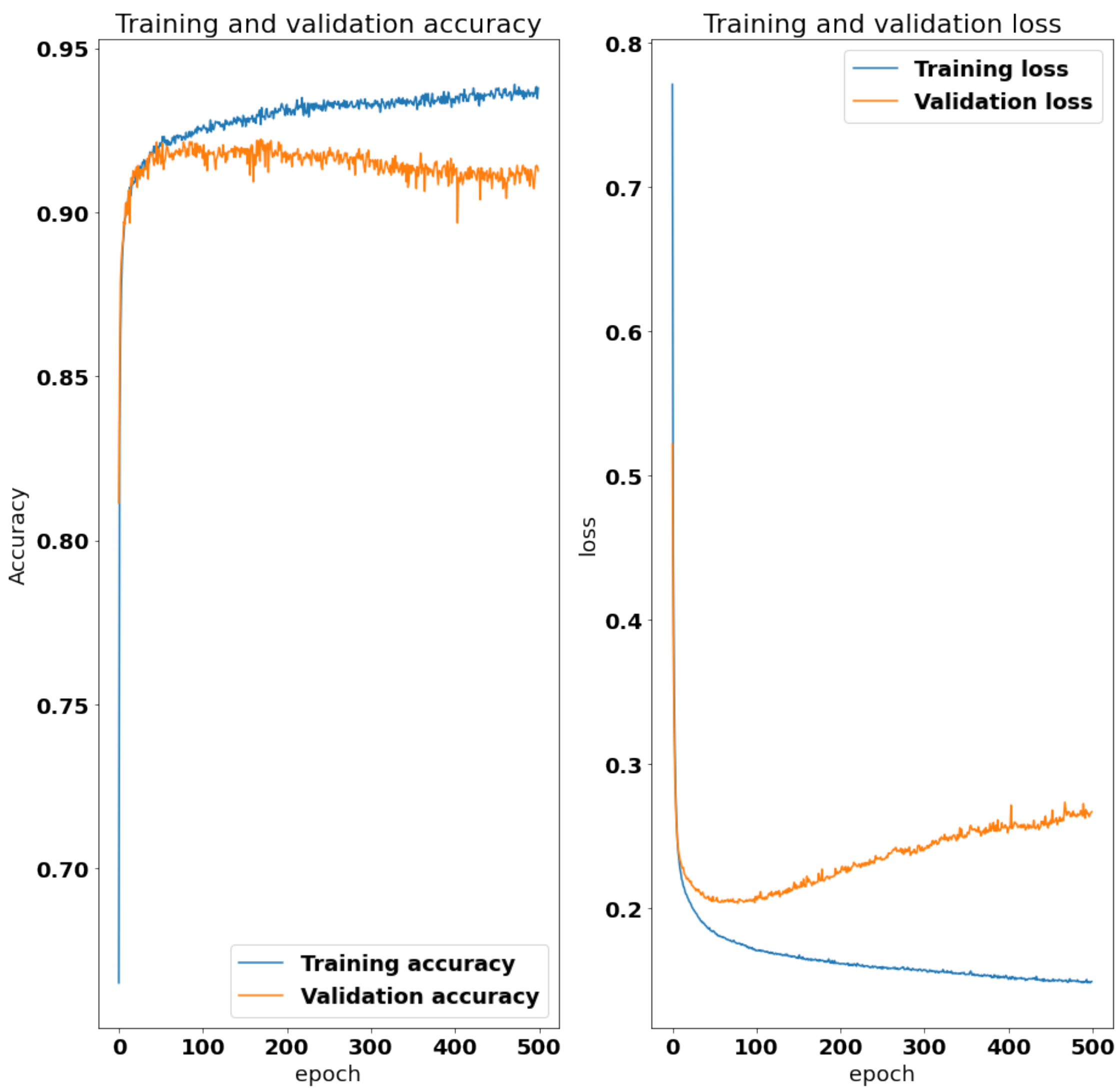
[ ]:
```
image = cv2.imread('4.png',  cv2.IMREAD_UNCHANGED)
cv2_imshow(image)
```



50th epoch —> 92%

0.6 Model 6: one hidden layer with 16 neurons and batch_size=50

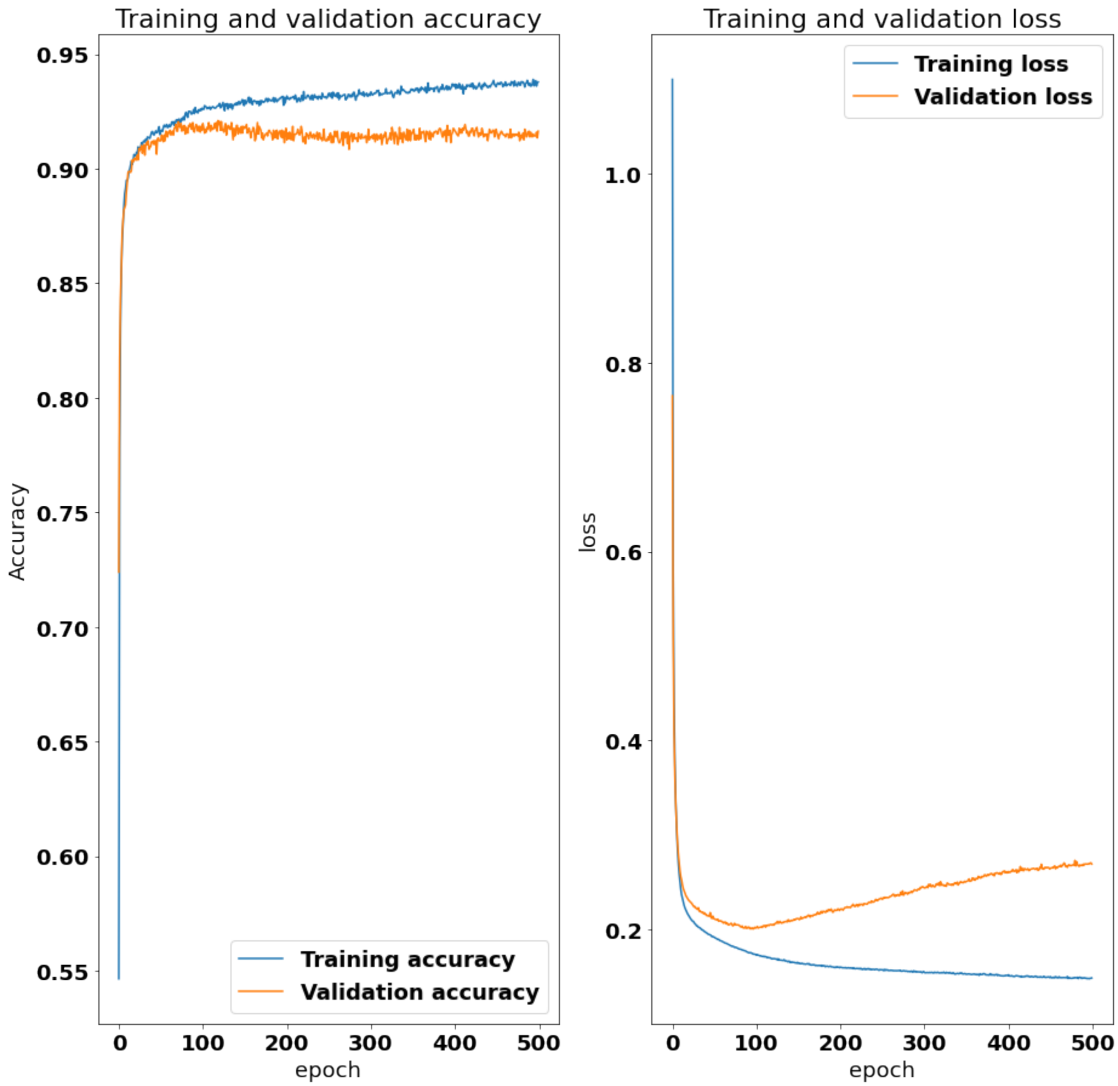
[ ]:
```
image = cv2.imread('6.png',  cv2.IMREAD_UNCHANGED)
cv2_imshow(image)
```



