physical

November 9, 2023

1 Study of the physical dataset

In this notebook, we will study how different models perform on the physical dataset. Some of the models we will study are: 1. Non-supervised: - Isolation Forest (IF) - Local Outlier Factor (LOF) 2. Neural physicals: - DNN - LSTM 3. Supervised classifiers: - Decision Tree - Random Forest - XGBoost

First, let's import the necessary libraries.

[78]:
```python
from preprocess_data import get_HITL, clean_HITL,␣
↪prepare_HTIL_physical_dataset, remove_physical_contextual_columns

from mlsecu.data_exploration_utils import (
    get_column_names,
    get_nb_of_dimensions,
    get_nb_of_rows,
    get_object_column_names,
    get_number_column_names,
)
from mlsecu.anomaly_detection_use_case import *
from mlsecu.data_preparation_utils import (
    get_one_hot_encoded_dataframe,
    remove_nan_through_mean_imputation,
)

from sklearn.model_selection import train_test_split
from sklearn.pipeline import make_pipeline
from sklearn.tree import DecisionTreeClassifier
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import (
    accuracy_score,
    precision_score,
    recall_score,
    f1_score,
    roc_auc_score,
    matthews_corrcoef,
    balanced_accuracy_score,
    confusion_matrix,
```

```
)

import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sns

import torch
import torch.nn as nn
import torch.nn.functional as F

import tensorflow as tf
from tensorflow.keras.activations import swish, sigmoid, softmax

BASE_PATH = "../../data/"
random_state = 42
np.random.seed(random_state)
tf.random.set_seed(random_state)

import warnings
warnings.simplefilter(action='ignore')
```

2 Load and prepare the dataset

We have defined multiple preprocessing functions in the `preprocessing.py` file. We will use them to load and prepare the dataset.

[79]:
```
hitl_dict = get_HITL("../../data/HardwareInTheLoop/", small=False)
_, df_physical = clean_HITL(hitl_dict) # Clean-up helper function

print("Physical dataset shape: ", df_physical.shape)
```

```
Physical dataset shape:  (9206, 44)
```

This dataset has way fewer rows than the network one, this might cause some problems later.

- The `get_HITL` loads all the csv files into a dictionnary that can be used later to load the data. Regarding the network dataset, we only keep 1% of the normal data to make the dataset more usable. The physical dataset is very small by default (9000 rows) so we keep the full version.
- The `clean_HITL` function takes all 3 attack files and the normal file and concatenates them into a single dataframe, for both dataframes. Then it performs these operations (among others, see the function for more details):
  - It also adds a column `label` to the dataframe which is 1 for attack and 0 for normal.
  - Fixes the misspelled column `lable_n` and merges it with the `label_n` column.
  - Convert the `timestamp` column to a datetime object.

[80]:
```
df_physical_prepared, df_physical_labels =␣
↪prepare_HTIL_physical_dataset(df_physical)
```

```
df_physical_prepared.head()
```

[80]:

```
           time  tank_1  tank_2  tank_3  tank_4  tank_5  tank_6  tank_7  \
0  1.630780e+09       0       0       0       0       0       0       0
1  1.630780e+09       0       0       0       0       0       0       0
2  1.630780e+09       0       0       0       0       0       0       0
3  1.630780e+09       0       0       0       0       0       0       0
4  1.630780e+09       0       0       0       0       0       0       0

   tank_8  pump_1  …  pump_6  flow_sensor_1  flow_sensor_2  flow_sensor_4  \
0       0       0  …       0              0              0              0
1       0       0  …       0              0              0              0
2       0       0  …       0              0              0              0
3       0       0  …       0              0              0              0
4       0       1  …       0              0              0              0

   valv_12  valv_15  valv_17  valv_18  valv_20  valv_22
0        0        0        0        0        0        0
1        0        0        0        0        0        0
2        0        0        0        0        0        0
3        0        0        0        0        0        0
4        0        0        0        0        0        0

[5 rows x 23 columns]
```

We prepare the dataset by calling `prepare_HTIL_physical_dataset`. This function does the following: - Remove NaN through mean imputation of numerical features. - Convert label categories to numerical values.

The features are : - `time`: the timestamp of the measurement - `tank_X`: the level of the tank X - `pump_Y`: the level of the pump Y - `valv_Z`: the level of the valve Z - `flow_sensor_W`: the amount of water flowing through the sensor W

[81]:
```
df_physical_labels.head()
```

[81]:

```
   label_n   label  attack  new_labels
0      0.0  normal       1           2
1      0.0  normal       1           2
2      0.0  normal       1           2
3      0.0  normal       1           2
4      0.0  normal       1           2
```

3 Models analysis

3.1 1. Non-supervised models

3.1.1 a. Isolation Forest

As a first step, let's try default parameters for the Isolation Forest model.

[5]:
```
df_physical_labels["label_n"].value_counts()
```

[5]:
```
label_n
0.0    7747
1.0    1459
Name: count, dtype: int64
```

[12]:
```
clf = IsolationForest(random_state=42)
y_pred = clf.fit_predict(df_physical_prepared)
if_outliers = df_physical_prepared[y_pred == -1].index.values.tolist()
len(if_outliers)
```

[12]: 5762

[8]:
```
df_physical_labels.iloc[if_outliers]["label_n"].value_counts()
```

[8]:
```
label_n
0.0    4607
1.0    1155
Name: count, dtype: int64
```

Out of the 5762 outliers found, 1155 are real anomalies (20%). This is not a great result knowing there are only 1459 outliers, let's see if we can do better with a fixed contamination rate.

[9]:
```
val_counts_labels = df_physical_labels["label_n"].value_counts()
contamination_rate = val_counts_labels[1] / (val_counts_labels[0] +␣
 ↪val_counts_labels[1])
contamination_rate
```

[9]: 0.1584835976537041

[17]:
```
clf = IsolationForest(n_estimators=100, n_jobs=-1, bootstrap=True,␣
 ↪random_state=42, contamination=contamination_rate)
y_pred = clf.fit_predict(df_physical_prepared)
if_outliers_cr = df_physical_prepared[y_pred == -1].index.values.tolist()
len(if_outliers_cr)
```

[17]: 1458

[15]:
```
df_physical_labels.iloc[if_outliers_cr]["label_n"].value_counts()
```

[15]:
```
label_n
0.0    936
1.0    522
Name: count, dtype: int64
```

With a fixed contamination rate, the model gets a total of 1459 outliers, out of which 522 are real anomalies (35.7%). This is a better result than with the default parameters and less false positives are found, however it's still not close to being usable in a real-world scenario.

3.1.2 b. Local Outlier Factor

[18]:
```
clf = LocalOutlierFactor(n_neighbors=5)
y_pred = clf.fit_predict(df_physical_prepared)
lof_outliers = df_physical_prepared[y_pred == -1].index.values.tolist()
len(lof_outliers)
```

[18]:
```
73
```

[19]:
```
df_physical_labels.iloc[lof_outliers]["label_n"].value_counts()
```

[19]:
```
label_n
0.0    48
1.0    25
Name: count, dtype: int64
```

We get terrible results, it barely detects outliers. This model isn't suited for the dataset.

What we saw with these two methods, is that they are not suited for this dataset. The dataset is surely too small for these methods to work properly and capture the outliers. Let's see if more complex models can do better.

3.2 2. Neural Networks

3.2.1 a. DNN

We will use only some of the columns for the DNN model. We are removing contextual information such as the time. To make it easier to manipulate, we will merge back the labels with the predictions.

Binary classification

[82]:
```
df = df_physical_prepared.copy()
df["label_n"] = df_physical_labels["label_n"]
df.head()
```

[82]:
```
           time  tank_1  tank_2  tank_3  tank_4  tank_5  tank_6  tank_7  \
0  1.630780e+09       0       0       0       0       0       0       0
1  1.630780e+09       0       0       0       0       0       0       0
2  1.630780e+09       0       0       0       0       0       0       0
3  1.630780e+09       0       0       0       0       0       0       0
4  1.630780e+09       0       0       0       0       0       0       0

   tank_8  pump_1  …  flow_sensor_1  flow_sensor_2  flow_sensor_4  valv_12  \
0       0       0  …              0              0              0        0
1       0       0  …              0              0              0        0
2       0       0  …              0              0              0        0
3       0       0  …              0              0              0        0
4       0       1  …              0              0              0        0

   valv_15  valv_17  valv_18  valv_20  valv_22  label_n
0        0        0        0        0        0      0.0
```

```
1         0         0         0         0         0       0.0
2         0         0         0         0         0       0.0
3         0         0         0         0         0       0.0
4         0         0         0         0         0       0.0

[5 rows x 24 columns]
```

[83]:
```
# convert bool columns to int
bool_cols = df.columns[df.dtypes == bool]
df[bool_cols] = df[bool_cols].astype(int)

# remove time column
if "Time" in df.columns:
    df.drop(columns=['Time'], inplace=True)

# Split data into train, validation, and test sets
train_df, test_df = train_test_split(df, test_size=0.2, random_state=42,␣
 ↪stratify=df['label_n'])
train_df, val_df = train_test_split(train_df, test_size=0.2, random_state=42,␣
 ↪stratify=train_df['label_n'])

# Separate features and target
X_train = train_df.drop(columns=['label_n'])
y_train = train_df['label_n']
X_val = val_df.drop(columns=['label_n'])
y_val = val_df['label_n']
X_test = test_df.drop(columns=['label_n'])
y_test = test_df['label_n']

# Normalize numerical features
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_val = scaler.transform(X_val)
X_test = scaler.transform(X_test)

X_train.shape, X_val.shape, X_test.shape
```

[83]:
```
((5891, 23), (1473, 23), (1842, 23))
```

[84]:
```
# Define the neural network model
model = tf.keras.Sequential([
    tf.keras.layers.Input(shape=(X_train[0].shape[0],)),  # Input layer
    tf.keras.layers.Dense(1024, activation=swish),  # Hidden layer 1
    tf.keras.layers.Dense(256, activation=swish),   # Hidden layer 2
    tf.keras.layers.Dense(64, activation=swish),    # Hidden layer 3
    tf.keras.layers.Dense(1, activation=sigmoid)  # Output layer
])
```

```python
# Compile the model
model.compile(optimizer='adam',
              loss='binary_crossentropy',
              metrics=['accuracy'])

model.summary()
```

```
Model: "sequential_2"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_8 (Dense)             (None, 1024)              24576

 dense_9 (Dense)             (None, 256)               262400

 dense_10 (Dense)            (None, 64)                16448

 dense_11 (Dense)            (None, 1)                 65

=================================================================
Total params: 303489 (1.16 MB)
Trainable params: 303489 (1.16 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

We are using a simple DNN with 3 hidden layers, but it should be enough to get good results. We are using the `binary_crossentropy` loss function, since we are focusing on binary classification, and the `adam` optimizer. We are using the `accuracy` metric to evaluate the model.

Let's define callbacks and train the model.

[85]:
```python
# callbacks
early_stopping = tf.keras.callbacks.EarlyStopping(
    monitor='val_loss', min_delta=0, patience=6, verbose=1,
    mode='auto', baseline=None, restore_best_weights=True
)
reduce_on_plateau = tf.keras.callbacks.ReduceLROnPlateau(
    monitor='val_loss', factor=0.1, patience=3, verbose=1,
    mode='auto', min_delta=0.0001, cooldown=0, min_lr=0
)

# Train the model
history = model.fit(X_train, y_train,
                    epochs=40,
                    batch_size=256,
                    validation_data=(X_val, y_val),
                    callbacks=[early_stopping, reduce_on_plateau])
```

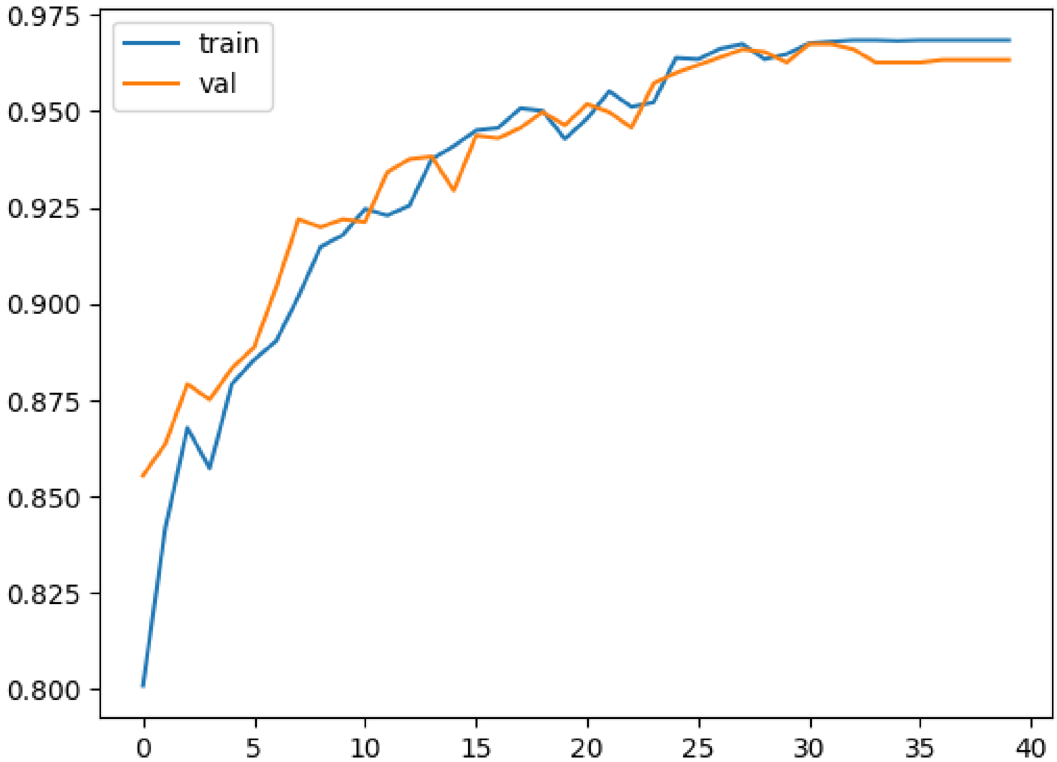
```
Epoch 1/40
24/24 [==============================] - 0s 9ms/step - loss: 0.4680 - accuracy:
0.8009 - val_loss: 0.3676 - val_accuracy: 0.8554 - lr: 0.0010
Epoch 2/40
24/24 [==============================] - 0s 6ms/step - loss: 0.3697 - accuracy:
0.8416 - val_loss: 0.3293 - val_accuracy: 0.8635 - lr: 0.0010
Epoch 3/40
24/24 [==============================] - 0s 6ms/step - loss: 0.3114 - accuracy:
0.8678 - val_loss: 0.2814 - val_accuracy: 0.8792 - lr: 0.0010
Epoch 4/40
24/24 [==============================] - 0s 6ms/step - loss: 0.3106 - accuracy:
0.8572 - val_loss: 0.2928 - val_accuracy: 0.8751 - lr: 0.0010
Epoch 5/40
24/24 [==============================] - 0s 8ms/step - loss: 0.2972 - accuracy:
0.8791 - val_loss: 0.2637 - val_accuracy: 0.8832 - lr: 0.0010
Epoch 6/40
24/24 [==============================] - 0s 6ms/step - loss: 0.2572 - accuracy:
0.8854 - val_loss: 0.2337 - val_accuracy: 0.8887 - lr: 0.0010
Epoch 7/40
24/24 [==============================] - 0s 6ms/step - loss: 0.2393 - accuracy:
0.8903 - val_loss: 0.2185 - val_accuracy: 0.9043 - lr: 0.0010
Epoch 8/40
24/24 [==============================] - 0s 6ms/step - loss: 0.2130 - accuracy:
0.9019 - val_loss: 0.1922 - val_accuracy: 0.9219 - lr: 0.0010
Epoch 9/40
24/24 [==============================] - 0s 6ms/step - loss: 0.1883 - accuracy:
0.9148 - val_loss: 0.1826 - val_accuracy: 0.9199 - lr: 0.0010
Epoch 10/40
24/24 [==============================] - 0s 6ms/step - loss: 0.1872 - accuracy:
0.9178 - val_loss: 0.1770 - val_accuracy: 0.9219 - lr: 0.0010
Epoch 11/40
24/24 [==============================] - 0s 6ms/step - loss: 0.1675 - accuracy:
0.9246 - val_loss: 0.1674 - val_accuracy: 0.9212 - lr: 0.0010
Epoch 12/40
24/24 [==============================] - 0s 6ms/step - loss: 0.1629 - accuracy:
0.9229 - val_loss: 0.1631 - val_accuracy: 0.9341 - lr: 0.0010
Epoch 13/40
24/24 [==============================] - 0s 7ms/step - loss: 0.1669 - accuracy:
0.9255 - val_loss: 0.1611 - val_accuracy: 0.9375 - lr: 0.0010
Epoch 14/40
24/24 [==============================] - 0s 6ms/step - loss: 0.1412 - accuracy:
0.9375 - val_loss: 0.1496 - val_accuracy: 0.9382 - lr: 0.0010
Epoch 15/40
24/24 [==============================] - 0s 6ms/step - loss: 0.1343 - accuracy:
0.9409 - val_loss: 0.1521 - val_accuracy: 0.9294 - lr: 0.0010
Epoch 16/40
24/24 [==============================] - 0s 6ms/step - loss: 0.1284 - accuracy:
0.9450 - val_loss: 0.1453 - val_accuracy: 0.9437 - lr: 0.0010
```

