Fall down recognition

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Clean and Prepare Data

Clean and prepare datasets

In [57]:
```
# Import necessary libraries
import pandas as pd
from IPython.display import display
```

In [58]:
```
FILE_FALLDOWN = "falldown.csv"
FILE_NORMAL = "normal.csv"

df_falldown = pd.read_csv("content/" + FILE_FALLDOWN, sep=",", encoding="utf-16")
df_normal = pd.read_csv("content/" + FILE_NORMAL, sep=",", encoding="utf-8")

# Strip and format spaces
df_falldown.columns = df_falldown.columns.str.strip()
df_normal.columns = df_falldown.columns.str.strip()

# Add result value per dataset
df_falldown["output"] = [int(1)]*df_falldown.shape[0]
df_normal["output"] = [int(0)]*df_normal.shape[0]

# All outputs in one data frame
frames = [df_falldown, df_normal]
df = pd.concat(frames, ignore_index=True)
df
```

Out[58]:

	accel_x	accel_y	accel_z	gyros_x	gyros_y	gyros_z	output
0	0.416	0.113	0.509	-44.312	26.489	-7.385	1
1	-0.326	-0.052	0.252	117.310	212.158	-7.385	1
2	0.012	0.224	-1.321	88.196	210.083	7.446	1
3	0.214	0.227	-3.074	112.183	21.912	14.404	1
4	0.225	0.258	-1.739	-15.442	-226.929	-23.865	1
...	...	...	...	...	...	...	...
899	0.900	-0.196	-0.083	-18.555	9.216	13.550	0
900	0.947	-0.133	-0.101	-21.179	6.042	16.357	0
901	0.952	-0.125	-0.108	-24.414	9.888	15.198	0
902	0.984	-0.047	-0.148	-12.268	1.343	5.493	0
903	0.981	-0.005	-0.132	-14.404	-1.892	0.244	0

904 rows × 7 columns

In [59]:
```
# Check size and data integrity
print("DF OUTPUT")
display(df.describe())
print("FALLDOWN OUTPUT")
display(df_falldown.describe())
print("NORMAL OUTPUT")
display(df_normal.describe())
```

```
DF OUTPUT
```

	accel_x	accel_y	accel_z	gyros_x	gyros_y	gyros_z	output
count	904.000000	904.000000	904.000000	904.000000	904.000000	904.000000	904.000000
mean	0.250320	0.055468	-0.265848	5.590790	-2.317041	7.439473	0.467920
std	1.115182	0.769094	1.041375	105.123193	192.222992	139.276433	0.499246
min	-4.000000	-4.000000	-4.000000	-474.915000	-1299.500000	-1087.952000	0.000000
25%	-0.222000	-0.128250	-0.497750	-26.260250	-21.072250	-10.315000	0.000000
50%	0.786500	0.052000	-0.150000	-0.305000	0.762500	-0.305000	0.000000
75%	0.955000	0.229250	0.074000	24.444500	19.698750	13.275500	1.000000
max	2.877000	4.000000	4.000000	1038.330000	1755.066000	1360.168000	1.000000

```
FALLDOWN OUTPUT
```

	accel_x	accel_y	accel_z	gyros_x	gyros_y	gyros_z	output
count	423.000000	423.000000	423.000000	423.000000	423.000000	423.000000	423.0
mean	-0.461038	0.026215	-0.380279	13.819324	-6.708232	16.739773	1.0
std	1.283616	1.100360	1.489061	148.305347	280.595576	203.017993	0.0
min	-4.000000	-4.000000	-4.000000	-474.915000	-1299.500000	-1087.952000	1.0
25%	-0.772000	-0.391000	-1.369000	-58.563000	-117.950500	-37.415000	1.0
50%	-0.249000	0.016000	-0.314000	4.211000	-4.944000	2.686000	1.0
75%	0.368000	0.457500	0.535000	63.324000	100.128500	52.246000	1.0
max	2.877000	4.000000	4.000000	1038.330000	1755.066000	1360.168000	1.0

```
NORMAL OUTPUT
```

	accel_x	accel_y	accel_z	gyros_x	gyros_y	gyros_z	output
count	481.000000	481.000000	481.000000	481.000000	481.000000	481.000000	481.0
mean	0.875900	0.081193	-0.165216	-1.645530	1.544651	-0.739376	0.0
std	0.230002	0.216485	0.262827	36.613209	16.107335	10.634243	0.0
min	-0.525000	-0.379000	-1.046000	-138.367000	-60.120000	-53.162000	0.0
25%	0.871000	-0.059000	-0.231000	-14.771000	-4.456000	-5.676000	0.0
50%	0.943000	0.063000	-0.129000	-0.916000	1.099000	-0.549000	0.0
75%	0.969000	0.159000	-0.008000	10.010000	8.362000	5.249000	0.0
max	1.253000	0.654000	0.291000	177.551000	62.317000	36.438000	0.0

