4_DNN

June 5, 2024

1 DNN applied to the IDS-2017

In this notebook, deep neural networks are used to create binary classifiers that distinguish between benign and malicious traffics in the ids-2017 dataset. Hyperparameters are optimized to obtain a model with the best results.

[2]:
```
from notebook_utils import load_processed_dataset_2017, plot_confusion_matrix,␣
↪metrics_report, upsample_dataset, extract_and_plot_metrics
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import glob
import os
from sklearn.model_selection import train_test_split, RandomizedSearchCV
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import classification_report, average_precision_score,␣
↪make_scorer, precision_score, accuracy_score, confusion_matrix
%matplotlib inline
%load_ext autoreload
%autoreload 2
file_path =␣
↪r"CIC-IDS-2017\CSVs\GeneratedLabelledFlows\TrafficLabelling\processed\ids2017_processed.
↪csv"
```

[3]:
```
X_train, Y_train, X_eval, Y_eval, X_test, Y_test, scaler =␣
↪load_processed_dataset_2017(file_path)
```

[4]:
```
performance_models = {}
```

[7]:
```
# Save the best model
def save_keras_model(model, model_name):
    file_path = f'models/{model_name}.keras'
    model.save(file_path)
```

```
    print(f'Model saved to {file_path}')
```

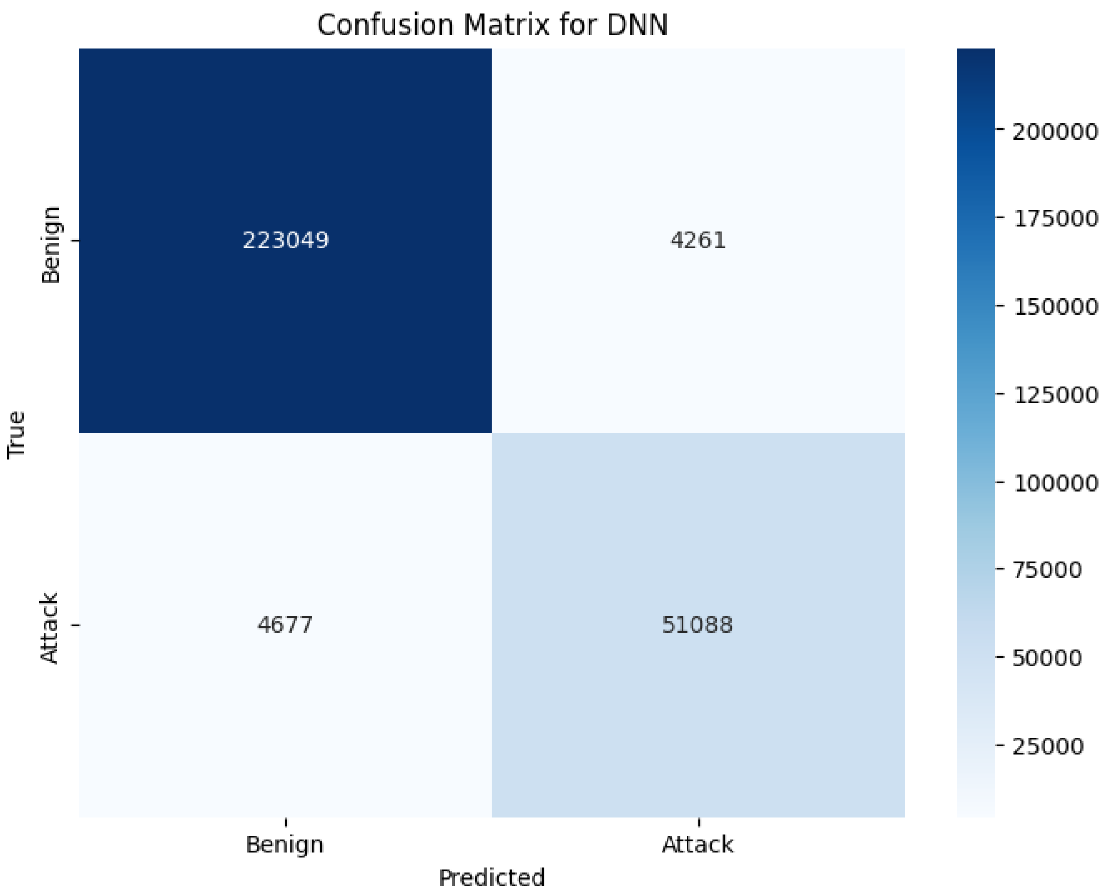
1.1 1. Prototype

[6]:

```
# Define the model architecture
model = Sequential([
    keras.layers.Input(shape=(scaler.transform(X_train).shape[1],)),
    keras.layers.Dense(128, activation='relu'),
    keras.layers.Dropout(0.5),
    keras.layers.Dense(64, activation='relu'),
    keras.layers.Dropout(0.5),
    keras.layers.Dense(1, activation='sigmoid')
])

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

# Add early stopping callback
early_stopping = keras.callbacks.EarlyStopping(monitor='val_loss', patience=5,␣
 ↪restore_best_weights=True)

# Train the model
history = model.fit(scaler.transform(X_train), Y_train.is_attack, epochs=50,␣
 ↪batch_size=32, validation_split=0.2, callbacks=[early_stopping])

# Predict probabilities on the evaluation set
y_pred_eval_prob = model.predict(scaler.transform(X_eval))
# Convert probabilities to binary predictions
y_pred_eval = (y_pred_eval_prob > 0.5).astype(int)
metrics_report("Evaluation", Y_eval.is_attack, y_pred_eval, print_avg=False)

# Predict and evaluate on the test set
y_pred_test_prob = model.predict(scaler.transform(X_test))
y_pred_test = (y_pred_test_prob > 0.5).astype(int)
metrics_report("Test", Y_test.is_attack, y_pred_test, print_avg=False)
plot_confusion_matrix("DNN", Y_test, y_pred_test)
```

```
Epoch 1/50
97279/97279              65s
662us/step - accuracy: 0.9370 - loss: 0.1561 - val_accuracy: 0.2789 - val_loss:
5.4997
Epoch 2/50
97279/97279              65s
664us/step - accuracy: 0.9537 - loss: 0.1100 - val_accuracy: 0.2945 - val_loss:
9.0536
Epoch 3/50
```

```
97279/97279            64s
657us/step - accuracy: 0.9555 - loss: 0.1065 - val_accuracy: 0.3193 - val_loss:
5.9944
Epoch 4/50
97279/97279            64s
656us/step - accuracy: 0.9565 - loss: 0.1151 - val_accuracy: 0.3333 - val_loss:
6.4783
Epoch 5/50
97279/97279            65s
666us/step - accuracy: 0.9572 - loss: 0.1012 - val_accuracy: 0.3396 - val_loss:
8.9501
Epoch 6/50
97279/97279            64s
655us/step - accuracy: 0.9575 - loss: 0.1150 - val_accuracy: 0.3347 - val_loss:
6.8928
8847/8847            4s 424us/step
Classification Report (Evaluation):
              precision    recall  f1-score   support

           0     0.9794    0.9808    0.9801    227310
           1     0.9215    0.9158    0.9186     55764

    accuracy                         0.9680    283074
   macro avg     0.9504    0.9483    0.9494    283074
weighted avg     0.9680    0.9680    0.9680    283074

Accuracy: 0.9680330938199906
8847/8847            4s 417us/step
Classification Report (Test):
              precision    recall  f1-score   support

           0     0.9795    0.9813    0.9804    227310
           1     0.9230    0.9161    0.9196     55765

    accuracy                         0.9684    283075
   macro avg     0.9512    0.9487    0.9500    283075
weighted avg     0.9683    0.9684    0.9684    283075

Accuracy: 0.9684253289764196
```



1.2 2. Hyperparameter Tuning

In this section, a random grid search is perform in an attempt to find a satisfying model. Previously, these hyperparameters were found to perform best. {'units_input': 480, 'num_layers': 2, 'units_0': 448, 'dropout_0': 0.30000000000000004, 'learning_rate': 0.006142607579766685, 'units_1': 224, 'dropout_1': 0.0, 'units_2': 256, 'dropout_2': 0.4}