```
Epoch 17/40
24/24 [==============================] - 0s 6ms/step - loss: 0.1206 - accuracy:
0.9457 - val_loss: 0.1369 - val_accuracy: 0.9430 - lr: 0.0010
Epoch 18/40
24/24 [==============================] - 0s 6ms/step - loss: 0.1146 - accuracy:
0.9508 - val_loss: 0.1323 - val_accuracy: 0.9457 - lr: 0.0010
Epoch 19/40
24/24 [==============================] - 0s 6ms/step - loss: 0.1147 - accuracy:
0.9501 - val_loss: 0.1296 - val_accuracy: 0.9498 - lr: 0.0010
Epoch 20/40
24/24 [==============================] - 0s 6ms/step - loss: 0.1306 - accuracy:
0.9428 - val_loss: 0.1351 - val_accuracy: 0.9464 - lr: 0.0010
Epoch 21/40
24/24 [==============================] - 0s 7ms/step - loss: 0.1148 - accuracy:
0.9481 - val_loss: 0.1216 - val_accuracy: 0.9518 - lr: 0.0010
Epoch 22/40
24/24 [==============================] - 0s 6ms/step - loss: 0.1071 - accuracy:
0.9552 - val_loss: 0.1321 - val_accuracy: 0.9498 - lr: 0.0010
Epoch 23/40
24/24 [==============================] - 0s 6ms/step - loss: 0.1248 - accuracy:
0.9511 - val_loss: 0.1323 - val_accuracy: 0.9457 - lr: 0.0010
Epoch 24/40
15/24 [================>…] - ETA: 0s - loss: 0.1020 - accuracy:
0.9549
Epoch 24: ReduceLROnPlateau reducing learning rate to 0.00010000000474974513.
24/24 [==============================] - 0s 8ms/step - loss: 0.1081 - accuracy:
0.9523 - val_loss: 0.1231 - val_accuracy: 0.9572 - lr: 0.0010
Epoch 25/40
24/24 [==============================] - 0s 6ms/step - loss: 0.0944 - accuracy:
0.9638 - val_loss: 0.1127 - val_accuracy: 0.9599 - lr: 1.0000e-04
Epoch 26/40
24/24 [==============================] - 0s 6ms/step - loss: 0.0894 - accuracy:
0.9635 - val_loss: 0.1092 - val_accuracy: 0.9620 - lr: 1.0000e-04
Epoch 27/40
24/24 [==============================] - 0s 6ms/step - loss: 0.0880 - accuracy:
0.9662 - val_loss: 0.1068 - val_accuracy: 0.9640 - lr: 1.0000e-04
Epoch 28/40
24/24 [==============================] - 0s 6ms/step - loss: 0.0870 - accuracy:
0.9674 - val_loss: 0.1052 - val_accuracy: 0.9661 - lr: 1.0000e-04
Epoch 29/40
24/24 [==============================] - 0s 6ms/step - loss: 0.0890 - accuracy:
0.9635 - val_loss: 0.1059 - val_accuracy: 0.9654 - lr: 1.0000e-04
Epoch 30/40
24/24 [==============================] - 0s 6ms/step - loss: 0.0860 - accuracy:
0.9649 - val_loss: 0.1056 - val_accuracy: 0.9627 - lr: 1.0000e-04
Epoch 31/40
22/24 [=========================>…] - ETA: 0s - loss: 0.0873 - accuracy:
0.9670
```

```
Epoch 31: ReduceLROnPlateau reducing learning rate to 1.0000000474974514e-05.
24/24 [==============================] - 0s 6ms/step - loss: 0.0869 - accuracy:
0.9676 - val_loss: 0.1056 - val_accuracy: 0.9674 - lr: 1.0000e-04
Epoch 32/40
24/24 [==============================] - 0s 6ms/step - loss: 0.0854 - accuracy:
0.9681 - val_loss: 0.1054 - val_accuracy: 0.9674 - lr: 1.0000e-05
Epoch 33/40
24/24 [==============================] - 0s 6ms/step - loss: 0.0851 - accuracy:
0.9684 - val_loss: 0.1053 - val_accuracy: 0.9661 - lr: 1.0000e-05
Epoch 34/40
22/24 [==========================>…] - ETA: 0s - loss: 0.0838 - accuracy:
0.9684
Epoch 34: ReduceLROnPlateau reducing learning rate to 1.0000000656873453e-06.
24/24 [==============================] - 0s 6ms/step - loss: 0.0851 - accuracy:
0.9684 - val_loss: 0.1051 - val_accuracy: 0.9627 - lr: 1.0000e-05
Epoch 35/40
24/24 [==============================] - 0s 7ms/step - loss: 0.0849 - accuracy:
0.9683 - val_loss: 0.1051 - val_accuracy: 0.9627 - lr: 1.0000e-06
Epoch 36/40
24/24 [==============================] - 0s 6ms/step - loss: 0.0849 - accuracy:
0.9684 - val_loss: 0.1051 - val_accuracy: 0.9627 - lr: 1.0000e-06
Epoch 37/40
24/24 [==============================] - 0s 6ms/step - loss: 0.0848 - accuracy:
0.9684 - val_loss: 0.1051 - val_accuracy: 0.9633 - lr: 1.0000e-06
Epoch 38/40
21/24 [=========================>…] - ETA: 0s - loss: 0.0852 - accuracy:
0.9689
Epoch 38: ReduceLROnPlateau reducing learning rate to 1.0000001111620805e-07.
24/24 [==============================] - 0s 6ms/step - loss: 0.0848 - accuracy:
0.9684 - val_loss: 0.1051 - val_accuracy: 0.9633 - lr: 1.0000e-06
Epoch 39/40
24/24 [==============================] - 0s 6ms/step - loss: 0.0848 - accuracy:
0.9684 - val_loss: 0.1050 - val_accuracy: 0.9633 - lr: 1.0000e-07
Epoch 40/40
24/24 [==============================] - 0s 6ms/step - loss: 0.0848 - accuracy:
0.9684 - val_loss: 0.1050 - val_accuracy: 0.9633 - lr: 1.0000e-07
```

[86]:

```
plt.plot(history.history['accuracy'], label='train')
plt.plot(history.history['val_accuracy'], label='val')
plt.legend()
plt.show()
```



The curves look very good and we see that the model is training very well. Let's evaluate the model on the test set.

Evaluation on the test set:

[26]:
```
test_loss, test_accuracy = model.evaluate(X_test, y_test)
print(f"Test accuracy: {test_accuracy * 100:.2f}%")
```

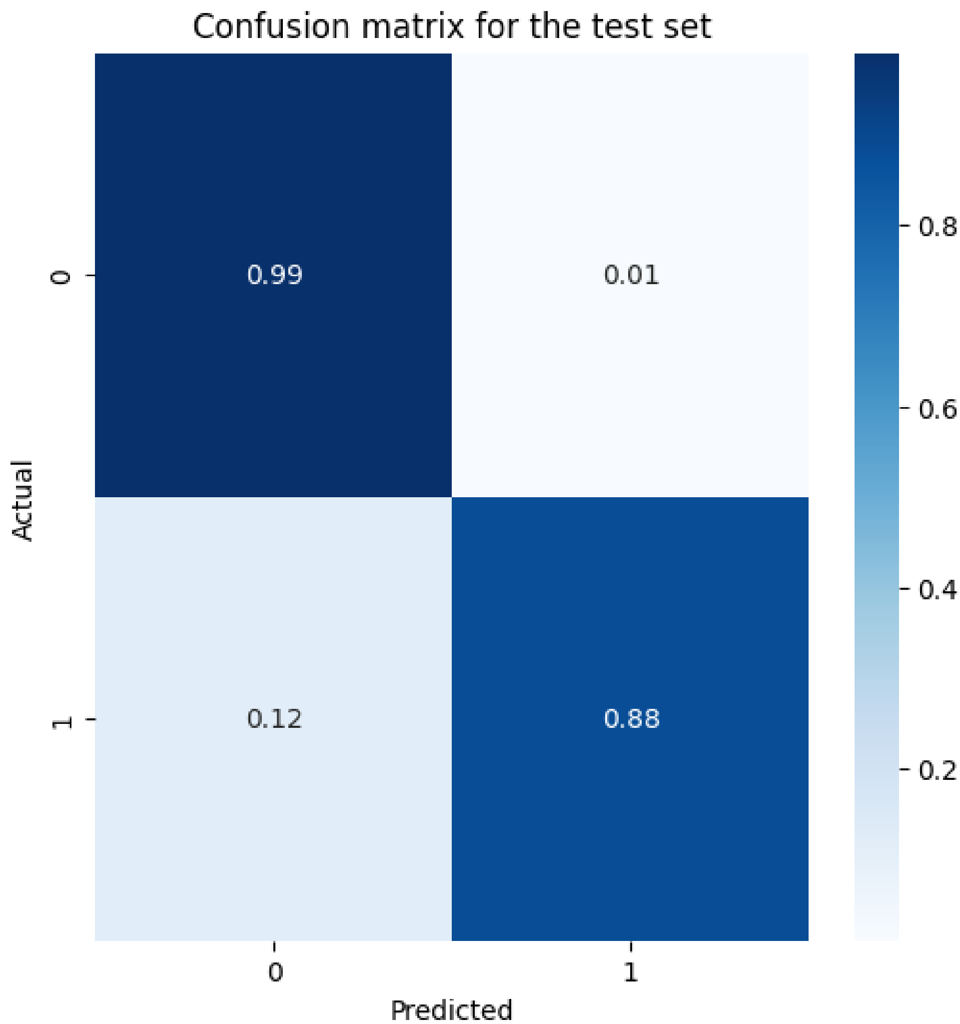
```
 1/58 […] - ETA: 0s - loss: 0.1101 - accuracy:
0.937558/58 [==============================] - 0s 1ms/step - loss: 0.0953 -
accuracy: 0.9723
Test accuracy: 97.23%
```

[27]:
```
def plot_confusion_matrix(y_true, y_pred, title=None):
    fig, ax = plt.subplots(figsize=(6, 6))
    cm = confusion_matrix(y_true, y_pred)

    # normalize it
    cm = cm.astype(float) / cm.sum(axis=1)[:, np.newaxis]

    sns.heatmap(cm, annot=True, ax=ax, cmap="Blues")
    ax.set_ylabel("Actual")
    ax.set_xlabel("Predicted")
```

```
    if title:
        ax.set_title(title)
    plt.show()
```

[28]:
```
y_pred = model.predict(X_test)
y_pred = np.round(y_pred).astype(int).reshape(-1)

plot_confusion_matrix(y_test, y_pred, title="Confusion matrix for the test set")
```

```
58/58 [==============================] - 0s 859us/step
```



The results are promising, we get a good recall and precision, and 97% of test accuracy which is brilliant. The model is able to detect 88% of the anomalies and has a low false positive rate. However we still have quite a lot of false negatives, and we hope we can fix that with the next model.

This notebook doesn't show it, but we tested several different architectures and parameters for the model, on it didn't improve the results significantly to justify the extra complexity.

Multiclass classification Now, we want to create an alternative DNN which will give us more precision on the type of attack. We will use the same architecture as before, but we will change the output layer to have 5 neurons, one for each type of attack.

[29]:
```
df.drop(columns=['label_n'], inplace=True)
df["new_labels"] = df_physical_labels["new_labels"]
df["new_labels"].value_counts()
```

[29]:
```
new_labels
2    7747
1     743
3     552
0     157
4       7
Name: count, dtype: int64
```

The 5th class has only 7 rows, which is not enough to train a model. We will remove it from the dataset.

[30]:
```
df = df[df["new_labels"] != 4]
```

[31]:
```
# Split data into train, validation, and test sets
train_df, test_df = train_test_split(df, test_size=0.2, random_state=42,␣
↪stratify=df['new_labels'])
train_df, val_df = train_test_split(train_df, test_size=0.2, random_state=42,␣
↪stratify=train_df['new_labels'])

# Separate features and target
X_train = train_df.drop(columns=['new_labels'])
y_train = train_df['new_labels']
X_val = val_df.drop(columns=['new_labels'])
y_val = val_df['new_labels']
X_test = test_df.drop(columns=['new_labels'])
y_test = test_df['new_labels']

# Normalize numerical features
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_val = scaler.transform(X_val)
X_test = scaler.transform(X_test)

X_train.shape, X_val.shape, X_test.shape
```

[31]:
```
((5887, 23), (1472, 23), (1840, 23))
```

[32]:
```
# Define the neural network model
model = tf.keras.Sequential([
    tf.keras.layers.Input(shape=(X_train[0].shape[0],)),  # Input layer
    tf.keras.layers.Dense(1024, activation=swish),  # Hidden layer 1
    tf.keras.layers.Dense(256, activation=swish),   # Hidden layer 2
    tf.keras.layers.Dense(64, activation=swish),    # Hidden layer 3
    tf.keras.layers.Dense(5, activation=softmax)  # Output layer
])

# Compile the model
optimizer = tf.keras.optimizers.Adam()
loss = tf.keras.losses.SparseCategoricalCrossentropy()
model.compile(optimizer=optimizer,
              loss=loss,
              metrics=['accuracy'])

model.summary()
```

```
WARNING:absl:At this time, the v2.11+ optimizer `tf.keras.optimizers.Adam` runs
slowly on M1/M2 Macs, please use the legacy Keras optimizer instead, located at
`tf.keras.optimizers.legacy.Adam`.

Model: "sequential_1"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_4 (Dense)             (None, 1024)              24576

 dense_5 (Dense)             (None, 256)               262400

 dense_6 (Dense)             (None, 64)                16448

 dense_7 (Dense)             (None, 5)                 325

=================================================================
Total params: 303749 (1.16 MB)
Trainable params: 303749 (1.16 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

[33]:
```
history = model.fit(X_train, y_train,
                    epochs=40,
                    batch_size=256,
                    validation_data=(X_val, y_val),
                    callbacks=[early_stopping, reduce_on_plateau])
```

```
Epoch 1/40
23/23 [==============================] - 1s 9ms/step - loss: 0.8469 - accuracy:
0.7872 - val_loss: 0.4732 - val_accuracy: 0.8546 - lr: 0.0010
```

