

## Create Model

```
In [ ]: # K.clear_session()

dropout1 = 0.5
dropout2 = 0.2

# learning_rate = 0.001

#conv1D and LSTM model
model_lstm = Sequential()
model_lstm.add(Conv1D(filters=64, kernel_size=1, activation='relu', input_shape=train.shape[1:], return_sequences=True))
model_lstm.add(LSTM(128, return_sequences=True))
model_lstm.add(Dropout(dropout1))
model_lstm.add(LSTM(64, return_sequences=False))
model_lstm.add(Dropout(dropout2))
model_lstm.add(Dense(12, activation='sigmoid'))

print(train.shape[1], train.shape[2])

model_lstm.compile(loss='binary_crossentropy', optimizer='adam', metrics=['
```

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## Train Model

Train the model with the training data and validate it with the test data.

Training configuration:

- 30 epochs
- Batch size of 64
- Early stopping to prevent overfitting
- Learning rate reduction on plateau
- Model checkpoint to save the best model based on validation loss

```
In [ ]: # Define callbacks
early_stopping = EarlyStopping(monitor='val_loss', patience=3, restore_best_weights=True)
reduce_lr = ReduceLROnPlateau(monitor='val_loss', factor=0.2, patience=5, min_lr=1e-6)
model_checkpoint = ModelCheckpoint('best_models/best_model_ConvLSTM.keras', save_best_only=True)

# Train the model
model_lstm_output = model_lstm.fit(train, y_train, epochs=30, batch_size=64, validation_data=(test, y_test), callbacks=[early_stopping, reduce_lr, model_checkpoint])
```

Epoch 1/30

2024-06-18 07:14:16.506213: I external/local\_xla/xla/stream\_executor/cuda/cuda\_dnn.cc:465] Loaded cuDNN version 8907

1759/1759 ————— 19s 8ms/step - accuracy: 0.0476 - loss: 0.0  
982 - val\_accuracy: 0.0144 - val\_loss: 0.0103 - learning\_rate: 0.0010  
Epoch 2/30

1759/1759 ————— 17s 8ms/step - accuracy: 0.1907 - loss: 0.0  
093 - val\_accuracy: 0.0244 - val\_loss: 0.0063 - learning\_rate: 0.0010  
Epoch 3/30

1759/1759 ————— 14s 8ms/step - accuracy: 0.2406 - loss: 0.0  
058 - val\_accuracy: 0.0769 - val\_loss: 0.0042 - learning\_rate: 0.0010  
Epoch 4/30

1759/1759 ————— 14s 8ms/step - accuracy: 0.0889 - loss: 0.0  
041 - val\_accuracy: 0.0444 - val\_loss: 0.0032 - learning\_rate: 0.0010  
Epoch 5/30

1759/1759 ————— 15s 9ms/step - accuracy: 0.0478 - loss: 0.0  
033 - val\_accuracy: 0.0406 - val\_loss: 0.0030 - learning\_rate: 0.0010  
Epoch 6/30

1759/1759 ————— 14s 8ms/step - accuracy: 0.0542 - loss: 0.0  
031 - val\_accuracy: 0.0365 - val\_loss: 0.0026 - learning\_rate: 0.0010  
Epoch 7/30

1759/1759 ————— 14s 8ms/step - accuracy: 0.0555 - loss: 0.0  
027 - val\_accuracy: 0.0363 - val\_loss: 0.0024 - learning\_rate: 0.0010  
Epoch 8/30

1759/1759 ————— 14s 8ms/step - accuracy: 0.0634 - loss: 0.0  
026 - val\_accuracy: 0.0371 - val\_loss: 0.0022 - learning\_rate: 0.0010  
Epoch 9/30

1759/1759 ————— 12s 7ms/step - accuracy: 0.0542 - loss: 0.0  
025 - val\_accuracy: 0.0408 - val\_loss: 0.0018 - learning\_rate: 0.0010  
Epoch 10/30

1759/1759 ————— 9s 5ms/step - accuracy: 0.0691 - loss: 0.00  
21 - val\_accuracy: 0.0388 - val\_loss: 0.0018 - learning\_rate: 0.0010  
Epoch 11/30

1759/1759 ————— 13s 7ms/step - accuracy: 0.0965 - loss: 0.0  
020 - val\_accuracy: 0.0462 - val\_loss: 0.0015 - learning\_rate: 0.0010  
Epoch 12/30

