thesis method-1

Machine Learning Based Unbalance Detection of a Rotating Shaft Using Vibration Data

Approach 1: Convolutional Neural Network on Raw Sensor Data

```
import pandas as pd
import numpy as np
import tensorflow as tf
import scipy as sc
import zipfile
from matplotlib import pyplot as plt
from matplotlib.colors import LogNorm
```

Reading Measurement Data and Preprocessing

```
use_reference_models = True
```

```
import os
```

```
pwd
```

```
'C:\\Users\\IITJMU'
```

```
model_path = 'reference'
```

```
import pandas as pd
data0D = pd.read_csv("0D.csv")
data0D
```

	V_in	Measured_RPM	Vibration_1	Vibration_2	Vibration_3
0	0.0	28.610235	0.000000	0.000000	0.000000
1	0.0	28.610235	0.000000	0.000000	0.000000
2	0.0	28.610235	0.000000	0.000000	0.000000
3	0.0	28.610235	0.000000	0.000000	0.000000
4	0.0	28.610235	0.000000	0.000000	0.000000
...	...	...	...	...	...
26423290	2.0	643.383380	0.001339	0.000769	0.003015
26423291	2.0	643.383380	0.001261	0.000952	0.003138
26423292	2.0	643.383380	0.000966	0.000895	0.003057
26423293	2.0	643.383380	0.000976	0.000744	0.002798
26423294	2.0	643.383380	0.000740	0.000880	0.002686

26423295 rows × 5 columns

```
data0E = pd.read_csv('0E.csv')
data1D = pd.read_csv('1D.csv')
data1E = pd.read_csv('1E.csv')
data2D = pd.read_csv('2D.csv')
data2E = pd.read_csv('2E.csv')
data3D = pd.read_csv('3D.csv')
data3E = pd.read_csv('3E.csv')
data4D = pd.read_csv('4D.csv')
data4E = pd.read_csv('4E.csv')
```

```
data4E
```

	V_in	Measured_RPM	Vibration_1	Vibration_2	Vibration_3
0	0.0	28.610235	0.000000	0.000000	0.000000
1	0.0	28.610235	0.000000	0.000000	0.000000
2	0.0	28.610235	0.000000	0.000000	0.000000
3	0.0	28.610235	0.000000	0.000000	0.000000
4	0.0	28.610235	0.000000	0.000000	0.000000
...	...	...	...	...	...
6914042	4.0	1080.458200	0.002939	-0.003955	0.002704
6914043	4.0	1080.458200	-0.000345	0.002913	0.000757
6914044	4.0	1080.458200	-0.003408	0.002537	-0.001725

```
skip = 50000
data0D = data0D.iloc[skip:,:]
data1D = data1D.iloc[skip:,:]
data2D = data2D.iloc[skip:,:]
data3D = data3D.iloc[skip:,:]
data4D = data4D.iloc[skip:,:]
data0E = data0E.iloc[skip:,:]
data1E = data1E.iloc[skip:,:]
data2E = data2E.iloc[skip:,:]
data3E = data3E.iloc[skip:,:]
data4E = data4E.iloc[skip:,:]
```

At the moment only the first vibration sensor **Vibration_1** is used for the analysis. All four data streams may need to be included in the future.

```
labels = {'no_unbalance':0, 'unbalance':1}
sensor = 'Vibration_1'
samples_per_second = 4096
seconds_per_analysis = 1.0
window = int(samples_per_second*seconds_per_analysis)

def get_features(data, label):
    n = int(np.floor(len(data)/window))
    data = data[:int(n)*window]
    X = data.values.reshape((n, window))
    y = np.ones(n)*labels[label]
    return X,y

X0,y0 = get_features(data0D[sensor], "no_unbalance")
X1,y1 = get_features(data1D[sensor], "unbalance")
X2,y2 = get_features(data2D[sensor], "unbalance")
X3,y3 = get_features(data3D[sensor], "unbalance")
X4,y4 = get_features(data4D[sensor], "unbalance")
X=np.concatenate([X0, X1, X2, X3, X4])
y=np.concatenate([y0, y1, y2, y3, y4])

X0_val, y0_val = get_features(data0E[sensor], "no_unbalance")
X1_val, y1_val = get_features(data1E[sensor], "unbalance")
X2_val, y2_val = get_features(data2E[sensor], "unbalance")
X3_val, y3_val = get_features(data3E[sensor], "unbalance")
X4_val, y4_val = get_features(data4E[sensor], "unbalance")
X_val=np.concatenate([X0_val, X1_val, X2_val, X3_val, X4_val])
y_val=np.concatenate([y0_val, y1_val, y2_val, y3_val, y4_val])
```

Now the dataset for training X contains 32142 samples with 4096 values each as well as the associated label information y with 32142 labels (one label per sample). The dataset for validating the trained model X_val contains 8420 samples plus the labels y_val accordingly.

```
print(X.shape, y.shape, X_val.shape, y_val.shape)
```

```
(32166, 4096) (32166,) (8359, 4096) (8359,)
```

