1D CNN (M1)-model

November 14, 2023

1 1D CNN (M1)

1.1 Importing modules

[27]:
```
from numpy import mean
from numpy import std
from numpy import dstack
from numpy import array
import pandas
from pandas import read_csv
from matplotlib import pyplot
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.layers import Flatten
from tensorflow.keras.optimizers import SGD
from tensorflow.keras.layers import Dropout
from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras.utils import to_categorical
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler, RobustScaler
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
↪recall_score, cohen_kappa_score, roc_auc_score, confusion_matrix
from tensorflow.keras.layers import LSTM
import keras
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Conv1D, Convolution1D, ZeroPadding1D,␣
↪MaxPooling1D, AveragePooling1D, BatchNormalization, Activation, Dropout,␣
↪Flatten, Dense
from sklearn.metrics import␣
↪confusion_matrix,accuracy_score,precision_score,recall_score,␣
↪matthews_corrcoef, f1_score
from sklearn.metrics import classification_report
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.optimizers import Adadelta
from tensorflow.keras.optimizers import Nadam
import time
```

```
import numpy as np

from matplotlib import pyplot as plt
```

1.2 Importing DataSet

[28]:
```
# Read the CSV file into a pandas DataFrame

dataframe = pandas.read_csv("/home/gerel/Documents/11.DataSet/
↪Datasets_with_port_protocol_project2/ddos_dataset.csv")
```

1.3 Exploring DataSet

[29]:
```
dataframe
```

[29]:
```
        Unnamed: 0        sw11        sw22        sw12    flow_stat  Protocol  \
0                0  321.464040  276.665291  330.655584   935.549686        17
1                1  309.711011  229.390828  276.175688   820.130424        17
2                2  388.028008  265.059110  351.008062  1006.247528        17
3                3  351.443368  260.581250  346.263900   963.385626        17
4                4  312.260013  242.773740  297.274629   846.970095        17
…              …         …         …         …          …       …
104541      104541  224.340118  119.928015  186.242752   526.839055        17
104542      104542  415.201915  200.064020  548.021813  1159.145286        17
104543      104543  463.785312  188.559746  489.979829  1136.569711        17
104544      104544  370.268584  167.753758  498.700647  1044.880801        17
104545      104545  249.949917  136.780967  215.209463   609.887321        17

        source_port  label
0             40423      0
1             40423      0
2             40423      0
3             40423      0
4             40423      0
…               …    …
104541        40423      1
104542        40423      1
104543        40423      1
104544        40423      1
104545        40423      1

[104546 rows x 8 columns]
```

[30]:
```
dataframe.head()
```

[30]:
```
   Unnamed: 0        sw11        sw22        sw12    flow_stat  Protocol  \
0           0  321.464040  276.665291  330.655584   935.549686        17
1           1  309.711011  229.390828  276.175688   820.130424        17
2           2  388.028008  265.059110  351.008062  1006.247528        17
3           3  351.443368  260.581250  346.263900   963.385626        17
4           4  312.260013  242.773740  297.274629   846.970095        17

   source_port  label
0        40423      0
1        40423      0
2        40423      0
3        40423      0
4        40423      0
```

[31]:
```python
dataframe.describe()
```

[31]:
```
          Unnamed: 0           sw11           sw22           sw12  \
count  104546.000000  104546.000000  104546.000000  104546.000000
mean    52272.500000     352.201907     237.309224     336.714896
std     30179.974959     120.119222      55.028820     132.239182
min         0.000000     152.000000     103.100000     123.400000
25%     26136.250000     303.148858     207.814786     281.793079
50%     52272.500000     329.773026     247.161254     323.476374
75%     78408.750000     378.003544     271.343743     349.905167
max    104545.000000    1445.842000     474.158000    1942.632000

           flow_stat  Protocol  source_port          label
count  104546.000000  104546.0     104546.0  104546.000000
mean      923.701285      17.0      40423.0       0.299973
std       260.484403       0.0          0.0       0.458248
min         3.000000      17.0      40423.0       0.000000
25%       819.361461      17.0      40423.0       0.000000
50%       909.569716      17.0      40423.0       0.000000
75%      1001.550422      17.0      40423.0       1.000000
max      2963.550000      17.0      40423.0       1.000000
```