85th epoch —> 92.1%

0.7 Model 7: one hidden layer with 16 neurons and batch_size=100

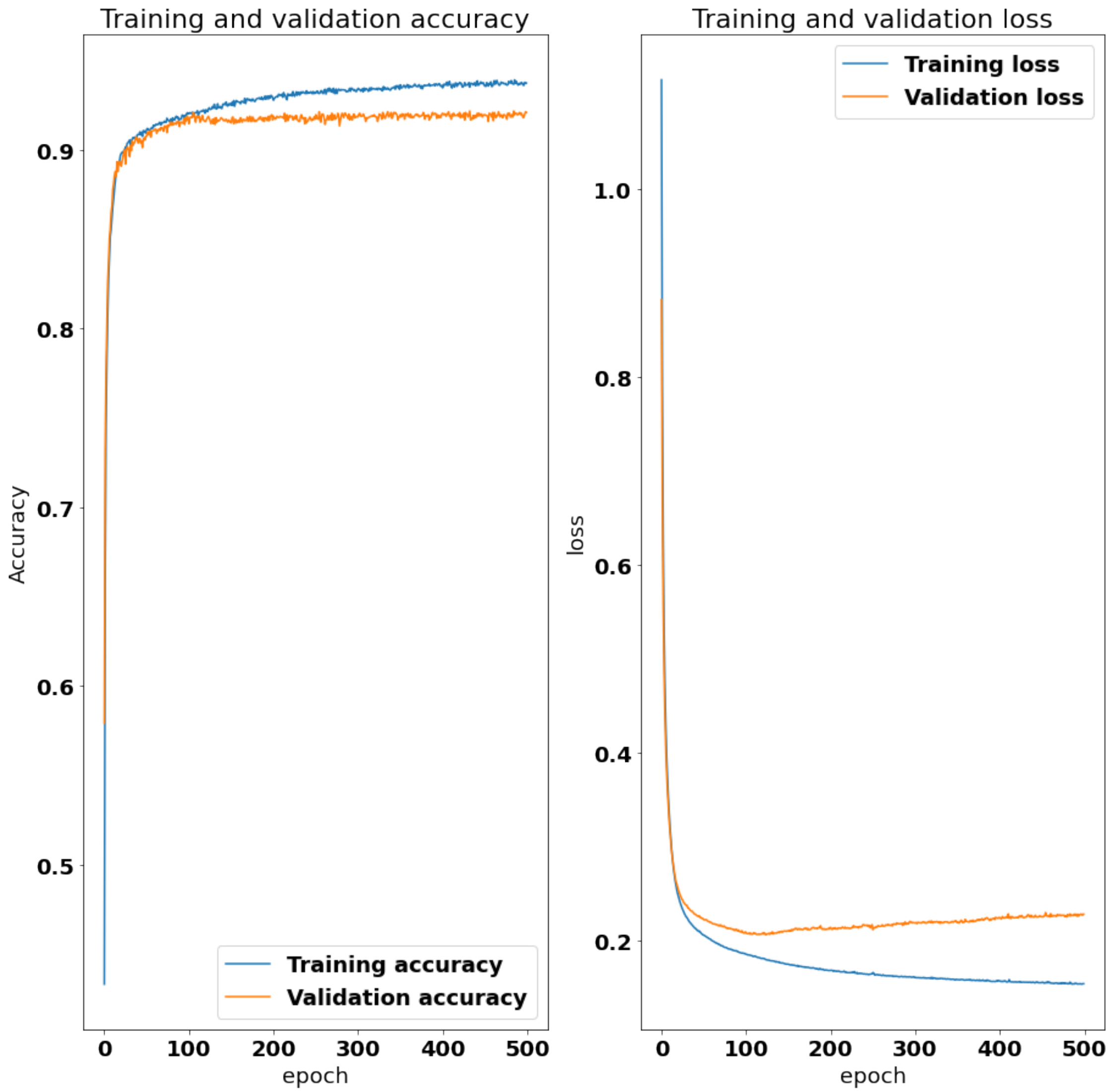
[ ]:
```
image = cv2.imread('7.png',  cv2.IMREAD_UNCHANGED)
cv2_imshow(image)
```



95th epoch —> 91.7%

0.8 Model 8: one hidden layer with 16 neurons and batch_size=200

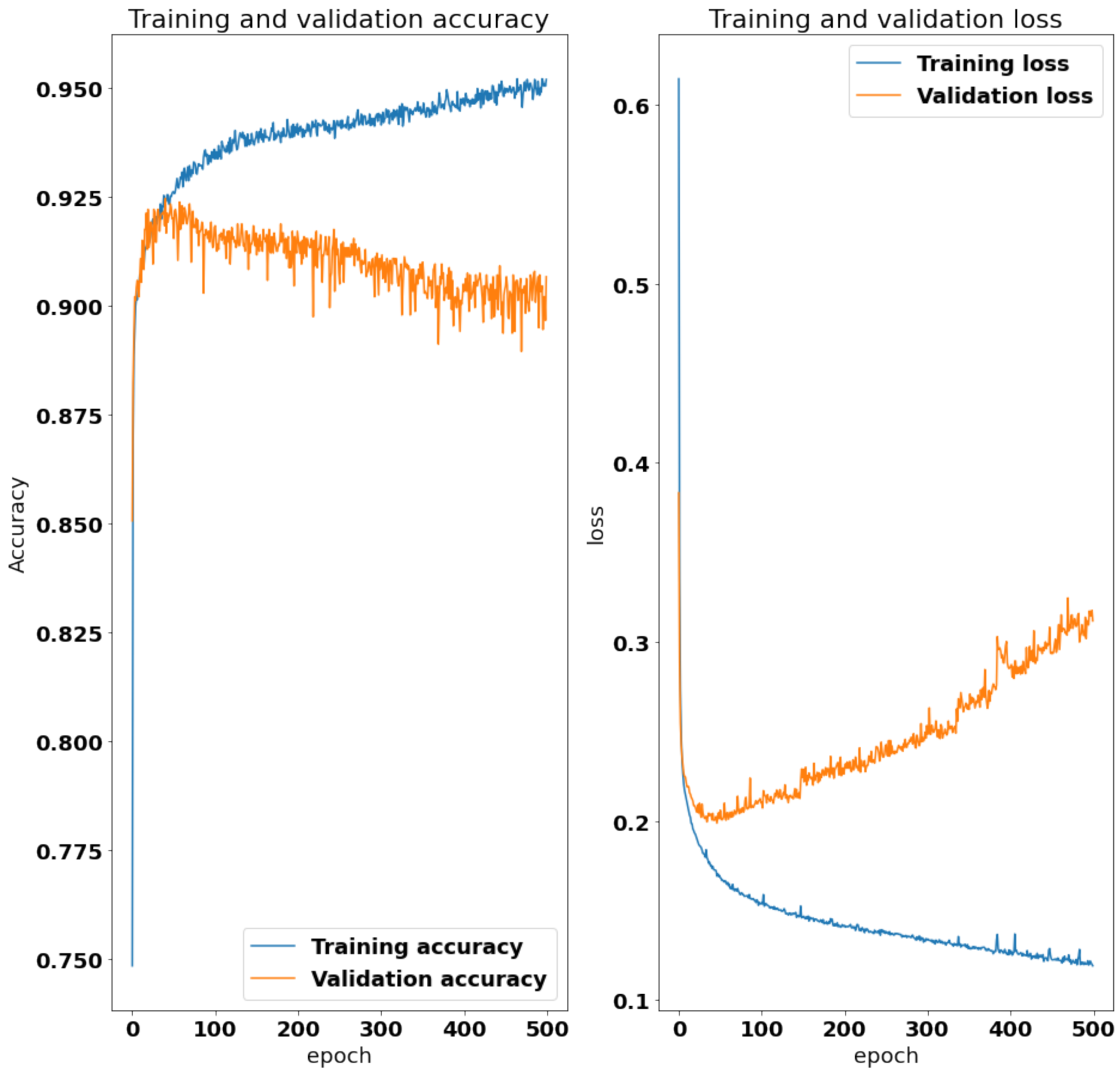
[ ]:
```
image = cv2.imread('8.png',  cv2.IMREAD_UNCHANGED)
cv2_imshow(image)
```