Train-Test-Split

The dataset for training (X,y) is splitted into two subsets (X_train,y_train) and (X_test,y_test).

```
from sklearn.model_selection import train_test_split
train_test_ratio = 0.9
X_train, X_test, y_train, y_test = train_test_split(X,y, test_size = 1-train_test_ratio, random_state = 0)
X_train = np.reshape(X_train, (X_train.shape[0], X_train.shape[1], 1))
```

```
X_test = np.reshape(X_test, (X_test.shape[0], X_test.shape[1], 1))
X_val = np.reshape(X_val, (X_val.shape[0], X_val.shape[1], 1))


print(X_train.shape, y_train.shape, X_test.shape, y_test.shape)
```

```
(28949, 4096, 1) (28949,) (3217, 4096, 1) (3217,)
```

Convolutional Neural Net (CNN)

Test with Different Layer Numbers

```
from tensorflow.keras.models import Sequential, load_model, Model
from tensorflow.keras.layers import BatchNormalization,LeakyReLU,Dense,Dropout
from tensorflow.keras.layers import Input,Conv1D,MaxPooling1D,Flatten,ReLU
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import ModelCheckpoint
from tensorflow.keras.regularizers import l1_l2

weight_for_0 = len(y)/(2*len(y[y==0]))
weight_for_1 = len(y)/(2*len(y[y==1]))
class_weight = {0: weight_for_0, 1: weight_for_1}

def train_models(n_conv_layers):
    #n_conv_layers = 3 # [1,2,3,4]
    n_dense_units = 128
    dropout_rate = 0.0
    use_batch_normalization = True # [True, False]
    filter_size = 9 # [5,7,9]
    learning_rate = 0.0001
    n_epochs = 100 # [50,100,200]

    X_in = Input(shape=(X_train.shape[1],1))
    x = X_in
    for j in range(n_conv_layers):
        print(j)
        x = Conv1D(filters=(j+1)*10,
                   kernel_size=filter_size,
                   strides=1,
                   activation='linear',
                   kernel_initializer='he_uniform')(x)
        if use_batch_normalization:
            x = BatchNormalization()(x)
        x = LeakyReLU(alpha=0.05)(x)
        x = MaxPooling1D(pool_size=5, strides=2)(x)
    x = Flatten()(x)
    x = Dense(units = n_dense_units, activation='linear')(x)
    x = ReLU()(x)
    x = Dropout(rate=dropout_rate)(x)
    X_out = Dense(units = 1, activation = 'sigmoid')(x)
    classifier = Model(X_in, X_out)
    classifier.summary()

    best_model_filepath = f"{model_path}/cnn_{n_conv_layers}_layers.h5"
    checkpoint = ModelCheckpoint(best_model_filepath, monitor='val_loss',
                                 verbose=1, save_best_only=True, mode='min')

    classifier.compile(optimizer = Adam(lr=learning_rate), loss = 'binary_crossentropy',
                       metrics = ['accuracy'])

    classifier.fit(X_train, y_train, epochs = n_epochs, batch_size = 64,
                   validation_data=(X_test, y_test), callbacks=[checkpoint],
                   class_weight=class_weight)
    classifier = load_model(best_model_filepath)
    score = classifier.evaluate(X_val, y_val)


if not use_reference_models:
    for i in range(1,5):
        train_models(i)
```

Evaluation

```
X_val_1 = X_val[:len(y0_val),:,:]
X_val_2 = X_val[len(y0_val):len(y0_val)+len(y1_val),:,:]
X_val_3 = X_val[len(y0_val)+len(y1_val):len(y0_val)+len(y1_val)+
```