[5]:
```
def build_model(hp):
    model = Sequential()
    model.add(Dense(units=hp.Int('units_input', min_value=32, max_value=512,␣
 ↪step=32), activation='relu', input_shape=(X_train.shape[1],)))

    for i in range(hp.Int('num_layers', 1, 3)):
        model.add(Dense(units=hp.Int(f'units_{i}', min_value=32, max_value=512,␣
 ↪step=32), activation='relu'))
        model.add(Dropout(rate=hp.Float(f'dropout_{i}', min_value=0.0,␣
 ↪max_value=0.5, step=0.1)))

    model.add(Dense(1, activation='sigmoid'))
```

```
    model.compile(
        optimizer=tf.keras.optimizers.Adam(learning_rate=hp.
↪Float('learning_rate', min_value=1e-4, max_value=1e-2, sampling='LOG',␣
↪default=1e-3)),
        loss='binary_crossentropy',
        metrics=['accuracy']
    )

    return model
```

[6]:
```
from keras_tuner import RandomSearch

directory_path = os.path.join(os.getcwd(), 'hyperparam_tuning')
tuner = RandomSearch(
    build_model,
    objective='val_accuracy',
    max_trials=10,
    executions_per_trial=2,
    directory=directory_path,
    project_name='intrusion_detection'
)

tuner.search_space_summary()

# Perform the search
tuner.search(scaler.transform(X_train), Y_train.is_attack, epochs=10,␣
↪validation_split=0.2)

best_hps = tuner.get_best_hyperparameters(num_trials=1)[0]
print("Best Hyperparameters:", best_hps.values)
```

```
Reloading Tuner from G:\Other computers\My PC\stage\ML-
NIDS\Notebooks\hyperparam_tuning\intrusion_detection\tuner0.json
Search space summary
Default search space size: 9
units_input (Int)
{'default': None, 'conditions': [], 'min_value': 32, 'max_value': 512, 'step':
32, 'sampling': 'linear'}
num_layers (Int)
{'default': None, 'conditions': [], 'min_value': 1, 'max_value': 3, 'step': 1,
'sampling': 'linear'}
units_0 (Int)
{'default': None, 'conditions': [], 'min_value': 32, 'max_value': 512, 'step':
32, 'sampling': 'linear'}
dropout_0 (Float)
{'default': 0.0, 'conditions': [], 'min_value': 0.0, 'max_value': 0.5, 'step':
0.1, 'sampling': 'linear'}
```

```
learning_rate (Float)
{'default': 0.001, 'conditions': [], 'min_value': 0.0001, 'max_value': 0.01,
'step': None, 'sampling': 'log'}
units_1 (Int)
{'default': None, 'conditions': [], 'min_value': 32, 'max_value': 512, 'step':
32, 'sampling': 'linear'}
dropout_1 (Float)
{'default': 0.0, 'conditions': [], 'min_value': 0.0, 'max_value': 0.5, 'step':
0.1, 'sampling': 'linear'}
units_2 (Int)
{'default': None, 'conditions': [], 'min_value': 32, 'max_value': 512, 'step':
32, 'sampling': 'linear'}
dropout_2 (Float)
{'default': 0.0, 'conditions': [], 'min_value': 0.0, 'max_value': 0.5, 'step':
0.1, 'sampling': 'linear'}
Best Hyperparameters: {'units_input': 480, 'num_layers': 2, 'units_0': 448,
'dropout_0': 0.30000000000000004, 'learning_rate': 0.00614260757976685,
'units_1': 224, 'dropout_1': 0.0, 'units_2': 256, 'dropout_2': 0.4}
```

Best Hyperparameters: {‘units_input’: 480, ‘num_layers’: 2, ‘units_0’: 448, ‘dropout_0’: 0.30000000000000004, ‘learning_rate’: 0.00614260757976685, ‘units_1’: 224, ‘dropout_1’: 0.0, ‘units_2’: 256, ‘dropout_2’: 0.4}

[7]:
```python
# Build the model with the best hyperparameters
model1 = build_model(best_hps)

# Train the model
history = model1.fit(scaler.transform(X_train), Y_train.is_attack, epochs=20,
    validation_split=0.2, verbose=1)

save_keras_model(model1, 'DNN_model1')
```

```
C:\Users\youss\AppData\Local\Programs\Python\Python312\Lib\site-
packages\keras\src\layers\core\dense.py:88: UserWarning: Do not pass an
`input_shape`/`input_dim` argument to a layer. When using Sequential models,
prefer using an `Input(shape)` object as the first layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

```
Epoch 1/20
97279/97279            199s 2ms/step
- accuracy: 0.9362 - loss: 0.1674 - val_accuracy: 0.2194 - val_loss: 23.5051
Epoch 2/20
97279/97279            193s 2ms/step
- accuracy: 0.9386 - loss: 0.2016 - val_accuracy: 0.2388 - val_loss: 24.9698
Epoch 3/20
97279/97279            194s 2ms/step
- accuracy: 0.9180 - loss: 0.2323 - val_accuracy: 0.2713 - val_loss: 7.7734
Epoch 4/20
97279/97279            186s 2ms/step
```

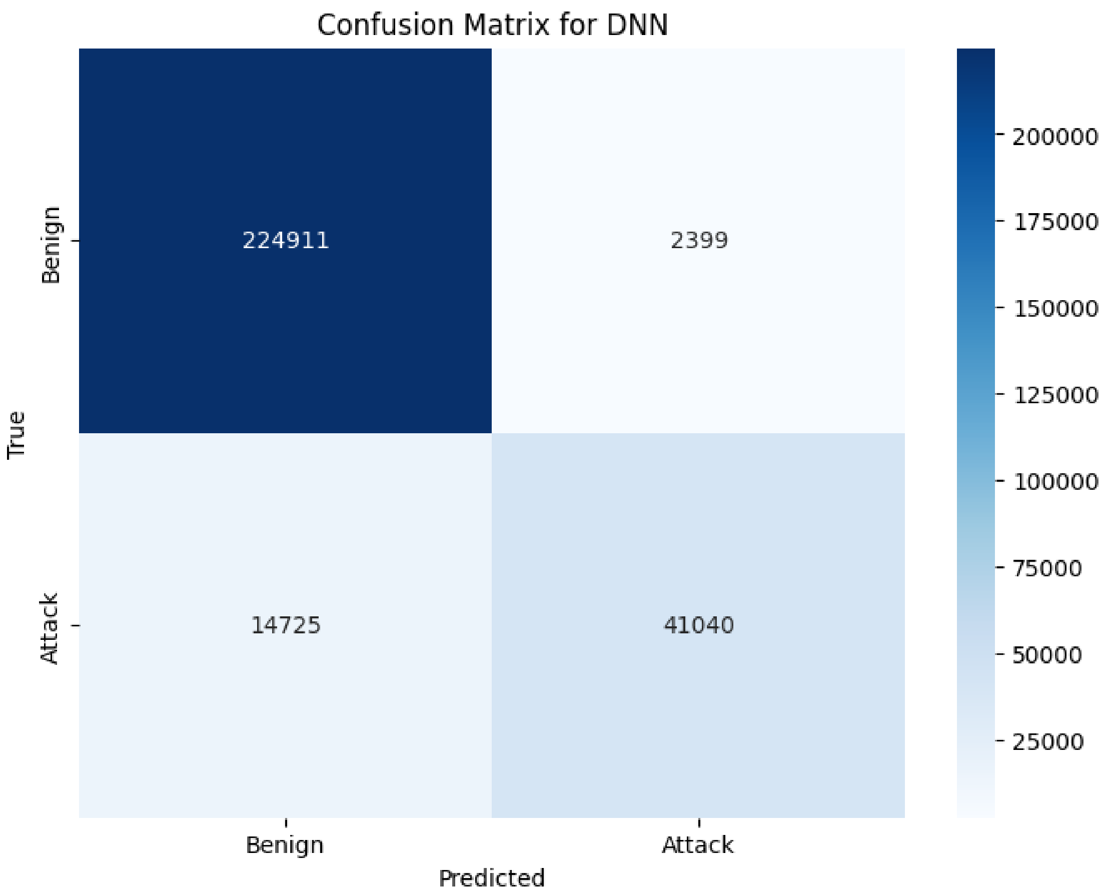
```
- accuracy: 0.9056 - loss: 0.3569 - val_accuracy: 0.4874 - val_loss: 1.3522
Epoch 5/20
97279/97279            159s 2ms/step
- accuracy: 0.9047 - loss: 0.2874 - val_accuracy: 0.5412 - val_loss: 10.9510
Epoch 6/20
97279/97279            181s 2ms/step
- accuracy: 0.9040 - loss: 0.3198 - val_accuracy: 0.5865 - val_loss: 8.1861
Epoch 7/20
97279/97279            188s 2ms/step
- accuracy: 0.9008 - loss: 0.3453 - val_accuracy: 0.5714 - val_loss: 43.7867
Epoch 8/20
97279/97279            170s 2ms/step
- accuracy: 0.9009 - loss: 0.3341 - val_accuracy: 0.5596 - val_loss: 2.2942
Epoch 9/20
97279/97279            187s 2ms/step
- accuracy: 0.8992 - loss: 0.3994 - val_accuracy: 0.2483 - val_loss: 16.2251
Epoch 10/20
97279/97279            178s 2ms/step
- accuracy: 0.8981 - loss: 0.3014 - val_accuracy: 0.2843 - val_loss: 7.9679
Epoch 11/20
97279/97279            182s 2ms/step
- accuracy: 0.8955 - loss: 0.3866 - val_accuracy: 0.2884 - val_loss: 5.5437
Epoch 12/20
97279/97279            188s 2ms/step
- accuracy: 0.8971 - loss: 0.3764 - val_accuracy: 0.2622 - val_loss: 10.5180
Epoch 13/20
97279/97279            189s 2ms/step
- accuracy: 0.8973 - loss: 0.6923 - val_accuracy: 0.2267 - val_loss: 12.5358
Epoch 14/20
97279/97279            193s 2ms/step
- accuracy: 0.8968 - loss: 0.6834 - val_accuracy: 0.2701 - val_loss: 13.9227
Epoch 15/20
97279/97279            205s 2ms/step
- accuracy: 0.8954 - loss: 0.8104 - val_accuracy: 0.2568 - val_loss: 16.7517
Epoch 16/20
97279/97279            203s 2ms/step
- accuracy: 0.8940 - loss: 0.4438 - val_accuracy: 0.2854 - val_loss: 47.6869
Epoch 17/20
97279/97279            212s 2ms/step
- accuracy: 0.8950 - loss: 0.4392 - val_accuracy: 0.2334 - val_loss: 25.7078
Epoch 18/20
97279/97279            212s 2ms/step
- accuracy: 0.8904 - loss: 0.4606 - val_accuracy: 0.2852 - val_loss: 9.0989
Epoch 19/20
97279/97279            212s 2ms/step
- accuracy: 0.8945 - loss: 0.3907 - val_accuracy: 0.2698 - val_loss: 21.3932
Epoch 20/20
97279/97279            202s 2ms/step
```

