Mathematical Statistician and Engineering Applications
ISSN: 2094-0343
2326-9865

Network Traffic Classification using Long-Short Term Memory Algorithm on UNSWNB15 and KDDCUP99 Data Set

Tarun Sharma and Dr. Sharanbasappa Gandage
Department of Computer Science & Engineering,
Dr. A. P. J. Abdul Kalam University, Indore (M.P.)
Corresponding Author Email: sharma_tarun_in@yahoo.com

Article Info
Page Number: 10166-10181
Publication Issue:
Vol. 71 No. 4 (2022)

Article History
Article Received:
12 September 2022
Revised: 16 October 2022
Accepted: 20 November 2022
Publication: 25 December 2022

Abstract
Many systems rely on the ability to categorize network traffic for purposes including intrusion detection, policy enforcement, and traffic management. Machine Learning (ML) and specifically Deep Learning (DL) based classifiers have shown excellent performance in network traffic categorization, even though most apps encrypt their network data and some dynamically alter their port numbers. Since network traffic flows may be correlated, this study provides a classification strategy based on graph convolution and Long-Short Term Memory (LSTM). To extract the spatial characteristics of the spatial topology and the temporal aspects of the LSTM, the traffic flow data must first undergo data preprocessing. Finally, the method is tested on a subset of the UNSWNB15 and KDDCUP99 datasets to measure its efficiency. The suggested technique has been shown to extract possible characteristics from network traffic data in experiments successfully. It demonstrates the efficacy of the suggested approach and outperforms alternatives such as feature selection, bidirectional LSTM (BiDLSTM), and CNN-LSTM in classification performance.

Keywords: Machine Learning, Deep Learning, Long-Short Term Memory, bidirectional LSTM, UNSWNB15, KDDCUP99.

I. INTRODUCTION

Classifying network traffic is essential for many uses, including administration and security. For instance, it allows network administrators to prioritize certain traffic types and use appropriate methods to tailor QoS and security rules to each application's requirements [1]. Industry and academics have long shown a strong interest in the topic. While the Internet and mobile technology continue to evolve, new applications and encryption protocols have emerged, bringing new difficulties [2].

When it comes to extracting discriminative features from network traffic, deep learning methods tend to perform better than feature selection methods [3]. Since deep learning techniques are adaptable, they can extract features from network data without resorting to a lengthy series of difficult procedures like feature engineering. Local aspects of network traffic may be extracted with filters using common extraction methods like Convolutional Neural Networks (CNNs) [4, 5]. The approach requires the network traffic data to be transformed from its original, one-dimensional format into a two-dimensional space [6].

Convolution of graphs with long-term and short-term memory is used in this study to provide a technique for categorizing network traffic. This approach uses the LSTM method to extract the temporal aspects of info on network traffic and the graph convolution method's strong topology extraction capability to recover its spatial aspects. Specifically, this study contributes primarily in the following ways:

By combining graph convolution with long short-term memory (LSTM), we propose a method for classifying network traffic that improves accuracy, abnormal traffic detection, and false alarm rates for regular traffic.

We compute metrics for each category, then evaluate them against deep learning models' feature selection techniques and other models to determine how well the proposed model classifies network traffic models are explained in the result section. The UNSW-NB15 is used as a reference data set for the assessment procedure.

The remaining parts of the paper are structured as follows. The second part of the paper examines the literature on the topic. The suggested traffic categorization model's comprehensive building procedure is presented in Section III. Evaluation and comparison of experimental results and productivity are reported in Sections IV and V. The last section of the paper provides a summary and forecast.

II. LITERATUREWORK

The machine learning (ML) strategies for traffic categorization were dissected in detail. The author provides the traffic obfuscation methods that may aid in the development of a more accurate classifier for the convenience of researchers. Key discoveries and open research issues for network traffic categorization are addressed, and suggestions for future research areas are provided. Overall, this study is a necessary addition to the literature since it compiles the most recent findings from studies on traffic categorization [7] and addresses gaps in the coverage of earlier studies.