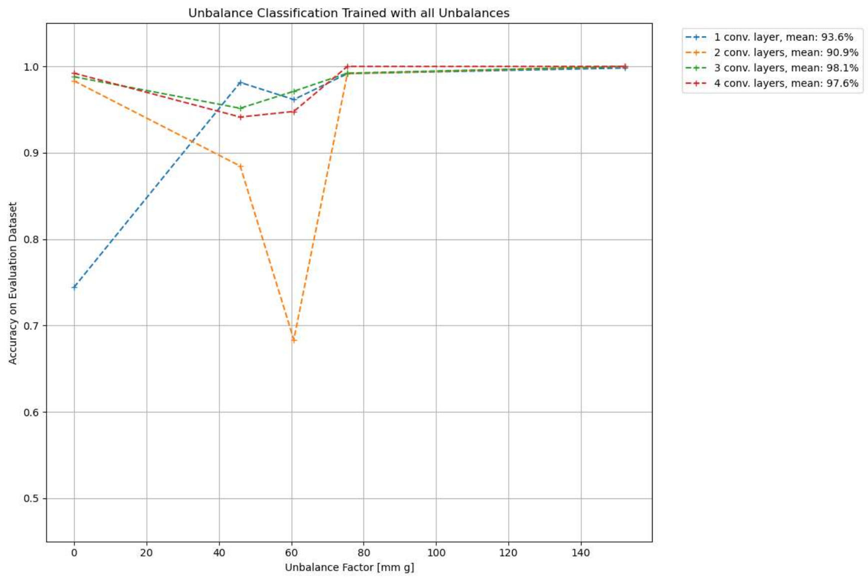
```
                len(y2_val),:,:]
X_val_4 = X_val[len(y0_val)+len(y1_val)+len(y2_val):len(y0_val)+
                len(y1_val)+len(y2_val)+len(y3_val),:,:]
X_val_5 = X_val[len(y0_val)+len(y1_val)+len(y2_val)+len(y3_val):len(y0_val)+
                len(y1_val)+len(y2_val)+len(y3_val)+len(y4_val),:,:]


accuracies = []
accuracies_all = []
for layer_n in range(1,5):

    filepath = f"{model_path}/cnn_{layer_n}_layers.h5"
    model_i = load_model(filepath)

    val_acc_1 = model_i.evaluate(X_val_1, y0_val)[1]
    val_acc_2 = model_i.evaluate(X_val_2, y1_val)[1]
    val_acc_3 = model_i.evaluate(X_val_3, y2_val)[1]
    val_acc_4 = model_i.evaluate(X_val_4, y3_val)[1]
    val_acc_5 = model_i.evaluate(X_val_5, y4_val)[1]
    val_acc_all = model_i.evaluate(X_val, y_val)[1]
    accuracies_layer_i = [val_acc_1, val_acc_2, val_acc_3, val_acc_4, val_acc_5]
    accuracies.append(accuracies_layer_i)
    accuracies_all.append(val_acc_all)

accuracies = np.array(accuracies)
accuracies_all = np.array(accuracies_all)
```

```
53/53 [==============================] - 3s 6ms/step - loss: 0.7369 - accuracy: 0.7443
53/53 [==============================] - 0s 5ms/step - loss: 0.0497 - accuracy: 0.9815
53/53 [==============================] - 0s 5ms/step - loss: 0.0909 - accuracy: 0.9617
53/53 [==============================] - 0s 5ms/step - loss: 0.0259 - accuracy: 0.9916
53/53 [==============================] - 0s 5ms/step - loss: 0.0038 - accuracy: 0.9982
262/262 [==============================] - 2s 6ms/step - loss: 0.1813 - accuracy: 0.9355
53/53 [==============================] - 1s 9ms/step - loss: 0.0589 - accuracy: 0.9832
53/53 [==============================] - 0s 8ms/step - loss: 0.3932 - accuracy: 0.8846
53/53 [==============================] - 0s 7ms/step - loss: 1.2903 - accuracy: 0.6836
53/53 [==============================] - 0s 8ms/step - loss: 0.0249 - accuracy: 0.9916
53/53 [==============================] - 0s 8ms/step - loss: 1.0724e-07 - accuracy: 1.0000
262/262 [==============================] - 2s 7ms/step - loss: 0.3531 - accuracy: 0.9087
53/53 [==============================] - 1s 10ms/step - loss: 0.0444 - accuracy: 0.9880
53/53 [==============================] - 1s 10ms/step - loss: 0.2956 - accuracy: 0.9516
53/53 [==============================] - 1s 10ms/step - loss: 0.1172 - accuracy: 0.9712
53/53 [==============================] - 1s 10ms/step - loss: 0.0334 - accuracy: 0.9922
53/53 [==============================] - 1s 10ms/step - loss: 1.5265e-16 - accuracy: 1.0000
262/262 [==============================] - 3s 10ms/step - loss: 0.0981 - accuracy: 0.9806
53/53 [==============================] - 1s 12ms/step - loss: 0.0518 - accuracy: 0.9922
53/53 [==============================] - 1s 12ms/step - loss: 0.5719 - accuracy: 0.9414
53/53 [==============================] - 1s 11ms/step - loss: 0.4952 - accuracy: 0.9479
53/53 [==============================] - 1s 12ms/step - loss: 1.0026e-05 - accuracy: 1.0000
53/53 [==============================] - 1s 17ms/step - loss: 6.1037e-24 - accuracy: 1.0000
262/262 [==============================] - 4s 13ms/step - loss: 0.2237 - accuracy: 0.9763
```

```
accuracies_all
```

```
array([0.93551862, 0.90872115, 0.98061967, 0.97631294])
```

```
fig=plt.figure(figsize=(12,8))
ax1=plt.subplot(111, title = "Unbalance Classification Trained with all Unbalances")
unbalances = np.array([0, 4.59e-5, 6.07e-5,7.55e-5,1.521e-4])
ax1.plot(1e6*unbalances, accuracies[0,:], label=f"1 conv. layer, mean: {100.0*accuracies_all[0]:.1f}%", marker="+", ls="--")
ax1.plot(1e6*unbalances, accuracies[1,:], label=f"2 conv. layers, mean: {100.0*accuracies_all[1]:.1f}%", marker="+", ls="--")
ax1.plot(1e6*unbalances, accuracies[2,:], label=f"3 conv. layers, mean: {100.0*accuracies_all[2]:.1f}%", marker="+", ls="--")
ax1.plot(1e6*unbalances, accuracies[3,:], label=f"4 conv. layers, mean: {100.0*accuracies_all[3]:.1f}%", marker="+", ls="--")
plt.ylabel("Accuracy on Evaluation Dataset")
plt.xlabel("Unbalance Factor [mm g]")
plt.legend(bbox_to_anchor=(1.04,1), loc="upper left")
plt.ylim([0.45, 1.05])
plt.grid(True)
plt.tight_layout()
plt.show()
```