```
- accuracy: 0.8942 - loss: 0.5829 - val_accuracy: 0.2575 - val_loss: 12.5091
Model saved to models/DNN_model1.keras
```

[8]:

```
# Predict probabilities on the evaluation set
y_pred_eval_prob = model1.predict(scaler.transform(X_eval))
# Convert probabilities to binary predictions
y_pred_eval = (y_pred_eval_prob > 0.5).astype(int)
metrics_report("Evaluation", Y_eval.is_attack, y_pred_eval, print_avg=False)

# Predict and evaluate on the test set
y_pred_test_prob = model1.predict(scaler.transform(X_test))
y_pred_test = (y_pred_test_prob > 0.5).astype(int)
performance_models["DNN1"] = metrics_report("Test", Y_test.is_attack,
 ↪y_pred_test, print_avg=False)
plot_confusion_matrix("DNN", Y_test, y_pred_test)
```

```
8847/8847            5s 612us/step
Classification Report (Evaluation):
              precision    recall  f1-score   support

           0     0.9382    0.9896    0.9632    227310
           1     0.9456    0.7342    0.8266     55764

    accuracy                         0.9393    283074
   macro avg     0.9419    0.8619    0.8949    283074
weighted avg     0.9396    0.9393    0.9363    283074

Accuracy: 0.9393126885549362
8847/8847            5s 593us/step
Classification Report (Test):
              precision    recall  f1-score   support

           0     0.9386    0.9894    0.9633    227310
           1     0.9448    0.7359    0.8274     55765

    accuracy                         0.9395    283075
   macro avg     0.9417    0.8627    0.8954    283075
weighted avg     0.9398    0.9395    0.9365    283075

Accuracy: 0.9395071977391151
```



1.3 3. Hyperparameter tuning with Hypermodel with 2 layers

[9]:
```
from tensorflow.keras import layers
import keras_tuner as kt

class MyHyperModel(kt.HyperModel):
    def build(self, hp):
        model = Sequential()
        model.add(layers.Input(shape=(X_train.shape[1],)))

        model.add(layers.Dense(units=hp.Int('units_input', min_value=32,␣
 ↪max_value=512, step=32), activation='relu'))
        model.add(layers.Dropout(rate=hp.Float('dropout_input', min_value=0.0,␣
 ↪max_value=0.5, step=0.1)))

        for i in range(hp.Int('num_layers', 1, 3)):
            model.add(layers.Dense(units=hp.Int(f'units_{i}', min_value=32,␣
 ↪max_value=512, step=32), activation='relu'))
```

```
            model.add(layers.Dropout(rate=hp.Float(f'dropout_{i}', min_value=0.
↪0, max_value=0.5, step=0.1)))

        model.add(layers.Dense(1, activation='sigmoid'))

        model.compile(
            optimizer=tf.keras.optimizers.Adam(learning_rate=hp.
↪Float('learning_rate', min_value=1e-4, max_value=1e-2, sampling='LOG',␣
↪default=1e-3)),
            loss='binary_crossentropy',
            metrics=['accuracy']
        )
        return model
```

[10]:
```
directory_path = os.path.join(os.getcwd(), 'hyperparam_tuning_hypermodel')
tuner = kt.RandomSearch(
    MyHyperModel(),
    objective='val_accuracy',
    max_trials=10,
    executions_per_trial=2,
    directory=directory_path,
    project_name='intrusion_detection_hypermodel'
)

tuner.search_space_summary()
```

```
Reloading Tuner from G:\Other computers\My PC\stage\ML-NIDS\Notebooks\hyperparam
_tuning_hypermodel\intrusion_detection_hypermodel\tuner0.json
Search space summary
Default search space size: 10
units_input (Int)
{'default': None, 'conditions': [], 'min_value': 32, 'max_value': 512, 'step':
32, 'sampling': 'linear'}
dropout_input (Float)
{'default': 0.0, 'conditions': [], 'min_value': 0.0, 'max_value': 0.5, 'step':
0.1, 'sampling': 'linear'}
num_layers (Int)
{'default': None, 'conditions': [], 'min_value': 1, 'max_value': 3, 'step': 1,
'sampling': 'linear'}
units_0 (Int)
{'default': None, 'conditions': [], 'min_value': 32, 'max_value': 512, 'step':
32, 'sampling': 'linear'}
dropout_0 (Float)
{'default': 0.0, 'conditions': [], 'min_value': 0.0, 'max_value': 0.5, 'step':
0.1, 'sampling': 'linear'}
learning_rate (Float)
{'default': 0.001, 'conditions': [], 'min_value': 0.0001, 'max_value': 0.01,
'step': None, 'sampling': 'log'}
```

```
units_1 (Int)
{'default': None, 'conditions': [], 'min_value': 32, 'max_value': 512, 'step':
32, 'sampling': 'linear'}
dropout_1 (Float)
{'default': 0.0, 'conditions': [], 'min_value': 0.0, 'max_value': 0.5, 'step':
0.1, 'sampling': 'linear'}
units_2 (Int)
{'default': None, 'conditions': [], 'min_value': 32, 'max_value': 512, 'step':
32, 'sampling': 'linear'}
dropout_2 (Float)
{'default': 0.0, 'conditions': [], 'min_value': 0.0, 'max_value': 0.5, 'step':
0.1, 'sampling': 'linear'}
```

[11]:

```
# Perform the search
tuner.search(scaler.transform(X_train), Y_train.is_attack, epochs=10,
 ↪validation_split=0.2)

# Get the best hyperparameters
best_hps = tuner.get_best_hyperparameters(num_trials=1)[0]
print("Best Hyperparameters:", best_hps.values)
```

```
Best Hyperparameters: {'units_input': 64, 'dropout_input': 0.30000000000000004,
'num_layers': 1, 'units_0': 128, 'dropout_0': 0.1, 'learning_rate':
0.009264436128630775, 'units_1': 96, 'dropout_1': 0.2, 'units_2': 320,
'dropout_2': 0.1}
```

Best Hyperparameters: {'units_input': 64, 'dropout_input': 0.30000000000000004, 'num_layers': 1, 'units_0': 128, 'dropout_0': 0.1, 'learning_rate': 0.009264436128630775, 'units_1': 96, 'dropout_1': 0.2, 'units_2': 320, 'dropout_2': 0.1}

[12]:

```
# Build the model with the best hyperparameters
hypermodel = MyHyperModel()
model2 = hypermodel.build(best_hps)

# Train the model
history = model2.fit(scaler.transform(X_train), Y_train.is_attack, epochs=20,
 ↪validation_split=0.2, verbose=1)

save_keras_model(model2, 'DNN_model2')
```

```
Epoch 1/20
97279/97279              64s
646us/step - accuracy: 0.9370 - loss: 0.1576 - val_accuracy: 0.3041 - val_loss:
9.0398
Epoch 2/20
97279/97279              65s
663us/step - accuracy: 0.9475 - loss: 0.2043 - val_accuracy: 0.2337 - val_loss:
9.1982
Epoch 3/20
```

```
97279/97279 64s
662us/step - accuracy: 0.9494 - loss: 0.1583 - val_accuracy: 0.2695 - val_loss:
8.0149
Epoch 4/20
97279/97279 65s
666us/step - accuracy: 0.9495 - loss: 0.1577 - val_accuracy: 0.3341 - val_loss:
5.3154
Epoch 5/20
97279/97279 64s
662us/step - accuracy: 0.9506 - loss: 0.1349 - val_accuracy: 0.4592 - val_loss:
6.7877
Epoch 6/20
97279/97279 65s
663us/step - accuracy: 0.9507 - loss: 0.1667 - val_accuracy: 0.5095 - val_loss:
4.0334
Epoch 7/20
97279/97279 64s
660us/step - accuracy: 0.9505 - loss: 0.2866 - val_accuracy: 0.4640 - val_loss:
2.5444
Epoch 8/20
97279/97279 65s
664us/step - accuracy: 0.9505 - loss: 0.8163 - val_accuracy: 0.3539 - val_loss:
13.1483
Epoch 9/20
97279/97279 65s
663us/step - accuracy: 0.9510 - loss: 0.1466 - val_accuracy: 0.5085 - val_loss:
5.3550
Epoch 10/20
97279/97279 65s
664us/step - accuracy: 0.9513 - loss: 0.6952 - val_accuracy: 0.4680 - val_loss:
7.3507
Epoch 11/20
97279/97279 65s
667us/step - accuracy: 0.9515 - loss: 0.7324 - val_accuracy: 0.4802 - val_loss:
3.3766
Epoch 12/20
97279/97279 65s
663us/step - accuracy: 0.9508 - loss: 0.1814 - val_accuracy: 0.4974 - val_loss:
4.5640
Epoch 13/20
97279/97279 65s
667us/step - accuracy: 0.9521 - loss: 0.1678 - val_accuracy: 0.3850 - val_loss:
21.5073
Epoch 14/20
97279/97279 65s
669us/step - accuracy: 0.9513 - loss: 0.3973 - val_accuracy: 0.4833 - val_loss:
4.1977
Epoch 15/20
```

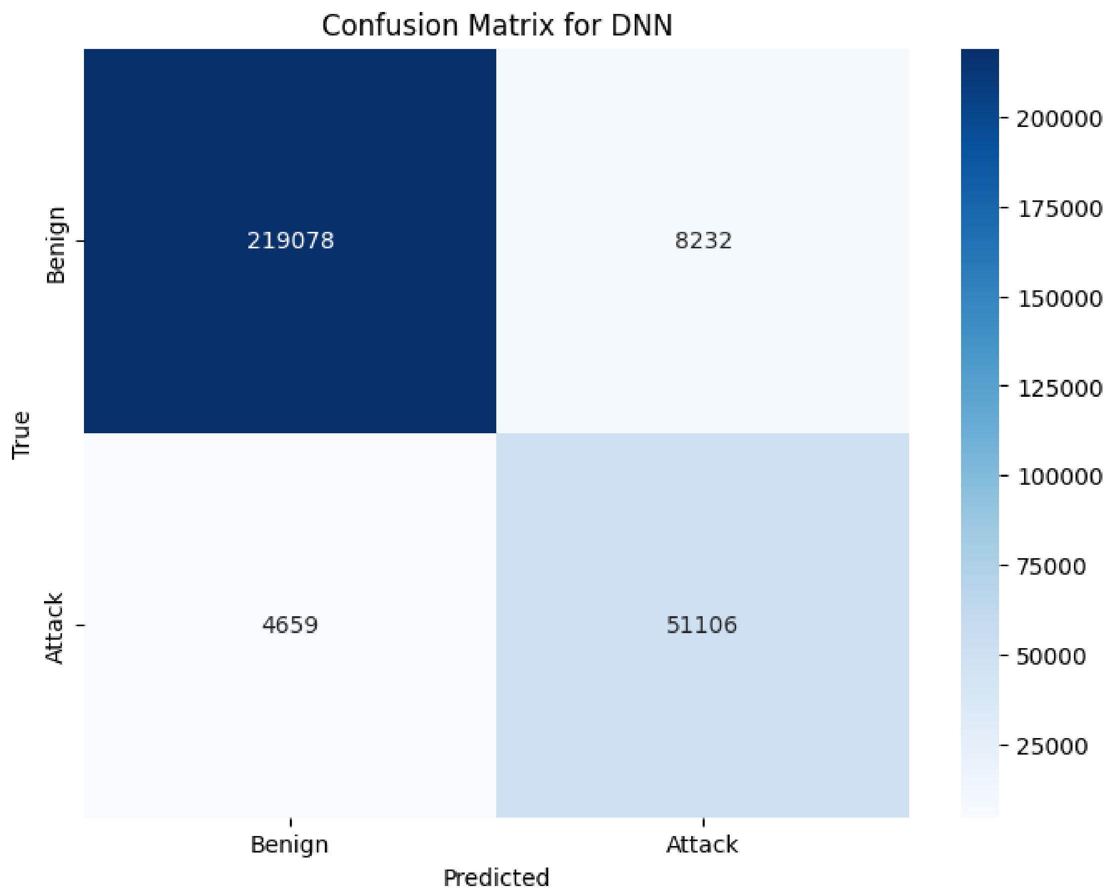
```
97279/97279          65s
667us/step - accuracy: 0.9514 - loss: 0.2019 - val_accuracy: 0.3560 - val_loss:
13.8358
Epoch 16/20
97279/97279          65s
663us/step - accuracy: 0.9518 - loss: 0.1403 - val_accuracy: 0.4858 - val_loss:
3.4603
Epoch 17/20
97279/97279          65s
667us/step - accuracy: 0.9508 - loss: 0.3133 - val_accuracy: 0.5045 - val_loss:
3.4912
Epoch 18/20
97279/97279          65s
667us/step - accuracy: 0.9501 - loss: 0.3443 - val_accuracy: 0.4809 - val_loss:
1.7908
Epoch 19/20
97279/97279          65s
666us/step - accuracy: 0.9510 - loss: 0.4606 - val_accuracy: 0.4932 - val_loss:
4.0004
Epoch 20/20
97279/97279          65s
668us/step - accuracy: 0.9505 - loss: 0.2129 - val_accuracy: 0.5225 - val_loss:
2.9548
Model saved to models/DNN_model2.keras
```

[13]:

```
# Predict probabilities on the evaluation set
y_pred_eval_prob = model2.predict(scaler.transform(X_eval))
# Convert probabilities to binary predictions
y_pred_eval = (y_pred_eval_prob > 0.5).astype(int)
metrics_report("Evaluation", Y_eval.is_attack, y_pred_eval, print_avg=False)

# Predict and evaluate on the test set
y_pred_test_prob = model2.predict(scaler.transform(X_test))
y_pred_test = (y_pred_test_prob > 0.5).astype(int)
performance_models["DNN2"] = metrics_report("Test", Y_test.is_attack,␣
↪y_pred_test, print_avg=False)
plot_confusion_matrix("DNN", Y_test, y_pred_test)
```

```
8847/8847          4s 422us/step
Classification Report (Evaluation):
              precision    recall  f1-score   support

           0     0.9796    0.9642    0.9718    227310
           1     0.8629    0.9180    0.8896     55764

    accuracy                         0.9551    283074
   macro avg     0.9212    0.9411    0.9307    283074
weighted avg     0.9566    0.9551    0.9556    283074
```

```
Accuracy: 0.9551177430636512
8847/8847              4s 413us/step
Classification Report (Test):
              precision    recall  f1-score   support

           0     0.9792    0.9638    0.9714    227310
           1     0.8613    0.9165    0.8880     55765

    accuracy                         0.9545    283075
   macro avg     0.9202    0.9401    0.9297    283075
weighted avg     0.9559    0.9545    0.9550    283075