1759/1759 ————— 10s 6ms/step - accuracy: 0.1136 - loss: 0.0  
018 - val\_accuracy: 0.0442 - val\_loss: 0.0019 - learning\_rate: 0.0010  
Epoch 13/30

1759/1759 ————— 10s 6ms/step - accuracy: 0.1219 - loss: 0.0  
017 - val\_accuracy: 0.0523 - val\_loss: 0.0017 - learning\_rate: 0.0010  
Epoch 14/30

1759/1759 ————— 10s 6ms/step - accuracy: 0.1280 - loss: 0.0  
016 - val\_accuracy: 0.0429 - val\_loss: 0.0013 - learning\_rate: 0.0010  
Epoch 15/30

1759/1759 ————— 13s 7ms/step - accuracy: 0.1197 - loss: 0.0  
014 - val\_accuracy: 0.0505 - val\_loss: 0.0018 - learning\_rate: 0.0010  
Epoch 16/30

1759/1759 ————— 12s 7ms/step - accuracy: 0.1195 - loss: 0.0  
015 - val\_accuracy: 0.0489 - val\_loss: 0.0014 - learning\_rate: 0.0010  
Epoch 17/30

1759/1759 ————— 21s 7ms/step - accuracy: 0.1189 - loss: 0.0  
013 - val\_accuracy: 0.0413 - val\_loss: 0.0013 - learning\_rate: 0.0010  
Epoch 18/30

1759/1759 ————— 15s 9ms/step - accuracy: 0.0846 - loss: 0.0  
014 - val\_accuracy: 0.0487 - val\_loss: 0.0012 - learning\_rate: 0.0010  
Epoch 19/30

1759/1759 ————— 12s 7ms/step - accuracy: 0.1441 - loss: 0.0  
013 - val\_accuracy: 0.0421 - val\_loss: 0.0011 - learning\_rate: 0.0010  
Epoch 20/30

1759/1759 ————— 22s 8ms/step - accuracy: 0.0988 - loss: 0.0  
013 - val\_accuracy: 0.0431 - val\_loss: 0.0012 - learning\_rate: 0.0010  
Epoch 21/30