Rotation Speed Dependent Evaluation

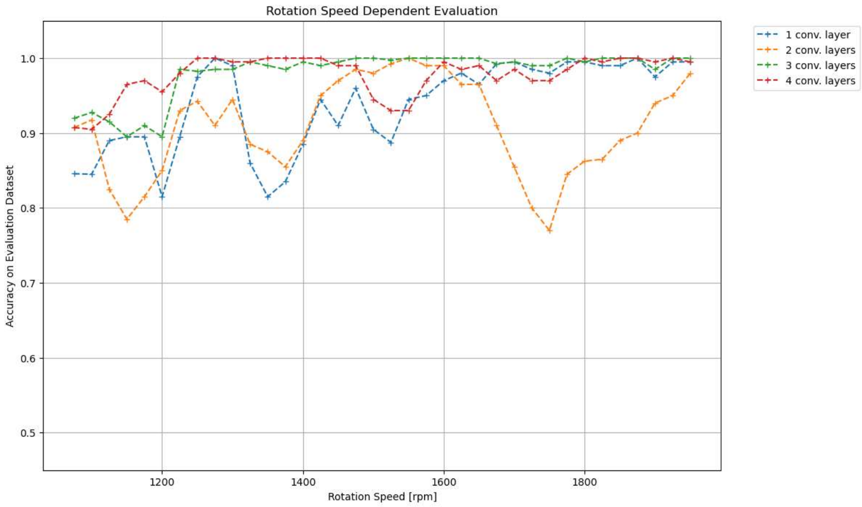
```
from tensorflow.keras.models import load_model

model1 = load_model(f"{model_path}/cnn_1_layers.h5")
model2 = load_model(f"{model_path}/cnn_2_layers.h5")
model3 = load_model(f"{model_path}/cnn_3_layers.h5")
model4 = load_model(f"{model_path}/cnn_4_layers.h5")


def v2rpm(v):
    return 212*v + 209

from scipy.stats import mode
# 3s ramp up
fade_in = np.arange(0.0, 4.0, 4.0/(3*4096))
# complete voltage sweep
measurement_cycle = np.repeat(np.arange(4.0, 8.2, 0.1), 4096*20.0)
# measurement: start-up + 2 voltage sweeps
measurement = np.concatenate([fade_in, np.tile(measurement_cycle,3)])
# select the data as actually used
measurement1 = measurement[50000:]
measurement1 = measurement1[:int(len(measurement1)/4096)*4096].reshape(-1,4096)
voltages_measurement = mode(measurement1, axis=1)[0]
voltages_used = np.concatenate([voltages_measurement[:len(X_val_1)],
                                voltages_measurement[:len(X_val_2)],
                                voltages_measurement[:len(X_val_3)],
                                voltages_measurement[:len(X_val_4)],
                                voltages_measurement[:len(X_val_5)]])
rpms_used = v2rpm(voltages_used)
```

```
C:\Users\IITJMU\AppData\Local\Temp\ipykernel_7636\1398942425.py:14: FutureWarning: Unlike other reduction functions (e.g. `skew`, `
  voltages_measurement = mode(measurement1, axis=1)[0]
```

```
rpm_borders = np.arange(1050, 1975, 25)
errors_per_rpm_range1 = []
errors_per_rpm_range2 = []
errors_per_rpm_range3 = []
errors_per_rpm_range4 = []
for i in range(len(rpm_borders)-1):
    eval_inds = np.where((rpms_used>rpm_borders[i])&(rpms_used<rpm_borders[i+1]))[0]
    errors_per_rpm_range1.append(
        1-np.mean(np.abs(np.int32(model1.predict(X_val[eval_inds])>0.5).reshape(-1)-y_val[eval_inds])))
    errors_per_rpm_range2.append(
        1-np.mean(np.abs(np.int32(model2.predict(X_val[eval_inds])>0.5).reshape(-1)-y_val[eval_inds])))
    errors_per_rpm_range3.append(
        1-np.mean(np.abs(np.int32(model3.predict(X_val[eval_inds])>0.5).reshape(-1)-y_val[eval_inds])))
    errors_per_rpm_range4.append(
        1-np.mean(np.abs(np.int32(model4.predict(X_val[eval_inds])>0.5).reshape(-1)-y_val[eval_inds])))
```

```
6/6 [==============================] - 0s 8ms/step
6/6 [==============================] - 0s 9ms/step
6/6 [==============================] - 0s 13ms/step
6/6 [==============================] - 0s 16ms/step
13/13 [==============================] - 0s 6ms/step
13/13 [==============================] - 0s 9ms/step
13/13 [==============================] - 0s 10ms/step
13/13 [==============================] - 0s 12ms/step
7/7 [==============================] - 0s 5ms/step
7/7 [==============================] - 0s 7ms/step
7/7 [==============================] - 0s 9ms/step
7/7 [==============================] - 0s 11ms/step
7/7 [==============================] - 0s 5ms/step
7/7 [==============================] - 0s 7ms/step