1.4 Data Preprocessing and Feature-Label Extraction

[32]:
```python
# Check the shape of the dataset
dataset.shape

# Extract the features (X) and labels (Y) from the DataFrame
# X contains all rows and all columns except the last column
X = dataframe.iloc[:, :-1]

# Y contains all rows and only the last column
```

```
Y = dataframe.iloc[:, -1]

# Convert Y (labels) to categorical values using one-hot encoding
Y = to_categorical(Y)

# Convert X to a numpy array
X = array(X[:])
```

1.5 Feature Scaling and Transformation.

[33]:
```
# Initialize a RobustScaler object
scaler = RobustScaler()

# Fit the scaler to the data (X) and transform the data using the RobustScaler
X = scaler.fit_transform(X)
```

1.6 Data Splitting for Training and Testing.

[34]:
```
# Split the dataset into training and testing sets
# X_train and X_test are the training and testing features, respectively
# y_train and y_test are the corresponding training and testing labels,␣
 ↪respectively
# The test_size parameter determines the proportion of the dataset used for␣
 ↪testing (in this case, 30%)
# The random_state parameter ensures reproducibility of the split

X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.3,␣
 ↪random_state=109)

'''This line of code uses train_test_split from Scikit-learn to divide the␣
 ↪dataset (X and Y) into training and testing sets. It assigns 70% of the data␣
 ↪to training (X_train and y_train) and 30% to testing (X_test and y_test).
The random_state parameter ensures that the data split is reproducible.'''
```

[34]:
```
'This line of code uses train_test_split from Scikit-learn to divide the dataset
(X and Y) into training and testing sets. It assigns 70% of the data to training
(X_train and y_train) and 30% to testing (X_test and y_test). \nThe random_state
parameter ensures that the data split is reproducible.'
```

[35]:
```
X_train.shape
```

[35]:
```
(73182, 7)
```

1.7 Data Reshaping for Convolutional Neural Network (Conv1D) Input

[36]:
```
# Reshape the training and testing features for compatibility with Conv1D model
# X_train is reshaped to have dimensions (samples, features, 1)
X_train = X_train.reshape(X_train.shape[0], X_train.shape[1], 1)

# X_test is reshaped to have dimensions (samples, features, 1)
X_test = X_test.reshape(X_test.shape[0], X_test.shape[1], 1)
```

[37]:
```
X_train.shape
```

[37]: (73182, 7, 1)

[38]:
```
X_test.shape[0]
```

[38]: 31364

[39]:
```
X_train.shape[1]  #- number of features
```

[39]: 7

1.8 Model Architecture Definition

[40]:
```
# Create a Sequential model
model = Sequential()

# Define input shape for the first layer based on the input data
layer0_input = (X_train.shape[1], 1)

# Add a 1D convolutional layer with 8 filters, kernel size of 3, using ReLU␣
↪activation
model.add(Conv1D(filters=8, kernel_size=3, padding='valid', activation='relu',␣
↪input_shape=layer0_input))

# Add another 1D convolutional layer with 8 filters, kernel size of 2, using␣
↪ReLU activation
model.add(Conv1D(8, 2, padding='valid', activation='relu'))

# Add one more 1D convolutional layer with 8 filters, kernel size of 2, using␣
↪ReLU activation
model.add(Conv1D(8, 2, padding='valid', activation='relu'))

# Flatten the output of the convolutional layers
layer4_flatten = model.add(Flatten())
```

```
# Add a dense layer with 16 neurons and ReLU activation
layer5_dense = model.add(Dense(16, activation='relu'))

# Add a Dropout layer with 20% dropout rate to prevent overfitting
layer6_Dropout = model.add(Dropout(0.2))

# Add a final dense layer with 2 neurons for classification using softmax␣
↪activation
model.add(Dense(2, activation='softmax'))
```