Neural Network

In [60]:
```
# Import necessary libraries
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import tensorflow as tf
from IPython.display import display
import random
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

print(f"TensorFlow version = {tf.__version__}\n")
```

```
TensorFlow version = 2.9.1
```

Analyze data

A continuación se tendrán tres Dataframes:

1. df_falldown --> Rreferido cuando se dectea una caida.
2. df_normal --> Cuando hay una sitiación normal en la persona que lleva el dispositivo.
3. df --> Los dos Dataframes mezclados

In [61]:
```
# La correlación es una medida estadística que expresa la relación lineal que existe entre dos variables
print(100*"-")
print("Descripción Dataframe DF")
display(df.describe().round(4))
print(100*"-")
print("Descripción Dataframe falldown")
display(df_falldown.describe().round(4))
print(100*"-")
print("Descripción Dataframe normal")
display(df_normal.describe().round(4))
print(100*"-")
```

```
----------------------------------------------------------------------------------------------------
Descripción Dataframe DF
```

	accel_x	accel_y	accel_z	gyros_x	gyros_y	gyros_z	output
count	904.0000	904.0000	904.0000	904.0000	904.0000	904.0000	904.0000
mean	0.2503	0.0555	-0.2658	5.5908	-2.3170	7.4395	0.4679
std	1.1152	0.7691	1.0414	105.1232	192.2230	139.2764	0.4992
min	-4.0000	-4.0000	-4.0000	-474.9150	-1299.5000	-1087.9520	0.0000
25%	-0.2220	-0.1282	-0.4978	-26.2602	-21.0722	-10.3150	0.0000
50%	0.7865	0.0520	-0.1500	-0.3050	0.7625	-0.3050	0.0000
75%	0.9550	0.2292	0.0740	24.4445	19.6987	13.2755	1.0000
max	2.8770	4.0000	4.0000	1038.3300	1755.0660	1360.1680	1.0000

```
----------------------------------------------------------------------------------------------------
Descripción Dataframe falldown
```

	accel_x	accel_y	accel_z	gyros_x	gyros_y	gyros_z	output
count	423.0000	423.0000	423.0000	423.0000	423.0000	423.0000	423.0
mean	-0.4610	0.0262	-0.3803	13.8193	-6.7082	16.7398	1.0
std	1.2836	1.1004	1.4891	148.3053	280.5956	203.0180	0.0
min	-4.0000	-4.0000	-4.0000	-474.9150	-1299.5000	-1087.9520	1.0
25%	-0.7720	-0.3910	-1.3690	-58.5630	-117.9505	-37.4150	1.0
50%	-0.2490	0.0160	-0.3140	4.2110	-4.9440	2.6860	1.0
75%	0.3680	0.4575	0.5350	63.3240	100.1285	52.2460	1.0
max	2.8770	4.0000	4.0000	1038.3300	1755.0660	1360.1680	1.0

```
----------------------------------------------------------------------------------------------------
Descripción Dataframe normal
```

	accel_x	accel_y	accel_z	gyros_x	gyros_y	gyros_z	output
count	481.0000	481.0000	481.0000	481.0000	481.0000	481.0000	481.0
mean	0.8759	0.0812	-0.1652	-1.6455	1.5447	-0.7394	0.0
std	0.2300	0.2165	0.2628	36.6132	16.1073	10.6342	0.0
min	-0.5250	-0.3790	-1.0460	-138.3670	-60.1200	-53.1620	0.0
25%	0.8710	-0.0590	-0.2310	-14.7710	-4.4560	-5.6760	0.0
50%	0.9430	0.0630	-0.1290	-0.9160	1.0990	-0.5490	0.0
75%	0.9690	0.1590	-0.0080	10.0100	8.3620	5.2490	0.0
max	1.2530	0.6540	0.2910	177.5510	62.3170	36.4380	0.0

```
----------------------------------------------------------------------------------------------------
```

