ADVANCED NETWORKS

PROJECT REPORT

DDoS DETECTION AND MITIGATION THROUGH ADVANCED BIDIRECTIONAL RECURRENT NEURAL NETWORKS

Submitted by

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ABSTRACT :

Distributed Denial of Service (DDoS) attacks poses a growing threat to Internet stability, demanding advanced detection mechanisms. This project introduces a sophisticated DDoS attack detection system for Software-Defined Networking (SDN) using a hybrid LSTM and RNN architecture, achieving an impressive 97.70% detection efficiency. Unlike traditional methods, this system employs deep learning to automatically extract high-level features from low-level network traffic data, overcoming limitations of statistical divergence models. In the dynamic realm of cybersecurity, where DDoS attacks evolve, conventional defenses, particularly statistical divergence methods in SDN, struggle due to a lack of granularity. Experimental results validate its effectiveness in SDN with a remarkable 97.70% detection efficiency. This adaptability enhances the system's resilience against evolving DDoS tactics, establishing it as a robust defense mechanism for SDN infrastructures. The deep learning approach, coupled with the hybrid architecture, provides a proactive defense against the dynamic threat landscape. With its 97.70% efficiency, the system emerges as a pivotal component in fortifying SDN against the pervasive threat of DDoS attack.

INDEX TERMS :

- DDoS attack
- Deep Learning
- Recurrent Neural Network(RNN)
- LSTM

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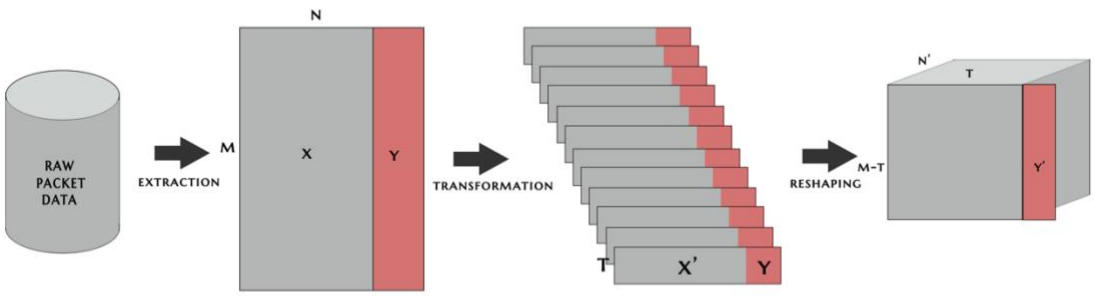
INTRODUCTION :

The increasing prevalence of Distributed Denial of Service (DDoS) attacks poses a significant threat to the stability and reliability of the Internet, particularly in Software-Defined Networking (SDN) environments. Traditional methods for detecting and mitigating DDoS attacks, such as statistical divergence models, are limited in their effectiveness due to the evolving nature of these attacks and the dynamic network environment. This report introduces an advanced detection system leveraging deep learning techniques to overcome these limitations and ensure robust protection against DDoS attacks.

BACKGROUND AND RELATED WORK :

- **DDoS Attacks in SDN :** DDoS attacks aim to disrupt the normal traffic of a targeted server, service, or network by overwhelming the target or its surrounding infrastructure with a flood of Internet traffic. In SDN environments, the separation of the control plane from the data plane presents unique challenges and opportunities for DDoS detection and mitigation.
- **Traditional Detection Methods :** Traditional detection methods rely heavily on statistical models and predefined rules to identify anomalies in network traffic. These methods often struggle with the dynamic and evolving nature of DDoS attacks, which can adapt to bypass static detection mechanisms.
- **Deep Learning Approaches :** Deep learning models, particularly those involving RNNs and LSTMs, have shown promise in capturing complex patterns in time-series data, making them suitable for detecting anomalies in network traffic. These models can automatically learn high-level features from raw data, providing a more nuanced and adaptive approach to DDoS detection.