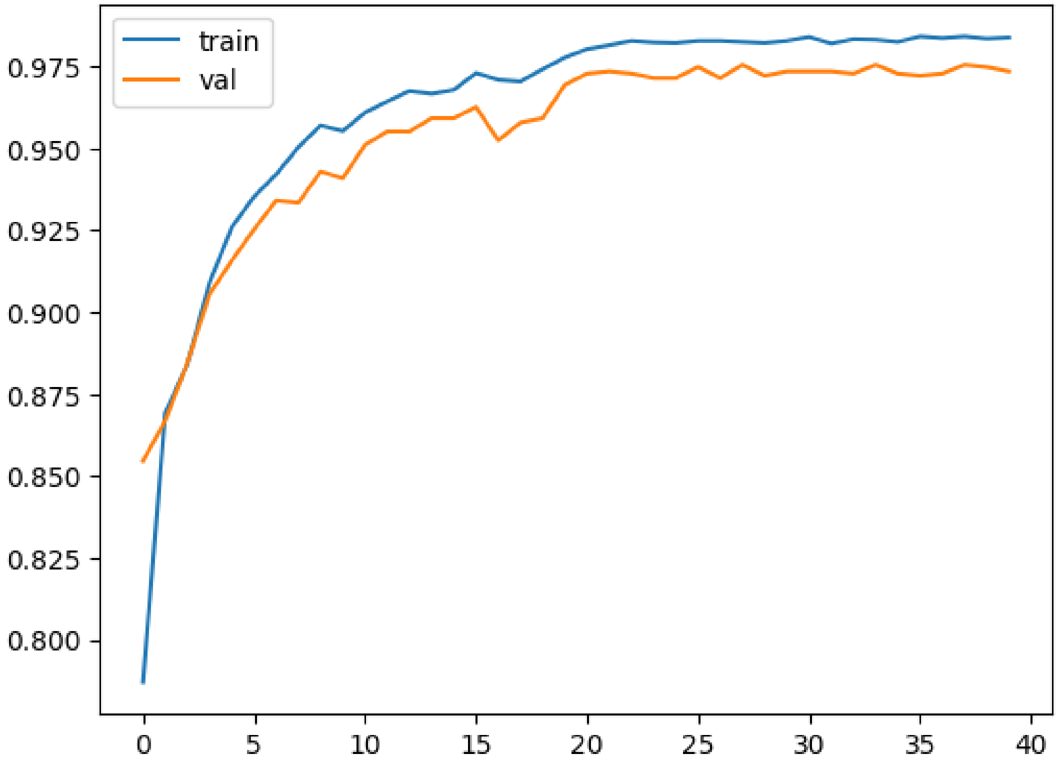
```
Epoch 2/40
23/23 [==============================] - 0s 7ms/step - loss: 0.3981 - accuracy:
0.8692 - val_loss: 0.3619 - val_accuracy: 0.8668 - lr: 0.0010
Epoch 3/40
23/23 [==============================] - 0s 6ms/step - loss: 0.3025 - accuracy:
0.8842 - val_loss: 0.2886 - val_accuracy: 0.8845 - lr: 0.0010
Epoch 4/40
23/23 [==============================] - 0s 7ms/step - loss: 0.2363 - accuracy:
0.9091 - val_loss: 0.2355 - val_accuracy: 0.9056 - lr: 0.0010
Epoch 5/40
23/23 [==============================] - 0s 7ms/step - loss: 0.1937 - accuracy:
0.9259 - val_loss: 0.2006 - val_accuracy: 0.9158 - lr: 0.0010
Epoch 6/40
23/23 [==============================] - 0s 7ms/step - loss: 0.1667 - accuracy:
0.9353 - val_loss: 0.1733 - val_accuracy: 0.9253 - lr: 0.0010
Epoch 7/40
23/23 [==============================] - 0s 7ms/step - loss: 0.1428 - accuracy:
0.9421 - val_loss: 0.1622 - val_accuracy: 0.9341 - lr: 0.0010
Epoch 8/40
23/23 [==============================] - 0s 7ms/step - loss: 0.1286 - accuracy:
0.9504 - val_loss: 0.1458 - val_accuracy: 0.9334 - lr: 0.0010
Epoch 9/40
23/23 [==============================] - 0s 6ms/step - loss: 0.1136 - accuracy:
0.9570 - val_loss: 0.1424 - val_accuracy: 0.9429 - lr: 0.0010
Epoch 10/40
23/23 [==============================] - 0s 9ms/step - loss: 0.1124 - accuracy:
0.9553 - val_loss: 0.1406 - val_accuracy: 0.9409 - lr: 0.0010
Epoch 11/40
23/23 [==============================] - 0s 8ms/step - loss: 0.1032 - accuracy:
0.9609 - val_loss: 0.1205 - val_accuracy: 0.9511 - lr: 0.0010
Epoch 12/40
23/23 [==============================] - 0s 7ms/step - loss: 0.0902 - accuracy:
0.9643 - val_loss: 0.1088 - val_accuracy: 0.9552 - lr: 0.0010
Epoch 13/40
23/23 [==============================] - 0s 7ms/step - loss: 0.0831 - accuracy:
0.9676 - val_loss: 0.1040 - val_accuracy: 0.9552 - lr: 0.0010
Epoch 14/40
23/23 [==============================] - 0s 7ms/step - loss: 0.0802 - accuracy:
0.9667 - val_loss: 0.1037 - val_accuracy: 0.9592 - lr: 0.0010
Epoch 15/40
23/23 [==============================] - 0s 6ms/step - loss: 0.0832 - accuracy:
0.9679 - val_loss: 0.1026 - val_accuracy: 0.9592 - lr: 0.0010
Epoch 16/40
23/23 [==============================] - 0s 7ms/step - loss: 0.0764 - accuracy:
0.9730 - val_loss: 0.0980 - val_accuracy: 0.9626 - lr: 0.0010
Epoch 17/40
23/23 [==============================] - 0s 6ms/step - loss: 0.0752 - accuracy:
0.9710 - val_loss: 0.1239 - val_accuracy: 0.9524 - lr: 0.0010
```

```
Epoch 18/40
23/23 [==============================] - 0s 6ms/step - loss: 0.0738 - accuracy:
0.9704 - val_loss: 0.1003 - val_accuracy: 0.9579 - lr: 0.0010
Epoch 19/40
21/23 [==========================>…] - ETA: 0s - loss: 0.0681 - accuracy:
0.9740
Epoch 19: ReduceLROnPlateau reducing learning rate to 0.00010000000474974513.
23/23 [==============================] - 0s 6ms/step - loss: 0.0691 - accuracy:
0.9742 - val_loss: 0.1039 - val_accuracy: 0.9592 - lr: 0.0010
Epoch 20/40
23/23 [==============================] - 0s 7ms/step - loss: 0.0582 - accuracy:
0.9777 - val_loss: 0.0840 - val_accuracy: 0.9694 - lr: 1.0000e-04
Epoch 21/40
23/23 [==============================] - 0s 10ms/step - loss: 0.0516 - accuracy:
0.9803 - val_loss: 0.0790 - val_accuracy: 0.9728 - lr: 1.0000e-04
Epoch 22/40
23/23 [==============================] - 0s 7ms/step - loss: 0.0504 - accuracy:
0.9815 - val_loss: 0.0790 - val_accuracy: 0.9735 - lr: 1.0000e-04
Epoch 23/40
23/23 [==============================] - 0s 7ms/step - loss: 0.0504 - accuracy:
0.9828 - val_loss: 0.0779 - val_accuracy: 0.9728 - lr: 1.0000e-04
Epoch 24/40
23/23 [==============================] - 0s 6ms/step - loss: 0.0499 - accuracy:
0.9823 - val_loss: 0.0781 - val_accuracy: 0.9715 - lr: 1.0000e-04
Epoch 25/40
23/23 [==============================] - 0s 7ms/step - loss: 0.0497 - accuracy:
0.9822 - val_loss: 0.0774 - val_accuracy: 0.9715 - lr: 1.0000e-04
Epoch 26/40
23/23 [==============================] - 0s 7ms/step - loss: 0.0494 - accuracy:
0.9828 - val_loss: 0.0774 - val_accuracy: 0.9749 - lr: 1.0000e-04
Epoch 27/40
23/23 [==============================] - 0s 6ms/step - loss: 0.0489 - accuracy:
0.9828 - val_loss: 0.0767 - val_accuracy: 0.9715 - lr: 1.0000e-04
Epoch 28/40
23/23 [==============================] - 0s 9ms/step - loss: 0.0485 - accuracy:
0.9825 - val_loss: 0.0770 - val_accuracy: 0.9755 - lr: 1.0000e-04
Epoch 29/40
23/23 [==============================] - 0s 7ms/step - loss: 0.0486 - accuracy:
0.9822 - val_loss: 0.0768 - val_accuracy: 0.9721 - lr: 1.0000e-04
Epoch 30/40
23/23 [==============================] - 0s 7ms/step - loss: 0.0480 - accuracy:
0.9828 - val_loss: 0.0763 - val_accuracy: 0.9735 - lr: 1.0000e-04
Epoch 31/40
23/23 [==============================] - 0s 7ms/step - loss: 0.0478 - accuracy:
0.9840 - val_loss: 0.0758 - val_accuracy: 0.9735 - lr: 1.0000e-04
Epoch 32/40
23/23 [==============================] - 0s 7ms/step - loss: 0.0481 - accuracy:
0.9820 - val_loss: 0.0760 - val_accuracy: 0.9735 - lr: 1.0000e-04
```

```
Epoch 33/40
23/23 [==============================] - 0s 7ms/step - loss: 0.0482 - accuracy:
0.9834 - val_loss: 0.0756 - val_accuracy: 0.9728 - lr: 1.0000e-04
Epoch 34/40
23/23 [==============================] - 0s 7ms/step - loss: 0.0469 - accuracy:
0.9832 - val_loss: 0.0758 - val_accuracy: 0.9755 - lr: 1.0000e-04
Epoch 35/40
23/23 [==============================] - 0s 7ms/step - loss: 0.0472 - accuracy:
0.9825 - val_loss: 0.0751 - val_accuracy: 0.9728 - lr: 1.0000e-04
Epoch 36/40
23/23 [==============================] - 0s 6ms/step - loss: 0.0465 - accuracy:
0.9842 - val_loss: 0.0749 - val_accuracy: 0.9721 - lr: 1.0000e-04
Epoch 37/40
23/23 [==============================] - 0s 6ms/step - loss: 0.0462 - accuracy:
0.9837 - val_loss: 0.0745 - val_accuracy: 0.9728 - lr: 1.0000e-04
Epoch 38/40
23/23 [==============================] - 0s 7ms/step - loss: 0.0462 - accuracy:
0.9842 - val_loss: 0.0747 - val_accuracy: 0.9755 - lr: 1.0000e-04
Epoch 39/40
23/23 [==============================] - 0s 7ms/step - loss: 0.0459 - accuracy:
0.9835 - val_loss: 0.0740 - val_accuracy: 0.9749 - lr: 1.0000e-04
Epoch 40/40
23/23 [==============================] - 0s 6ms/step - loss: 0.0459 - accuracy:
0.9839 - val_loss: 0.0747 - val_accuracy: 0.9735 - lr: 1.0000e-04
```

[34]:

```
plt.plot(history.history['accuracy'], label='train')
plt.plot(history.history['val_accuracy'], label='val')
plt.legend()
plt.show()
```



The curves are very similar than with the binary classification, which is a good sign. Let's evaluate the model on the test set.

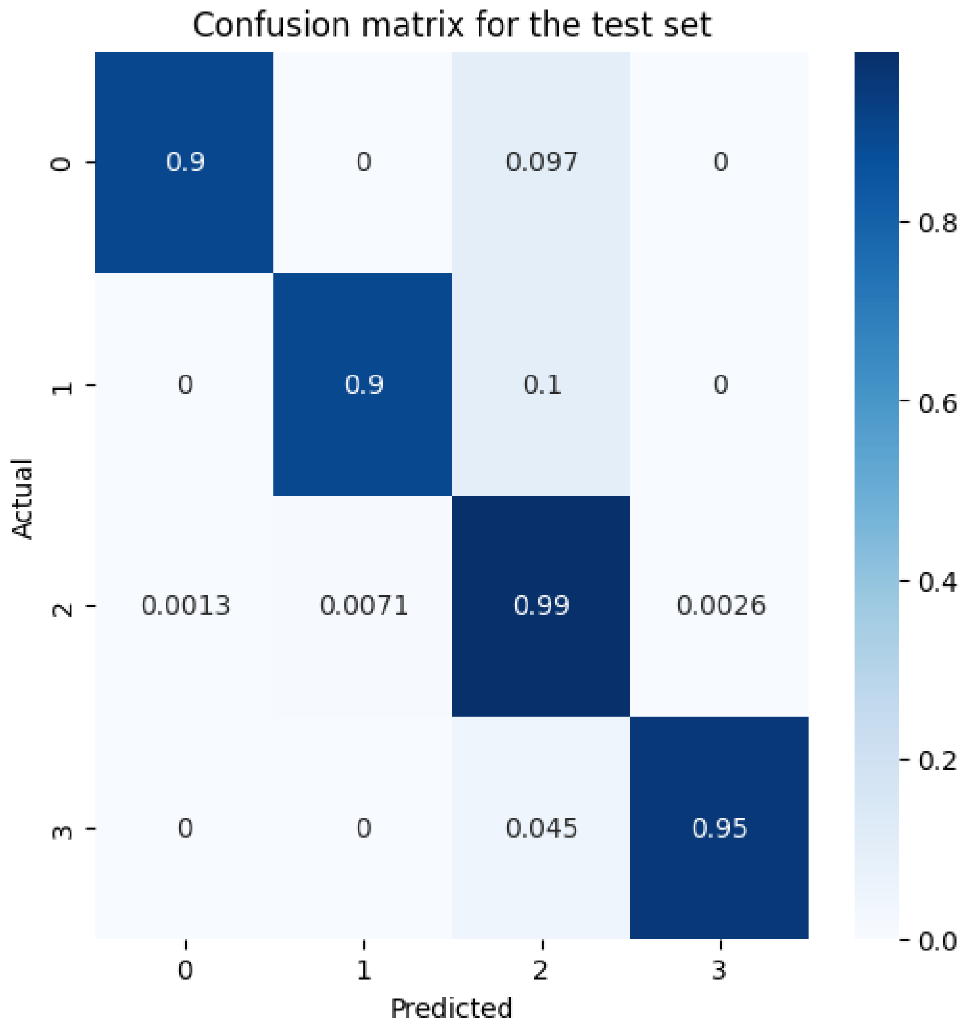
Evaluate on the test set:

[35]:
```
test_loss, test_accuracy = model.evaluate(X_test, y_test)
print(f"Test accuracy: {test_accuracy * 100:.2f}%")
```

```
 1/58 […] - ETA: 0s - loss: 0.1262 - accuracy:
0.937558/58 [==============================] - 0s 976us/step - loss: 0.0636 -
accuracy: 0.9783
Test accuracy: 97.83%
```

[36]:
```
y_pred = model.predict(X_test)
y_pred = y_pred = np.argmax(y_pred, axis=1)

plot_confusion_matrix(y_test, y_pred, title="Confusion matrix for the test set")
```

```
58/58 [==============================] - 0s 752us/step
```

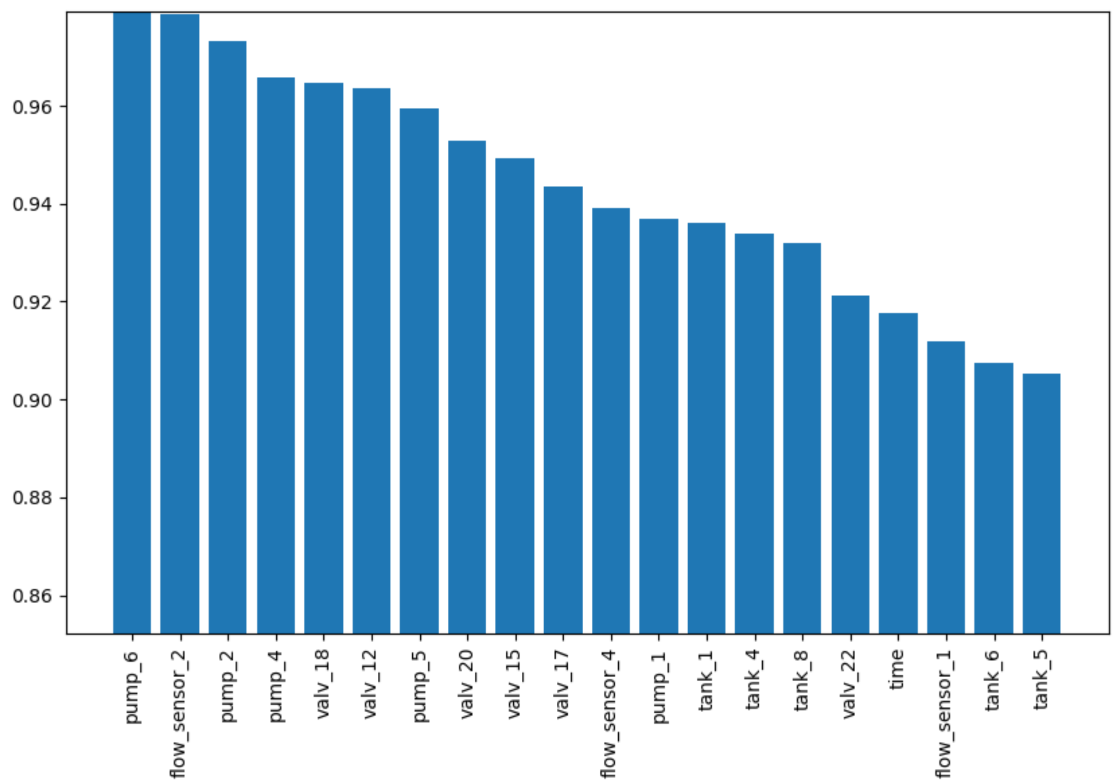


[37]:
```
print("Recall: ", recall_score(y_test, y_pred, average='macro'))
print("Precision: ", precision_score(y_test, y_pred, average='macro'))
print("F1-score: ", f1_score(y_test, y_pred, average='macro'))
print("Accuracy: ", accuracy_score(y_test, y_pred))
```

```
Recall:  0.9365330945304965
Precision:  0.9514981314147057
F1-score:  0.9439058055650589
Accuracy:  0.9782608695652174
```

The model has better results overall with 98% accuracy. The number of false negatives has been significantly reduced, but we still have a lot of false positives. We could say this is an improvement from before, as it's generally better for security to have false positives than false negatives.

[39]:
```python
def get_feature_importance(model, X_train, y_train):
    feature_importance = np.zeros(X_train.shape[1])
    for i in range(X_train.shape[1]):
        X_train_perm = X_train.copy()
        np.random.shuffle(X_train_perm[:, i])
        feature_importance[i] = model.evaluate(X_train_perm, y_train, verbose=0)[1]
    return feature_importance

feature_importance = get_feature_importance(model, X_train, y_train)

topk = 20
top_features = np.argsort(feature_importance)[::-1][:topk]
plt.figure(figsize=(10, 6))
plt.bar(range(topk), feature_importance[top_features])
plt.xticks(range(topk), df.columns[top_features], rotation=90)
plt.ylim(feature_importance.min(), feature_importance.max())
plt.show()
```



Many features seems to be as important as the others. This tells us that the model is not overfitting and that the features are all relevant.

Looking at these results, we can say that such a model could be used in production without compromising too much the overall system. Obviously, the model struggles more with MITM and DoS attacks because they are less linked to physical parameters, but it still performs well.

Adversarial attacks Let's try to look at the robustness of our model against adversarial attacks

As our model is a DNN (deep neural network) trained with gradient descent, we will use an evasion attack called FastGradientMethod to generate the adversarial samples from both the training and the test set. It works as follow:

The Fast Gradient Sign Method (FGSM) is a technique for crafting adversarial examples to fool machine learning models:

- Start with a legitimate input.
- Compute the gradient of the loss.
- Take the sign of the gradient.
- Multiply by a small constant   for perturbation.
- Add this perturbation to the input.
- The modified input often fools the model into making incorrect predictions. FGSM is efficient and widely used but has led to research in defense mechanisms against such attacks.

[69]:
```python
from art.attacks.evasion import FastGradientMethod
from art.estimators.classification import TensorFlowV2Classifier
from copy import deepcopy

model_copy = deepcopy(model)
loss = tf.keras.losses.SparseCategoricalCrossentropy()
optimizer = tf.keras.optimizers.Adam()

classifier = TensorFlowV2Classifier(model=model_copy, nb_classes=5, input_shape=(X_train.shape[0],), loss_object=loss, optimizer=optimizer, clip_values=(X_train.min(), X_train.max()))
```

Let's verify we still have the same accuracy

[70]:
```python
predictions = classifier.predict(X_test)
accuracy = np.sum(np.argmax(predictions, axis=1) == y_test) / len(y_test)
print("Accuracy on benign test examples: {}%".format(accuracy * 100))
```

```
Accuracy on benign test examples: 97.77173913043478%
```

Generate adversarial test examples by using Fast Gradient Method

[71]:
```python
attack = FastGradientMethod(estimator=classifier, eps=0.2)
x_test_adv = attack.generate(x=X_test)
```

[72]:
```python
predictions = classifier.predict(x_test_adv)
accuracy = np.sum(np.argmax(predictions, axis=1) == y_test) / len(y_test)
print("Accuracy on adversarial test examples: {}%".format(accuracy * 100))
```

```
Accuracy on adversarial test examples: 48.69565217391305%
```

[73]:
```
model_copy.evaluate(x_test_adv, y_test)
```

```
58/58 [==============================] - 0s 2ms/step - loss: 2.6133 - accuracy:
0.4870
```

[73]:
```
[2.6133041381835938, 0.48695650696754456]
```

We can see that the accuracy dropped from 97% to 49% on the attack exemples. Let's see if we fine tune our base model with the adversarial attacks if we can make it robuster

[74]:
```
x_train_adv = attack.generate(x=X_train)
x_train_adv.shape
```

[74]:
```
(5887, 41)
```

Let's generate different adversarial examples with different epsilons, this will be useful in the next steps