In [62]:
```
# La correlación es una medida estadística que expresa la relación lineal que existe entre dos variables
print(100*"-")
print("Correlación Dataframe DF")
display(df.corr().round(4))
print(100*"-")
print("Correlación Dataframe falldown")
display(df_falldown.corr().round(4))
print(100*"-")
print("Correlación Dataframe normal")
display(df_normal.corr().round(4))
print(100*"-")
```

```
----------------------------------------------------------------------------------------------------
Correlación Dataframe DF
```

	accel_x	accel_y	accel_z	gyros_x	gyros_y	gyros_z	output
accel_x	1.0000	-0.0180	0.0997	-0.1098	0.0082	-0.1851	-0.5985
accel_y	-0.0180	1.0000	-0.2172	-0.0250	-0.0393	-0.0611	-0.0357
accel_z	0.0997	-0.2172	1.0000	-0.0024	0.0733	0.0468	-0.1031
gyros_x	-0.1098	-0.0250	-0.0024	1.0000	-0.0369	-0.0099	0.0734
gyros_y	0.0082	-0.0393	0.0733	-0.0369	1.0000	0.2320	-0.0214
gyros_z	-0.1851	-0.0611	0.0468	-0.0099	0.2320	1.0000	0.0627
output	-0.5985	-0.0357	-0.1031	0.0734	-0.0214	0.0627	1.0000

```
----------------------------------------------------------------------------------------------------
Correlación Dataframe falldown
```

	accel_x	accel_y	accel_z	gyros_x	gyros_y	gyros_z	output
accel_x	1.0000	-0.0525	0.0240	-0.0857	-0.0060	-0.1879	NaN
accel_y	-0.0525	1.0000	-0.2419	-0.0293	-0.0416	-0.0596	NaN
accel_z	0.0240	-0.2419	1.0000	0.0080	0.0726	0.0552	NaN
gyros_x	-0.0857	-0.0293	0.0080	1.0000	-0.0391	-0.0126	NaN
gyros_y	-0.0060	-0.0416	0.0726	-0.0391	1.0000	0.2346	NaN
gyros_z	-0.1879	-0.0596	0.0552	-0.0126	0.2346	1.0000	NaN
output	NaN	NaN	NaN	NaN	NaN	NaN	NaN

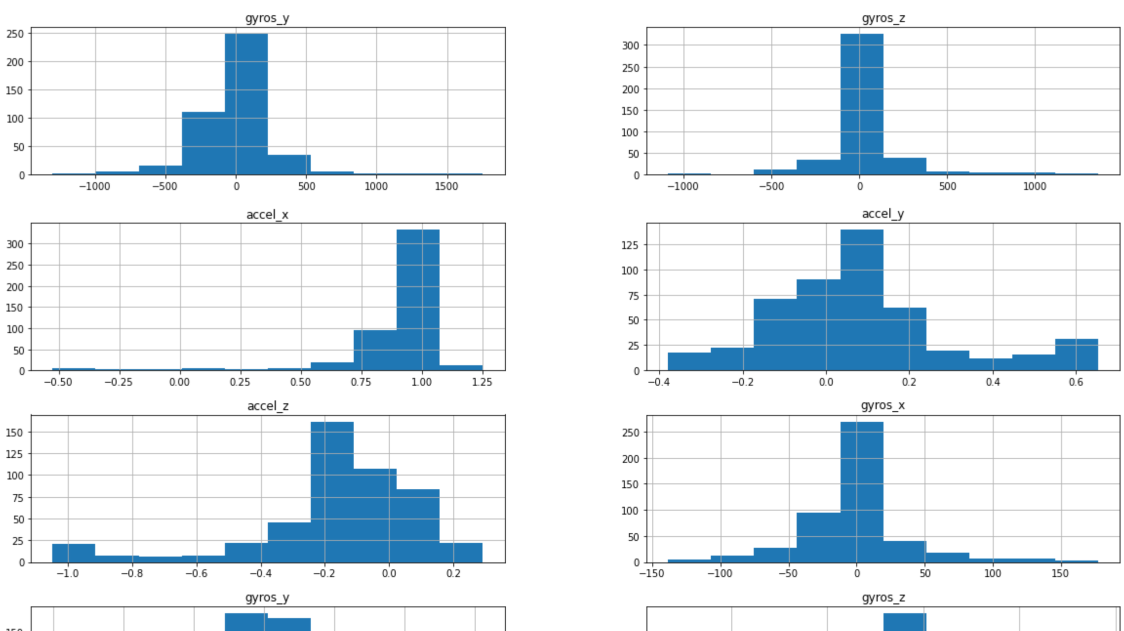
```
----------------------------------------------------------------------------------------------------
Correlación Dataframe normal
```