7/7 [==============================] - 0s 9ms/step
7/7 [==============================] - 0s 11ms/step
7/7 [==============================] - 0s 6ms/step
7/7 [==============================] - 0s 7ms/step
7/7 [==============================] - 0s 9ms/step
7/7 [==============================] - 0s 11ms/step
7/7 [==============================] - 0s 5ms/step
7/7 [==============================] - 0s 7ms/step
7/7 [==============================] - 0s 10ms/step
7/7 [==============================] - 0s 11ms/step
7/7 [==============================] - 0s 5ms/step
7/7 [==============================] - 0s 7ms/step
7/7 [==============================] - 0s 10ms/step
7/7 [==============================] - 0s 11ms/step
13/13 [==============================] - 0s 5ms/step
13/13 [==============================] - 0s 8ms/step
13/13 [==============================] - 0s 10ms/step
13/13 [==============================] - 0s 13ms/step
7/7 [==============================] - 0s 5ms/step
7/7 [==============================] - 0s 7ms/step
7/7 [==============================] - 0s 9ms/step
7/7 [==============================] - 0s 11ms/step
7/7 [==============================] - 0s 5ms/step
7/7 [==============================] - 0s 7ms/step
7/7 [==============================] - 0s 9ms/step
7/7 [==============================] - 0s 11ms/step
7/7 [==============================] - 0s 5ms/step
7/7 [==============================] - 0s 7ms/step
7/7 [==============================] - 0s 9ms/step
7/7 [==============================] - 0s 11ms/step
7/7 [==============================] - 0s 5ms/step
7/7 [==============================] - 0s 7ms/step
7/7 [==============================] - 0s 9ms/step
7/7 [==============================] - 0s 11ms/step
13/13 [==============================] - 0s 5ms/step
13/13 [==============================] - 0s 7ms/step
13/13 [==============================] - 0s 10ms/step
13/13 [==============================] - 0s 12ms/step
7/7 [==============================] - 0s 5ms/step
7/7 [==============================] - 0s 7ms/step
7/7 [==============================] - 0s 10ms/step
7/7 [==============================] - 0s 12ms/step
7/7 [==============================] - 0s 5ms/step
7/7 [==============================] - 0s 7ms/step
```

```
fig=plt.figure(figsize=(12,8))
ax1=plt.subplot(111, title = "Rotation Speed Dependent Evaluation")
ax1.plot(np.array(rpm_borders[:-1])+25, errors_per_rpm_range1, marker="+", ls="--", label="1 conv. layer")
ax1.plot(np.array(rpm_borders[:-1])+25, errors_per_rpm_range2, marker="+", ls="--", label="2 conv. layers")
ax1.plot(np.array(rpm_borders[:-1])+25, errors_per_rpm_range3, marker="+", ls="--", label="3 conv. layers")
ax1.plot(np.array(rpm_borders[:-1])+25, errors_per_rpm_range4, marker="+", ls="--", label="4 conv. layers")
plt.ylabel("Accuracy on Evaluation Dataset")
plt.xlabel("Rotation Speed [rpm]")
plt.legend(bbox_to_anchor=(1.04,1), loc="upper left")
plt.ylim([0.45, 1.05])
plt.grid(True)
plt.show()
```