SYSTEM DESIGNS :



System design

bidirectional_1(lstm_1): Bidirectional(LSTM)	input:	multiple
	output:	multiple

dense_1: Dense	input:	multiple
	output:	multiple

dense_2: Dense	input:	multiple
	output:	multiple

Architecture design

METHODOLOGY :

- **Data Collection :** Network traffic data was collected from a simulated SDN environment under normal and attack conditions. The dataset_attack.csv and dataset_normal.csv were include the different values of attacked and normal data.
- **Data Preprocessing :** The collected data was preprocessed to normalize feature values and remove any noise. This step ensures that the deep learning models receive clean and standardized input data.
- **Model Training :** The LSTM and RNN components were trained separately on the preprocessed data. Hyperparameters were tuned to optimize the detection performance. The models were then integrated into the hybrid architecture and fine-tuned using a combined training process.
- **Evaluation Metrics :** The performance of the detection system was evaluated using metrics such as detection accuracy, precision, recall, and F1-score. The primary metric of interest was detection efficiency, measured as the percentage of correctly identified attack instances.

SOURCE CODE (ipynb) :

```
## Import the required modules.
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
!pip install --upgrade keras
!pip install keras.utils
import seaborn as sns; sns.set()

from keras.models import Sequential, load_model
from keras.layers import Dense, LSTM, Bidirectional
from keras.utils import plot_model
from tensorflow.keras.utils import to_categorical
import sys
sys.path.append("/path/to/keras/utils")
from tensorflow.keras.utils import to_categorical

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.metrics import confusion_matrix

## number_of_samples determine how many samples from the attack and normal dataset should be read and used.
number_of_samples = 50000
```