	accel_x	accel_y	accel_z	gyros_x	gyros_y	gyros_z	output
accel_x	1.0000	0.0324	0.7074	-0.0216	0.0064	-0.0274	NaN
accel_y	0.0324	1.0000	0.2748	0.1003	0.0364	-0.0620	NaN
accel_z	0.7074	0.2748	1.0000	-0.0500	0.0192	-0.0477	NaN
gyros_x	-0.0216	0.1003	-0.0500	1.0000	0.1485	-0.1666	NaN
gyros_y	0.0064	0.0364	0.0192	0.1485	1.0000	0.0146	NaN
gyros_z	-0.0274	-0.0620	-0.0477	-0.1666	0.0146	1.0000	NaN
output	NaN	NaN	NaN	NaN	NaN	NaN	NaN

```
----------------------------------------------------------------------------------------------------
```

In [63]:
```
display(df_falldown[df_falldown.columns[:-1]].hist(figsize=(20,10)))
display(df_normal[df_normal.columns[:-1]].hist(figsize=(20,10)))
```

```
array([[<AxesSubplot:title={'center':'accel_x'}>,
        <AxesSubplot:title={'center':'accel_y'}>],
       [<AxesSubplot:title={'center':'accel_z'}>,
        <AxesSubplot:title={'center':'gyros_x'}>],
       [<AxesSubplot:title={'center':'gyros_y'}>,
        <AxesSubplot:title={'center':'gyros_z'}>]], dtype=object)
array([[<AxesSubplot:title={'center':'accel_x'}>,
        <AxesSubplot:title={'center':'accel_y'}>],
       [<AxesSubplot:title={'center':'accel_z'}>,
        <AxesSubplot:title={'center':'gyros_x'}>],
       [<AxesSubplot:title={'center':'gyros_y'}>,
        <AxesSubplot:title={'center':'gyros_z'}>]], dtype=object)
```



In [64]:
```
# Split dependent and independent variables
y = df.output
X = df[df.columns[:-1]]

# Split dataset in train and test
test_portion = 0.3
seed = random.randint(2,100)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=test_portion, random_state=seed)
```

Normalize data

In [65]:
```
# Set a fixed random seed value, for reproducibility, this will allow us to get
# the same random numbers each time the notebook is run
SEED = 1000
np.random.seed(SEED)
tf.random.set_seed(SEED)

# the list of gestures that data is available for
STATES = [
    "normal",
    "falldown",
]
SAMPLES_PER_STATE = df.shape[0]

inputs = []
outputs = []
tensor = []

for index in range(SAMPLES_PER_STATE):
    # normalize the input data, between 0 to 1:
    # - acceleration is between: -4 to +4
    # - gyroscope is between: -2000 to +2000
    tensor = [
        (df['accel_x'][index] + 4) / 8,
        (df['accel_y'][index] + 4) / 8,
        (df['accel_z'][index] + 4) / 8,
        (df['gyros_x'][index] + 2000) / 4000,
        (df['gyros_y'][index] + 2000) / 4000,
        (df['gyros_z'][index] + 2000) / 4000
    ]
    output = df["output"][index]

    inputs.append(tensor)
    outputs.append(output)

# convert the list to numpy array
inputs = np.array(inputs)
outputs = np.array(outputs)
```

Split train, validate and test dataset

Randomly split input and output pairs into sets of data: 60% for training, 20% for validation, and 20% for testing.

- the training set is used to train the model
- the validation set is used to measure how well the model is performing during training
- the testing set is used to test the model after training

In [66]:
```
# Randomize the order of the inputs, so they can be evenly distributed for training, testing, and validation
num_inputs = len(inputs)
randomize = np.arange(num_inputs)
np.random.shuffle(randomize)

# Swap the consecutive indexes (0, 1, 2, etc) with the randomized indexes
inputs = inputs[randomize]
outputs = outputs[randomize]

# Split the recordings (group of samples) into three sets: training, testing and validation
TRAIN_SPLIT = int(0.6 * num_inputs)
TEST_SPLIT = int(0.2 * num_inputs + TRAIN_SPLIT)

inputs_train, inputs_test, inputs_validate = np.split(inputs, [TRAIN_SPLIT, TEST_SPLIT])
outputs_train, outputs_test, outputs_validate = np.split(outputs, [TRAIN_SPLIT, TEST_SPLIT])

print("Data set randomization and splitting complete.")
```

```
Data set randomization and splitting complete.
```