Accuracy: 0.9544608319349995
```



1.4 4. Hyperparameter Tuning for 3 layers

[14]:
```
from tensorflow.keras.layers import Input

# Define the HyperModel class
def build_model2(hp):
    model = Sequential()
    model.add(Input(shape=(X_train.shape[1],)))
    model.add(Dense(units=hp.Int('units_1', min_value=32, max_value=256,␣
↪step=32), activation='relu'))
    model.add(Dropout(rate=hp.Float('dropout_1', min_value=0.1, max_value=0.5,␣
↪step=0.1)))
    model.add(Dense(units=hp.Int('units_2', min_value=16, max_value=256,␣
↪step=32), activation='relu'))
    model.add(Dropout(rate=hp.Float('dropout_2', min_value=0.1, max_value=0.5,␣
↪step=0.1)))
    model.add(Dense(units=hp.Int('units_3', min_value=16, max_value=256,␣
↪step=32), activation='relu'))
    model.add(Dropout(rate=hp.Float('dropout_3', min_value=0.1, max_value=0.5,␣
↪step=0.1)))
    model.add(Dense(1, activation='sigmoid'))

    model.compile(
        optimizer=tf.keras.optimizers.Adam(learning_rate=hp.
↪Float('learning_rate', min_value=1e-4, max_value=1e-2, sampling='log')),
        loss='binary_crossentropy',
        metrics=['accuracy']
    )

    return model
```

[15]:
```
# Initialize the tuner
directory_path = os.path.join(os.getcwd(), 'hyperparam_tuning_hypermodel2')
tuner = kt.RandomSearch(
    build_model2,
    objective='val_accuracy',
    max_trials=10,
    executions_per_trial=2,
    directory=directory_path,
    project_name='intrusion_detection_hypermodel2'
)
tuner.search_space_summary()
```

```
Reloading Tuner from G:\Other computers\My PC\stage\ML-NIDS\Notebooks\hyperparam
_tuning_hypermodel2\intrusion_detection_hypermodel2\tuner0.json
Search space summary
Default search space size: 7
units_1 (Int)
```

```
{'default': None, 'conditions': [], 'min_value': 32, 'max_value': 256, 'step':
32, 'sampling': 'linear'}
dropout_1 (Float)
{'default': 0.1, 'conditions': [], 'min_value': 0.1, 'max_value': 0.5, 'step':
0.1, 'sampling': 'linear'}
units_2 (Int)
{'default': None, 'conditions': [], 'min_value': 16, 'max_value': 256, 'step':
32, 'sampling': 'linear'}
dropout_2 (Float)
{'default': 0.1, 'conditions': [], 'min_value': 0.1, 'max_value': 0.5, 'step':
0.1, 'sampling': 'linear'}
units_3 (Int)
{'default': None, 'conditions': [], 'min_value': 16, 'max_value': 256, 'step':
32, 'sampling': 'linear'}
dropout_3 (Float)
{'default': 0.1, 'conditions': [], 'min_value': 0.1, 'max_value': 0.5, 'step':
0.1, 'sampling': 'linear'}
learning_rate (Float)
{'default': 0.0001, 'conditions': [], 'min_value': 0.0001, 'max_value': 0.01,
'step': None, 'sampling': 'log'}
```

[16]:

```
# Perform the search
tuner.search(scaler.transform(X_train), Y_train.is_attack, epochs=10,␣
 ↪validation_split=0.2)
# Get the best hyperparameters
best_hps = tuner.get_best_hyperparameters(num_trials=1)[0]
print("Best Hyperparameters:", best_hps.values)
```

```
Best Hyperparameters: {'units_1': 160, 'dropout_1': 0.30000000000000004,
'units_2': 176, 'dropout_2': 0.1, 'units_3': 80, 'dropout_3':
0.30000000000000004, 'learning_rate': 0.001395388438752399}
```

Best Hyperparameters: {'units_1': 160, 'dropout_1': 0.30000000000000004, 'units_2': 176, 'dropout_2': 0.1, 'units_3': 80, 'dropout_3': 0.30000000000000004, 'learning_rate': 0.001395388438752399}

[17]:

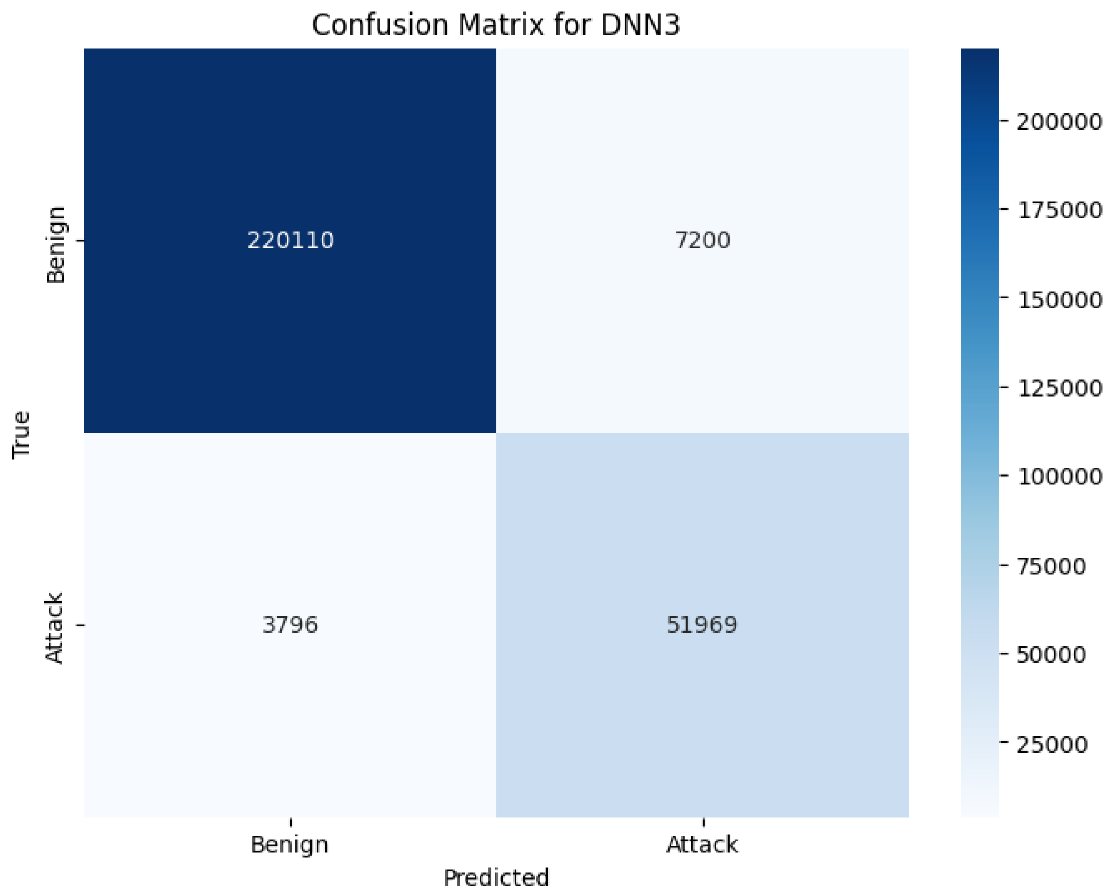
```
# Build the model with the best hyperparameters
model3 = build_model2(best_hps)

# Add early stopping callback
early_stopping = tf.keras.callbacks.EarlyStopping(monitor='val_loss',␣
 ↪patience=5, restore_best_weights=True)