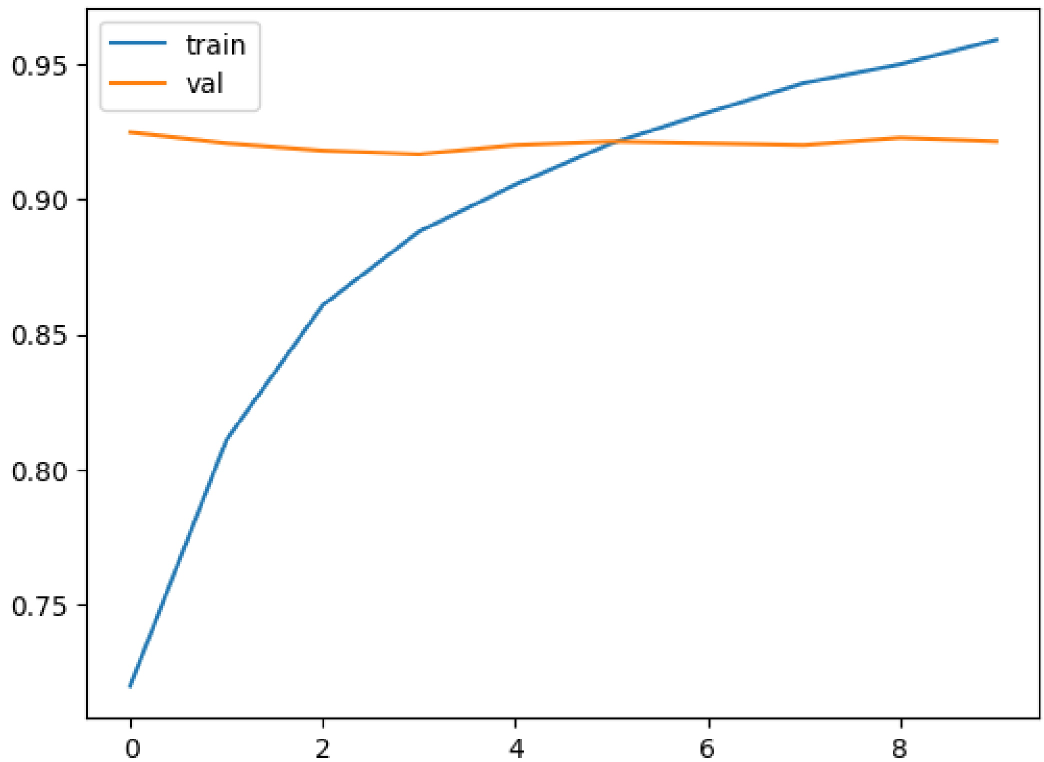
[75]:
```
epsilons = [0.01, 0.05, 0.1, 0.15, 0.2, 0.25, 0.3, 0.5, 1]
attack_points = {}
for e in epsilons:
    attack = FastGradientMethod(estimator=classifier, eps=e)
    x_adv = attack.generate(x=X_test)
    attack_points[e] = x_adv
```

[76]:
```
history_fine_tune = model_copy.fit(x_train_adv, y_train, epochs=10,␣
 ↪batch_size=256, validation_data=(X_val, y_val))
```

```
Epoch 1/10
23/23 [==============================] - 1s 12ms/step - loss: 1.6219 - accuracy:
0.7201 - val_loss: 0.2673 - val_accuracy: 0.9246
Epoch 2/10
23/23 [==============================] - 0s 8ms/step - loss: 0.6856 - accuracy:
0.8109 - val_loss: 0.1949 - val_accuracy: 0.9205
Epoch 3/10
23/23 [==============================] - 0s 8ms/step - loss: 0.4278 - accuracy:
0.8607 - val_loss: 0.1940 - val_accuracy: 0.9178
Epoch 4/10
23/23 [==============================] - 0s 8ms/step - loss: 0.3192 - accuracy:
0.8879 - val_loss: 0.1741 - val_accuracy: 0.9164
Epoch 5/10
23/23 [==============================] - 0s 8ms/step - loss: 0.2567 - accuracy:
0.9052 - val_loss: 0.1709 - val_accuracy: 0.9198
Epoch 6/10
23/23 [==============================] - 0s 8ms/step - loss: 0.2154 - accuracy:
0.9205 - val_loss: 0.1678 - val_accuracy: 0.9212
Epoch 7/10
23/23 [==============================] - 0s 8ms/step - loss: 0.1850 - accuracy:
0.9319 - val_loss: 0.1655 - val_accuracy: 0.9205
Epoch 8/10
```

```
23/23 [==============================] - 0s 8ms/step - loss: 0.1624 - accuracy:
0.9428 - val_loss: 0.1627 - val_accuracy: 0.9198
Epoch 9/10
23/23 [==============================] - 0s 8ms/step - loss: 0.1446 - accuracy:
0.9497 - val_loss: 0.1615 - val_accuracy: 0.9226
Epoch 10/10
23/23 [==============================] - 0s 11ms/step - loss: 0.1299 - accuracy:
0.9587 - val_loss: 0.1605 - val_accuracy: 0.9212
```

[77]:
```
plt.plot(history_fine_tune.history['accuracy'], label='train')
plt.plot(history_fine_tune.history['val_accuracy'], label='val')
plt.legend()
plt.show()
```



[78]:
```
model_copy.evaluate(X_test, y_test)
```

```
58/58 [==============================] - 0s 4ms/step - loss: 0.1506 - accuracy:
0.9315
```

[78]: [0.1505502313375473, 0.9315217137336731]

[79]:
```
model_copy.evaluate(x_test_adv, y_test)
```

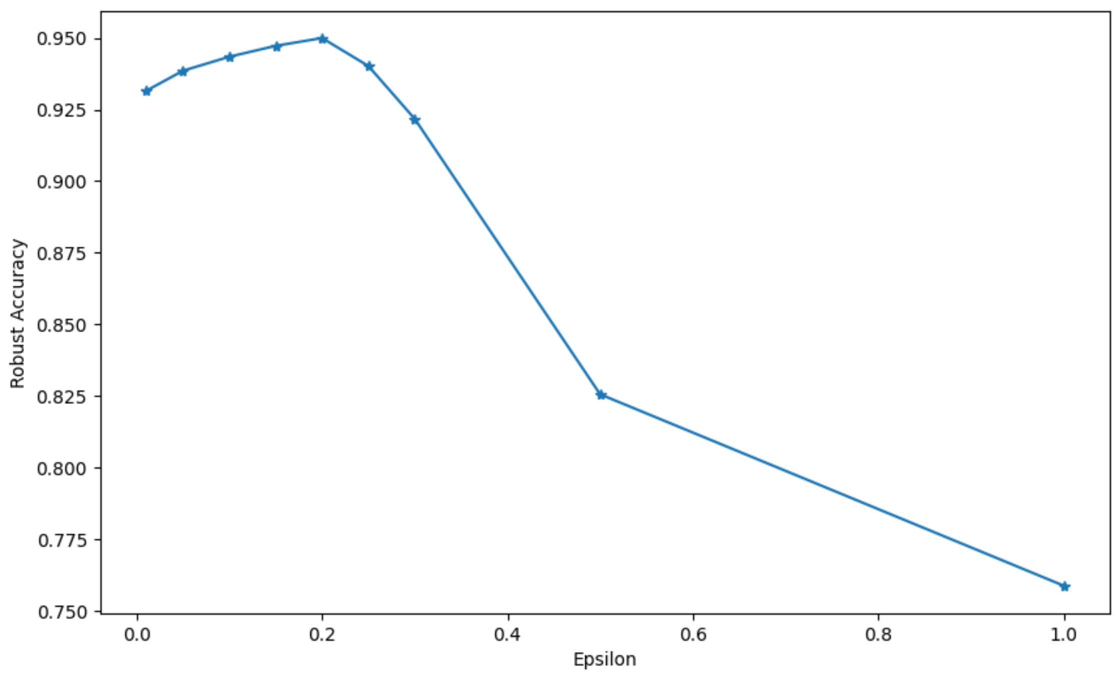
```
 1/58 [...] - ETA: 1s - loss: 0.1315 - accuracy:
0.906258/58 [==============================] - 0s 2ms/step - loss: 0.1558 -
accuracy: 0.9500
```

[79]:
```
[0.15580178797245026, 0.949999988079071]
```

We 've lost 2% on the accuracy on normal exemple but we improved from 0.47 to 0.94 on adversarial sample which means that our model is way more robust now.

Let's see the robustness as a function of the perturbation

[81]:
```
accuracies = []
for pts in attack_points.values():
    scores = model_copy.evaluate(pts, y_test, verbose=0)
    accuracies.append(scores[1])

plt.figure(figsize=(10, 6))
plt.plot(attack_points.keys(), accuracies, "*-")
plt.xlabel("Epsilon")
plt.ylabel("Robust Accuracy")
plt.show()
```



We can see that after the fine tuning the model is pretty robust with a slighty increase until 0.2 before falling down. It's logical since the model has been fine tuned with adversarial exemple that were generated using a value of 0.2 for the epsilon.

3.2.2 b. LSTM

Binary classification

[40]:
```
X_train, X_test, y_train, y_test = train_test_split(df_physical_prepared,␣
↪df_physical_labels[["new_labels", "label_n"]], test_size=0.2,␣
↪random_state=random_state)
X_train, X_val, y_train, y_val = train_test_split(X_train, y_train, test_size=0.
↪2, random_state=random_state)
```

[41]:
```
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
X_val_scaled = scaler.transform(X_val)
```

Let's create a PyTorch dataset

[42]:
```
class HITLDataset(torch.utils.data.Dataset):
    def __init__(self, X, y):
        self.X = torch.tensor(X).float()
        self.y = torch.tensor(y).long()

    def __len__(self):
        return len(self.X)

    def __getitem__(self, idx):
        return self.X[idx], self.y[idx]


train_dataset = HITLDataset(X_train_scaled, y_train["label_n"].to_numpy())
test_dataset = HITLDataset(X_test_scaled, y_test["label_n"].to_numpy())
val_dataset = HITLDataset(X_val_scaled, y_val["label_n"].to_numpy())

# Create pytorch dataloader
train_loader = torch.utils.data.DataLoader(train_dataset, batch_size=32,␣
↪shuffle=True)
test_loader = torch.utils.data.DataLoader(test_dataset, batch_size=32,␣
↪shuffle=False)
val_loader = torch.utils.data.DataLoader(val_dataset, batch_size=32,␣
↪shuffle=True)
```

[43]:
```
class LSTM(nn.Module):
    def __init__(self, input_dim, hidden_dim, output_dim):
        super().__init__()
        self.hidden_dim = hidden_dim
        self.lstm = nn.LSTM(input_dim, hidden_dim, batch_first=True)
        self.fc = nn.Linear(hidden_dim, output_dim)

    def forward(self, x):
```

```
        out, _ = self.lstm(x)
        out = self.fc(out)
        return out

input_dim = X_train_scaled.shape[1]
output_dim = len(y_train["label_n"].unique())
hidden_dim = 32
model = LSTM(input_dim, hidden_dim, output_dim)
model
```

[43]:
```
LSTM(
  (lstm): LSTM(23, 32, batch_first=True)
  (fc): Linear(in_features=32, out_features=2, bias=True)
)
```

[44]:
```
criterion = nn.CrossEntropyLoss()
optimizer = torch.optim.Adam(model.parameters(), lr=0.001)
```

[45]:
```
from tqdm import tqdm

def train(model, train_loader, val_loader, criterion, optimizer):
    model.train()
    train_loss = 0
    train_acc = 0
    val_loss = 0
    val_acc = 0
    for X, y in tqdm(train_loader, total=len(train_loader)):
        optimizer.zero_grad()
        y_pred = model(X)
        loss = criterion(y_pred, y)
        loss.backward()
        optimizer.step()
        train_loss += loss.item()
        train_acc += (y_pred.argmax(1) == y).sum().item()

    model.eval()
    with torch.no_grad():
        for X, y in tqdm(val_loader, total=len(val_loader)):
            y_pred = model(X)
            loss = criterion(y_pred, y)
            val_loss += loss.item()
            val_acc += (y_pred.argmax(1) == y).sum().item()
    return train_loss / len(train_loader), train_acc / len(train_loader.
 ↪dataset), val_loss / len(val_loader), val_acc / len(val_loader.dataset)

def test(model, test_loader, criterion):
    model.eval()
```

```
    test_loss = 0
    test_acc = 0
    y_pred_list = []
    y_true_list = []
    with torch.no_grad():
        for X, y in test_loader:
            y_pred = model(X)
            loss = criterion(y_pred, y)
            test_loss += loss.item()
            test_acc += (y_pred.argmax(1) == y).sum().item()
            y_pred_list.append(y_pred.argmax(1).cpu().numpy())
            y_true_list.append(y.cpu().numpy())
    return test_loss / len(test_loader), test_acc / len(test_loader.dataset)
```

[46]:
```
EPOCHS = 50
train_loss_list = []
train_acc_list = []
val_loss_list = []
val_acc_list = []

for _ in range(EPOCHS):
    train_loss, train_acc, val_loss, val_acc = train(model, train_loader,␣
 ↪val_loader, criterion, optimizer)
    train_loss_list.append(train_loss)
    train_acc_list.append(train_acc)
    val_loss_list.append(val_loss)
    val_acc_list.append(val_acc)
    print(f"Train loss: {train_loss:.4f}, Train acc: {train_acc:.4f}, Val loss:␣
 ↪{val_loss:.4f}, Val acc: {val_acc:.4f}")

# Plot train loss and accuracy
plt.plot(train_acc_list, label="train acc")
plt.plot(val_acc_list, label="val acc")
plt.legend()
plt.show()
```