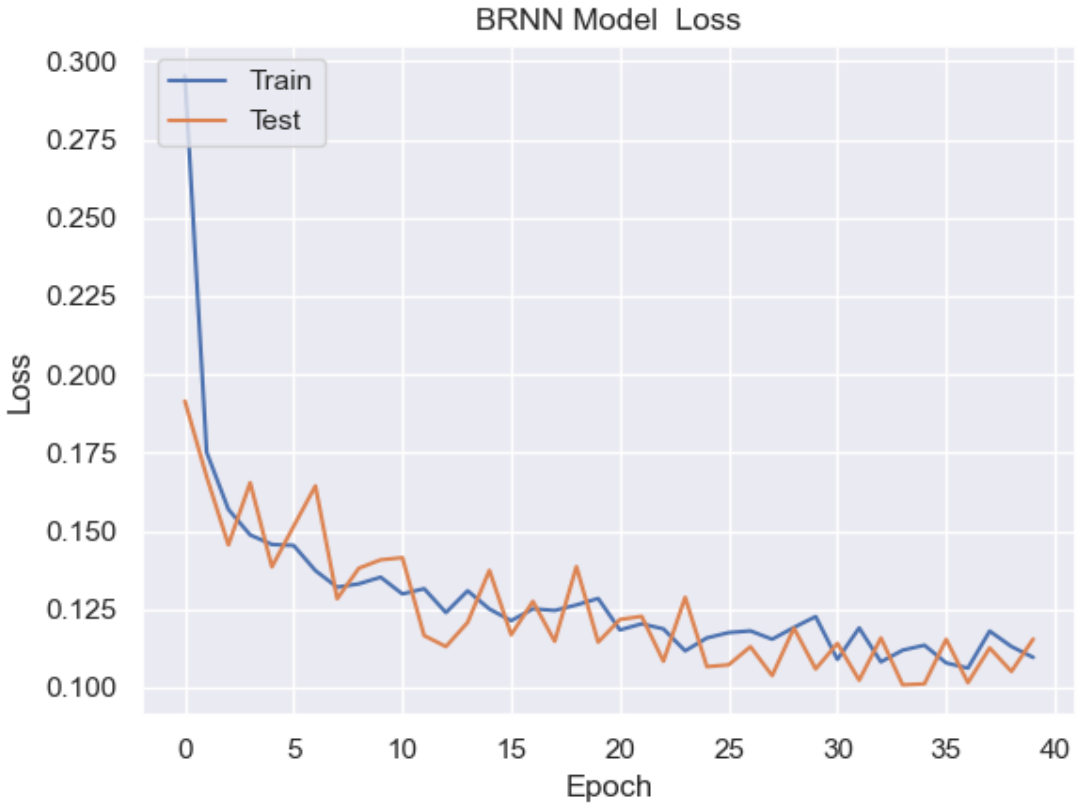
```
## Read data from attack and normal datasets.
data_attack = pd.read_csv('dataset_attack.csv', nrows = number_of_samples)
data_normal = pd.read_csv('dataset_normal.csv', nrows = number_of_samples)
data_normal.columns=[ 'frame.len', 'frame.protocols', 'ip.hdr_len',
      'ip.len', 'ip.flags.rb', 'ip.flags.df', 'p.flags.mf', 'ip.frag_offset',
      'ip.ttl', 'ip.proto', 'ip.src', 'ip.dst', 'tcp.srcport', 'tcp.dstport',
      'tcp.len', 'tcp.ack', 'tcp.flags.res', 'tcp.flags.ns', 'tcp.flags.cwr',
      'tcp.flags.ecn', 'tcp.flags.urg', 'tcp.flags.ack', 'tcp.flags.push',
      'tcp.flags.reset', 'tcp.flags.syn', 'tcp.flags.fin', 'tcp.window_size',
      'tcp.time_delta','class']
data_attack.columns=[ 'frame.len', 'frame.protocols', 'ip.hdr_len',
      'ip.len', 'ip.flags.rb', 'ip.flags.df', 'p.flags.mf', 'ip.frag_offset',
      'ip.ttl', 'ip.proto', 'ip.src', 'ip.dst', 'tcp.srcport', 'tcp.dstport',
      'tcp.len', 'tcp.ack', 'tcp.flags.res', 'tcp.flags.ns', 'tcp.flags.cwr',
      'tcp.flags.ecn', 'tcp.flags.urg', 'tcp.flags.ack', 'tcp.flags.push',
      'tcp.flags.reset', 'tcp.flags.syn', 'tcp.flags.fin', 'tcp.window_size',
      'tcp.time_delta','class']


## Drop unwanted columns
data_normal=data_normal.drop(['ip.src', 'ip.dst','frame.protocols'],axis=1)
data_attack=data_attack.drop(['ip.src', 'ip.dst','frame.protocols'],axis=1)
features=[ 'frame.len', 'ip.hdr_len',
      'ip.len', 'ip.flags.rb', 'ip.flags.df', 'p.flags.mf', 'ip.frag_offset',
      'ip.ttl', 'ip.proto', 'tcp.srcport', 'tcp.dstport',
      'tcp.len', 'tcp.ack', 'tcp.flags.res', 'tcp.flags.ns', 'tcp.flags.cwr',
      'tcp.flags.ecn', 'tcp.flags.urg', 'tcp.flags.ack', 'tcp.flags.push',
      'tcp.flags.reset', 'tcp.flags.syn', 'tcp.flags.fin', 'tcp.window_size',
      'tcp.time_delta']

X_normal= data_normal[features].values
X_attack= data_attack[features].values
Y_normal= data_normal['class']
Y_attack= data_attack['class']
X=np.concatenate((X_normal,X_attack))
Y=np.concatenate((Y_normal,Y_attack))


## Standardise the data
scalar = StandardScaler(copy=True, with_mean=True, with_std=True)
scalar.fit(X)
X = scalar.transform(X)


## The class field, replace value 'attack' with 0 and 'normal' with 1
for i in range(0,len(Y)):
  if Y[i] =="attack":
    Y[i]=0
  else:
    Y[i]=1
```