[41]:
```
model.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv1d_6 (Conv1D)            (None, 5, 8)              32
_________________________________________________________________
conv1d_7 (Conv1D)            (None, 4, 8)              136
_________________________________________________________________
conv1d_8 (Conv1D)            (None, 3, 8)              136
_________________________________________________________________
flatten_2 (Flatten)          (None, 24)                0
_________________________________________________________________
dense_4 (Dense)              (None, 16)                400
_________________________________________________________________
dropout_2 (Dropout)          (None, 16)                0
_________________________________________________________________
dense_5 (Dense)              (None, 2)                 34
=================================================================
Total params: 738
Trainable params: 738
Non-trainable params: 0
_________________________________________________________________
```

1.9 Model Hyperparameters Configuration

[42]:
```
epoch= 18
batch_size= 128
learning_rate=0.001
```

1.10 Model Compilation and Configuration

[43]:
```
# Initialize the Adam optimizer with a specific learning rate
adam = Adam(learning_rate=learning_rate)

# Compile the model with binary cross-entropy loss for binary classification
# Using the Adam optimizer initialized above and tracking accuracy as a metric
model.compile(loss='binary_crossentropy', optimizer='adam',␣
↪metrics=['accuracy'])
```

1.11 Training the Model with Early Stopping

[44]:
```
#early stopping hiihes epoch-iin toond hurehees omno zogsoj bolno
startTime = time.time()
history = model.fit(X_train, y_train, epochs=epoch, batch_size=batch_size,␣
↪validation_split=0.3,callbacks=[EarlyStopping(monitor='val_loss',␣
↪patience=3, min_delta=0.0001)])
```

```
Epoch 1/18
401/401 [==============================] - 25s 60ms/step - loss: 0.1968 -
accuracy: 0.9586 - val_loss: 0.0187 - val_accuracy: 0.9967
Epoch 2/18
401/401 [==============================] - 28s 69ms/step - loss: 0.0204 -
accuracy: 0.9959 - val_loss: 0.0113 - val_accuracy: 0.9976
Epoch 3/18
401/401 [==============================] - 26s 66ms/step - loss: 0.0133 -
accuracy: 0.9974 - val_loss: 0.0073 - val_accuracy: 0.9980
Epoch 4/18
401/401 [==============================] - 27s 68ms/step - loss: 0.0095 -
accuracy: 0.9980 - val_loss: 0.0046 - val_accuracy: 0.9988
Epoch 5/18
401/401 [==============================] - 27s 67ms/step - loss: 0.0066 -
accuracy: 0.9985 - val_loss: 0.0035 - val_accuracy: 0.9994
Epoch 6/18
401/401 [==============================] - 26s 65ms/step - loss: 0.0053 -
accuracy: 0.9987 - val_loss: 0.0023 - val_accuracy: 0.9995
Epoch 7/18
401/401 [==============================] - 26s 65ms/step - loss: 0.0037 -
accuracy: 0.9990 - val_loss: 0.0016 - val_accuracy: 0.9995
Epoch 8/18
401/401 [==============================] - 26s 65ms/step - loss: 0.0030 -
accuracy: 0.9993 - val_loss: 9.8156e-04 - val_accuracy: 0.9997
Epoch 9/18
401/401 [==============================] - 25s 62ms/step - loss: 0.0022 -
accuracy: 0.9994 - val_loss: 9.0514e-04 - val_accuracy: 0.9997
Epoch 10/18
```

```
401/401 [==============================] - 13s 33ms/step - loss: 0.0018 -
accuracy: 0.9995 - val_loss: 5.4586e-04 - val_accuracy: 0.9999
Epoch 11/18
401/401 [==============================] - 25s 63ms/step - loss: 0.0015 -
accuracy: 0.9997 - val_loss: 4.5992e-04 - val_accuracy: 0.9998
Epoch 12/18
401/401 [==============================] - 24s 60ms/step - loss: 0.0016 -
accuracy: 0.9996 - val_loss: 6.9914e-04 - val_accuracy: 0.9998
Epoch 13/18
401/401 [==============================] - 26s 65ms/step - loss: 0.0011 -
accuracy: 0.9997 - val_loss: 2.5899e-04 - val_accuracy: 1.0000
Epoch 14/18
401/401 [==============================] - 22s 54ms/step - loss: 0.0013 -
accuracy: 0.9997 - val_loss: 2.4345e-04 - val_accuracy: 1.0000
Epoch 15/18
401/401 [==============================] - 26s 65ms/step - loss: 8.9778e-04 -
accuracy: 0.9998 - val_loss: 8.0056e-04 - val_accuracy: 0.9998
Epoch 16/18
401/401 [==============================] - 25s 62ms/step - loss: 9.6259e-04 -
accuracy: 0.9998 - val_loss: 1.8618e-04 - val_accuracy: 1.0000
```