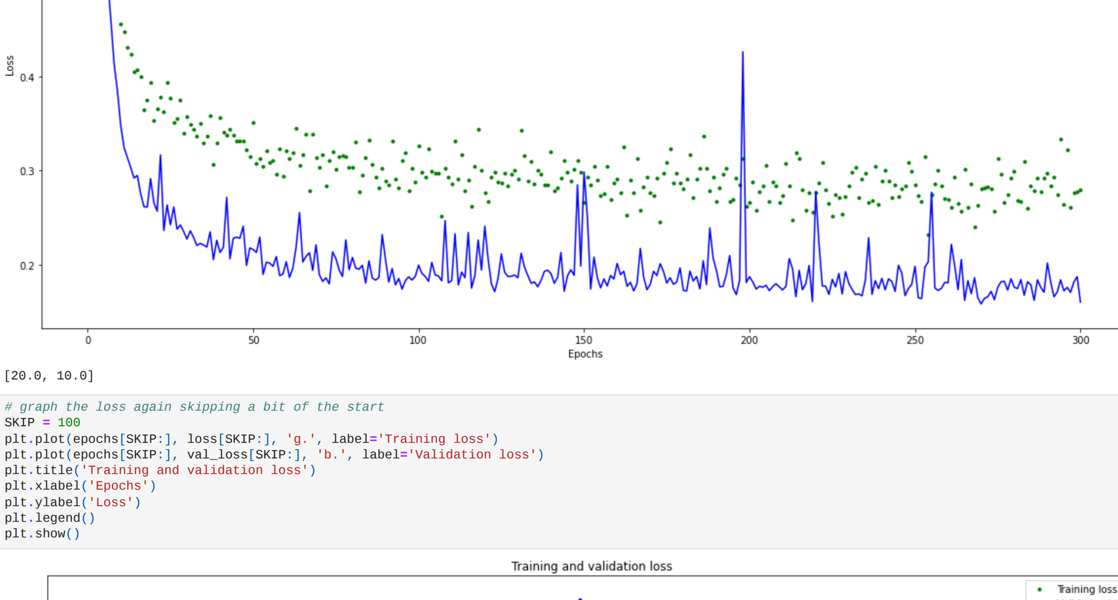
Train model

In [67]:
```
EPOCHS = 300
BATCH_SIZE = 1

# build the model and train it
model = tf.keras.Sequential()

model.add(tf.keras.layers.Dense(16, activation='relu')) # relu is used for performance
model.add(tf.keras.layers.Dropout(0.3, seed=SEED)) # Evitamos conexiones de neuronas, así no entramos en overfitting

model.add(tf.keras.layers.Dense(8, activation='relu'))
model.add(tf.keras.layers.Dropout(0.3, seed=SEED)) # Evitamos conexiones de neuronas, así no entramos en overfitting

model.add(tf.keras.layers.Dense(1, activation='sigmoid')) # Sigmoid, because we expect one state per input

# Compile model
model.compile(loss='binary_crossentropy',
              optimizer="adam",
              metrics=['acc'])

# Create a class to print every epoch_interval the log of the training model
class SelectiveProgbarLogger(tf.keras.callbacks.ProgbarLogger):
    def __init__(self, verbose, epoch_interval, *args, **kwargs):
        super().__init__(*args, **kwargs)
        self.default_verbose = verbose
        self.epoch_interval = epoch_interval

    def on_epoch_begin(self, epoch, *args, **kwargs):
        self.verbose = (
                        0
                        if epoch % self.epoch_interval != 0
                        else self.default_verbose
        )
        super().on_epoch_begin(epoch, *args, **kwargs)

history = model.fit(inputs_train, outputs_train, epochs=EPOCHS, batch_size=BATCH_SIZE,
                    use_multiprocessing=True, callbacks=[SelectiveProgbarLogger(verbose=1, epoch_interval=EPOCHS/6)], verbose=0,
                    validation_data=(inputs_validate, outputs_validate))

print(model.summary())
```

```
Epoch 1/300
542/542 [==============================] - 2s 3ms/sample - loss: 0.6709 - acc: 0.5572 - val_loss: 0.6489 - val_acc: 0.8187
Epoch 51/300
542/542 [==============================] - 1s 1ms/sample - loss: 0.3073 - acc: 0.8856 - val_loss: 0.2129 - val_acc: 0.9451
Epoch 101/300
542/542 [==============================] - 1s 1ms/sample - loss: 0.2979 - acc: 0.8875 - val_loss: 0.1905 - val_acc: 0.9560
Epoch 151/300
542/542 [==============================] - 1s 1ms/sample - loss: 0.2928 - acc: 0.8948 - val_loss: 0.2507 - val_acc: 0.9286
Epoch 201/300
542/542 [==============================] - 1s 1ms/sample - loss: 0.2884 - acc: 0.8875 - val_loss: 0.1814 - val_acc: 0.9560
Epoch 251/300
542/542 [==============================] - 1s 1ms/sample - loss: 0.2734 - acc: 0.8893 - val_loss: 0.1647 - val_acc: 0.9560
Model: "sequential_25"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_75 (Dense)            (1, 16)                   112

 dropout_50 (Dropout)        (1, 16)                   0

 dense_76 (Dense)            (1, 8)                    136

 dropout_51 (Dropout)        (1, 8)                    0

 dense_77 (Dense)            (1, 1)                    9

=================================================================
Total params: 257
Trainable params: 257
Non-trainable params: 0
_________________________________________________________________
None
```