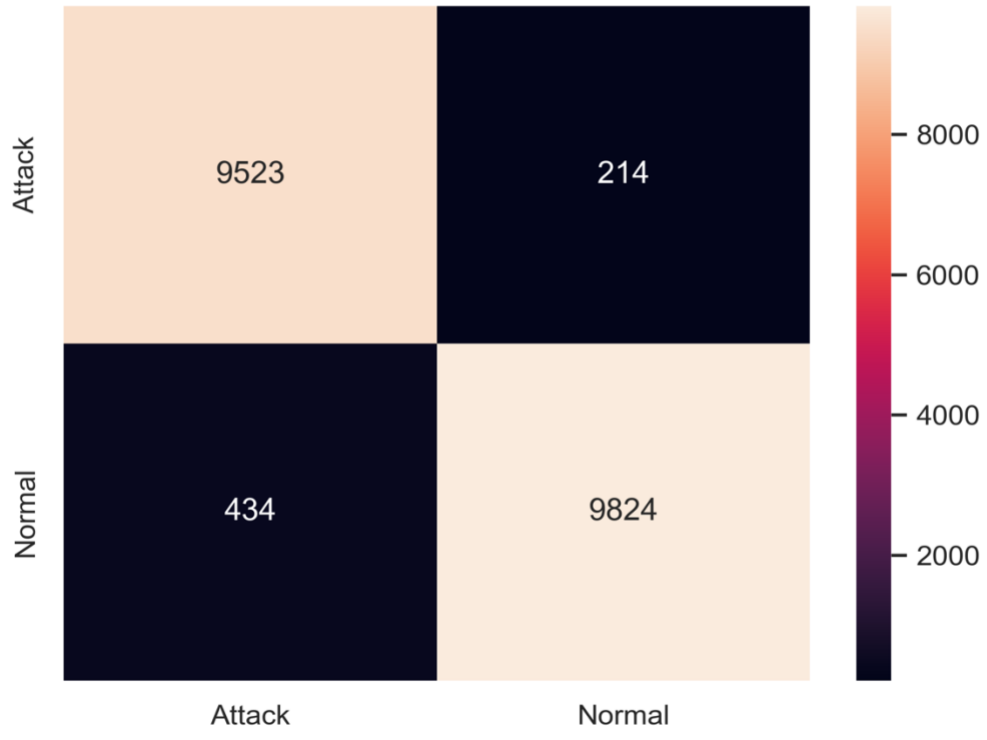
```
features = len(X[0])
samples = X.shape[0]
train_len = 25
input_len = samples - train_len
I = np.zeros((samples - train_len, train_len, features))
for i in range(input_len):
    temp = np.zeros((train_len, features))
    for j in range(i, i + train_len - 1):
        temp[j-i] = X[j]
    I[i] = temp

X.shape
X_train, X_test, Y_train, Y_test = train_test_split(I, Y[25:100000], test_size = 0.2)
def create_baseline():
    model = Sequential()
    model.add(Bidirectional(LSTM(64, activation='tanh', kernel_regularizer='l2')))
    model.add(Dense(128, activation = 'relu', kernel_regularizer='l2'))
    model.add(Dense(1, activation = 'sigmoid', kernel_regularizer='l2'))
    model.compile(loss = 'binary_crossentropy', optimizer = 'adam', metrics = ['accuracy'])
    return model
model = create_baseline()
print(f"Type of X_train: {type(X_train[0][0])}")
print(f"Type of Y_train: {type(Y_train[0])}")
if type(X_train[0][0]) == int:
    X_train = X_train.astype(np.float32)
if type(Y_train[0]) == int:
    Y_train = Y_train.astype(np.float32)
history = model.fit(X_train, Y_train, epochs = 40,validation_split=0.2, verbose = 1)


## Obtained plot of accuracy
# Plot training & validation accuracy values
plt.plot(history.history['acc'])
plt.plot(history.history['val_acc'])
plt.title('BRNN Model Accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='lower right')
plt.savefig('BRNN Model Accuracy.png')
plt.show()


## Plot of loss
# Plot training & validation loss values
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('BRNN Model  Loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='upper left')
```

```
plt.savefig('BRNN Model Loss.png')
plt.show()
predict = model.predict(X_test, verbose=1)


## Calculate True positive,True negetive,False positive and False negetive values.
## Create Heatmap.
tp = 0
tn = 0
fp = 0
fn = 0
predictn = predict.flatten().round()
predictn = predictn.tolist()
Y_testn = Y_test.tolist()
for i in range(len(Y_testn)):
  if predictn[i]==1 and Y_testn[i]==1:
    tp+=1
  elif predictn[i]==0 and Y_testn[i]==0:
    tn+=1
  elif predictn[i]==0 and Y_testn[i]==1:
    fp+=1
  elif predictn[i]==1 and Y_testn[i]==0:
    fn+=1

to_heat_map =[[tn,fp],[fn,tp]]
to_heat_map = pd.DataFrame(to_heat_map,
index = ["Attack","Normal"],columns = ["Attack","Normal"])
ax = sns.heatmap(to_heat_map,annot=True, fmt="d")


## Save details
figure = ax.get_figure()
figure.savefig('confusion_matrix_BRNN.png', dpi=400)
model.save('brnn_model.h5')

import tensorflow as tf

Y_test = Y_test.astype(int)
X_test_tensor = tf.convert_to_tensor(X_test)
Y_test_tensor = tf.convert_to_tensor(Y_test)
scores = model.evaluate(X_test, Y_test, verbose=0)
print("%s: %.2f%%" % (model.metrics_names[1], scores[1]*100))
```