100th epoch —> 91.8%

0.9 Model 9: one hidden layer with 32 neurons

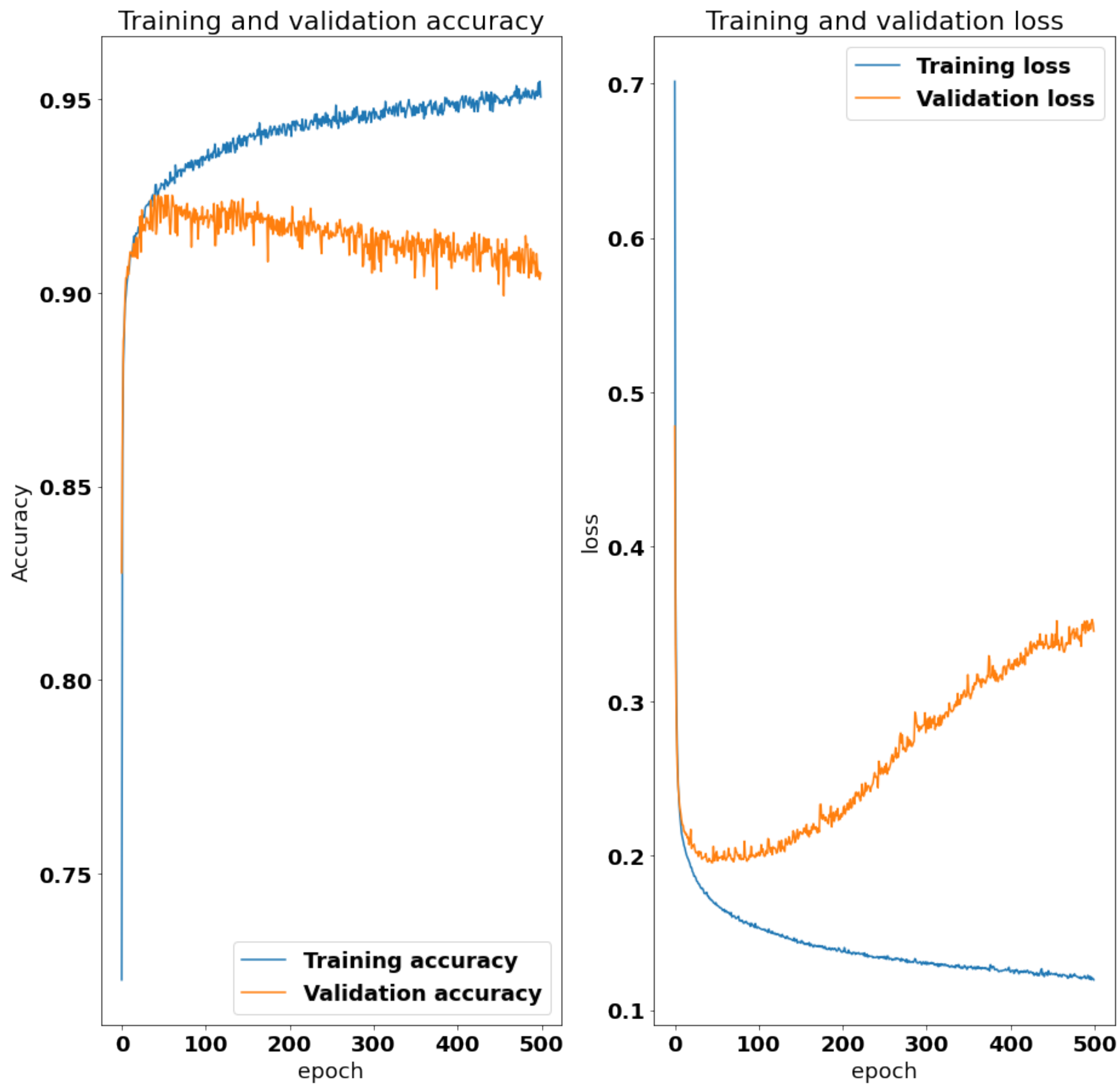
[ ]:
```
image = cv2.imread('9.png',  cv2.IMREAD_UNCHANGED)
cv2_imshow(image)
```



61th epoch —> 92.3%

0.10 Model 10: one hidden layer with 32 neurons and batch_size=50

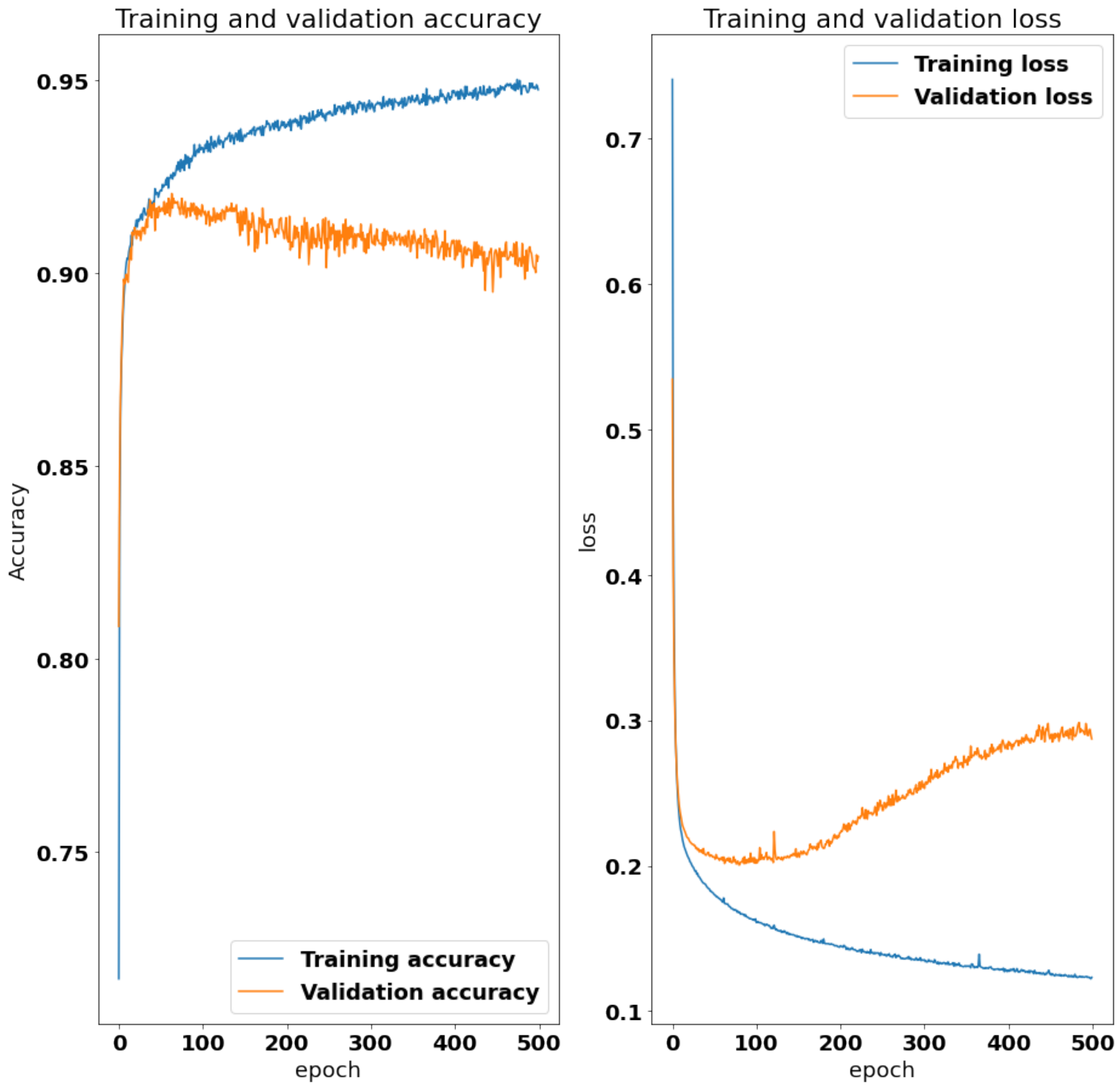
[ ]:
```
image = cv2.imread('10.png',  cv2.IMREAD_UNCHANGED)
cv2_imshow(image)
```