[ ]:
```
## Model Evaluation and Performance Analysis
```

[50]:
```
# Evaluate the model's accuracy on the testing data
# The model.evaluate() function computes the accuracy using the testing␣
↪features (X_test) and labels (y_test)
# The batch_size parameter determines the number of samples per gradient update
accuracy = model.evaluate(X_test, y_test, batch_size=batch_size, verbose=0)

# Print the accuracy achieved by the model on the testing data
print('Accuracy:', accuracy)

# Calculate and print the total time taken for the process to run
# time.time() returns the current time, and startTime stores the initial time
print("This Process run %s seconds" % str(time.time() - startTime))
```

```
Accuracy: [0.0005091042839922011, 0.999808669090271]
This Process run 978.0278453826904 seconds
```

1.12 Visualization of Training and Validation Accuracy Trends

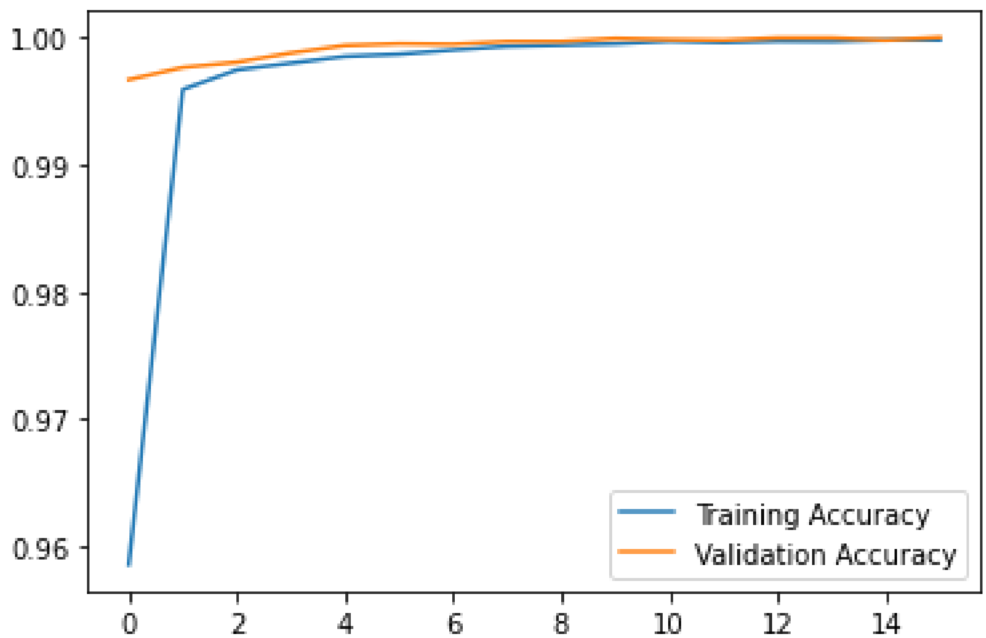
[46]:
```
# Plotting the training and validation accuracy over epochs

# Plot the training accuracy stored in the 'accuracy' key of the history object
plt.plot(history.history["accuracy"], label="Training Accuracy")
```

```
# Plot the validation accuracy stored in the 'val_accuracy' key of the history␣
↪object
plt.plot(history.history["val_accuracy"], label="Validation Accuracy")

# Adding a legend to the plot to differentiate between training and validation␣
↪accuracy
plt.legend()

# Display the plot
plt.show()
```