# Train the model
history = model3.fit(scaler.transform(X_train), Y_train.is_attack, epochs=50,␣
 ↪batch_size=32, validation_split=0.2, callbacks=[early_stopping])

save_keras_model(model3, 'DNN_model3')
```

```
Epoch 1/50
97279/97279              84s
852us/step - accuracy: 0.9483 - loss: 0.1202 - val_accuracy: 0.2989 - val_loss:
3.5517
Epoch 2/50
97279/97279              82s
846us/step - accuracy: 0.9582 - loss: 0.0960 - val_accuracy: 0.4244 - val_loss:
3.1263
Epoch 3/50
97279/97279              82s
844us/step - accuracy: 0.9590 - loss: 0.0976 - val_accuracy: 0.4823 - val_loss:
2.1240
Epoch 4/50
97279/97279              82s
845us/step - accuracy: 0.9591 - loss: 0.2004 - val_accuracy: 0.4903 - val_loss:
1.5908
Epoch 5/50
97279/97279              82s
843us/step - accuracy: 0.9591 - loss: 0.2509 - val_accuracy: 0.5100 - val_loss:
2.1942
Epoch 6/50
97279/97279              82s
840us/step - accuracy: 0.9593 - loss: 0.0987 - val_accuracy: 0.5200 - val_loss:
2.1992
Epoch 7/50
97279/97279              82s
843us/step - accuracy: 0.9590 - loss: 0.0979 - val_accuracy: 0.4766 - val_loss:
4.7340
Epoch 8/50
97279/97279              83s
848us/step - accuracy: 0.9589 - loss: 0.1134 - val_accuracy: 0.4948 - val_loss:
3.9055
Epoch 9/50
97279/97279              82s
843us/step - accuracy: 0.9588 - loss: 0.1252 - val_accuracy: 0.4815 - val_loss:
11.9395
Model saved to models/DNN_model3.keras
```

[18]:
```python
# Evaluate the best model
# Predict probabilities on the evaluation set
y_pred_eval_prob = model3.predict(scaler.transform(X_eval))
# Convert probabilities to binary predictions
y_pred_eval = (y_pred_eval_prob > 0.5).astype(int)
metrics_report("Evaluation", Y_eval.is_attack, y_pred_eval, print_avg=False)

# Predict and evaluate on the test set
y_pred_test_prob = model3.predict(scaler.transform(X_test))
```

```
y_pred_test = (y_pred_test_prob > 0.5).astype(int)
performance_models["DNN3"] = metrics_report("Test", Y_test.is_attack,␣
↪y_pred_test, print_avg=False)
plot_confusion_matrix("DNN3", Y_test, y_pred_test)
```

```
8847/8847              4s 450us/step
Classification Report (Evaluation):
              precision    recall  f1-score   support

           0     0.9831    0.9692    0.9761    227310
           1     0.8815    0.9320    0.9060     55764

    accuracy                         0.9619    283074
   macro avg     0.9323    0.9506    0.9411    283074
weighted avg     0.9631    0.9619    0.9623    283074

Accuracy: 0.96191455237853
8847/8847              4s 442us/step
Classification Report (Test):
              precision    recall  f1-score   support

           0     0.9830    0.9683    0.9756    227310
           1     0.8783    0.9319    0.9043     55765

    accuracy                         0.9612    283075
   macro avg     0.9307    0.9501    0.9400    283075
weighted avg     0.9624    0.9612    0.9616    283075

Accuracy: 0.9611551708911066
```



1.5 5. Hyperparameter Tuning with 4 layers

[19]:
```
# Define the build_model3 function with four dense layers
def build_model3(hp):
    model = Sequential()
    model.add(Input(shape=(X_train.shape[1],)))
    model.add(Dense(units=hp.Int('units_1', min_value=32, max_value=256,␣
 ↪step=32), activation='relu'))
    model.add(Dropout(rate=hp.Float('dropout_1', min_value=0.1, max_value=0.5,␣
 ↪step=0.1)))
    model.add(Dense(units=hp.Int('units_2', min_value=16, max_value=256,␣
 ↪step=32), activation='relu'))
    model.add(Dropout(rate=hp.Float('dropout_2', min_value=0.1, max_value=0.5,␣
 ↪step=0.1)))
    model.add(Dense(units=hp.Int('units_3', min_value=16, max_value=256,␣
 ↪step=32), activation='relu'))
    model.add(Dropout(rate=hp.Float('dropout_3', min_value=0.1, max_value=0.5,␣
 ↪step=0.1)))
```

```
    model.add(Dense(units=hp.Int('units_4', min_value=16, max_value=256,␣
↪step=32), activation='relu'))
    model.add(Dropout(rate=hp.Float('dropout_4', min_value=0.1, max_value=0.5,␣
↪step=0.1)))
    model.add(Dense(1, activation='sigmoid'))

    model.compile(
        optimizer=tf.keras.optimizers.Adam(learning_rate=hp.
↪Float('learning_rate', min_value=1e-4, max_value=1e-2, sampling='log')),
        loss='binary_crossentropy',
        metrics=['accuracy']
    )

    return model
```

[20]:

```
# Initialize the tuner
directory_path = os.path.join(os.getcwd(), 'hyperparam_tuning_hypermodel3')
tuner = kt.RandomSearch(
    build_model3,
    objective='val_accuracy',
    max_trials=10,
    executions_per_trial=2,
    directory=directory_path,
    project_name='intrusion_detection_hypermodel3'
)
tuner.search_space_summary()
```

```
Reloading Tuner from G:\Other computers\My PC\stage\ML-NIDS\Notebooks\hyperparam
_tuning_hypermodel3\intrusion_detection_hypermodel3\tuner0.json
Search space summary
Default search space size: 9
units_1 (Int)
{'default': None, 'conditions': [], 'min_value': 32, 'max_value': 256, 'step':
32, 'sampling': 'linear'}
dropout_1 (Float)
{'default': 0.1, 'conditions': [], 'min_value': 0.1, 'max_value': 0.5, 'step':
0.1, 'sampling': 'linear'}
units_2 (Int)
{'default': None, 'conditions': [], 'min_value': 16, 'max_value': 256, 'step':
32, 'sampling': 'linear'}
dropout_2 (Float)
{'default': 0.1, 'conditions': [], 'min_value': 0.1, 'max_value': 0.5, 'step':
0.1, 'sampling': 'linear'}
units_3 (Int)
{'default': None, 'conditions': [], 'min_value': 16, 'max_value': 256, 'step':
32, 'sampling': 'linear'}
dropout_3 (Float)
```

```
{'default': 0.1, 'conditions': [], 'min_value': 0.1, 'max_value': 0.5, 'step':
0.1, 'sampling': 'linear'}
units_4 (Int)
{'default': None, 'conditions': [], 'min_value': 16, 'max_value': 256, 'step':
32, 'sampling': 'linear'}
dropout_4 (Float)
{'default': 0.1, 'conditions': [], 'min_value': 0.1, 'max_value': 0.5, 'step':
0.1, 'sampling': 'linear'}
learning_rate (Float)
{'default': 0.0001, 'conditions': [], 'min_value': 0.0001, 'max_value': 0.01,
'step': None, 'sampling': 'log'}
```

[21]:

```
# Perform the search
tuner.search(scaler.transform(X_train), Y_train['is_attack'], epochs=10,␣
↪validation_split=0.2)

# Get the best hyperparameters
best_hps = tuner.get_best_hyperparameters(num_trials=1)[0]
print("Best Hyperparameters:", best_hps.values)
```

```
Best Hyperparameters: {'units_1': 192, 'dropout_1': 0.4, 'units_2': 16,
'dropout_2': 0.30000000000000004, 'units_3': 16, 'dropout_3': 0.4, 'units_4':
208, 'dropout_4': 0.30000000000000004, 'learning_rate': 0.0025675045227976654}
```

Best Hyperparameters: {'units_1': 192, 'dropout_1': 0.4, 'units_2': 16, 'dropout_2': 0.30000000000000004, 'units_3': 16, 'dropout_3': 0.4, 'units_4': 208, 'dropout_4': 0.30000000000000004, 'learning_rate': 0.0025675045227976654}

[22]:

```
# Build the model with the best hyperparameters
model4 = build_model3(best_hps)
# Add early stopping callback
early_stopping = tf.keras.callbacks.EarlyStopping(monitor='val_loss',␣
↪patience=5, restore_best_weights=True)
# Train the model
history = model4.fit(scaler.transform(X_train), Y_train.is_attack, epochs=50,␣
↪batch_size=32, validation_split=0.2, callbacks=[early_stopping])
save_keras_model(model4, 'DNN_model4')
```