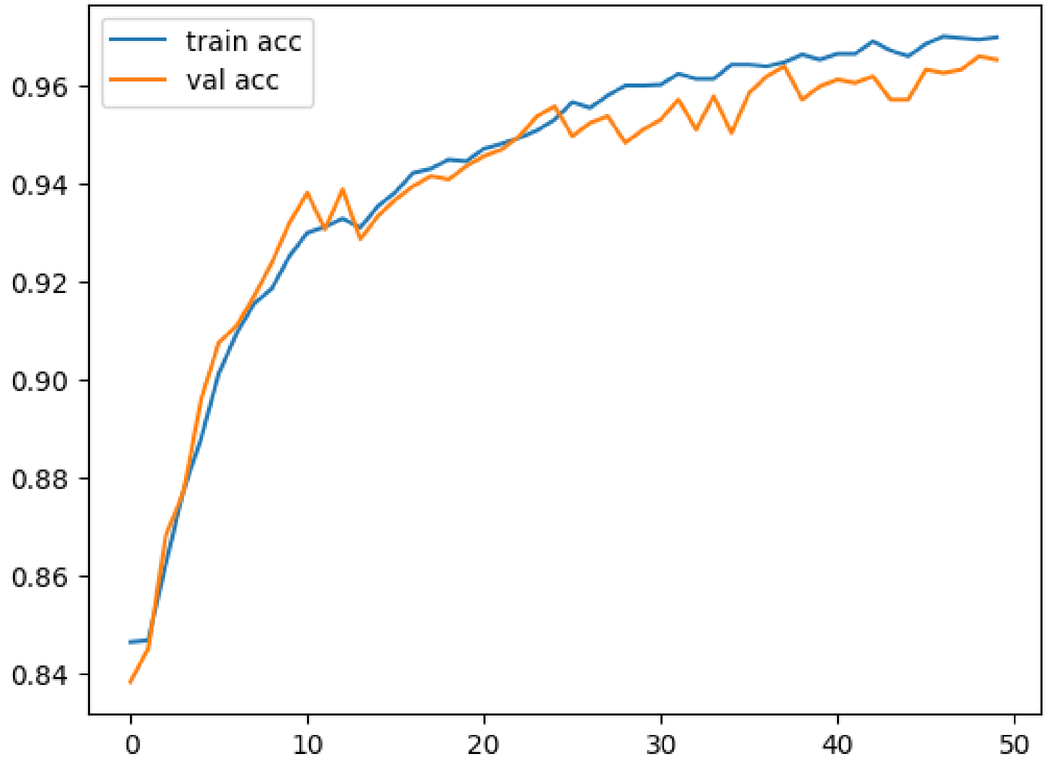
```
100%|          | 185/185 [00:00<00:00, 237.56it/s]
100%|          | 47/47 [00:00<00:00, 1704.54it/s]

Train loss: 0.4592, Train acc: 0.8465, Val loss: 0.4282, Val acc: 0.8384

100%|          | 185/185 [00:00<00:00, 322.10it/s]
100%|          | 47/47 [00:00<00:00, 1709.84it/s]

Train loss: 0.3867, Train acc: 0.8469, Val loss: 0.3622, Val acc: 0.8452

100%|          | 185/185 [00:00<00:00, 306.38it/s]
100%|          | 47/47 [00:00<00:00, 1664.79it/s]

Train loss: 0.3405, Train acc: 0.8625, Val loss: 0.3144, Val acc: 0.8683
```

```
100%|      | 185/185 [00:00<00:00, 320.40it/s]
100%|      | 47/47 [00:00<00:00, 1724.45it/s]

Train loss: 0.2942, Train acc: 0.8774, Val loss: 0.2917, Val acc: 0.8771

100%|      | 185/185 [00:00<00:00, 323.77it/s]
100%|      | 47/47 [00:00<00:00, 1753.60it/s]

Train loss: 0.2642, Train acc: 0.8881, Val loss: 0.2495, Val acc: 0.8961

100%|      | 185/185 [00:00<00:00, 322.99it/s]
100%|      | 47/47 [00:00<00:00, 1720.54it/s]

Train loss: 0.2395, Train acc: 0.9014, Val loss: 0.2287, Val acc: 0.9077

100%|      | 185/185 [00:00<00:00, 323.63it/s]
100%|      | 47/47 [00:00<00:00, 1737.08it/s]

Train loss: 0.2204, Train acc: 0.9095, Val loss: 0.2092, Val acc: 0.9111

100%|      | 185/185 [00:00<00:00, 322.56it/s]
100%|      | 47/47 [00:00<00:00, 1685.67it/s]

Train loss: 0.2067, Train acc: 0.9156, Val loss: 0.1975, Val acc: 0.9172

100%|      | 185/185 [00:00<00:00, 303.03it/s]
100%|      | 47/47 [00:00<00:00, 1628.44it/s]

Train loss: 0.1951, Train acc: 0.9187, Val loss: 0.1920, Val acc: 0.9240

100%|      | 185/185 [00:00<00:00, 308.36it/s]
100%|      | 47/47 [00:00<00:00, 1682.91it/s]

Train loss: 0.1854, Train acc: 0.9253, Val loss: 0.1837, Val acc: 0.9321

100%|      | 185/185 [00:00<00:00, 318.37it/s]
100%|      | 47/47 [00:00<00:00, 1672.06it/s]

Train loss: 0.1745, Train acc: 0.9301, Val loss: 0.1698, Val acc: 0.9382

100%|      | 185/185 [00:00<00:00, 314.17it/s]
100%|      | 47/47 [00:00<00:00, 1755.56it/s]

Train loss: 0.1681, Train acc: 0.9313, Val loss: 0.1657, Val acc: 0.9308

100%|      | 185/185 [00:00<00:00, 323.88it/s]
100%|      | 47/47 [00:00<00:00, 1731.58it/s]

Train loss: 0.1647, Train acc: 0.9329, Val loss: 0.1600, Val acc: 0.9389

100%|      | 185/185 [00:00<00:00, 312.08it/s]
100%|      | 47/47 [00:00<00:00, 1662.72it/s]

Train loss: 0.1562, Train acc: 0.9311, Val loss: 0.1638, Val acc: 0.9287

100%|      | 185/185 [00:00<00:00, 324.54it/s]
100%|      | 47/47 [00:00<00:00, 1667.32it/s]

Train loss: 0.1507, Train acc: 0.9355, Val loss: 0.1497, Val acc: 0.9335
```

```
100%|     | 185/185 [00:00<00:00, 324.31it/s]
100%|     | 47/47 [00:00<00:00, 1696.02it/s]

Train loss: 0.1472, Train acc: 0.9384, Val loss: 0.1431, Val acc: 0.9369

100%|     | 185/185 [00:00<00:00, 322.54it/s]
100%|     | 47/47 [00:00<00:00, 1716.13it/s]

Train loss: 0.1415, Train acc: 0.9423, Val loss: 0.1713, Val acc: 0.9396

100%|     | 185/185 [00:00<00:00, 323.31it/s]
100%|     | 47/47 [00:00<00:00, 1675.34it/s]

Train loss: 0.1349, Train acc: 0.9431, Val loss: 0.1377, Val acc: 0.9416

100%|     | 185/185 [00:00<00:00, 321.10it/s]
100%|     | 47/47 [00:00<00:00, 1682.42it/s]

Train loss: 0.1330, Train acc: 0.9450, Val loss: 0.1382, Val acc: 0.9409

100%|     | 185/185 [00:00<00:00, 301.13it/s]
100%|     | 47/47 [00:00<00:00, 1563.28it/s]

Train loss: 0.1305, Train acc: 0.9447, Val loss: 0.1520, Val acc: 0.9437

100%|     | 185/185 [00:00<00:00, 299.24it/s]
100%|     | 47/47 [00:00<00:00, 1650.91it/s]

Train loss: 0.1266, Train acc: 0.9472, Val loss: 0.1275, Val acc: 0.9457

100%|     | 185/185 [00:00<00:00, 322.17it/s]
100%|     | 47/47 [00:00<00:00, 1649.99it/s]

Train loss: 0.1231, Train acc: 0.9482, Val loss: 0.1295, Val acc: 0.9470

100%|     | 185/185 [00:00<00:00, 322.48it/s]
100%|     | 47/47 [00:00<00:00, 1683.87it/s]

Train loss: 0.1205, Train acc: 0.9494, Val loss: 0.1300, Val acc: 0.9498

100%|     | 185/185 [00:00<00:00, 322.15it/s]
100%|     | 47/47 [00:00<00:00, 1681.87it/s]

Train loss: 0.1177, Train acc: 0.9509, Val loss: 0.1236, Val acc: 0.9538

100%|     | 185/185 [00:00<00:00, 321.37it/s]
100%|     | 47/47 [00:00<00:00, 1687.91it/s]

Train loss: 0.1187, Train acc: 0.9531, Val loss: 0.1206, Val acc: 0.9559

100%|     | 185/185 [00:00<00:00, 305.06it/s]
100%|     | 47/47 [00:00<00:00, 1690.77it/s]

Train loss: 0.1133, Train acc: 0.9567, Val loss: 0.1189, Val acc: 0.9498

100%|     | 185/185 [00:00<00:00, 322.87it/s]
100%|     | 47/47 [00:00<00:00, 1702.35it/s]

Train loss: 0.1126, Train acc: 0.9555, Val loss: 0.1208, Val acc: 0.9525
```

```
100%|          | 185/185 [00:00<00:00, 314.49it/s]
100%|          | 47/47 [00:00<00:00, 1713.37it/s]

Train loss: 0.1079, Train acc: 0.9581, Val loss: 0.1175, Val acc: 0.9538

100%|          | 185/185 [00:00<00:00, 322.98it/s]
100%|          | 47/47 [00:00<00:00, 1677.75it/s]

Train loss: 0.1061, Train acc: 0.9601, Val loss: 0.1198, Val acc: 0.9484

100%|          | 185/185 [00:00<00:00, 322.47it/s]
100%|          | 47/47 [00:00<00:00, 1685.55it/s]

Train loss: 0.1049, Train acc: 0.9601, Val loss: 0.1117, Val acc: 0.9511

100%|          | 185/185 [00:00<00:00, 322.67it/s]
100%|          | 47/47 [00:00<00:00, 1672.60it/s]

Train loss: 0.1027, Train acc: 0.9603, Val loss: 0.1197, Val acc: 0.9532

100%|          | 185/185 [00:00<00:00, 309.40it/s]
100%|          | 47/47 [00:00<00:00, 1626.34it/s]

Train loss: 0.1007, Train acc: 0.9625, Val loss: 0.1098, Val acc: 0.9572

100%|          | 185/185 [00:00<00:00, 322.46it/s]
100%|          | 47/47 [00:00<00:00, 1678.21it/s]

Train loss: 0.0987, Train acc: 0.9615, Val loss: 0.1097, Val acc: 0.9511

100%|          | 185/185 [00:00<00:00, 322.72it/s]
100%|          | 47/47 [00:00<00:00, 1692.60it/s]

Train loss: 0.0982, Train acc: 0.9615, Val loss: 0.1165, Val acc: 0.9579

100%|          | 185/185 [00:00<00:00, 322.65it/s]
100%|          | 47/47 [00:00<00:00, 1727.87it/s]

Train loss: 0.0951, Train acc: 0.9644, Val loss: 0.1177, Val acc: 0.9504

100%|          | 185/185 [00:00<00:00, 322.55it/s]
100%|          | 47/47 [00:00<00:00, 1762.69it/s]

Train loss: 0.0959, Train acc: 0.9644, Val loss: 0.1052, Val acc: 0.9586

100%|          | 185/185 [00:00<00:00, 310.75it/s]
100%|          | 47/47 [00:00<00:00, 1673.25it/s]

Train loss: 0.0956, Train acc: 0.9640, Val loss: 0.1011, Val acc: 0.9620

100%|          | 185/185 [00:00<00:00, 321.22it/s]
100%|          | 47/47 [00:00<00:00, 1697.43it/s]

Train loss: 0.0924, Train acc: 0.9649, Val loss: 0.1030, Val acc: 0.9640

100%|          | 185/185 [00:00<00:00, 323.35it/s]
100%|          | 47/47 [00:00<00:00, 1724.09it/s]

Train loss: 0.0943, Train acc: 0.9664, Val loss: 0.1069, Val acc: 0.9572
```

```
100%|     | 185/185 [00:00<00:00, 321.88it/s]
100%|     | 47/47 [00:00<00:00, 1673.36it/s]

Train loss: 0.0909, Train acc: 0.9654, Val loss: 0.1071, Val acc: 0.9599

100%|     | 185/185 [00:00<00:00, 323.36it/s]
100%|     | 47/47 [00:00<00:00, 1718.47it/s]

Train loss: 0.0882, Train acc: 0.9666, Val loss: 0.0985, Val acc: 0.9613

100%|     | 185/185 [00:00<00:00, 322.92it/s]
100%|     | 47/47 [00:00<00:00, 1675.94it/s]

Train loss: 0.0875, Train acc: 0.9666, Val loss: 0.1019, Val acc: 0.9606

100%|     | 185/185 [00:00<00:00, 308.08it/s]
100%|     | 47/47 [00:00<00:00, 1669.81it/s]

Train loss: 0.0847, Train acc: 0.9691, Val loss: 0.1010, Val acc: 0.9620

100%|     | 185/185 [00:00<00:00, 322.33it/s]
100%|     | 47/47 [00:00<00:00, 1707.29it/s]

Train loss: 0.0875, Train acc: 0.9672, Val loss: 0.1169, Val acc: 0.9572

100%|     | 185/185 [00:00<00:00, 323.58it/s]
100%|     | 47/47 [00:00<00:00, 1687.01it/s]

Train loss: 0.0854, Train acc: 0.9660, Val loss: 0.1246, Val acc: 0.9572

100%|     | 185/185 [00:00<00:00, 301.37it/s]
100%|     | 47/47 [00:00<00:00, 1713.58it/s]

Train loss: 0.0842, Train acc: 0.9686, Val loss: 0.1009, Val acc: 0.9633

100%|     | 185/185 [00:00<00:00, 311.88it/s]
100%|     | 47/47 [00:00<00:00, 1655.99it/s]

Train loss: 0.0813, Train acc: 0.9701, Val loss: 0.1061, Val acc: 0.9627

100%|     | 185/185 [00:00<00:00, 311.96it/s]
100%|     | 47/47 [00:00<00:00, 1523.25it/s]

Train loss: 0.0804, Train acc: 0.9698, Val loss: 0.0951, Val acc: 0.9633

100%|     | 185/185 [00:00<00:00, 308.89it/s]
100%|     | 47/47 [00:00<00:00, 1711.53it/s]

Train loss: 0.0808, Train acc: 0.9694, Val loss: 0.0930, Val acc: 0.9661

100%|     | 185/185 [00:00<00:00, 322.63it/s]
100%|     | 47/47 [00:00<00:00, 1680.73it/s]

Train loss: 0.0789, Train acc: 0.9700, Val loss: 0.0930, Val acc: 0.9654
```

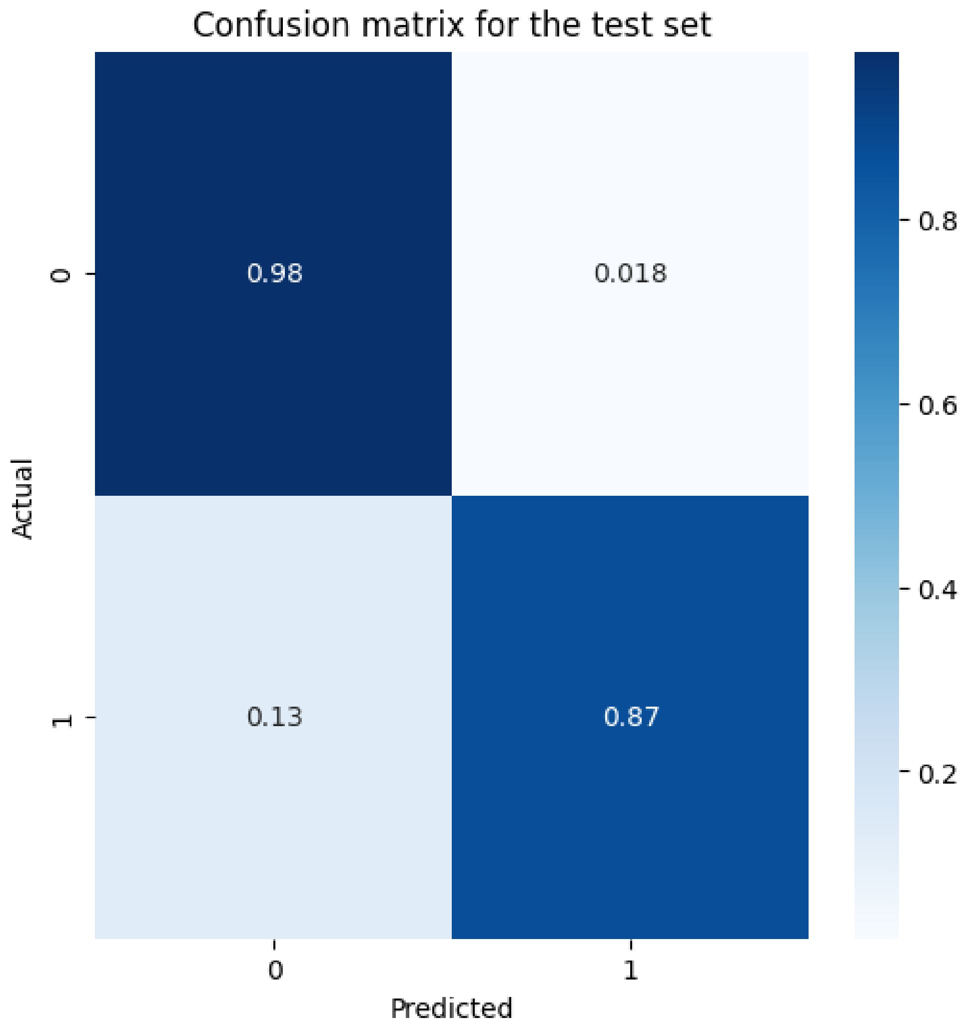


[47]:
```
test_loss, test_acc = test(model, test_loader, criterion)
print(f"Test loss: {test_loss:.4f}, Test acc: {test_acc:.4f}")
```

```
Test loss: 0.0866, Test acc: 0.9631
```

The LSTM model is training in the same way as the DNN model, let's see how the performance compares.

[48]:
```
y_pred_list = []
y_true_list = []
with torch.no_grad():
    for X, y in test_loader:
        y_pred = model(X)
        y_pred_list.append(y_pred.argmax(1).cpu().numpy())
        y_true_list.append(y.cpu().numpy())

y_pred = np.concatenate(y_pred_list)
y_true = np.concatenate(y_true_list)

plot_confusion_matrix(y_true, y_pred, title="Confusion matrix for the test set")
```



The binary class LSTM has quite a lot of false negatives, just like the DNN, let's see if the multiclass LSTM can do better.

Multiclass classification

[49]:
```
train_dataset = HITLDataset(X_train_scaled, y_train["new_labels"].to_numpy())
test_dataset = HITLDataset(X_test_scaled, y_test["new_labels"].to_numpy())
val_dataset = HITLDataset(X_val_scaled, y_val["new_labels"].to_numpy())

train_loader = torch.utils.data.DataLoader(train_dataset, batch_size=32,␣
 ↪shuffle=True)
test_loader = torch.utils.data.DataLoader(test_dataset, batch_size=32,␣
 ↪shuffle=False)
val_loader = torch.utils.data.DataLoader(val_dataset, batch_size=32,␣
 ↪shuffle=True)
```

[50]:
```
input_dim = X_train_scaled.shape[1]
output_dim = len(y_train["new_labels"].unique())
hidden_dim = 32
model = LSTM(input_dim, hidden_dim, output_dim)

criterion = nn.CrossEntropyLoss()
optimizer = torch.optim.Adam(model.parameters(), lr=0.001)
```

[51]:
```
EPOCHS = 50
train_loss_list = []
train_acc_list = []
val_loss_list = []
val_acc_list = []

for _ in range(EPOCHS):
    train_loss, train_acc, val_loss, val_acc = train(model, train_loader,␣
 ↪val_loader, criterion, optimizer)
    train_loss_list.append(train_loss)
    train_acc_list.append(train_acc)
    val_loss_list.append(val_loss)
    val_acc_list.append(val_acc)
    print(f"Train loss: {train_loss:.4f}, Train acc: {train_acc:.4f}, Val loss:␣
 ↪{val_loss:.4f}, Val acc: {val_acc:.4f}")

plt.plot(train_acc_list, label="train acc")
plt.plot(val_acc_list, label="val acc")
plt.legend()
plt.show()
```