1.13 Visualization of Training and Validation Loss Trends

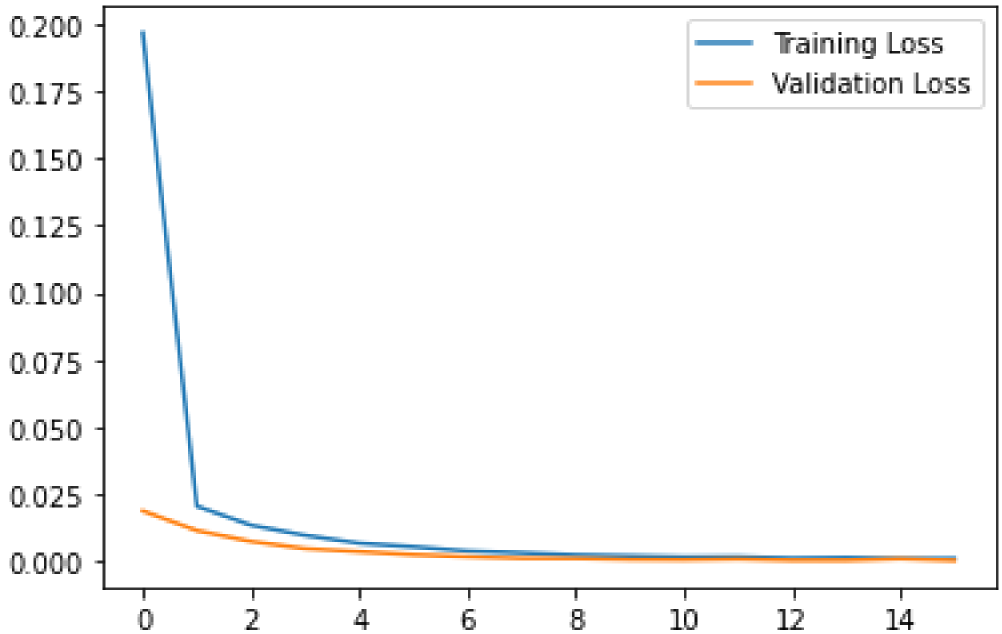
[47]:
```
# Plotting the training and validation loss over epochs

# Plot the training loss stored in the 'loss' key of the history object
plt.plot(history.history["loss"], label="Training Loss")

# Plot the validation loss stored in the 'val_loss' key of the history object
plt.plot(history.history["val_loss"], label="Validation Loss")

# Adding a legend to the plot to differentiate between training and validation␣
↪loss
plt.legend()
```

```
# Display the plot
plt.show()
```



2 Model performance evaluation

[48]:
```
def calc(target, predicted, num_class=2):
    # Calculate various evaluation metrics
    Acc = accuracy_score(target, predicted)  # Accuracy
    Pre = precision_score(target, predicted)  # Precision
    Rec = recall_score(target, predicted)  # Recall
    F1_Score = f1_score(target, predicted)  # F1 Score
    MCC = matthews_corrcoef(target, predicted)  # Matthews Correlation␣
 ↪Coefficient
    # Generate confusion matrix as a string for display purposes
    conf_matrix = str(confusion_matrix(target, predicted)).replace('\n', ',')
    # Return evaluation metrics as a NumPy array
    return np.array([Acc, Pre, Rec, F1_Score, MCC, conf_matrix])
```

[49]:
```
# Predict using the trained model on the testing data
predicted_y = model.predict(X_test, verbose=2)

# Calculate evaluation metrics using the calc function
```

```python
[Acc, Pre, Rec, F1_Score, MCC, conf_matrix] = calc(np.argmax(y_test, axis=1),
 ↪np.argmax(predicted_y, axis=1))

# Print evaluation metrics (converted to string for printing)
print("Acc " + str(Acc))
print("Pre " + str(Pre))
print("Rec " + str(Rec))
print("F1_Score " + str(F1_Score))
print("MCC " + str(MCC))
print("conf_matrix " + conf_matrix)
#
```

```
981/981 - 2s
Acc 0.9998086978701696
Pre 0.9997881804702393
Rec 0.9995764506565015
F1_Score 0.9996823043524303
MCC 0.9995454607576147
conf_matrix [[21918     2], [    4  9440]]
```

[ ]:

```python

```