We investigate the challenge of classifying nano-network traffic collected at the micro/nano-gateway and apply five supervised machine learning methods. Experimentally comparing and contrasting the presented models reveals the best classifier for nano-network traffic, with high accuracy and performance scores [8].

This study primarily examines three procedures: The first step was to develop an image representation for the sequences in the road sound datasets; the second was to propose a convolutional neural network model for feature extraction; and the third was to use a hybrid approach for the classification stage, combining a convolutional neural network with other machine learning models. To test our hypotheses, we have compiled a dataset of road sounds from an asymmetric urban road at various times of day (such as the morning and the evening). In particular, the implementations have shown encouraging results, with accuracies ranging from 92% to 95% when identifying traffic levels throughout time [9].

To detect and categorize diverse traffic flows in 5G network slicing, a framework based on the multi-lane Capsule Networks (CapsNet) deep learning approach has been developed. In

addition, the author employs deep learning methods to compare the model with the literature mentioned above. Compared to other classifiers in the literature [10], the experimental findings show substantial performance improvement, with an accuracy of 97.3975%.

In this research, we create two unique traffic categorization methods to help with this problem. The first implements the Random Forest technique on the plaintext bytes of TLS Hello messages. It is quite easy to implement and works well for categorizing traffic based on throughput. Additionally, the classification quality is improved while processing times are reduced by a factor of three compared to state-of-the-art techniques. The second method enhances the first by paying special attention to the handshake's information. As a result, it can rapidly extract information from the transaction and obtain the best possible categorization quality across the board. In addition to accurately classifying ECH traffic [11], its error rate is three times lower than that of state-of-the-art algorithms.

In this study, we provide a unique method for decrypting network data and spotting encrypted, tunnelled, and anonymous communication. The suggested identification system uses the highly wanted deep learning techniques to recognize anonymous network traffic and extract Voice over IP (VoIP) and non-VoIP ones from encrypted traffic flows. The collected data has been separated into four groups: VPN Voice over IP (VoIP), VPN Data Only (Data Only), TOR Voice over IP (VoIP), and TOR Data Only (VoIP). Through extensive testing, we have discovered that our identification engine is resistant to disruptions in VPN and TOR connections [12].

Simulation results show that the enhanced Harris Eagle, in conjunction with fuzzy clustering, outperforms the conventional fuzzy clustering method, the particle swarm algorithm-based clustering method, and the grey wolf algorithm in terms of intra-class compactness and inter-class separation on the data traffic sample set. As a result, the recall and accuracy of clustering are improved to about 90% [13].

The suggested technique has been shown to extract possible characteristics from network traffic data in experiments successfully. It demonstrates the proposed approach's efficacy and outperforms competing for classification performance techniques [14], including feature selection, bidirectional LSTM (BiDLSTM), and CNN-LSTM.

Maximum classification accuracy is achieved by using a Convolutional Neural Network (CNN) classifier. To achieve a fine-grained deconstruction of the traffic for the four monitored radio cells in a live and unsupervised way [15], the CNN classifier is enhanced with the capacity to reject sessions whose patterns do not fit those learnt during the training phase.

Reviewing the existing research in the topic, this article presents an overview of AL and places it within the framework of NTC. Furthermore, difficulties and unanswered questions about categorizing network traffic using AL are highlighted. In addition, several experiments are carried out as a means of providing a technical overview, demonstrating the extensive potential of AL in NTC. Simulation results demonstrate that accuracy may be achieved using less data when using AL [16].

Since our method generates a unique cost matrix for each division, the costs associated with each category of misclassification are distinct. The author applies the suggested cost-sensitive learning approach to stacked autoencoder and convolution neural networks, two deep learning classifiers, to evaluate its usefulness. In our trials on the ISCX VPN-nonVPN dataset, we found that the suggested methodology outperformed three state-of-the-art NTC algorithms [17] regarding classification performance for low-frequency classes.