Pairwise Unbalance Training and Evaluation

```
X_dev = [X0, X1, X2, X3, X4]
y_dev = [y0, y1, y2, y3, y4]

X_val_separated = [X_val_1, X_val_2, X_val_3, X_val_4, X_val_5]
y_val_separated = [y0_val, y1_val, y2_val, y3_val, y4_val]


for n_conv_layers in range(1,5):
    for dataset_i in range(4):
        X_dev_i = np.concatenate([X_dev[0], X_dev[dataset_i+1]])
        y_dev_i = np.concatenate([y_dev[0], y_dev[dataset_i+1]])
        X_val_i = np.concatenate([X_val_separated[0], X_val_separated[dataset_i+1]])
        y_val_i = np.concatenate([y_val_separated[0], y_val_separated[dataset_i+1]])

        train_test_ratio = 0.9
        X_train_i, X_test_i, y_train_i, y_test_i = train_test_split(
            X_dev_i,y_dev_i, test_size = 1-train_test_ratio, random_state = 0)
        X_train_i = np.reshape(X_train_i, (X_train_i.shape[0], X_train_i.shape[1], 1))
        X_test_i = np.reshape(X_test_i, (X_test_i.shape[0], X_test_i.shape[1], 1))


        if not use_reference_models:
            weight_for_0 = len(y_dev_i)/(2*len(y_dev_i[y_dev_i==0]))
            weight_for_1 = len(y_dev_i)/(2*len(y_dev_i[y_dev_i==1]))
            class_weight = {0: weight_for_0, 1: weight_for_1}

            n_dense_units = 128
            dropout_rate = 0.0
            use_batch_normalization = True # [True, False]
            filter_size = 9 # [5,7,9]
            learning_rate = 0.0001
            n_epochs = 100 # [50,100,200]

            X_in = Input(shape=(X_train.shape[1],1))
            x = X_in
            for j in range(n_conv_layers):
                print(j)
                x = Conv1D(filters=(j+1)*10,
                           kernel_size=filter_size,
                           strides=1,
                           activation='linear',
                           kernel_initializer='he_uniform')(x)
                if use_batch_normalization:
                    x = BatchNormalization()(x)
                x = LeakyReLU(alpha=0.05)(x)
                x = MaxPooling1D(pool_size=5, strides=2)(x)
            x = Flatten()(x)
            x = Dense(units = n_dense_units, activation='linear')(x)
            x = ReLU()(x)
            x = Dropout(rate=dropout_rate)(x)
            X_out = Dense(units = 1, activation = 'sigmoid')(x)
            classifier = Model(X_in, X_out)

            best_model_filepath = f"{model_path}/cnn_{n_conv_layers}_layers_dataset_pair_{dataset_i}.h5"
            checkpoint = ModelCheckpoint(best_model_filepath, monitor='val_loss',
                                         verbose=1, save_best_only=True, mode='min')
```

```
            classifier.compile(optimizer = Adam(lr=learning_rate), loss = 'binary_crossentropy',
                               metrics = ['accuracy'])
            classifier.summary()

            classifier.fit(X_train_i, y_train_i, epochs = n_epochs, batch_size = 128,
                        validation_data=(X_test_i, y_test_i), callbacks=[checkpoint],
                            class_weight=class_weight)

        best_model_filepath = f"{model_path}/cnn_{n_conv_layers}_layers_dataset_pair_{dataset_i}.h5"
        classifier = load_model(best_model_filepath)
        train_acc = classifier.evaluate(X_train_i, y_train_i)
        val_acc = classifier.evaluate(X_val_i, y_val_i)
        print(f"Layers: {layer_n}, dataset pair {dataset_i}")
        print(train_acc)
        print(val_acc)
```

```
362/362 [==============================] - 2s 5ms/step - loss: 0.0754 - accuracy: 0.9675
105/105 [==============================] - 1s 5ms/step - loss: 1.3558 - accuracy: 0.8118
Layers: 4, dataset pair 0
[0.07540404796600342, 0.9675414562225342]
[1.3558255434036255, 0.8118456602096558]
362/362 [==============================] - 2s 5ms/step - loss: 0.1535 - accuracy: 0.9345
105/105 [==============================] - 1s 5ms/step - loss: 0.9981 - accuracy: 0.6370
Layers: 4, dataset pair 1
[0.15350987017154694, 0.9344785809516907]
[0.998137891292572, 0.6370170712471008]
362/362 [==============================] - 2s 5ms/step - loss: 0.1788 - accuracy: 0.9203
105/105 [==============================] - 1s 5ms/step - loss: 0.8464 - accuracy: 0.6777
Layers: 4, dataset pair 2
[0.17882083356380463, 0.9203004837036133]
[0.8464228510856628, 0.6777378916740417]
362/362 [==============================] - 2s 5ms/step - loss: 0.0661 - accuracy: 0.9858
105/105 [==============================] - 1s 5ms/step - loss: 0.0255 - accuracy: 0.9949
Layers: 4, dataset pair 3
[0.06612363457679749, 0.9858388900756836]
[0.025488944724202156, 0.9949178099632263]
362/362 [==============================] - 3s 9ms/step - loss: 0.0327 - accuracy: 0.9953
105/105 [==============================] - 1s 7ms/step - loss: 2.8528 - accuracy: 0.7496
Layers: 4, dataset pair 0
[0.032745297998189926, 0.9952520728111267]
[2.8528213500976562, 0.749626100063324]
362/362 [==============================] - 3s 7ms/step - loss: 0.0354 - accuracy: 0.9919
105/105 [==============================] - 1s 8ms/step - loss: 3.2444 - accuracy: 0.6053
Layers: 4, dataset pair 1
[0.03537148982286453, 0.9918853640556335]
[3.244418144226074, 0.60527104139328]
362/362 [==============================] - 3s 8ms/step - loss: 0.0862 - accuracy: 0.9597
105/105 [==============================] - 1s 8ms/step - loss: 0.5635 - accuracy: 0.8196
Layers: 4, dataset pair 2
[0.08616558462381363, 0.9596753120422363]
[0.5634729266166687, 0.8195691108703613]
362/362 [==============================] - 3s 8ms/step - loss: 0.0172 - accuracy: 0.9987
105/105 [==============================] - 1s 8ms/step - loss: 0.0232 - accuracy: 0.9955
Layers: 4, dataset pair 3
[0.017239928245544434, 0.9987047910690308]
[0.023241624236106873, 0.9955157041549683]
362/362 [==============================] - 4s 10ms/step - loss: 0.0099 - accuracy: 0.9983
105/105 [==============================] - 1s 10ms/step - loss: 4.6237 - accuracy: 0.7284
Layers: 4, dataset pair 0
[0.009891502559185028, 0.998273491859436]
[4.623722076416016, 0.7283876538276672]
362/362 [==============================] - 6s 15ms/step - loss: 0.0194 - accuracy: 0.9942
105/105 [==============================] - 2s 10ms/step - loss: 6.6829 - accuracy: 0.5810
Layers: 4, dataset pair 1
[0.01937815546989441, 0.9942161440849304]
[6.682938098907471, 0.5810123085975647]
362/362 [==============================] - 4s 10ms/step - loss: 0.0125 - accuracy: 0.9952
105/105 [==============================] - 1s 10ms/step - loss: 1.0235 - accuracy: 0.8130
Layers: 4, dataset pair 2
[0.012512973509728909, 0.9951645135879517]
[1.0235258340835571, 0.8129862546920776]
362/362 [==============================] - 4s 11ms/step - loss: 0.0036 - accuracy: 0.9990
105/105 [==============================] - 1s 12ms/step - loss: 0.0042 - accuracy: 0.9982
Layers: 4, dataset pair 3
```