69th epoch —> 92.2%

0.11 Model 11: one hidden layer with 32 neurons and batch_size=100

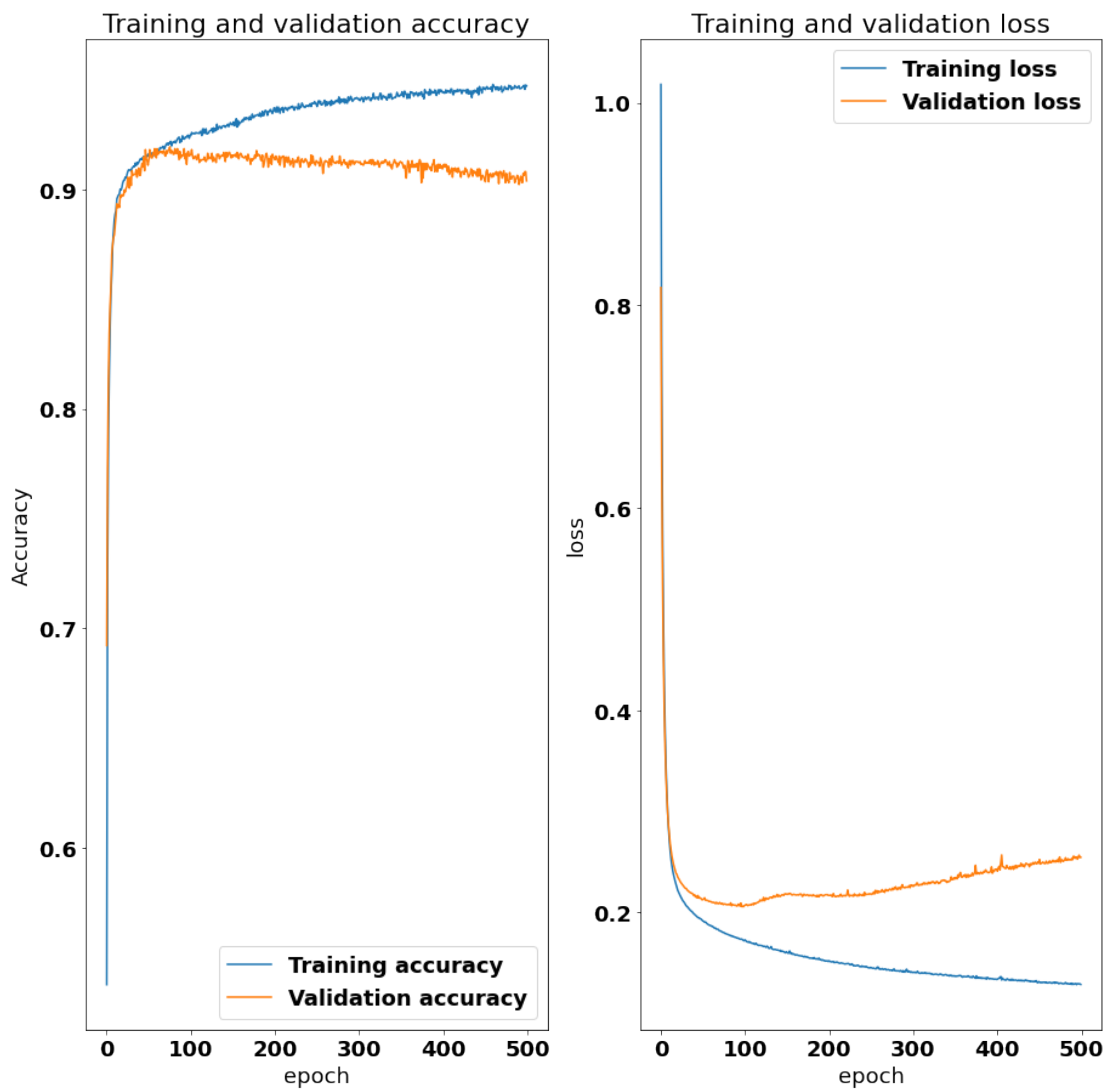
[ ]:
```
image = cv2.imread('11.png',  cv2.IMREAD_UNCHANGED)
cv2_imshow(image)
```



80th epoch —> 91.8%

0.12 Model 12: one hidden layer with 32 neurons and batch_size=200

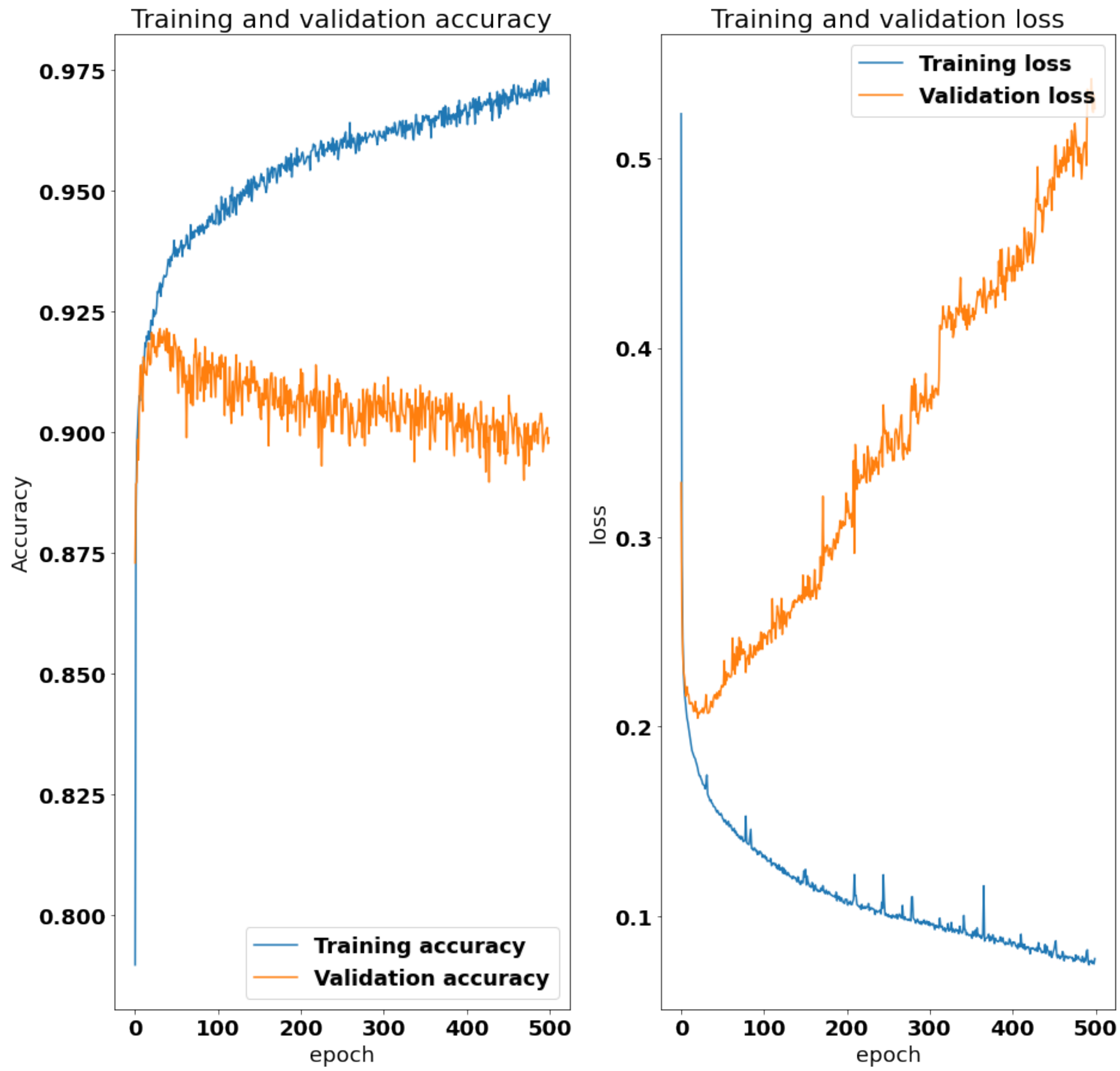
[ ]:
```
image = cv2.imread('12.png',  cv2.IMREAD_UNCHANGED)
cv2_imshow(image)
```