```
Epoch 1/50
97279/97279            80s
810us/step - accuracy: 0.9361 - loss: 0.1683 - val_accuracy: 0.3888 - val_loss:
2.8339
Epoch 2/50
97279/97279            79s
807us/step - accuracy: 0.9498 - loss: 0.1208 - val_accuracy: 0.3020 - val_loss:
7.9926
Epoch 3/50
97279/97279            79s
807us/step - accuracy: 0.9504 - loss: 0.1189 - val_accuracy: 0.3899 - val_loss:
```

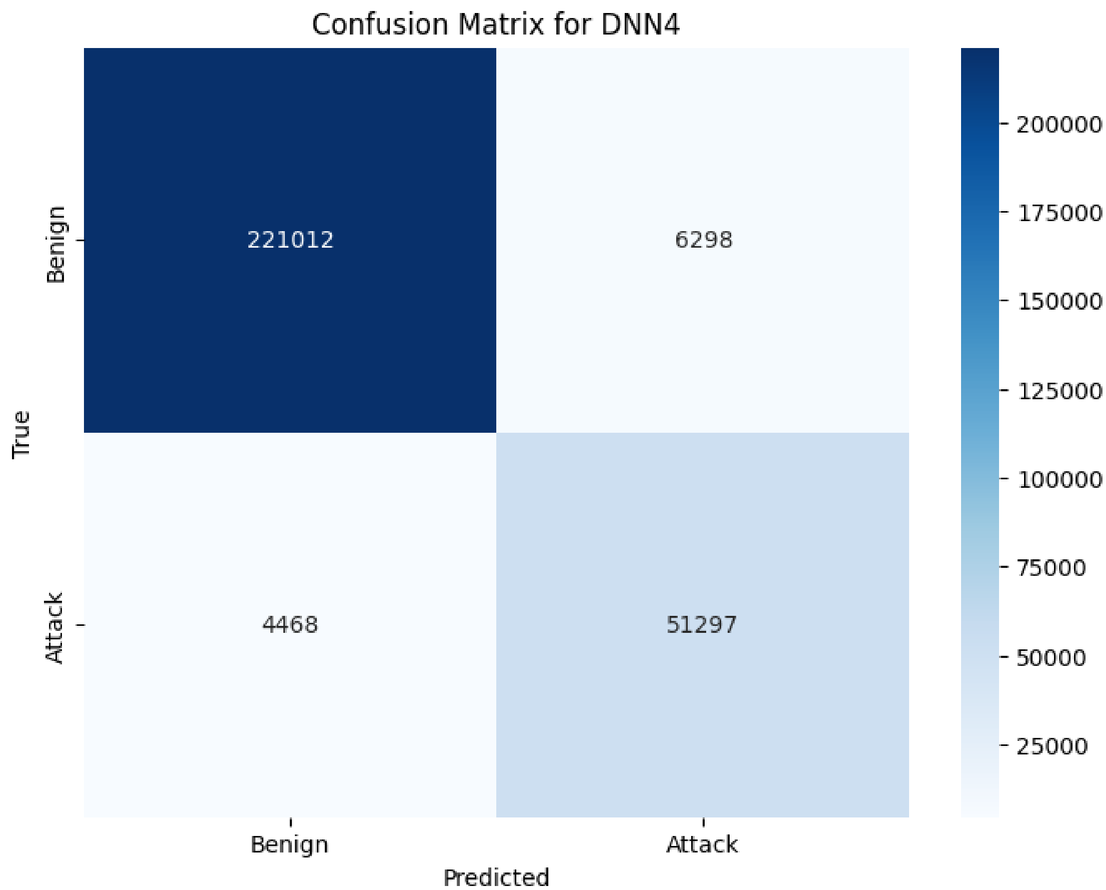
```
7.1006
Epoch 4/50
97279/97279            79s
807us/step - accuracy: 0.9509 - loss: 0.1244 - val_accuracy: 0.2968 - val_loss:
6.0990
Epoch 5/50
97279/97279            82s
845us/step - accuracy: 0.9512 - loss: 0.1144 - val_accuracy: 0.3563 - val_loss:
4.7947
Epoch 6/50
97279/97279            81s
830us/step - accuracy: 0.9518 - loss: 0.1171 - val_accuracy: 0.4314 - val_loss:
3.1019
Model saved to models/DNN_model4.keras
```

[23]:

```
# Evaluate the best model
# Predict probabilities on the evaluation set
y_pred_eval_prob = model4.predict(scaler.transform(X_eval))
# Convert probabilities to binary predictions
y_pred_eval = (y_pred_eval_prob > 0.5).astype(int)
metrics_report("Evaluation", Y_eval.is_attack, y_pred_eval, print_avg=False)

# Predict and evaluate on the test set
y_pred_test_prob = model4.predict(scaler.transform(X_test))
y_pred_test = (y_pred_test_prob > 0.5).astype(int)
performance_models["DNN4"] = metrics_report("Test", Y_test.is_attack,␣
  ↪y_pred_test, print_avg=False)
plot_confusion_matrix("DNN4", Y_test, y_pred_test)
```

```
8847/8847            4s 452us/step
Classification Report (Evaluation):
              precision    recall  f1-score   support

           0     0.9806    0.9733    0.9769    227310
           1     0.8944    0.9214    0.9077     55764

    accuracy                         0.9631    283074
   macro avg     0.9375    0.9474    0.9423    283074
weighted avg     0.9636    0.9631    0.9633    283074

Accuracy: 0.9630909232214898
8847/8847            4s 439us/step
Classification Report (Test):
              precision    recall  f1-score   support

           0     0.9802    0.9723    0.9762    227310
           1     0.8907    0.9199    0.9050     55765
```

```
    accuracy                         0.9620    283075
   macro avg     0.9354    0.9461    0.9406    283075
weighted avg     0.9625    0.9620    0.9622    283075

Accuracy: 0.9619676764108451
```



1.6 5. Layers and different metric for hyperparameter optimization

[24]:
```python
# Define the build_model3 function with four dense layers
def build_model4(hp):
    model = Sequential()
    model.add(Input(shape=(X_train.shape[1],)))
    model.add(Dense(units=hp.Int('units_1', min_value=32, max_value=256, step=32), activation='relu'))
    model.add(Dropout(rate=hp.Float('dropout_1', min_value=0.1, max_value=0.5, step=0.1)))
    model.add(Dense(units=hp.Int('units_2', min_value=16, max_value=256, step=32), activation='relu'))
```

```
    model.add(Dropout(rate=hp.Float('dropout_2', min_value=0.1, max_value=0.5,␣
↪step=0.1)))
    model.add(Dense(units=hp.Int('units_3', min_value=16, max_value=256,␣
↪step=32), activation='relu'))
    model.add(Dropout(rate=hp.Float('dropout_3', min_value=0.1, max_value=0.5,␣
↪step=0.1)))
    model.add(Dense(units=hp.Int('units_4', min_value=16, max_value=256,␣
↪step=32), activation='relu'))
    model.add(Dropout(rate=hp.Float('dropout_4', min_value=0.1, max_value=0.5,␣
↪step=0.1)))
    model.add(Dense(1, activation='sigmoid'))

    model.compile(
        optimizer=tf.keras.optimizers.Adam(learning_rate=hp.
↪Float('learning_rate', min_value=1e-4, max_value=1e-2, sampling='log')),
        loss='binary_crossentropy',
        metrics=['accuracy']
    )

    return model
```

[25]:
```
# Initialize the tuner
directory_path = os.path.join(os.getcwd(), 'hyperparam_tuning_hypermodel4')
tuner = kt.RandomSearch(
    build_model4,
    objective='accuracy',
    max_trials=10,
    executions_per_trial=2,
    directory=directory_path,
    project_name='intrusion_detection_hypermodel4'
)
tuner.search_space_summary()
```

```
Search space summary
Default search space size: 9
units_1 (Int)
{'default': None, 'conditions': [], 'min_value': 32, 'max_value': 256, 'step':
32, 'sampling': 'linear'}
dropout_1 (Float)
{'default': 0.1, 'conditions': [], 'min_value': 0.1, 'max_value': 0.5, 'step':
0.1, 'sampling': 'linear'}
units_2 (Int)
{'default': None, 'conditions': [], 'min_value': 16, 'max_value': 256, 'step':
32, 'sampling': 'linear'}
dropout_2 (Float)
{'default': 0.1, 'conditions': [], 'min_value': 0.1, 'max_value': 0.5, 'step':
0.1, 'sampling': 'linear'}
```

```
units_3 (Int)
{'default': None, 'conditions': [], 'min_value': 16, 'max_value': 256, 'step':
32, 'sampling': 'linear'}
dropout_3 (Float)
{'default': 0.1, 'conditions': [], 'min_value': 0.1, 'max_value': 0.5, 'step':
0.1, 'sampling': 'linear'}
units_4 (Int)
{'default': None, 'conditions': [], 'min_value': 16, 'max_value': 256, 'step':
32, 'sampling': 'linear'}
dropout_4 (Float)
{'default': 0.1, 'conditions': [], 'min_value': 0.1, 'max_value': 0.5, 'step':
0.1, 'sampling': 'linear'}
learning_rate (Float)
{'default': 0.0001, 'conditions': [], 'min_value': 0.0001, 'max_value': 0.01,
'step': None, 'sampling': 'log'}
```

[26]:

```python
# Perform the search
tuner.search(scaler.transform(X_train), Y_train['is_attack'], epochs=10,␣
↪validation_split=0.2)

# Get the best hyperparameters
best_hps = tuner.get_best_hyperparameters(num_trials=1)[0]
print("Best Hyperparameters:", best_hps.values)
```

```
Trial 10 Complete [00h 39m 48s]
accuracy: 0.9534268975257874

Best accuracy So Far: 0.9665588438510895
Total elapsed time: 05h 49m 06s
Best Hyperparameters: {'units_1': 192, 'dropout_1': 0.1, 'units_2': 80,
'dropout_2': 0.1, 'units_3': 16, 'dropout_3': 0.2, 'units_4': 240, 'dropout_4':
0.4, 'learning_rate': 0.00011617848168321534}
```

[27]:

```python
# Build the model with the best hyperparameters
model5 = build_model4(best_hps)
# Add early stopping callback
early_stopping = tf.keras.callbacks.EarlyStopping(monitor='val_loss',␣
↪patience=5, restore_best_weights=True)
# Train the model
history = model5.fit(scaler.transform(X_train), Y_train.is_attack, epochs=50,␣
↪batch_size=32, validation_split=0.2, callbacks=[early_stopping])
save_keras_model(model5, 'DNN_model5')
```

```
Epoch 1/50
97279/97279            114s 1ms/step
- accuracy: 0.9380 - loss: 0.1428 - val_accuracy: 0.3551 - val_loss: 4.4268
Epoch 2/50
97279/97279            108s 1ms/step
```

```
- accuracy: 0.9609 - loss: 0.0864 - val_accuracy: 0.3682 - val_loss: 2.2838
Epoch 3/50
97279/97279            108s 1ms/step
- accuracy: 0.9633 - loss: 0.0815 - val_accuracy: 0.3609 - val_loss: 2.0058
Epoch 4/50
97279/97279            108s 1ms/step
- accuracy: 0.9640 - loss: 0.0797 - val_accuracy: 0.3459 - val_loss: 1.9149
Epoch 5/50
97279/97279            108s 1ms/step
- accuracy: 0.9645 - loss: 0.0783 - val_accuracy: 0.3781 - val_loss: 1.7849
Epoch 6/50
97279/97279            108s 1ms/step
- accuracy: 0.9648 - loss: 0.0772 - val_accuracy: 0.4870 - val_loss: 1.3252
Epoch 7/50
97279/97279            109s 1ms/step
- accuracy: 0.9654 - loss: 0.0756 - val_accuracy: 0.4858 - val_loss: 1.5551
Epoch 8/50
97279/97279            108s 1ms/step
- accuracy: 0.9657 - loss: 0.0804 - val_accuracy: 0.4936 - val_loss: 1.5810
Epoch 9/50
97279/97279            109s 1ms/step
- accuracy: 0.9658 - loss: 0.0747 - val_accuracy: 0.4816 - val_loss: 1.5042
Epoch 10/50
97279/97279            109s 1ms/step
- accuracy: 0.9663 - loss: 0.0746 - val_accuracy: 0.4943 - val_loss: 1.3685
Epoch 11/50
97279/97279            109s 1ms/step
- accuracy: 0.9666 - loss: 0.0736 - val_accuracy: 0.4701 - val_loss: 1.3679
Model saved to models/DNN_model5.keras
```

[28]:

```python
# Evaluate the best model
# Predict probabilities on the evaluation set
y_pred_eval_prob = model5.predict(scaler.transform(X_eval))
# Convert probabilities to binary predictions
y_pred_eval = (y_pred_eval_prob > 0.5).astype(int)
metrics_report("Evaluation", Y_eval.is_attack, y_pred_eval, print_avg=False)

# Predict and evaluate on the test set
y_pred_test_prob = model5.predict(scaler.transform(X_test))
y_pred_test = (y_pred_test_prob > 0.5).astype(int)
performance_models["DNN5"] = metrics_report("Test", Y_test.is_attack,␣
 ↪y_pred_test, print_avg=False)
plot_confusion_matrix("DNN5", Y_test, y_pred_test)
```

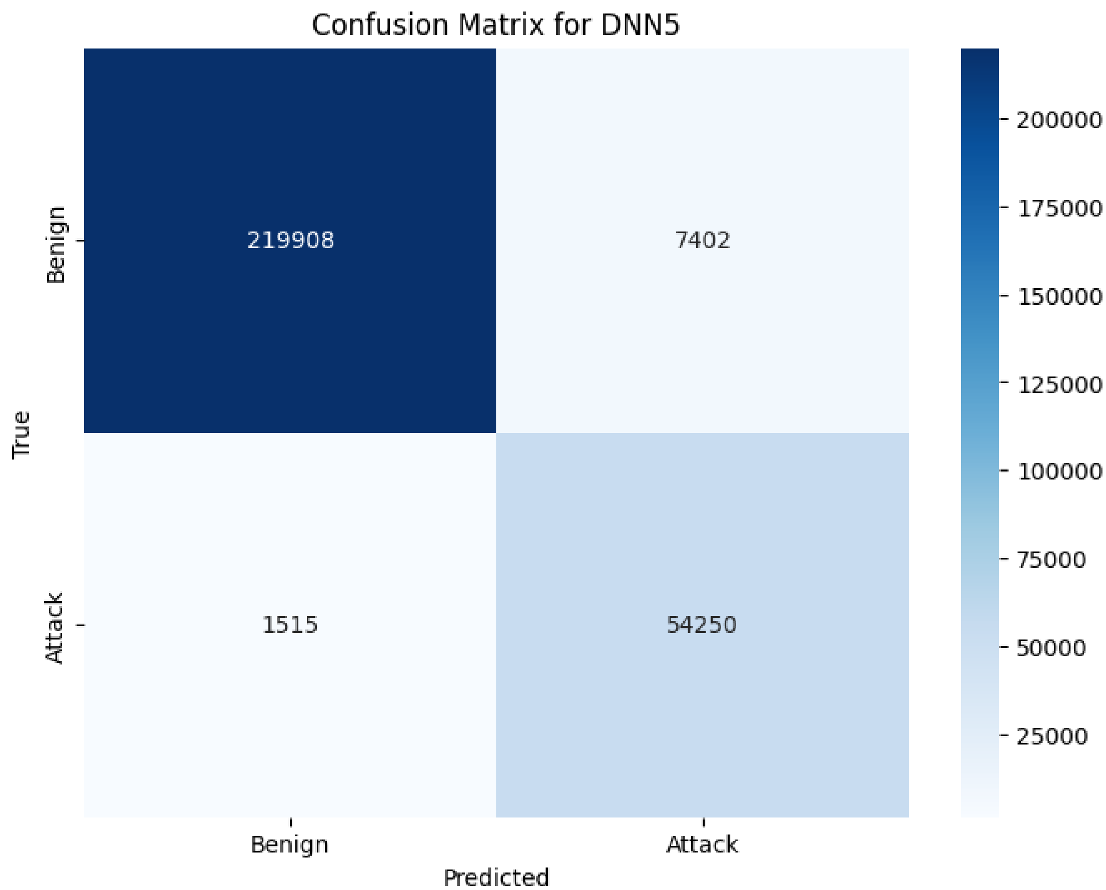
```
8847/8847          4s 492us/step
Classification Report (Evaluation):
              precision    recall  f1-score   support
```

	precision	recall	f1-score	support
0	0.9931	0.9680	0.9804	227310
1	0.8817	0.9725	0.9249	55764
accuracy			0.9689	283074
macro avg	0.9374	0.9703	0.9526	283074
weighted avg	0.9711	0.9689	0.9694	283074

Accuracy: 0.9688773960165893
8847/8847 4s 496us/step
Classification Report (Test):

	precision	recall	f1-score	support
0	0.9932	0.9674	0.9801	227310
1	0.8799	0.9728	0.9241	55765
accuracy			0.9685	283075
macro avg	0.9365	0.9701	0.9521	283075
weighted avg	0.9709	0.9685	0.9691	283075

Accuracy: 0.9684995142630045



1.7 6. Conclusion

[29]:
```
extract_and_plot_metrics(performance_models)
```

```
[0.9395071977391151, 0.9544608319349995, 0.9611551708911066, 0.9619676764108451,
0.9684995142630045]
['DNN1', 'DNN2', 'DNN3', 'DNN4', 'DNN5']
```