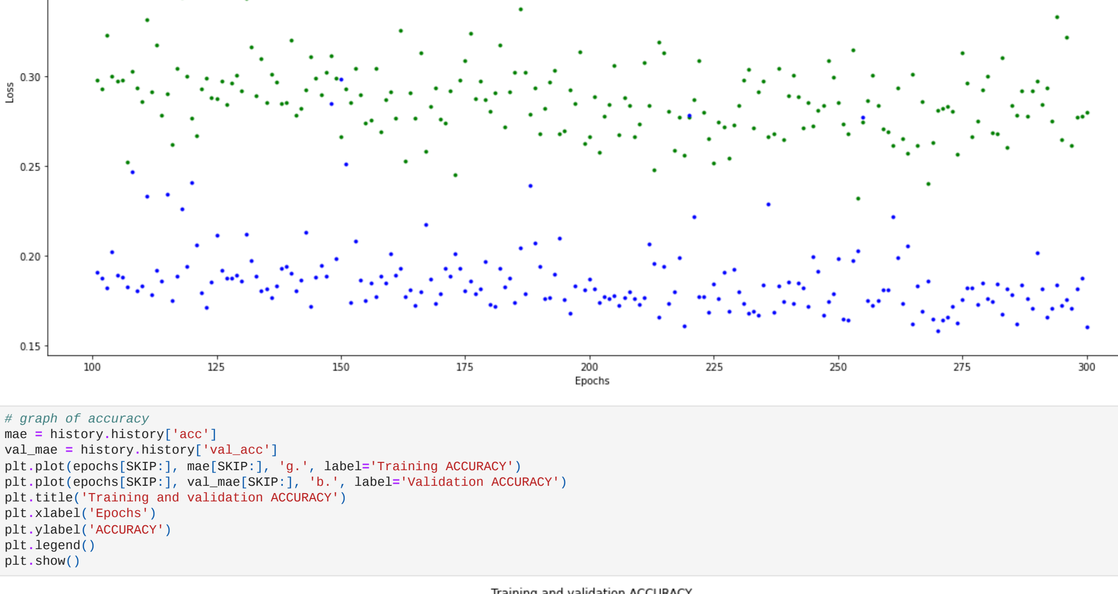
Validate binary classification model

In [68]:
```
# increase the size of the graphs. The default size is (6,4).
plt.rcParams["figure.figsize"] = (20,10)

# graph the loss, the model above is configure to use "accuracy" as the loss function
loss = history.history['loss']
val_loss = history.history['val_loss']
epochs = range(1, len(loss) + 1)
plt.plot(epochs, loss, 'g.', label='Training loss')
plt.plot(epochs, val_loss, 'b', label='Validation loss')
plt.title('Training and validation loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()

print(plt.rcParams["figure.figsize"])
```