95th epoch —> 91.6%

0.13 Model 13: one hidden layer with 64 neurons

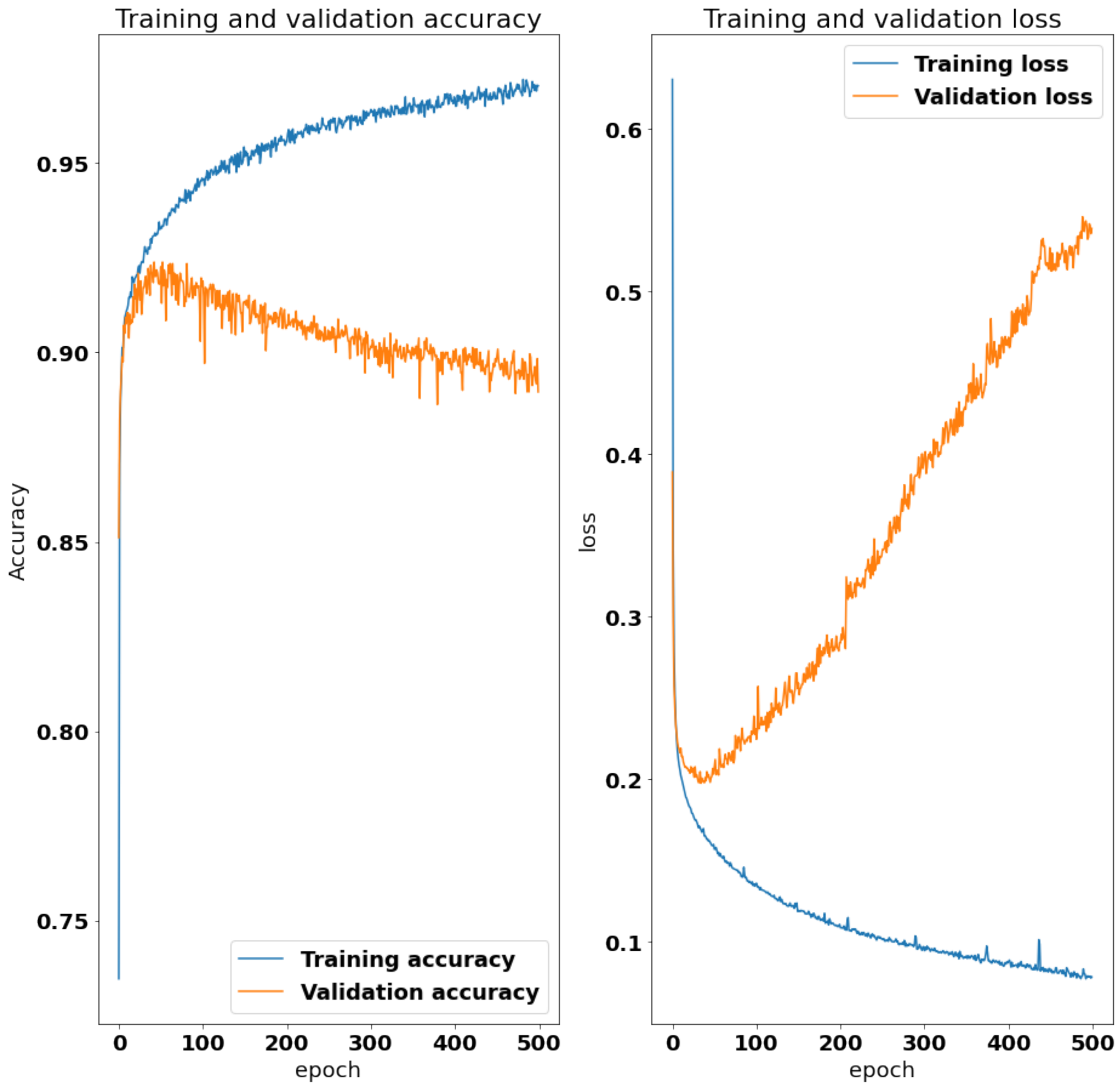
[ ]:
```
image = cv2.imread('13.png',  cv2.IMREAD_UNCHANGED)
cv2_imshow(image)
```