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1759/1759 ————— 15s 8ms/step - accuracy: 0.1515 - loss: 0.0
012 - val_accuracy: 0.0480 - val_loss: 0.0012 - learning_rate: 0.0010
Epoch 22/30
1759/1759 ————— 20s 8ms/step - accuracy: 0.1173 - loss: 0.0
012 - val_accuracy: 0.0456 - val_loss: 0.0011 - learning_rate: 0.0010
Epoch 23/30
1759/1759 ————— 14s 8ms/step - accuracy: 0.1313 - loss: 0.0
013 - val_accuracy: 0.0444 - val_loss: 0.0010 - learning_rate: 0.0010
Epoch 24/30
1759/1759 ————— 14s 8ms/step - accuracy: 0.1403 - loss: 0.0
011 - val_accuracy: 0.0507 - val_loss: 0.0014 - learning_rate: 0.0010
Epoch 25/30
1759/1759 ————— 12s 7ms/step - accuracy: 0.1283 - loss: 0.0
012 - val_accuracy: 0.0440 - val_loss: 0.0010 - learning_rate: 0.0010
Epoch 26/30
1759/1759 ————— 9s 5ms/step - accuracy: 0.1094 - loss: 0.00
11 - val_accuracy: 0.0490 - val_loss: 0.0012 - learning_rate: 0.0010
Epoch 27/30
1759/1759 ————— 8s 5ms/step - accuracy: 0.1559 - loss: 0.00
12 - val_accuracy: 0.0473 - val_loss: 0.0012 - learning_rate: 0.0010
Epoch 28/30
1753/1759 ————— 0s 5ms/step - accuracy: 0.1354 - loss: 0.00
11
Epoch 28: ReduceLROnPlateau reducing learning rate to 0.000200000009499490
26.
1759/1759 ————— 9s 5ms/step - accuracy: 0.1354 - loss: 0.00
11 - val_accuracy: 0.0560 - val_loss: 0.0011 - learning_rate: 0.0010

```

## RESULTS

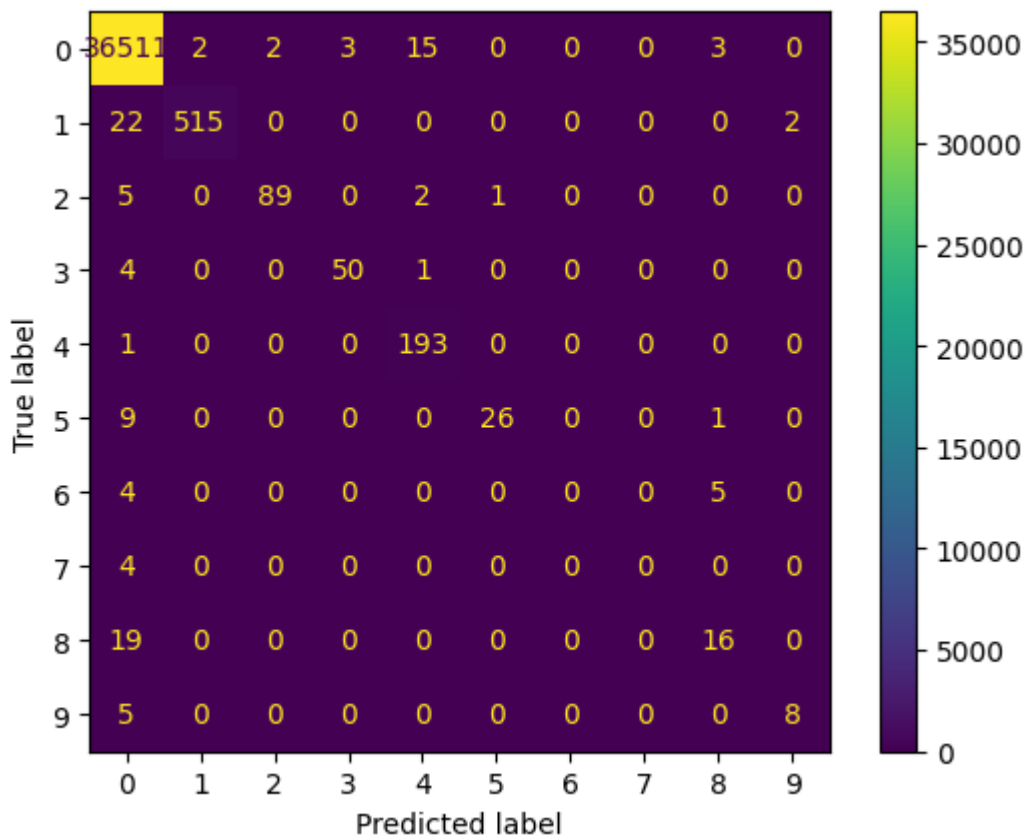
```

In [ ]: # clabels = ['AccelY', 'BreakY', 'TurnRightX', 'Turn LeftX', 'PositiveZ',

# cm_display = metrics.ConfusionMatrixDisplay(confusion_matrix = conf_mat
cm_display = metrics.ConfusionMatrixDisplay(confusion_matrix = conf_mat)

# display matrix
cm_display.plot()
plt.show()

```



## Performance Metrics

- Accuracy =  $\frac{\text{Correct Predictions}}{\text{All Predictions}}$
- Precision for a given class =  $\frac{\text{Correct Predictions for the Class}}{\text{All Predictions for the Class}}$
- Recall for a given class =  $\frac{\text{Correct Predictions for the Class}}{\text{All Instances of the Class}}$
- Averaging is a way to get a single number for multiclass. Depending on the importance one wants to give to minority classes:

- Macro average: Compute the metric for each class, and returns the average without considering the proportion for each class in the dataset. For instance:

$$\text{Precision} = \frac{P_{class1} + P_{class2} + \dots + P_{classn}}{N}$$

- Weighted average: Compute the metric for each class, and returns the average considering the proportion (weighted) for each class in the dataset. For instance:

$$\text{Precision} = \frac{N_1 * P_{class1} + N_2 * P_{class2} + \dots + N_n * P_{classn}}{N}$$

```
In [ ]: # Calculates performance metrics
acc = accuracy_score(y_true = y_test, y_pred = pred)
print(f'Accuracy : {np.round(acc*100,2)}%')
```

```
precision = precision_score(y_true = y_test, y_pred = pred, average='macro')
print(f'Precision - Macro: {np.round(precision*100,2)}%')

recall = recall_score(y_true = y_test, y_pred = pred, average='macro')
print(f'Recall - Macro: {np.round(recall*100,2)}%')

f1 = f1_score(y_true = y_test, y_pred = pred, average='macro')
print(f'F1-score - Macro: {np.round(f1*100,2)}%')

precision = precision_score(y_true = y_test, y_pred = pred, average='weighted')
print(f'Precision - Weighted: {np.round(precision*100,2)}%')