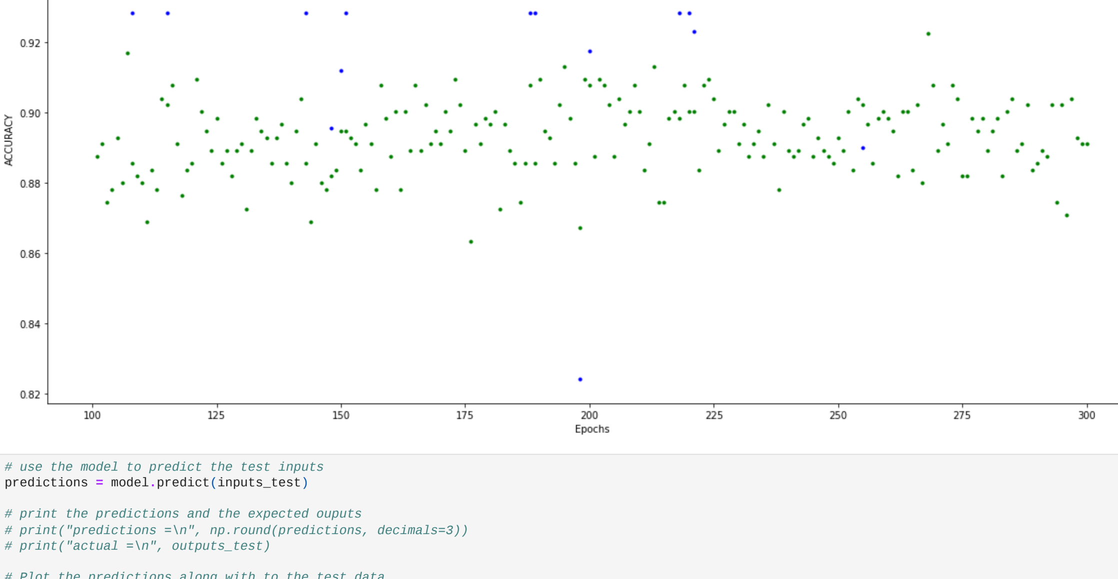



```
[20.0, 10.0]
```

In [69]:
```
# graph the loss again skipping a bit of the start
SKIP = 100
plt.plot(epochs[SKIP:], loss[SKIP:], 'g.', label='Training loss')
plt.plot(epochs[SKIP:], val_loss[SKIP:], 'b.', label='Validation loss')
plt.title('Training and validation loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```

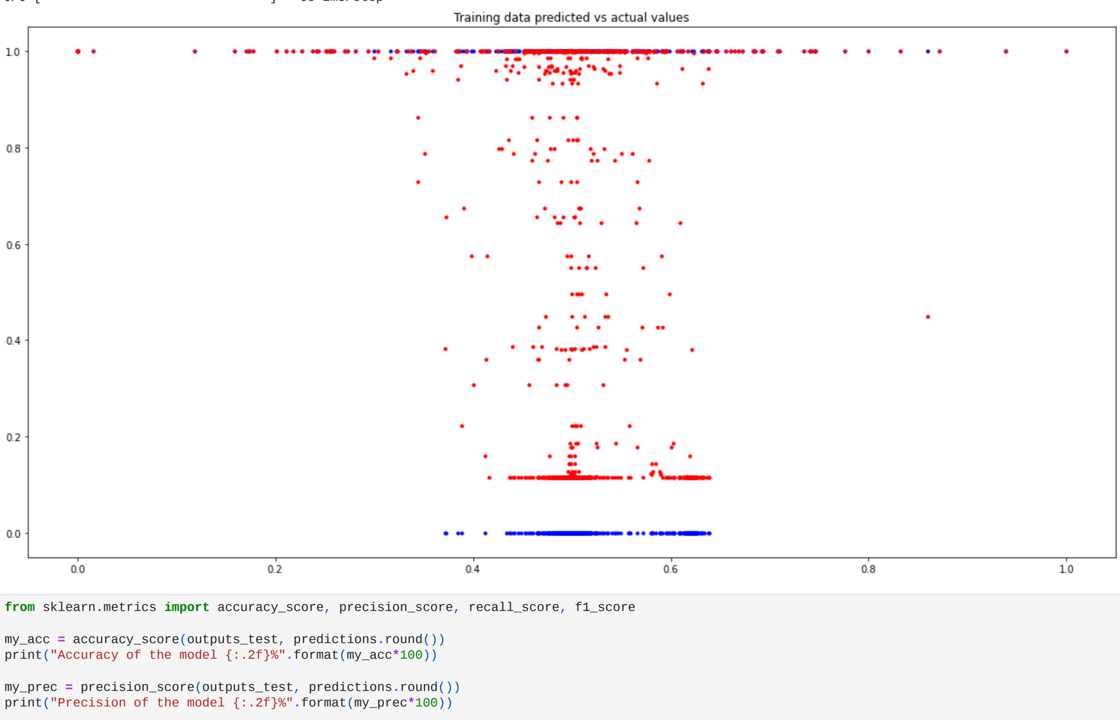


In [70]:
```
# graph of accuracy
mae = history.history['acc']
val_mae = history.history['val_acc']
plt.plot(epochs[SKIP:], mae[SKIP:], 'g.', label='Training ACCURACY')
plt.plot(epochs[SKIP:], val_mae[SKIP:], 'b.', label='Validation ACCURACY')
plt.title('Training and validation ACCURACY')
plt.xlabel('Epochs')
plt.ylabel('ACCURACY')
plt.legend()
plt.show()
```



In [71]:
```
# use the model to predict the test inputs
predictions = model.predict(inputs_test)