48th epoch —> 92%

0.14 Model 14: one hidden layer with 64 neurons and batch_size=50

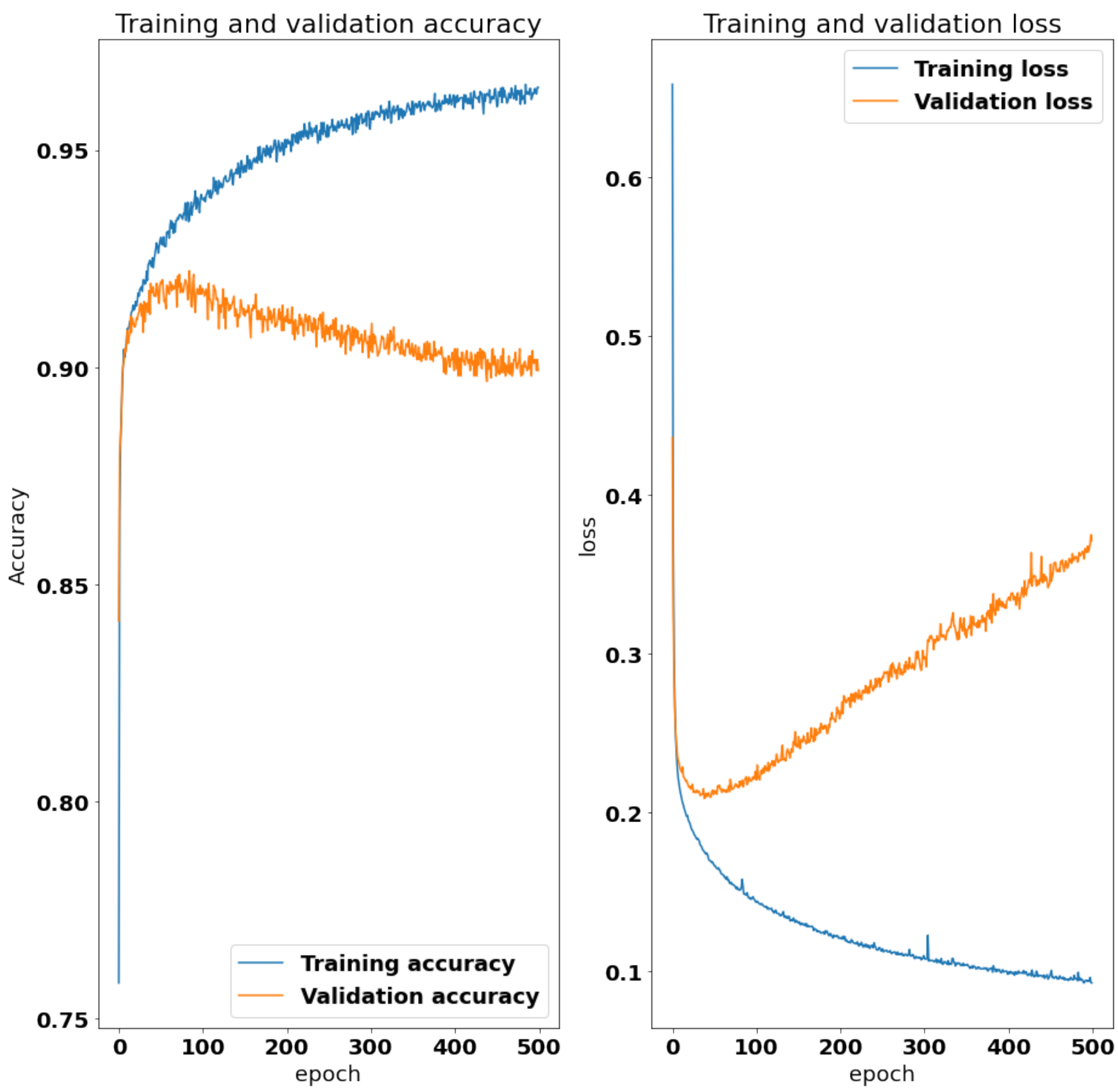
[ ]:
```
image = cv2.imread('14.png',  cv2.IMREAD_UNCHANGED)
cv2_imshow(image)
```



46th epoch —> 92.2%

0.15 Model 15: one hidden layer with 64 neurons and batch_size=100

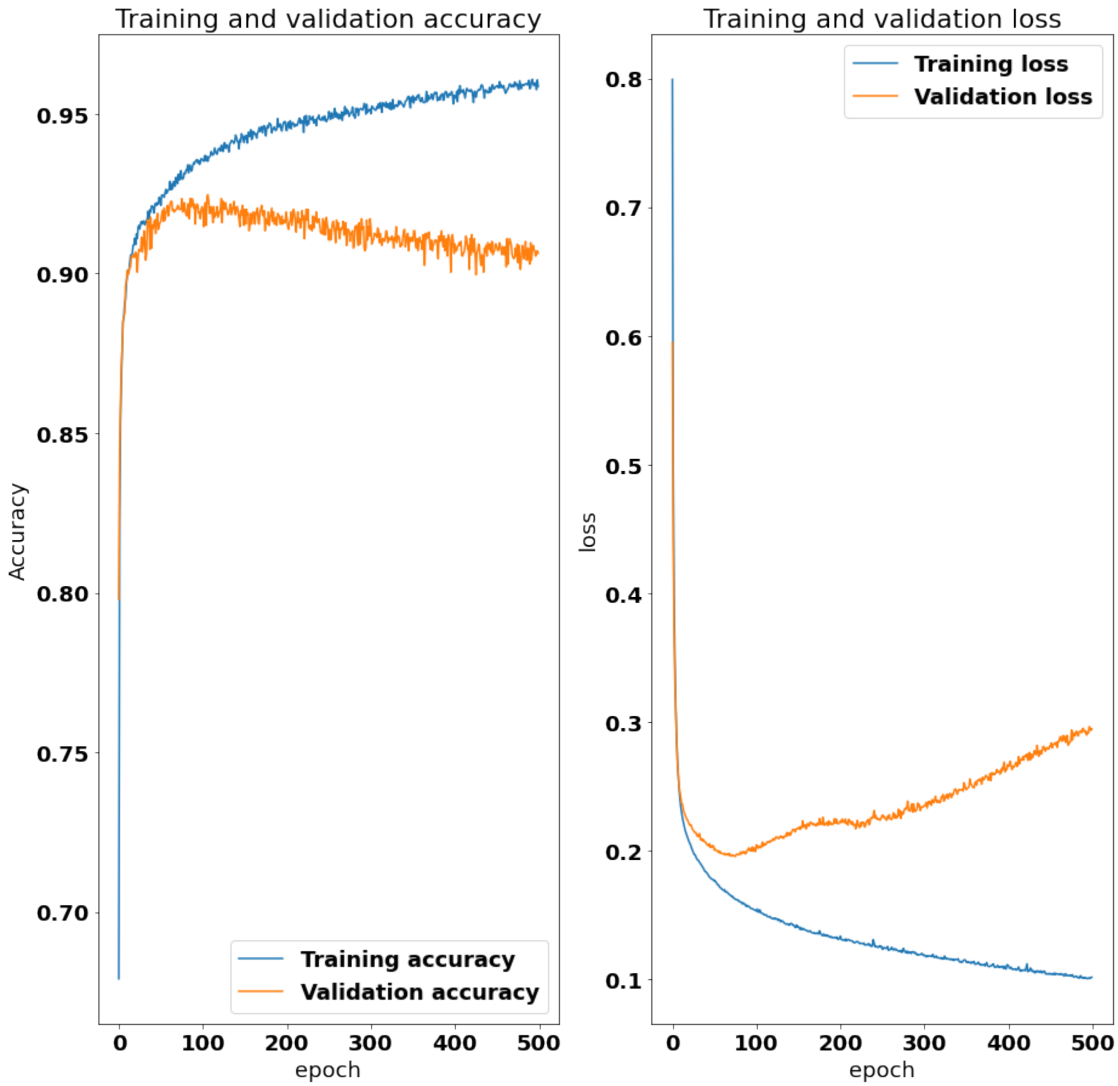
[ ]:
```
image = cv2.imread('15.png',  cv2.IMREAD_UNCHANGED)
cv2_imshow(image)
```