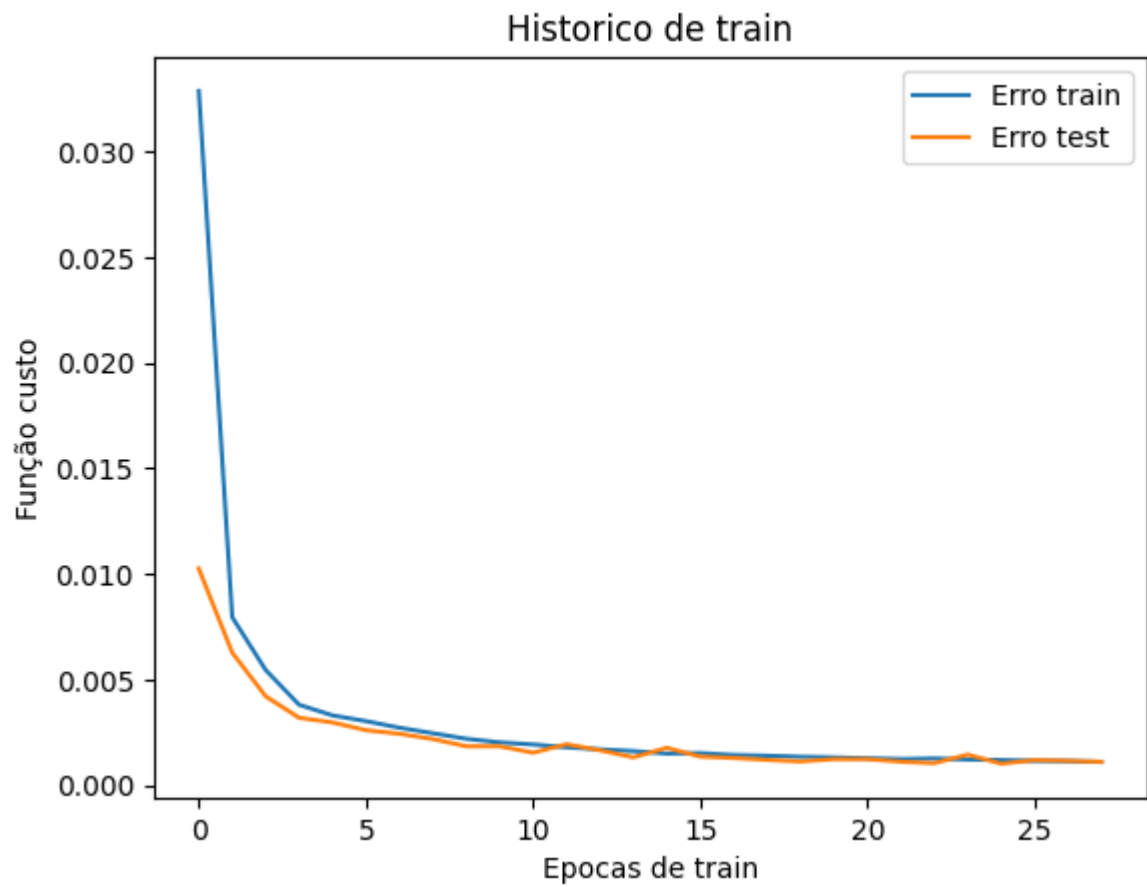
recall = recall_score(y_true = y_test, y_pred = pred, average='weighted')
print(f'Recall - Weighted: {np.round(recall*100,2)}%')

f1 = f1_score(y_true = y_test, y_pred = pred, average='weighted')
print(f'F1-score - Weighted: {np.round(f1*100,2)}%')
```

Accuracy : 99.71%  
Precision - Macro: 72.33%  
Recall - Macro: 65.71%  
F1-score - Macro: 68.54%  
Precision - Weighted: 99.66%  
Recall - Weighted: 99.71%  
F1-score - Weighted: 99.68%

## TEST THE NETWORK

```
In [ ]: plt.plot(model_lstm_output.history['loss'])
plt.plot(model_lstm_output.history['val_loss'])
plt.title('Historico de train')
plt.xlabel('Epocas de train')
plt.ylabel('Função custo')
plt.legend(['Erro train', 'Erro test'])
plt.show()
```



```
In [ ]: test[0]  
test.shape
```

```
Out[ ]:
```