# print the predictions and the expected ouputs
# print("predictions =\n", np.round(predictions, decimals=3))
# print("actual =\n", outputs_test)

# Plot the predictions along with to the test data
plt.clf()
plt.title('Training data predicted vs actual values')
plt.plot(inputs_test, outputs_test, 'b.', label='Actual')
plt.plot(inputs_test, predictions, 'r.', label='Predicted')
plt.show()
```

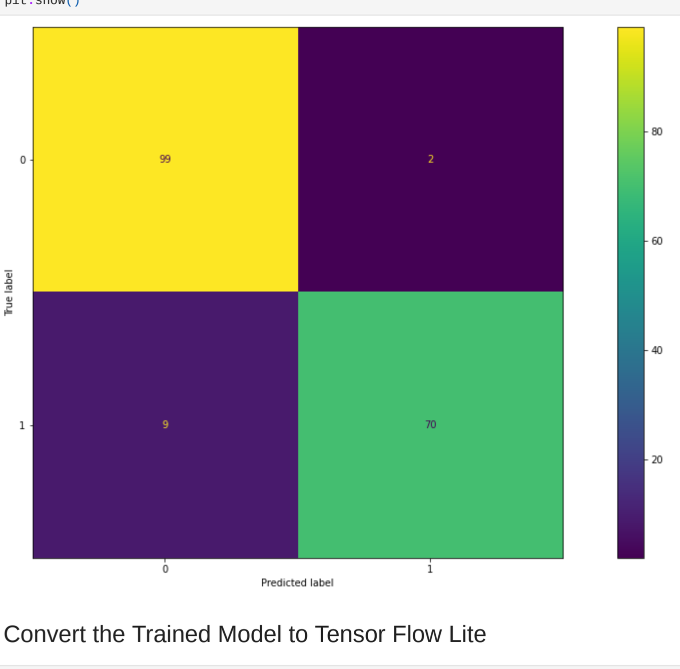
```
6/6 [==============================] - 0s 2ms/step
```



In [72]:
```
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score

my_acc = accuracy_score(outputs_test, predictions.round())
print("Accuracy of the model {:.2f}%".format(my_acc*100))

my_prec = precision_score(outputs_test, predictions.round())
print("Precision of the model {:.2f}%".format(my_prec*100))

my_recall = recall_score(outputs_test, predictions.round())
print("Recall score of the model {:.2f}%".format(my_recall*100))

my_f1 = f1_score(outputs_test, predictions.round())
print("F1 score of the model {:.2f}%".format(my_f1*100))
```

```
Accuracy of the model 93.89%
Precision of the model 97.22%
Recall score of the model 88.61%
F1 score of the model 92.72%
```

In [73]:
```
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay

rounded_predictions = predictions.round()
cm = confusion_matrix(y_true=outputs_test, y_pred=rounded_predictions)
disp = ConfusionMatrixDisplay(confusion_matrix=cm)
disp.plot()
plt.show()
```



Convert the Trained Model to Tensor Flow Lite

In [74]:
```
# Convert the model to the TensorFlow Lite format without quantization
converter = tf.lite.TFLiteConverter.from_keras_model(model)
tflite_model = converter.convert()

# Save the model to disk
open("state_model.tflite", "wb").write(tflite_model)

import os
basic_model_size = os.path.getsize("state_model.tflite")
print("Model is %d bytes" % basic_model_size)
```

```
INFO:tensorflow:Assets written to: C:\Users\Ruben\AppData\Local\Temp\tmpg358yzg_\assets
INFO:tensorflow:Assets written to: C:\Users\Ruben\AppData\Local\Temp\tmpg358yzg_\assets
Model is 3116 bytes
```

In [78]:
```
!echo "const unsigned char model[] = {" > /content/model.h
!cat gesture_model.tflite | xxd -i      >> /content/model.h
!echo "};"                              >> /content/model.h
import os
PATH = "./content/model.h"
model_h_size = os.path.getsize(PATH)
print(f"Header file, model.h, is {model_h_size:,} bytes.")
print("\nOpen the side panel (refresh if needed). Double click model.h to download the file.")
```

```
The system cannot find the path specified.
The system cannot find the path specified.
Header file, model.h, is 19,313 bytes.

Open the side panel (refresh if needed). Double click model.h to download the file.
The system cannot find the path specified.
```