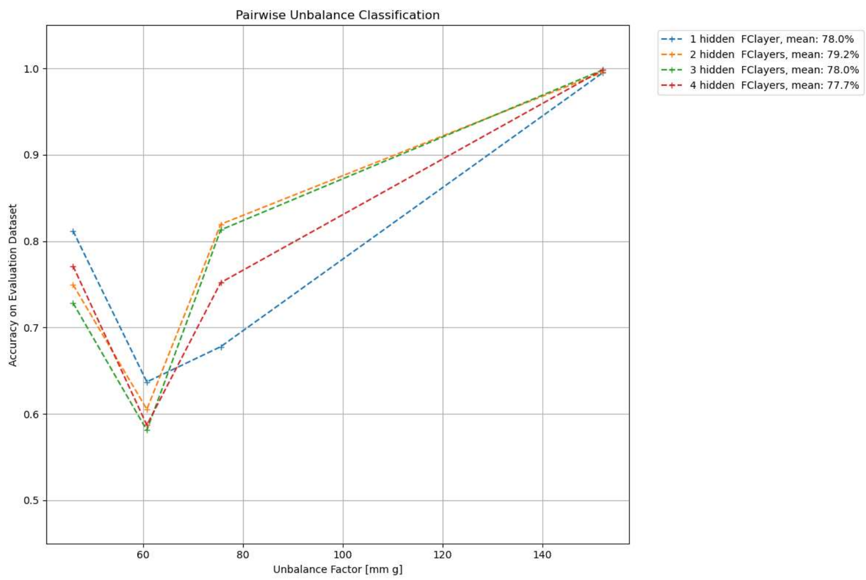
```
accuracies_single = []
for layer_n in range(1,5):
    accuracies_layer_i = []
    for dataset_i in range(4):
        X_val_i = np.concatenate([X_val_separated[0], X_val_separated[dataset_i+1]])
        y_val_i = np.concatenate([y_val_separated[0], y_val_separated[dataset_i+1]])
        filepath = f"{model_path}/cnn_{layer_n}_layers_dataset_pair_{dataset_i}.h5"
        model_i = load_model(filepath)
        accuracies_layer_i.append(model_i.evaluate(X_val_i, y_val_i)[1])
    accuracies_single.append(accuracies_layer_i)
accuracies_single = np.array(accuracies_single)
```

```
105/105 [==============================] - 1s 5ms/step - loss: 1.3558 - accuracy: 0.8118
105/105 [==============================] - 1s 6ms/step - loss: 0.9981 - accuracy: 0.6370
105/105 [==============================] - 1s 5ms/step - loss: 0.8464 - accuracy: 0.6777
105/105 [==============================] - 1s 5ms/step - loss: 0.0255 - accuracy: 0.9949
105/105 [==============================] - 1s 8ms/step - loss: 2.8528 - accuracy: 0.7496
105/105 [==============================] - 1s 8ms/step - loss: 3.2444 - accuracy: 0.6053
105/105 [==============================] - 1s 7ms/step - loss: 0.5635 - accuracy: 0.8196
105/105 [==============================] - 1s 7ms/step - loss: 0.0232 - accuracy: 0.9955
105/105 [==============================] - 1s 10ms/step - loss: 4.6237 - accuracy: 0.7284
105/105 [==============================] - 1s 10ms/step - loss: 6.6829 - accuracy: 0.5810
105/105 [==============================] - 1s 10ms/step - loss: 1.0235 - accuracy: 0.8130
105/105 [==============================] - 2s 13ms/step - loss: 0.0042 - accuracy: 0.9982
105/105 [==============================] - 2s 12ms/step - loss: 3.4709 - accuracy: 0.7712
105/105 [==============================] - 1s 12ms/step - loss: 10.4930 - accuracy: 0.5870
105/105 [==============================] - 2s 12ms/step - loss: 3.2669 - accuracy: 0.7519
105/105 [==============================] - 2s 12ms/step - loss: 0.0059 - accuracy: 0.9982
```

```
np.mean(accuracies_single, axis=1)
```

```
array([0.78037961, 0.79249549, 0.78014812, 0.77707924])
```

```
fig=plt.figure(figsize=(12,8))
ax1=plt.subplot(111, title = "Pairwise Unbalance Classification")
unbalances = np.array([0, 4.59e-5, 6.07e-5,7.55e-5,1.521e-4])
ax1.plot(1e6*unbalances[1:], accuracies_single[0,:],
         label=f"1 hidden  FClayer, mean: {100.0*np.mean(accuracies_single[0,:]):.1f}%", marker="+", ls="--")
ax1.plot(1e6*unbalances[1:], accuracies_single[1,:],
         label=f"2 hidden  FClayers, mean: {100.0*np.mean(accuracies_single[1,:]):.1f}%", marker="+", ls="--")
ax1.plot(1e6*unbalances[1:], accuracies_single[2,:],
         label=f"3 hidden  FClayers, mean: {100.0*np.mean(accuracies_single[2,:]):.1f}%", marker="+", ls="--")
ax1.plot(1e6*unbalances[1:], accuracies_single[3,:],
         label=f"4 hidden  FClayers, mean: {100.0*np.mean(accuracies_single[3,:]):.1f}%", marker="+", ls="--")
plt.ylabel("Accuracy on Evaluation Dataset")
plt.xlabel("Unbalance Factor [mm g]")
plt.legend(bbox_to_anchor=(1.04,1), loc="upper left")
plt.ylim([0.45, 1.05])
plt.grid(True)
plt.tight_layout()
plt.show()
```