39th epoch —> 91.9%

0.16 Model 16: one hidden layer with 64 neurons and batch_size=200

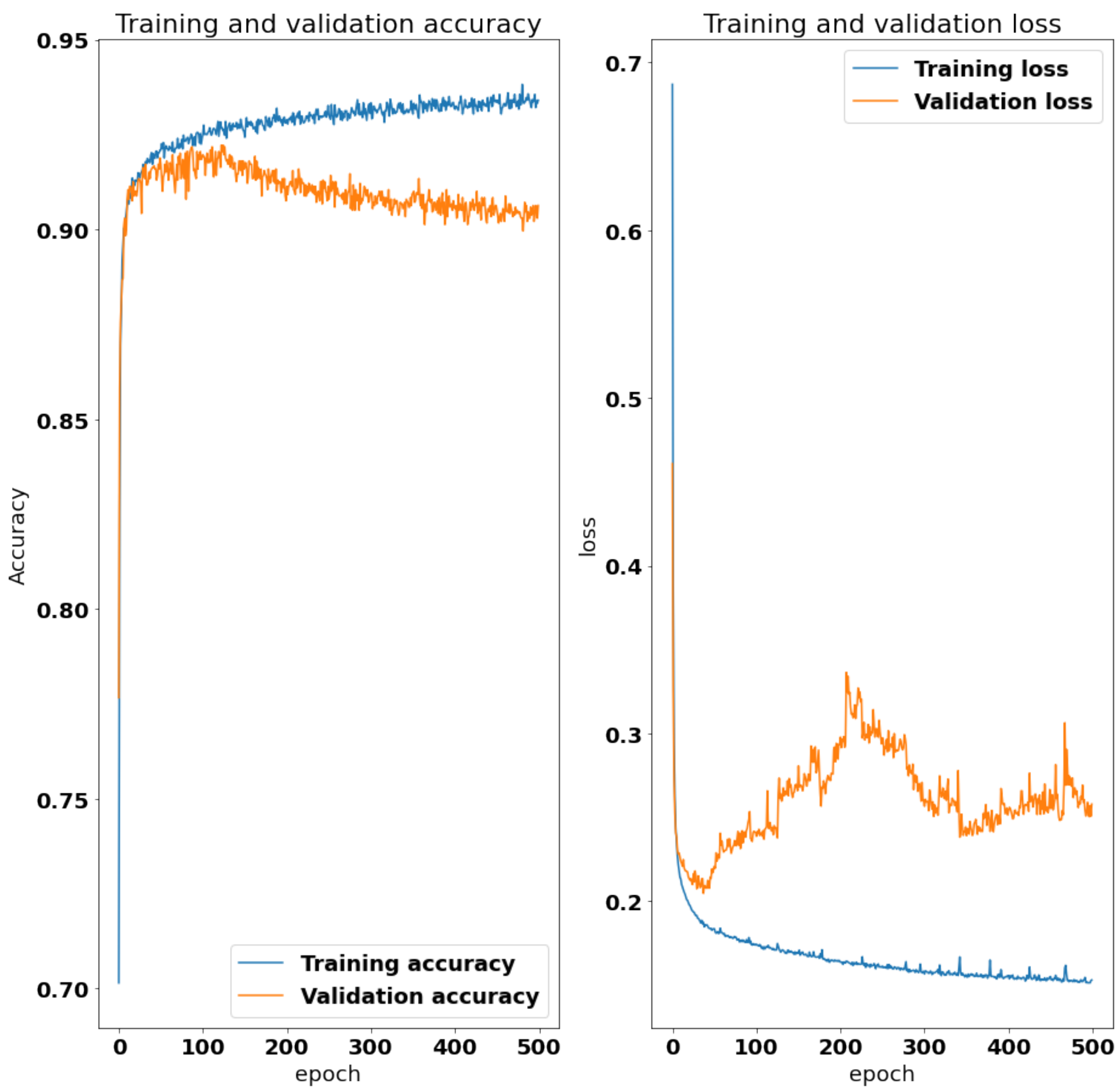
[ ]:
```
image = cv2.imread('16.png',  cv2.IMREAD_UNCHANGED)
cv2_imshow(image)
```



88th epoch —> 92.3%

0.17 Model 17: There are two hidden layers, each with 10 neurons

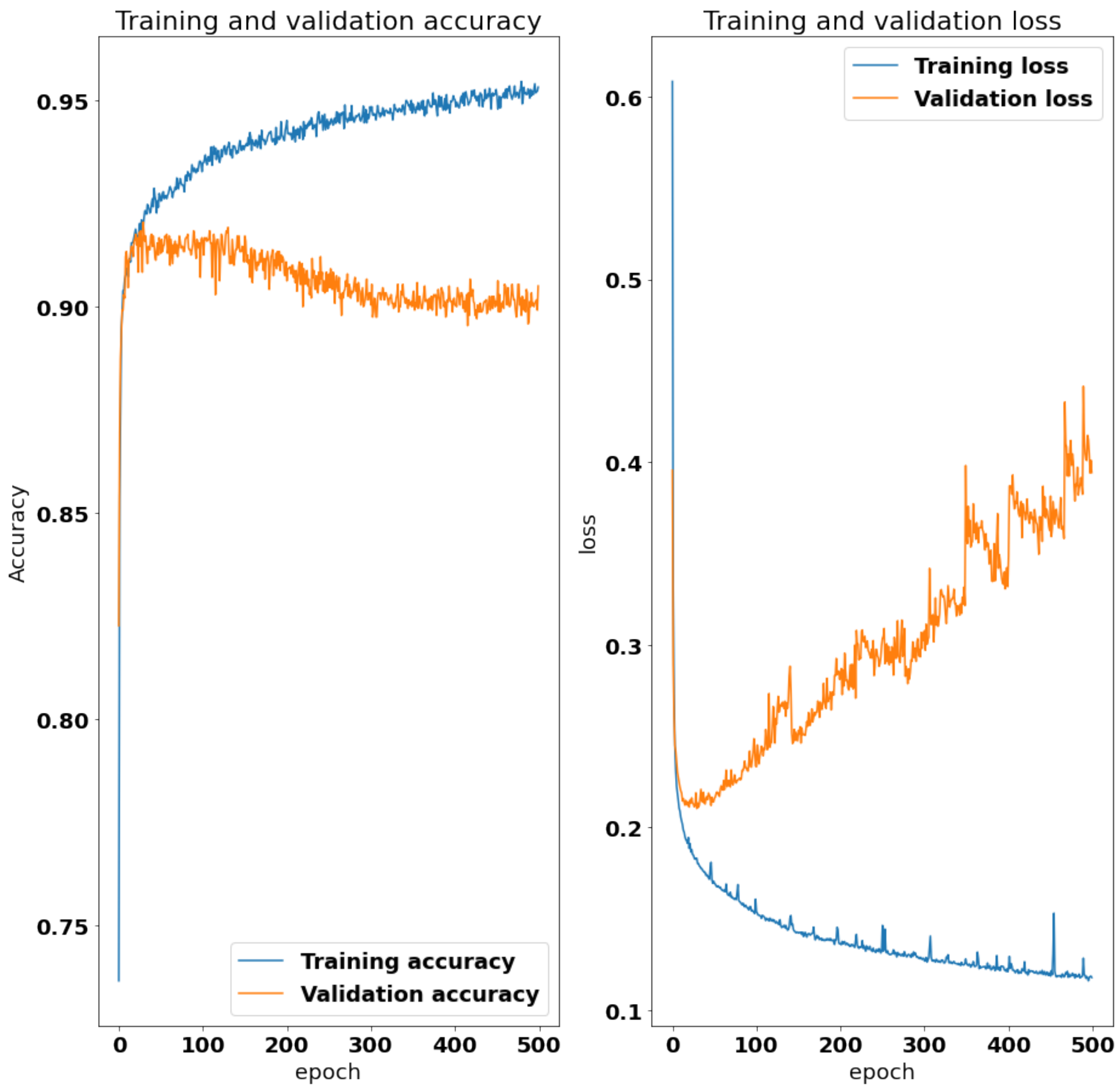
[ ]:
```
image = cv2.imread('17.png',  cv2.IMREAD_UNCHANGED)
cv2_imshow(image)
```