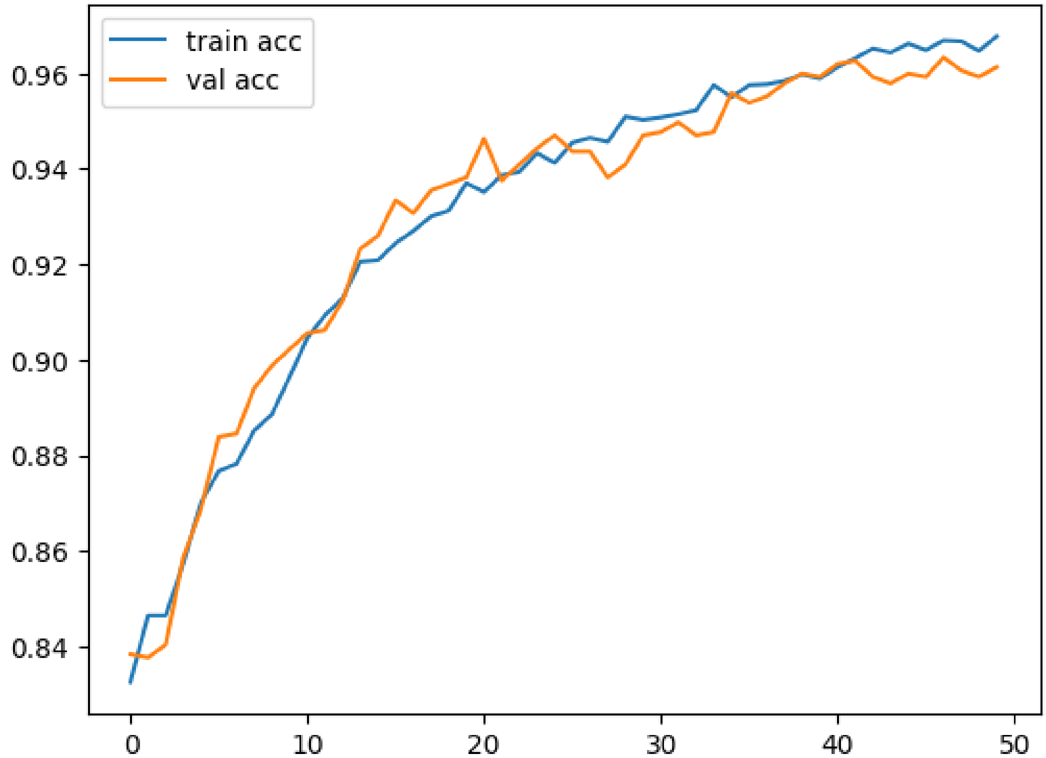
```
100%|          | 185/185 [00:00<00:00, 278.13it/s]
100%|          | 47/47 [00:00<00:00, 1685.44it/s]

Train loss: 0.8103, Train acc: 0.8326, Val loss: 0.6008, Val acc: 0.8384

100%|          | 185/185 [00:00<00:00, 246.79it/s]
100%|          | 47/47 [00:00<00:00, 1719.41it/s]

Train loss: 0.5472, Train acc: 0.8465, Val loss: 0.5328, Val acc: 0.8377

100%|          | 185/185 [00:00<00:00, 268.27it/s]
100%|          | 47/47 [00:00<00:00, 1467.42it/s]

Train loss: 0.4855, Train acc: 0.8465, Val loss: 0.4654, Val acc: 0.8405

100%|          | 185/185 [00:00<00:00, 274.39it/s]
100%|          | 47/47 [00:00<00:00, 1676.18it/s]

Train loss: 0.4397, Train acc: 0.8576, Val loss: 0.4572, Val acc: 0.8588

100%|          | 185/185 [00:00<00:00, 308.55it/s]
100%|          | 47/47 [00:00<00:00, 1761.62it/s]
```

```
Train loss: 0.4012, Train acc: 0.8703, Val loss: 0.3896, Val acc: 0.8690

100%|          | 185/185 [00:00<00:00, 297.62it/s]
100%|          | 47/47 [00:00<00:00, 1725.02it/s]

Train loss: 0.3685, Train acc: 0.8768, Val loss: 0.3665, Val acc: 0.8839

100%|          | 185/185 [00:00<00:00, 320.16it/s]
100%|          | 47/47 [00:00<00:00, 1773.57it/s]

Train loss: 0.3448, Train acc: 0.8783, Val loss: 0.3351, Val acc: 0.8846

100%|          | 185/185 [00:00<00:00, 319.42it/s]
100%|          | 47/47 [00:00<00:00, 1751.43it/s]

Train loss: 0.3162, Train acc: 0.8852, Val loss: 0.3194, Val acc: 0.8941

100%|          | 185/185 [00:00<00:00, 299.36it/s]
100%|          | 47/47 [00:00<00:00, 1713.03it/s]

Train loss: 0.2976, Train acc: 0.8886, Val loss: 0.2962, Val acc: 0.8988

100%|          | 185/185 [00:00<00:00, 320.78it/s]
100%|          | 47/47 [00:00<00:00, 1747.86it/s]

Train loss: 0.2848, Train acc: 0.8965, Val loss: 0.2794, Val acc: 0.9022

100%|          | 185/185 [00:00<00:00, 322.21it/s]
100%|          | 47/47 [00:00<00:00, 1749.36it/s]

Train loss: 0.2633, Train acc: 0.9046, Val loss: 0.2676, Val acc: 0.9056

100%|          | 185/185 [00:00<00:00, 303.15it/s]
100%|          | 47/47 [00:00<00:00, 1738.99it/s]

Train loss: 0.2481, Train acc: 0.9094, Val loss: 0.2490, Val acc: 0.9063

100%|          | 185/185 [00:00<00:00, 318.29it/s]
100%|          | 47/47 [00:00<00:00, 1724.65it/s]

Train loss: 0.2366, Train acc: 0.9129, Val loss: 0.2323, Val acc: 0.9124

100%|          | 185/185 [00:00<00:00, 320.95it/s]
100%|          | 47/47 [00:00<00:00, 1664.79it/s]

Train loss: 0.2250, Train acc: 0.9206, Val loss: 0.2208, Val acc: 0.9233

100%|          | 185/185 [00:00<00:00, 323.99it/s]
100%|          | 47/47 [00:00<00:00, 1692.78it/s]

Train loss: 0.2153, Train acc: 0.9209, Val loss: 0.2115, Val acc: 0.9260

100%|          | 185/185 [00:00<00:00, 323.08it/s]
100%|          | 47/47 [00:00<00:00, 1781.86it/s]

Train loss: 0.2029, Train acc: 0.9245, Val loss: 0.2020, Val acc: 0.9335

100%|          | 185/185 [00:00<00:00, 307.64it/s]
100%|          | 47/47 [00:00<00:00, 1687.86it/s]
```

```
Train loss: 0.1951, Train acc: 0.9270, Val loss: 0.1964, Val acc: 0.9308

100%|          | 185/185 [00:00<00:00, 323.40it/s]
100%|          | 47/47 [00:00<00:00, 1759.18it/s]

Train loss: 0.1906, Train acc: 0.9301, Val loss: 0.1885, Val acc: 0.9355

100%|          | 185/185 [00:00<00:00, 320.60it/s]
100%|          | 47/47 [00:00<00:00, 1767.18it/s]

Train loss: 0.1822, Train acc: 0.9313, Val loss: 0.1940, Val acc: 0.9369

100%|          | 185/185 [00:00<00:00, 321.35it/s]
100%|          | 47/47 [00:00<00:00, 1715.51it/s]

Train loss: 0.1762, Train acc: 0.9370, Val loss: 0.1881, Val acc: 0.9382

100%|          | 185/185 [00:00<00:00, 318.36it/s]
100%|          | 47/47 [00:00<00:00, 1758.05it/s]

Train loss: 0.1734, Train acc: 0.9352, Val loss: 0.1733, Val acc: 0.9464

100%|          | 185/185 [00:00<00:00, 316.36it/s]
100%|          | 47/47 [00:00<00:00, 1769.97it/s]

Train loss: 0.1653, Train acc: 0.9387, Val loss: 0.1684, Val acc: 0.9375

100%|          | 185/185 [00:00<00:00, 310.36it/s]
100%|          | 47/47 [00:00<00:00, 1753.16it/s]

Train loss: 0.1607, Train acc: 0.9394, Val loss: 0.1636, Val acc: 0.9409

100%|          | 185/185 [00:00<00:00, 317.69it/s]
100%|          | 47/47 [00:00<00:00, 1760.24it/s]

Train loss: 0.1564, Train acc: 0.9433, Val loss: 0.1617, Val acc: 0.9443

100%|          | 185/185 [00:00<00:00, 305.45it/s]
100%|          | 47/47 [00:00<00:00, 1771.20it/s]

Train loss: 0.1515, Train acc: 0.9413, Val loss: 0.1540, Val acc: 0.9470

100%|          | 185/185 [00:00<00:00, 327.03it/s]
100%|          | 47/47 [00:00<00:00, 1739.45it/s]

Train loss: 0.1512, Train acc: 0.9455, Val loss: 0.1533, Val acc: 0.9437

100%|          | 185/185 [00:00<00:00, 325.11it/s]
100%|          | 47/47 [00:00<00:00, 1764.14it/s]

Train loss: 0.1456, Train acc: 0.9465, Val loss: 0.1498, Val acc: 0.9437

100%|          | 185/185 [00:00<00:00, 326.79it/s]
100%|          | 47/47 [00:00<00:00, 1601.40it/s]

Train loss: 0.1407, Train acc: 0.9457, Val loss: 0.1545, Val acc: 0.9382

100%|          | 185/185 [00:00<00:00, 321.02it/s]
100%|          | 47/47 [00:00<00:00, 1780.23it/s]
```

```
Train loss: 0.1389, Train acc: 0.9509, Val loss: 0.1445, Val acc: 0.9409

100%|      | 185/185 [00:00<00:00, 323.92it/s]
100%|      | 47/47 [00:00<00:00, 1753.08it/s]

Train loss: 0.1352, Train acc: 0.9503, Val loss: 0.1436, Val acc: 0.9470

100%|      | 185/185 [00:00<00:00, 322.75it/s]
100%|      | 47/47 [00:00<00:00, 1778.15it/s]

Train loss: 0.1332, Train acc: 0.9508, Val loss: 0.1394, Val acc: 0.9477

100%|      | 185/185 [00:00<00:00, 320.12it/s]
100%|      | 47/47 [00:00<00:00, 1749.61it/s]

Train loss: 0.1299, Train acc: 0.9515, Val loss: 0.1376, Val acc: 0.9498

100%|      | 185/185 [00:00<00:00, 326.65it/s]
100%|      | 47/47 [00:00<00:00, 1781.99it/s]

Train loss: 0.1262, Train acc: 0.9523, Val loss: 0.1382, Val acc: 0.9470

100%|      | 185/185 [00:00<00:00, 296.14it/s]
100%|      | 47/47 [00:00<00:00, 1785.80it/s]

Train loss: 0.1235, Train acc: 0.9576, Val loss: 0.1357, Val acc: 0.9477

100%|      | 185/185 [00:00<00:00, 325.22it/s]
100%|      | 47/47 [00:00<00:00, 1743.47it/s]

Train loss: 0.1233, Train acc: 0.9550, Val loss: 0.1305, Val acc: 0.9559

100%|      | 185/185 [00:00<00:00, 322.82it/s]
100%|      | 47/47 [00:00<00:00, 1744.56it/s]

Train loss: 0.1205, Train acc: 0.9576, Val loss: 0.1410, Val acc: 0.9538

100%|      | 185/185 [00:00<00:00, 323.74it/s]
100%|      | 47/47 [00:00<00:00, 1781.84it/s]

Train loss: 0.1175, Train acc: 0.9577, Val loss: 0.1229, Val acc: 0.9552

100%|      | 185/185 [00:00<00:00, 323.70it/s]
100%|      | 47/47 [00:00<00:00, 1771.58it/s]

Train loss: 0.1173, Train acc: 0.9584, Val loss: 0.1255, Val acc: 0.9579

100%|      | 185/185 [00:00<00:00, 321.95it/s]
100%|      | 47/47 [00:00<00:00, 1781.39it/s]

Train loss: 0.1118, Train acc: 0.9598, Val loss: 0.1276, Val acc: 0.9599

100%|      | 185/185 [00:00<00:00, 307.52it/s]
100%|      | 47/47 [00:00<00:00, 1775.31it/s]

Train loss: 0.1118, Train acc: 0.9589, Val loss: 0.1225, Val acc: 0.9593

100%|      | 185/185 [00:00<00:00, 311.86it/s]
100%|      | 47/47 [00:00<00:00, 1673.96it/s]
```

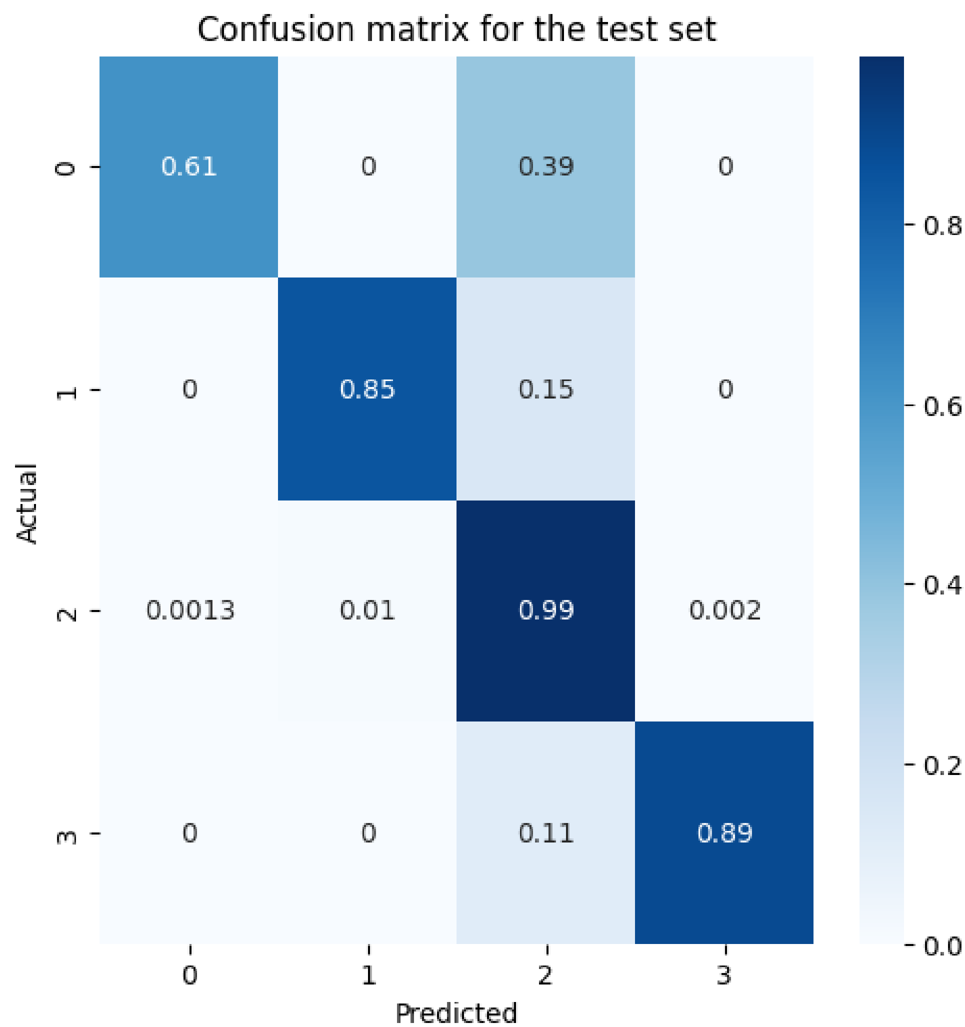
```
Train loss: 0.1078, Train acc: 0.9613, Val loss: 0.1168, Val acc: 0.9620

100%|      | 185/185 [00:00<00:00, 323.02it/s]
100%|      | 47/47 [00:00<00:00, 1751.07it/s]

Train loss: 0.1079, Train acc: 0.9632, Val loss: 0.1170, Val acc: 0.9627

100%|      | 185/185 [00:00<00:00, 327.49it/s]
100%|      | 47/47 [00:00<00:00, 1763.46it/s]

Train loss: 0.1056, Train acc: 0.9652, Val loss: 0.1225, Val acc: 0.9593

100%|      | 185/185 [00:00<00:00, 325.39it/s]
100%|      | 47/47 [00:00<00:00, 1744.16it/s]

Train loss: 0.1044, Train acc: 0.9644, Val loss: 0.1171, Val acc: 0.9579

100%|      | 185/185 [00:00<00:00, 327.21it/s]
100%|      | 47/47 [00:00<00:00, 1767.59it/s]

Train loss: 0.1019, Train acc: 0.9662, Val loss: 0.1180, Val acc: 0.9599

100%|      | 185/185 [00:00<00:00, 310.23it/s]
100%|      | 47/47 [00:00<00:00, 1797.18it/s]

Train loss: 0.1012, Train acc: 0.9649, Val loss: 0.1141, Val acc: 0.9593

100%|      | 185/185 [00:00<00:00, 314.04it/s]
100%|      | 47/47 [00:00<00:00, 1412.52it/s]

Train loss: 0.1003, Train acc: 0.9669, Val loss: 0.1154, Val acc: 0.9633

100%|      | 185/185 [00:00<00:00, 315.27it/s]
100%|      | 47/47 [00:00<00:00, 1708.03it/s]

Train loss: 0.0967, Train acc: 0.9667, Val loss: 0.1103, Val acc: 0.9606

100%|      | 185/185 [00:00<00:00, 321.67it/s]
100%|      | 47/47 [00:00<00:00, 1773.38it/s]

Train loss: 0.0969, Train acc: 0.9647, Val loss: 0.1111, Val acc: 0.9593

100%|      | 185/185 [00:00<00:00, 316.55it/s]
100%|      | 47/47 [00:00<00:00, 1710.21it/s]

Train loss: 0.0961, Train acc: 0.9677, Val loss: 0.1123, Val acc: 0.9613
```



[52]:
```
test_loss, test_acc = test(model, test_loader, criterion)
print(f"Test loss: {test_loss:.4f}, Test acc: {test_acc:.4f}")
```

```
Test loss: 0.1039, Test acc: 0.9609
```

[53]:
```
# Predict on test set
y_pred_list = []
y_true_list = []
with torch.no_grad():
    for X, y in test_loader:
        y_pred = model(X)
        y_pred_list.append(y_pred.argmax(1).cpu().numpy())
        y_true_list.append(y.cpu().numpy())

y_pred = np.concatenate(y_pred_list)
y_true = np.concatenate(y_true_list)

# Plot confusion matrix
plot_confusion_matrix(y_true, y_pred, title="Confusion matrix for the test set")
```



This is better overall, however we can see that the model is struggly with the 1st class, as it's confusing it with other classes. It's because the class is more present in the dataset. The LSTM architecture is not suited for this kind of problem as its sensitive to the class imbalance.

The DNN performs better than the LSTM and give very satisfying results.

3.3 3. Supervised classifiers

3.3.1 a. Decision Tree

Multiclass classification We will not use the Decision Tree for the binary classification, as we want to focus on the features importance.