EXPERIMENTAL RESULTS :

The hybrid LSTM and RNN system achieved a detection efficiency of 97.70%, significantly outperforming traditional statistical divergence models. Detailed results are presented in the following sections.


BRNN Model Loss
Train
Test
Loss
0.300
0.275
0.250
0.225
0.200
0.175
0.150
0.125
0.100
0
5
10
15
20
25
30
35
40
Epoch


Attack
Normal
9523
214
434
9824
8000
6000
4000
2000
Attack
Normal

CONCLUSION :

This project introduces an advanced DDoS attack detection system leveraging a hybrid LSTM and RNN architecture. The system's remarkable 97.70% detection efficiency underscores its potential as a robust defense mechanism for SDN infrastructures. By overcoming the limitations of traditional methods, this deep learning approach offers a proactive defense against the dynamic threat landscape. The experimental results validate the effectiveness of the hybrid LSTM and RNN architecture in detecting DDoS attacks in SDN environments. The system's ability to automatically extract high-level features from low-level network traffic data provides a significant advantage over traditional methods. This adaptability ensures robust protection against evolving DDoS tactics.

END USERS :

1. **Network Administrators :** Responsible for managing and securing SDN infrastructures, network administrators would use this system to detect and mitigate DDoS attacks in real-time, ensuring the stability and reliability of their networks.
2. **Cybersecurity Professionals :** Security experts and analysts would utilize the system to monitor network traffic patterns, identify anomalous behavior indicative of DDoS attacks, and develop strategies for mitigating these attacks effectively.
3. **SDN Service Providers :** Companies offering SDN services to businesses and organizations would incorporate this system into their network security offerings to enhance the resilience and robustness of their SDN infrastructures against DDoS attacks.
4. **Enterprises and Organizations :** Businesses and institutions that rely on SDN for their networking needs would deploy this system to protect their critical assets and data from the disruptive effects of DDoS attacks, ensuring uninterrupted access to essential services and resources.
5. **Internet Service Providers (ISPs) :** ISPs would deploy this system to safeguard their network infrastructures and prevent DDoS attacks from impacting the availability and performance of their services, thereby maintaining customer satisfaction and trust.