38th epoch —> 91.3%

0.18 Model 18: There are two hidden layers, each with 16 neurons

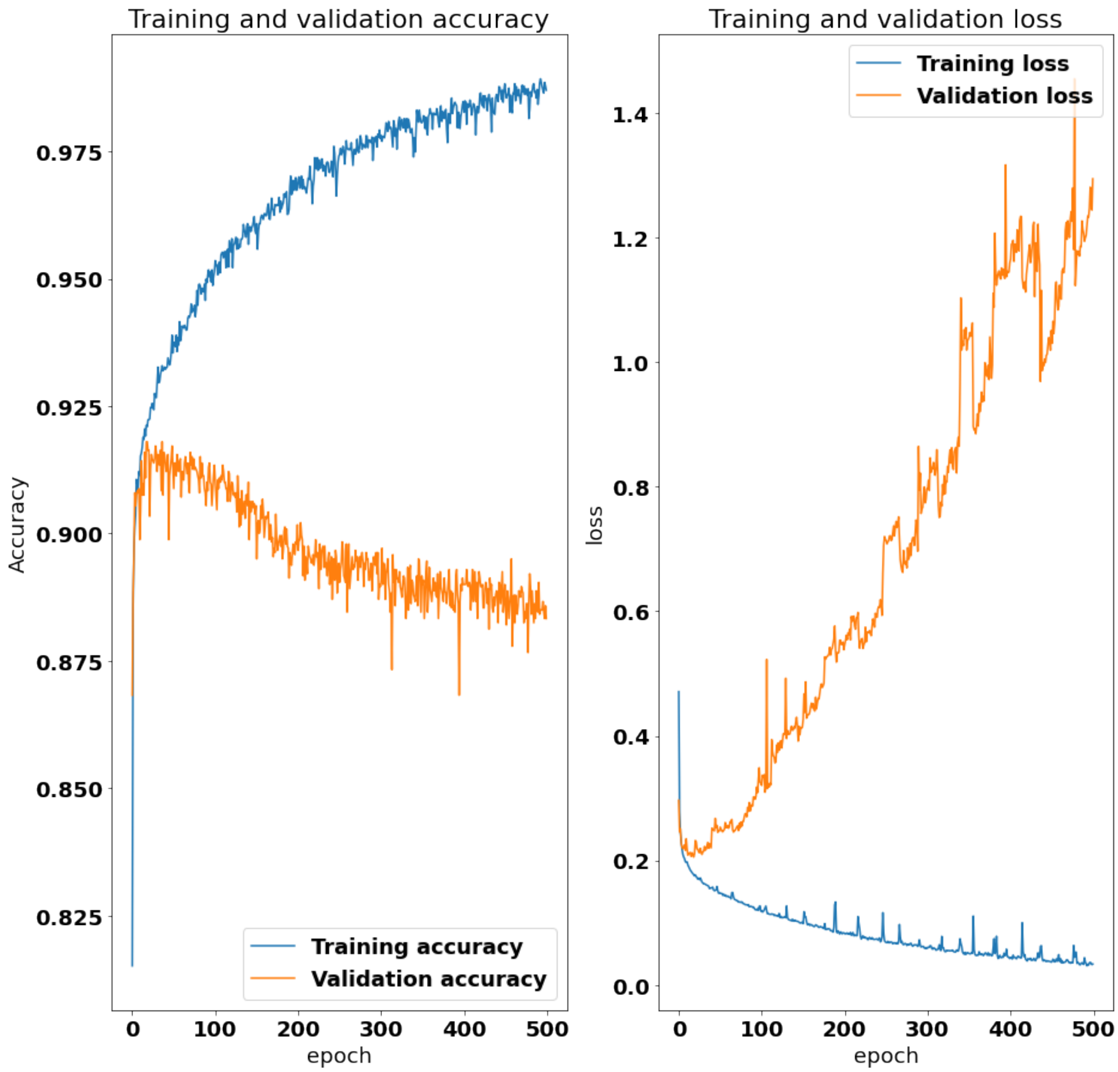
[ ]:
```
image = cv2.imread('18.png',  cv2.IMREAD_UNCHANGED)
cv2_imshow(image)
```



30th epoch —> 92.1%

0.19 Model 19: There are two hidden layers, each with 32 neurons

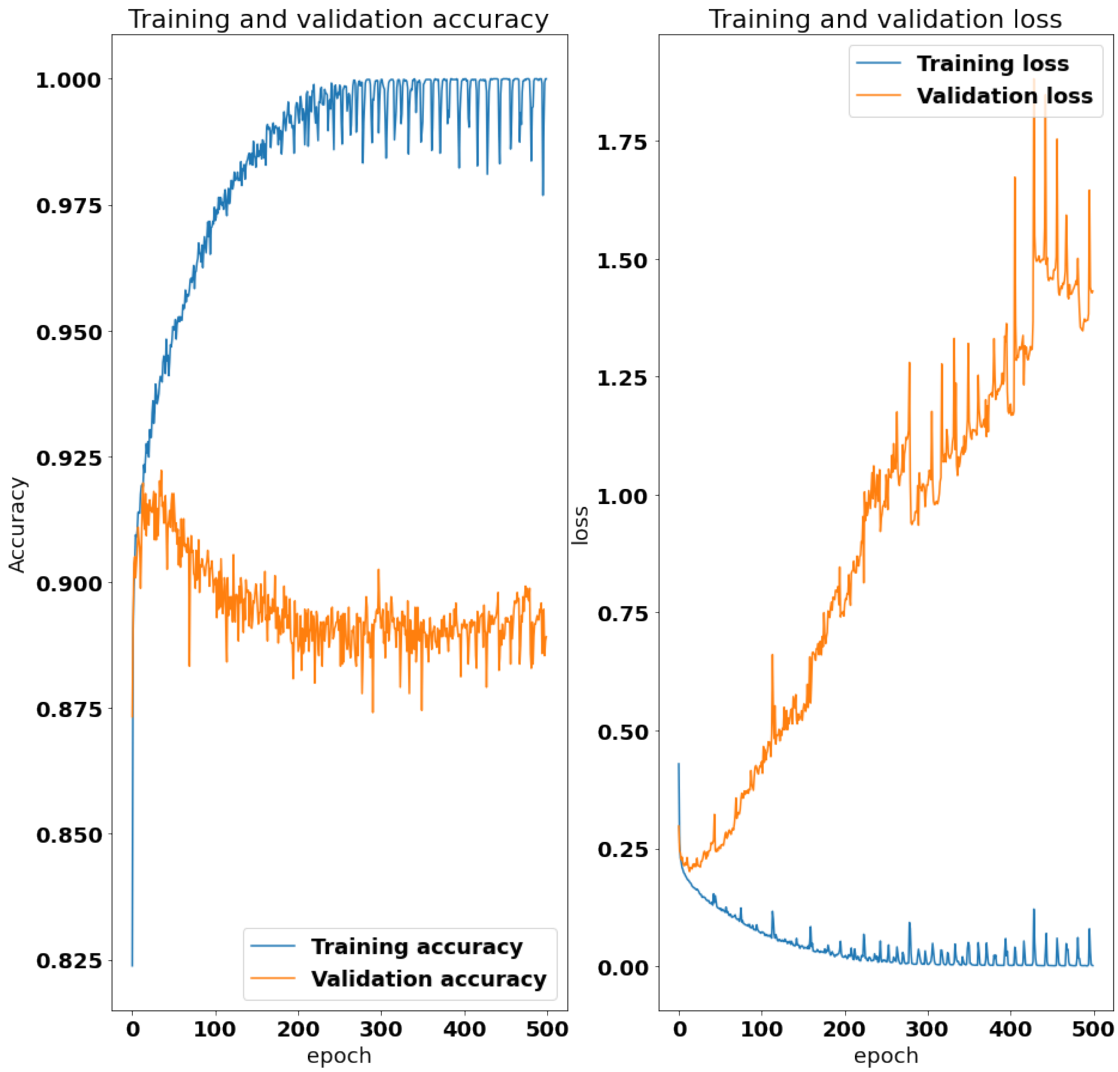
[ ]:
```
image = cv2.imread('19.png',  cv2.IMREAD_UNCHANGED)
cv2_imshow(image)
```



29th epoch —> 91.7%

0.20 Model 20: There are two hidden layers, each with 64 neurons

[ ]:
```
image = cv2.imread('20.png',  cv2.IMREAD_UNCHANGED)
cv2_imshow(image)
```



14th epoch —> 92%

1 Final words

Comparing 20 neural network models, I found that there is only a very slight difference in accuracy, which is 92%, but they have their own characteristics in terms of loss graphs. The validation loss graph for model 4 shows a slight reduction in the 200th epoch, sometimes it is better to check higher epochs to see if there is another local minimum. In model 17, for example, there are two local minimums. The first one is around the 38th epoch, while the second is around the 350th epoch, although the first one has higher accuracy. As layers and neurons are raised after local minima, the shapes of validation loss are extremely ascending and jagged, which is a sign of overfitting.