[55]:

```python
X_train, X_test, y_train, y_test = train_test_split(df_physical_prepared,␣
↪df_physical_labels[["new_labels", "label_n"]], test_size=0.2,␣
↪random_state=random_state)
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

[55]: ((7364, 23), (1842, 23), (7364, 2), (1842, 2))

Define the model with empirical parameters

[56]:
```python
params = {
    'max_depth': 8,
    'criterion': 'gini',
    'splitter': 'best',
    'random_state': random_state
}

clf = DecisionTreeClassifier(**params)
```

[57]:
```python
pipeline = make_pipeline(
    StandardScaler(),
    clf
)

pipeline.fit(X_train, y_train["new_labels"])
```

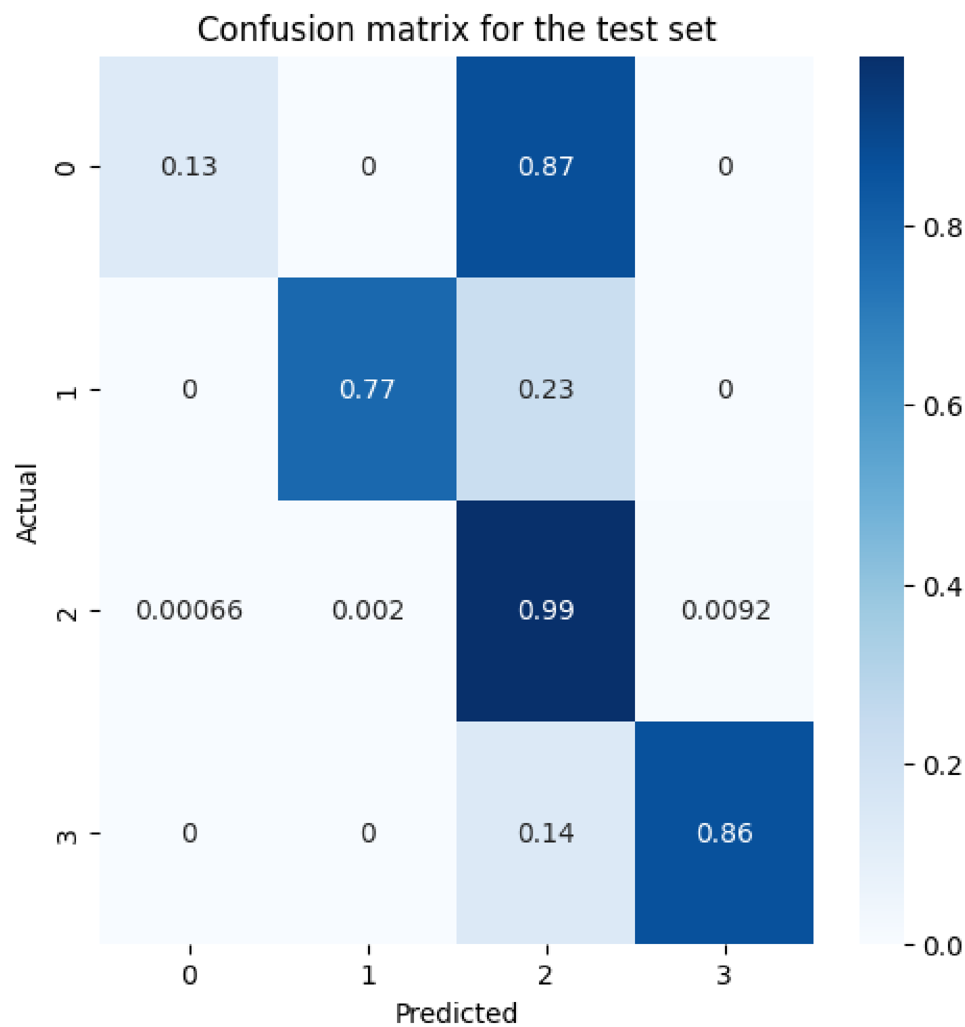
[57]:
```
Pipeline(steps=[('standardscaler', StandardScaler()),
                ('decisiontreeclassifier',
                 DecisionTreeClassifier(max_depth=8, random_state=42))])
```

[58]:
```python
preds = pipeline.predict(X_test)
```

[59]:
```python
print("Accuracy: ", accuracy_score(y_test["new_labels"], preds.round()))
print("Recall: ", recall_score(y_test["new_labels"], preds.round(),␣
↪average="macro"))
print("F1: ", f1_score(y_test["new_labels"], preds.round(), average="macro"))
print("MCC: ", matthews_corrcoef(y_test["new_labels"], preds.round()))
print("Balanced accuracy: ", balanced_accuracy_score(y_test["new_labels"],␣
↪preds.round()))
```

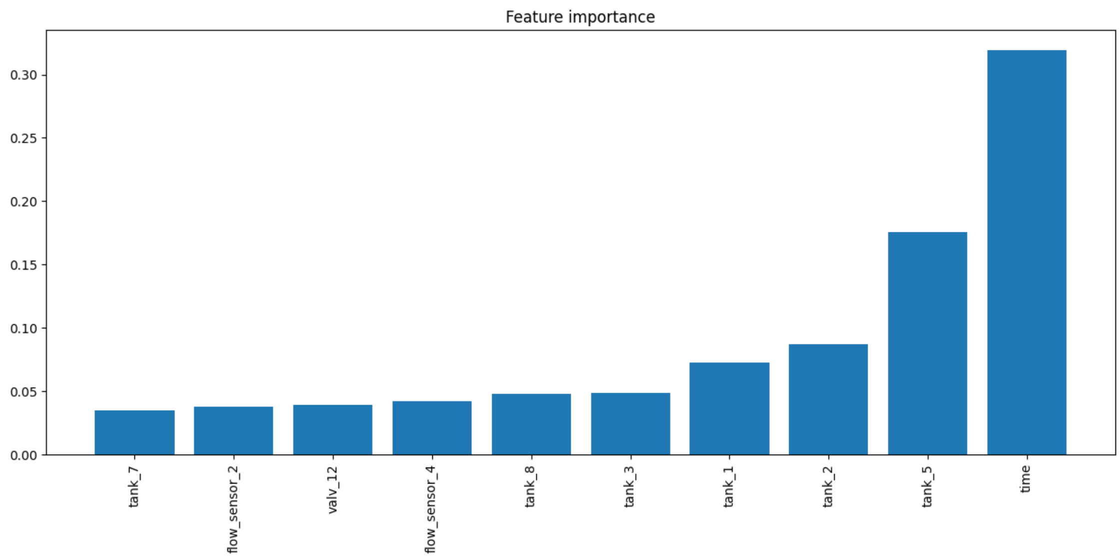
```
Accuracy:  0.9462540716612378
Recall:  0.6880059330578738
F1:  0.7314654460625277
MCC:  0.8115226264628511
Balanced accuracy:  0.6880059330578738
```

[60]:
```python
plot_confusion_matrix(y_test["new_labels"], preds.round(), title="Confusion␣
↪matrix for the test set")
```



The decision tree is very sensitive to data imbalance, explaining the bad results.

[61]:
```
def plot_feature_importance(clf):
    importance = clf.feature_importances_
    idx = np.argsort(importance)[-10:]
    importance = importance[idx]

    plt.figure(figsize=(15, 6))
    plt.title("Feature importance")
    plt.bar([x for x in range(len(importance))], importance)
    plt.xticks([x for x in range(len(importance))], X_train.columns[idx],␣
 ↪rotation='vertical')
    plt.show()

plot_feature_importance(clf)
```



The model is focusing too much on the time column, which is not relevant for the classification. Let's remove it and see if the model performs better. We will also try to handle class imbalance by using the `class_weight` parameter.

Without contextual information

[62]:
```
df_physical_no_context = remove_physical_contextual_columns(df_physical)
df_physical_no_context
```

[62]:
```
      tank_1  tank_2  tank_3  tank_4  tank_5  tank_6  tank_7  tank_8  pump_1  \
0          0       0       0       0       0       0       0       0       0
1          0       0       0       0       0       0       0       0       0
2          0       0       0       0       0       0       0       0       0
3          0       0       0       0       0       0       0       0       0
4          0       0       0       0       0       0       0       0       1
…        …     …     …     …     …     …     …     …     …
9201       4    1037       7     452     300     432      80       0       1
9202       3    1059       7     439     296     431      88       0       1
9203       4    1091       8     429     291     431      96       0       1
9204       4    1131       8     417     288     421      96       0       1
9205       4    1135       7     404     282     421     112       0       1

      pump_2  …  valv_16  valv_17  valv_18  valv_19  valv_20  valv_21  \
0          0  …        0        0        0        0        0        0
1          0  …        0        0        0        0        0        0
2          0  …        0        0        0        0        0        0
3          0  …        0        0        0        0        0        0
4          1  …        0        0        0        0        0        0
…        …  …      …      …      …      …      …      …
9201       0  …        0        0        0        0        1        0
```

```
9202        0  …        0        0        0        0        1        0
9203        0  …        0        0        0        0        1        0
9204        0  …        0        0        0        0        1        0
9205        0  …        0        0        0        0        1        0

      valv_22  label_n   label  attack
0           0      0.0  normal       1
1           0      0.0  normal       1
2           0      0.0  normal       1
3           0      0.0  normal       1
4           0      0.0  normal       1
…         …       …       …      …
9201        0      0.0  normal       0
9202        0      0.0  normal       0
9203        0      0.0  normal       0
9204        0      0.0  normal       0
9205        0      0.0  normal       0

[9206 rows x 43 columns]
```

[63]:
```
df_physical_prepared, df_physical_labels =␣
 ↪prepare_HTIL_physical_dataset(df_physical_no_context)
df_physical_prepared.head()
```

[63]:
```
   tank_1  tank_2  tank_3  tank_4  tank_5  tank_6  tank_7  tank_8  pump_1  \
0       0       0       0       0       0       0       0       0       0
1       0       0       0       0       0       0       0       0       0
2       0       0       0       0       0       0       0       0       0
3       0       0       0       0       0       0       0       0       0
4       0       0       0       0       0       0       0       0       1

   pump_2  …  pump_6  flow_sensor_1  flow_sensor_2  flow_sensor_4  valv_12  \
0       0  …       0              0              0              0        0
1       0  …       0              0              0              0        0
2       0  …       0              0              0              0        0
3       0  …       0              0              0              0        0
4       1  …       0              0              0              0        0

   valv_15  valv_17  valv_18  valv_20  valv_22
0        0        0        0        0        0
1        0        0        0        0        0
2        0        0        0        0        0
3        0        0        0        0        0
4        0        0        0        0        0

[5 rows x 22 columns]
```

[64]:
```
X_train, X_test, y_train, y_test = train_test_split(df_physical_prepared,␣
↪df_physical_labels[["new_labels", "label_n"]], test_size=0.2,␣
↪random_state=random_state)
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

[64]: ((7364, 22), (1842, 22), (7364, 2), (1842, 2))

[65]:
```
params = {
    'max_depth': 8,
    'criterion': 'gini',
    'splitter': 'best',
    'random_state': random_state
}

clf = DecisionTreeClassifier(**params)
```

[66]:
```
pipeline = make_pipeline(
    StandardScaler(),
    clf
)

pipeline.fit(X_train, y_train["new_labels"])
```

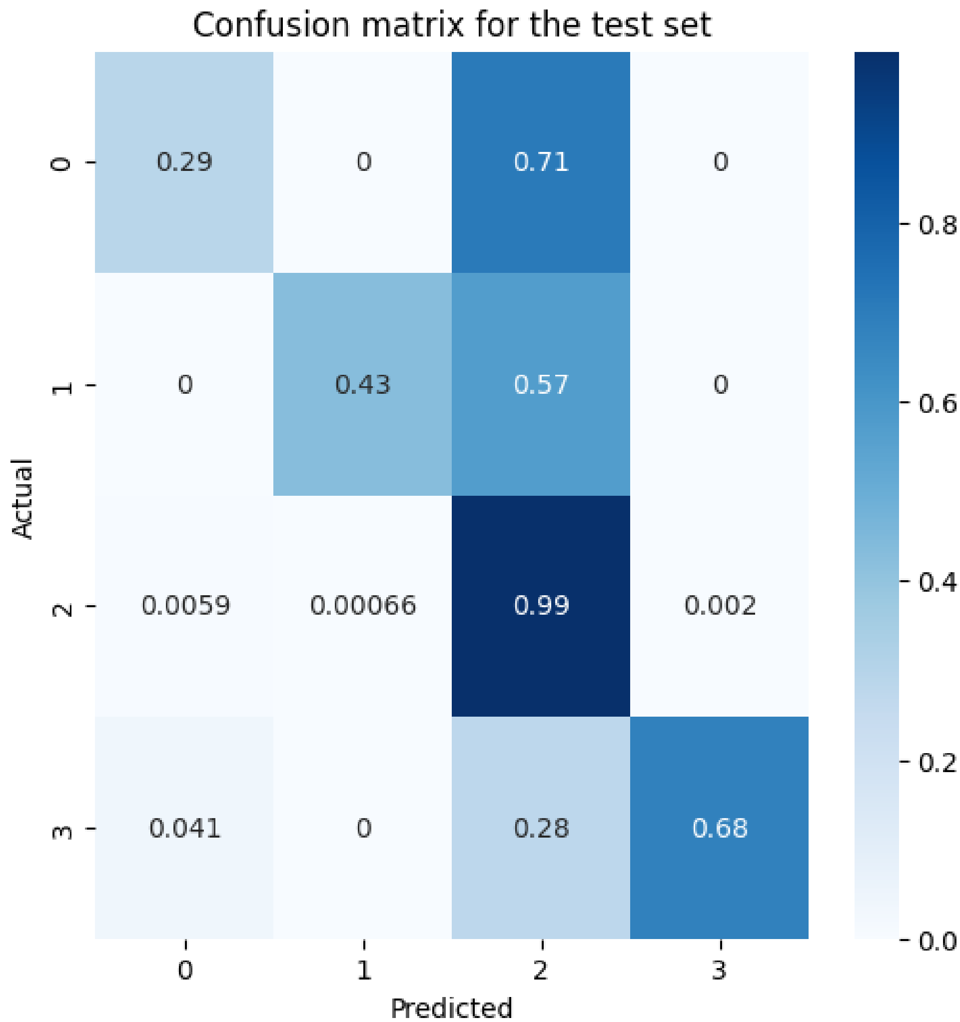
[66]:
```
Pipeline(steps=[('standardscaler', StandardScaler()),
                ('decisiontreeclassifier',
                 DecisionTreeClassifier(max_depth=8, random_state=42))])
```

[67]:
```
preds = pipeline.predict(X_test)
```

[68]:
```
print("Accuracy: ", accuracy_score(y_test["new_labels"], preds.round()))
print("Recall: ", recall_score(y_test["new_labels"], preds.round(),␣
↪average="macro"))
print("F1: ", f1_score(y_test["new_labels"], preds.round(), average="macro"))
print("MCC: ", matthews_corrcoef(y_test["new_labels"], preds.round()))
print("Balanced accuracy: ", balanced_accuracy_score(y_test["new_labels"],␣
↪preds.round()))
```

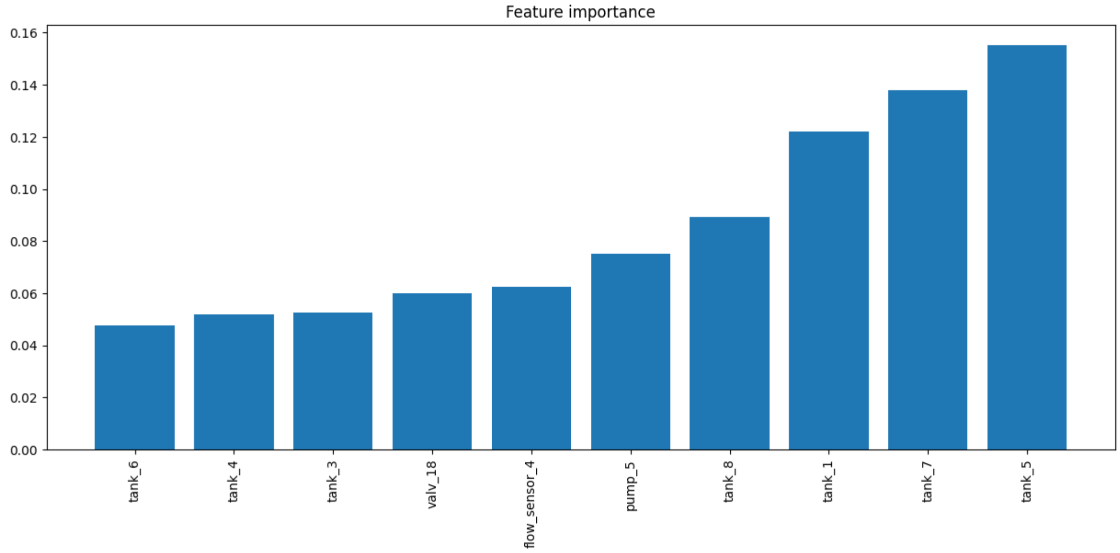
```
Accuracy:  0.9093376764386536
Recall:  0.5985431681275639
F1:  0.6701941184992033
MCC:  0.6636310742802625
Balanced accuracy:  0.5985431681275639
```

[69]:
```
plot_confusion_matrix(y_test["new_labels"], preds.round(), title="Confusion␣
↪matrix for the test set")
```



It is still not great, but it's better than before. We will try to fix this by using the `class_weight` parameter.