Plotting all Experiments

```
fig=plt.figure(figsize=(15,5))
ax1=plt.subplot(132, title = "Unbalance Classification Trained\nwith all Unbalances")
unbalances = np.array([0, 4.59e-5, 6.07e-5,7.55e-5,1.521e-4])
ax1.plot(1e6*unbalances, accuracies[0,:],
         label=f"1 conv. layer, mean: {100.0*np.mean(accuracies[0,:]):.1f}%", marker="+", ls="--")
ax1.plot(1e6*unbalances, accuracies[1,:],
         label=f"2 conv. layers, mean: {100.0*np.mean(accuracies[1,:]):.1f}%", marker="+", ls="--")
ax1.plot(1e6*unbalances, accuracies[2,:],
         label=f"3 conv. layers, mean: {100.0*np.mean(accuracies[2,:]):.1f}%", marker="+", ls="--")
ax1.plot(1e6*unbalances, accuracies[3,:],
         label=f"4 conv. layers, mean: {100.0*np.mean(accuracies[3,:]):.1f}%", marker="+", ls="--")
plt.ylabel("Accuracy on Evaluation Dataset")
plt.xlabel("Unbalance Factor [mm g]")
plt.ylim([0.45, 1.05])
plt.legend(loc="lower right")
ax1.text(-20, 1.05,"(b)", fontsize=12)
ax2=plt.subplot(131, title = "Pairwise Unbalance Classification")
ax2.plot(1e6*unbalances[1:], accuracies_single[0,:],
         label=f"1 conv. layer, mean: {100.0*np.mean(accuracies_single[0,:]):.1f}%", marker="+", ls="--")
ax2.plot(1e6*unbalances[1:], accuracies_single[1,:],
         label=f"2 conv. layers, mean: {100.0*np.mean(accuracies_single[1,:]):.1f}%", marker="+", ls="--")
ax2.plot(1e6*unbalances[1:], accuracies_single[2,:],
         label=f"3 conv. layers, mean: {100.0*np.mean(accuracies_single[2,:]):.1f}%", marker="+", ls="--")
ax2.plot(1e6*unbalances[1:], accuracies_single[3,:],
         label=f"4 conv. layers, mean: {100.0*np.mean(accuracies_single[3,:]):.1f}%", marker="+", ls="--")
plt.ylabel("Accuracy on Evaluation Dataset")
plt.xlabel("Unbalance Factor [mm g]")
plt.ylim([0.45, 1.05])
plt.legend()
ax2.text(33, 1.05,"(a)", fontsize=12)
ax3 = plt.subplot(133, title="Unbalance Classification Trained with all\nUnbalances: Rotation Speed Dependency")
ax3.plot(np.array(rpm_borders[:-1])+25, errors_per_rpm_range1,
         label=f"1 conv. layer, mean: {100.0*np.mean(accuracies[0,:]):.1f}%", marker="+", ls="--")
ax3.plot(np.array(rpm_borders[:-1])+25, errors_per_rpm_range2,
         label=f"2 conv. layers, mean: {100.0*np.mean(accuracies[1,:]):.1f}%", marker="+", ls="--")
ax3.plot(np.array(rpm_borders[:-1])+25, errors_per_rpm_range3,
         label=f"3 conv. layers, mean: {100.0*np.mean(accuracies[2,:]):.1f}%", marker="+", ls="--")
ax3.plot(np.array(rpm_borders[:-1])+25, errors_per_rpm_range4,
         label=f"4 conv. layers, mean: {100.0*np.mean(accuracies[3,:]):.1f}%", marker="+", ls="--")

plt.ylabel("Accuracy on Evaluation Dataset")
plt.xlabel("Rotation Speed [RPM]")
plt.ylim([0.45, 1.05])
plt.legend(loc="lower right")
ax3.text(960, 1.05,"(c)", fontsize=12)
plt.tight_layout()
plt.show()
```