[70]:
```
plot_feature_importance(clf)
```

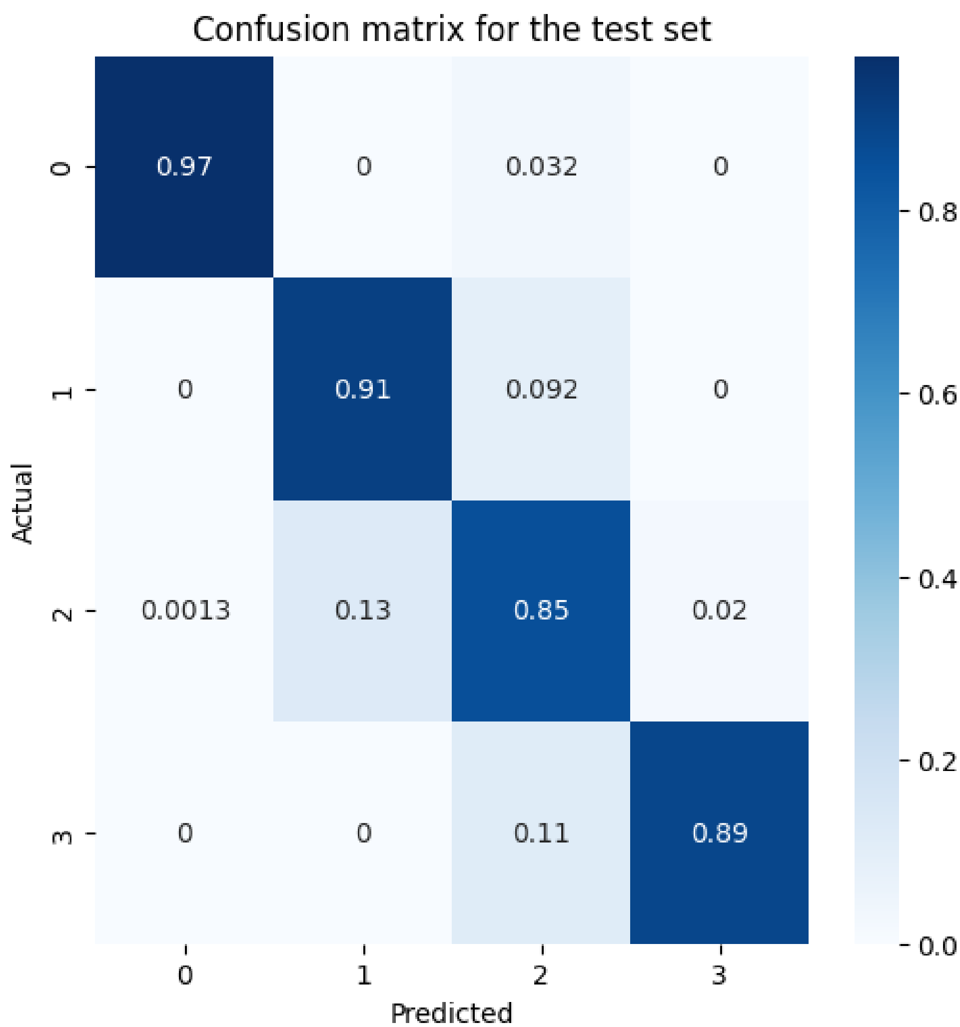


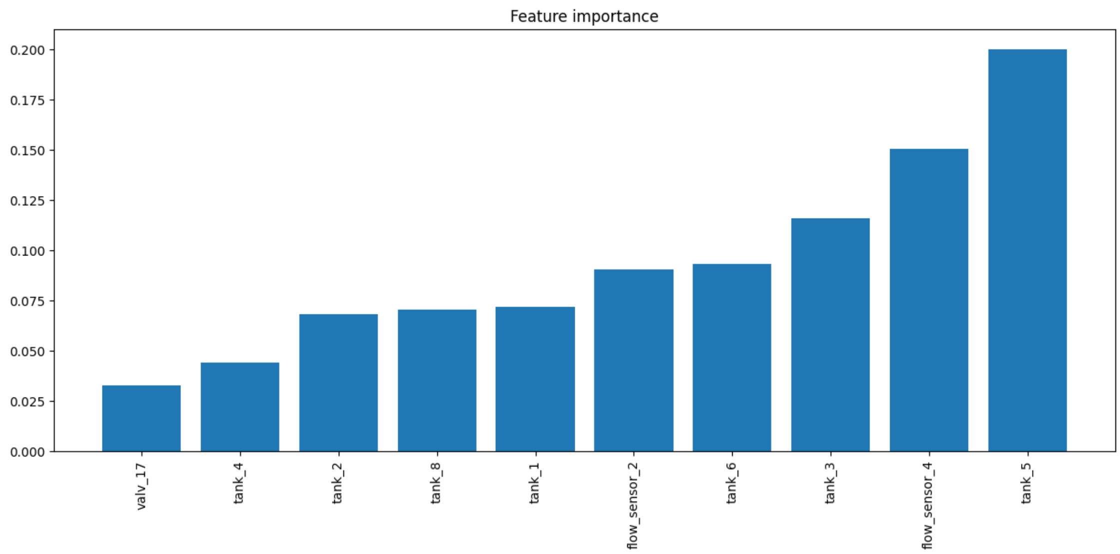
[71]:

```
params = {
    'max_depth': 8,
    'criterion': 'gini',
    'splitter': 'best',
    'random_state': random_state,
    'class_weight': 'balanced'
}

clf = DecisionTreeClassifier(**params)

pipeline = make_pipeline(
    StandardScaler(),
    clf
)

X_train = X_train[y_train["new_labels"] != 4]
y_train = y_train[y_train["new_labels"] != 4]
X_test = X_test[y_test["new_labels"] != 4]
y_test = y_test[y_test["new_labels"] != 4]

pipeline.fit(X_train, y_train["new_labels"])

preds = pipeline.predict(X_test)

print("Accuracy: ", accuracy_score(y_test["new_labels"], preds.round()))
print("Recall: ", recall_score(y_test["new_labels"], preds.round(),
 ↪average="macro"))
print("F1: ", f1_score(y_test["new_labels"], preds.round(), average="macro"))
```

```
print("MCC: ", matthews_corrcoef(y_test["new_labels"], preds.round()))
print("Balanced accuracy: ", balanced_accuracy_score(y_test["new_labels"],␣
 ↪preds.round()))

plot_confusion_matrix(y_test["new_labels"], preds.round(), title="Confusion␣
 ↪matrix for the test set")

plot_feature_importance(clf)
```

```
Accuracy:  0.8604777415852335
Recall:  0.9032609495946987
F1:  0.8198354103357238
MCC:  0.663623364956895
Balanced accuracy:  0.9032609495946987
```





After applying the balanced class weight, the results are better. The model is able to detect 90% of the anomalies, but it has a lot of confusion between 2->1 and 3->2. The feature importance is pretty even, with a bigger focus on `tank_5`, but it doesn't seem to be a problem.

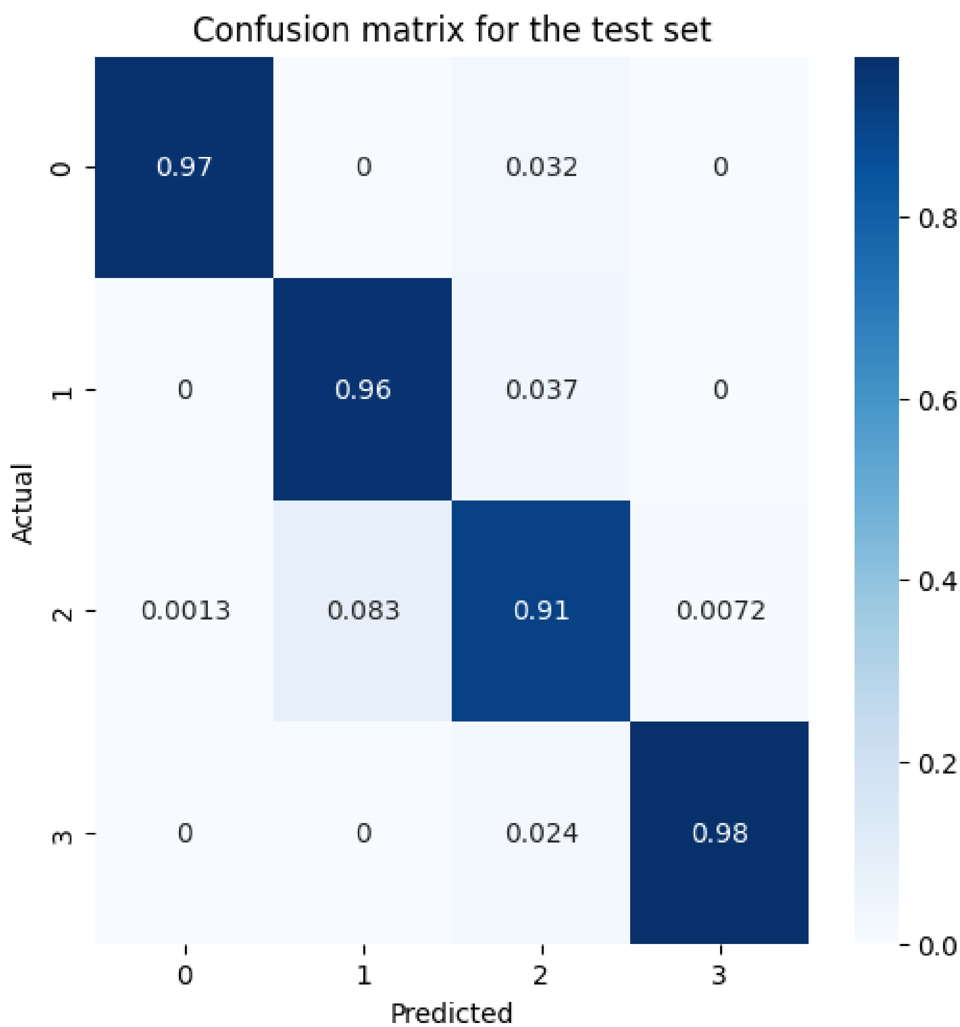
3.3.2 b. Random Forest

Let's apply the balanced class weights everytime from now on.

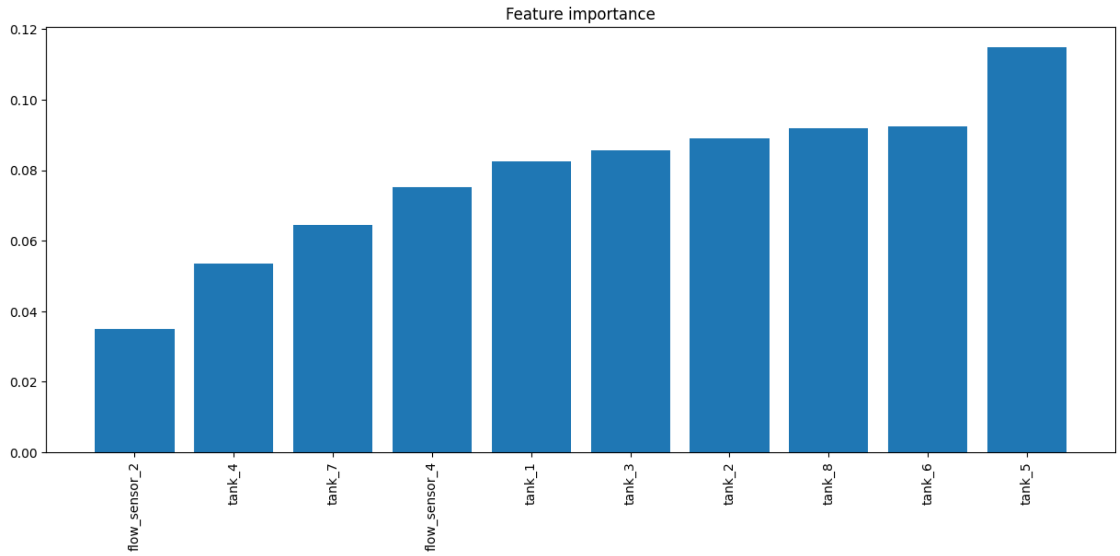
[72]:
```python
from sklearn.ensemble import RandomForestClassifier

params = {
    'max_depth': 8,
    'criterion': 'gini',
    'n_estimators': 100,
    'random_state': 42,
    'class_weight': 'balanced'
}

clf = RandomForestClassifier(**params)

pipeline = make_pipeline(
    StandardScaler(),
    clf
)

pipeline.fit(X_train, y_train["new_labels"])

preds = pipeline.predict(X_test)
```

```
print("Accuracy: ", accuracy_score(y_test["new_labels"], preds.round()))
print("Recall: ", recall_score(y_test["new_labels"], preds.round(),␣
 ↪average="macro"))
print("F1: ", f1_score(y_test["new_labels"], preds.round(), average="macro"))
print("MCC: ", matthews_corrcoef(y_test["new_labels"], preds.round()))
print("Balanced accuracy: ", balanced_accuracy_score(y_test["new_labels"],␣
 ↪preds.round()))

plot_confusion_matrix(y_test["new_labels"], preds.round(), title="Confusion␣
 ↪matrix for the test set")
```

```
Accuracy:  0.9185667752442996
Recall:  0.9536846492354968
F1:  0.8870884573107226
MCC:  0.787780941145144
Balanced accuracy:  0.9536846492354968
```



```
[73]: plot_feature_importance(clf)
```



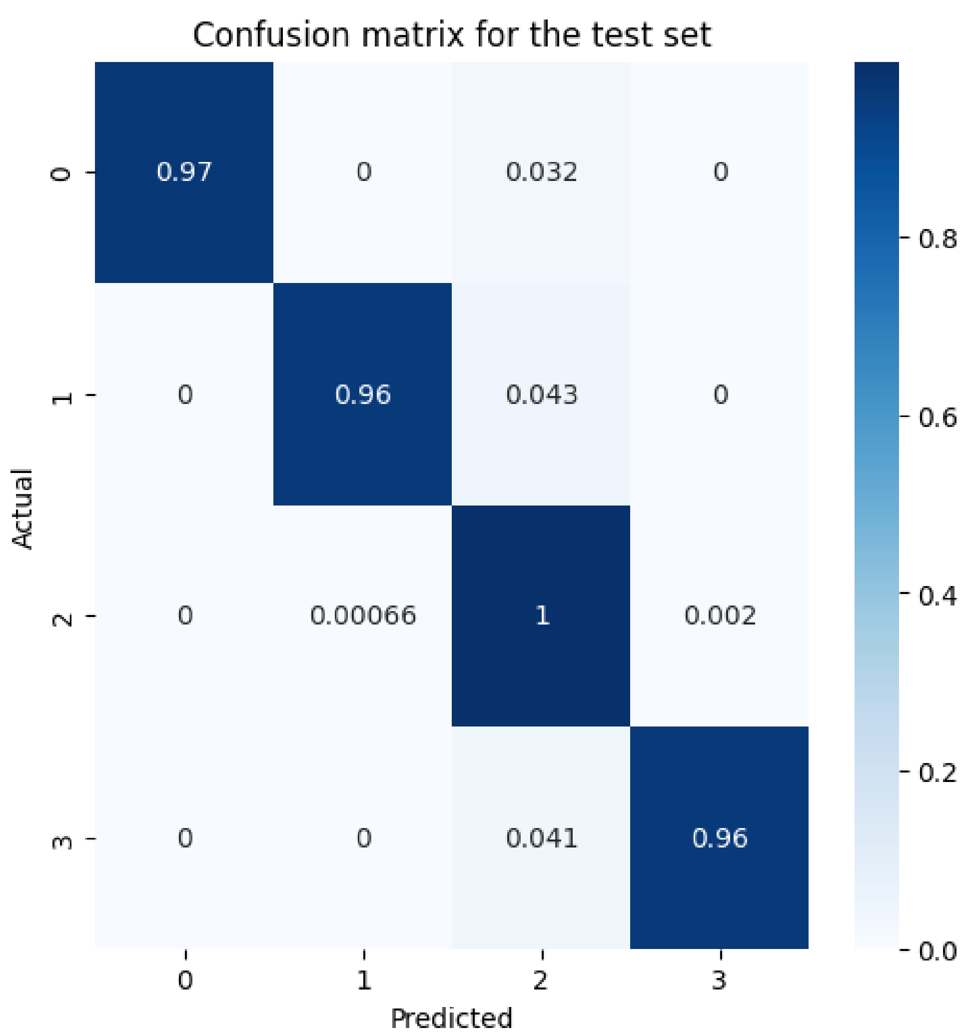
Here, using class weights and after removing the time information, we observe even better results than with the Decision Tree. The feature `tank_5` is still the most important, but the model is able to detect 95% of the anomalies.

3.3.3 c. XGBoost

```
[74]: from xgboost import XGBClassifier

params = {
    'max_depth': 8,
    'n_estimators': 100,
    'random_state': 42
}

clf = XGBClassifier(**params)

pipeline = make_pipeline(
    StandardScaler(),
    clf
)

pipeline.fit(X_train, y_train["new_labels"])

preds = pipeline.predict(X_test)
```

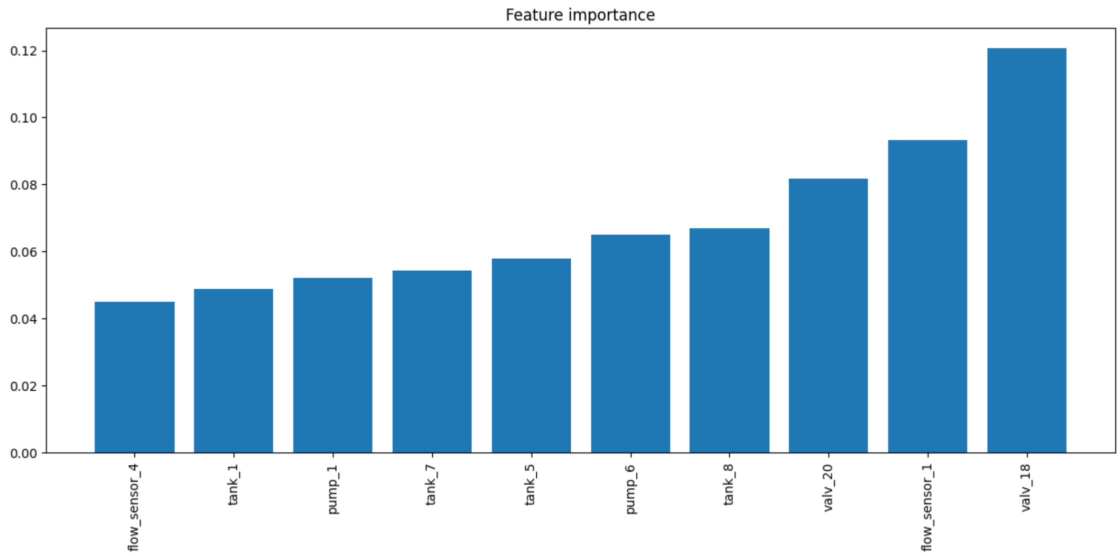
```
print("Accuracy: ", accuracy_score(y_test["new_labels"], preds.round()))
print("Recall: ", recall_score(y_test["new_labels"], preds.round(),␣
 ↪average="macro"))
print("F1: ", f1_score(y_test["new_labels"], preds.round(), average="macro"))
print("MCC: ", matthews_corrcoef(y_test["new_labels"], preds.round()))
print("Balanced accuracy: ", balanced_accuracy_score(y_test["new_labels"],␣
 ↪preds.round()))

plot_confusion_matrix(y_test["new_labels"], preds.round(), title="Confusion␣
 ↪matrix for the test set")
```

```
Accuracy:  0.990770901194354
Recall:  0.9703809482210151
F1:  0.9800655751102632
MCC:  0.9691964167380849
Balanced accuracy:  0.9703809482210151
```



The XGBoost model is the best so far, with almost 97% Recall and 99% Accuracy.

[75]:
```
plot_feature_importance(clf)
```



[94]:
```
import plotly.express as px

df_plot = df_physical_prepared.copy()
df_plot["new_labels"] = df_physical_labels["new_labels"]

fig = px.scatter_3d(df_plot, x='valv_18', y='flow_sensor_1', z='valv_20',␣
  ↪color='new_labels')
fig.show()
```

This 3D visualization is very interesting, as we see clear clusters and we can understand why XGBoost is the best classifier so far. The 3 most important features draw a clear separation between the normal and the attack data. Also, these 3 features are not used by the other models, which explains why XGBoost is better.

3.4 4. Conclusion

In conclusion, the XGBoost model is the best one for this dataset. It has the best recall and accuracy. The DNN model is also a good choice, as it has a good recall and precision, but it's not as good as the XGBoost.

The multiclass classification is better than the binary classification, as it has a better recall and accuracy. The binary classification is not suited for this dataset, as it gives us a lot of false negatives in most models.

Removing contextual information such as the time is a good idea, as it improves the results of the models. However, it's not enough to get good results, we also need to balance the classes. Once done, the results are much better.