Important characteristics are initially extracted from network traces via processing. After reviewing previous survey studies, the author settled on cutting-edge machine-learning techniques to categorize IoT traffic. The author then compared the results of several machine learning methods regarding classification precision, speed, training duration, etc. Finally, the author recommended an appropriate machine-learning algorithm for various applications [18].

In particular, speed is enhanced by learning side-channel properties from header segments. Last but not least, the softmax function is used to determine the packet's label. In addition, by analyzing the first packets, EBSNN can categorize the traffic patterns in a network. Extensive trials on real-world datasets demonstrate that EBSNN outperforms state-of-the-art algorithms on both application identification and website identification tasks [19].

Compared to state-of-the-art systems based on machine learning, our traffic classification method achieves up to 97.7% accuracy in flow classification using just 9 first initial packets of flows. The authors show that using just 0.5% of all flows for GMM training is sufficient to attain a 96.6% accuracy rate in flow classification. Half Total Error Rate (HTER) of 7.65 or below is achieved using our technique using just the first six packets in a flow [20].

Reciprocal operating characteristic (ROC) curves, several classification metrics, and confusion matrices are used to evaluate the proposed model's classification results, ensuring the model's effectiveness. Experiments demonstrate that the proposed model outperforms popular anomalous traffic detection models in classification effect while having a smaller model size [21].

III. PROPOSED WORK

First, let's talk about the GC MODEL. It has been shown that Graph Convolutional Networks (GCNs) are useful for learning graph representation [22],[23] because of their ability to excerptlongitudinal aspects of topological arrangements. GC (Simple_Graph_Convolutional) [24] is an optimization that builds on GCN that does away with The Effect of Nonlinearity on GCN and drastically cuts down the amount of time it takes to run the model by doing the calculations ahead of time.

Model LSTM is a specialized thoughtful of RNN that is often used to address the RNN dependence issue over the long term [25], [26]. Through a more intricate hidden layer unit structure, LSTM can circumvent the gradient disappearance issue. In Fig.1, we see the LSTM's fundamental building block.

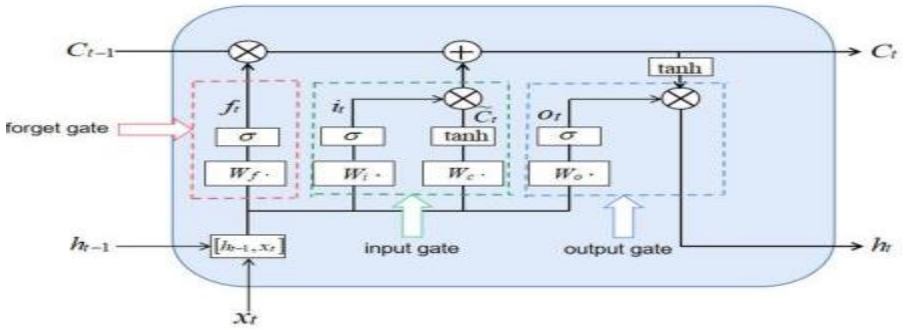


Figure 1. The framework of the LSTM unit.

Differentiating features of the LSTM model include image-recording devices such as the forget gate, input gate, and output gate. These three gate structures provide the following purposes:

The first kind of gate is called a forget gate, which determines the probability with which the current LSTM unit forgets the state of the higher hidden unit.

Second, the sequence's input is processed by the input gate.

Finally, the third gate is the output gate, which reveals the concealed state ht at time t.

C. Using a Generalized Classifier of Graph Convolution(GC) and a Short-Term Long Memory (LSTM) to Design, a Classification Model for Network Traffic

Layers of the proposed GC-LSTM model are shown in Figure 2. These layers consist of a GC graph convolutional layer, an LSTM layer, a fully connected layer, and an output layer. Before exploiting correlations between traffic flows to build the topological graph, the raw data is prepared. When the data has been cleaned and prepared, it is passed to the GC model for a spatial representation, and the output of GC is fed into the LSTM layer for a temporal representation. In the next step of the model training process, we add an output layer and a fully connected layer on top of the LSTM layer.

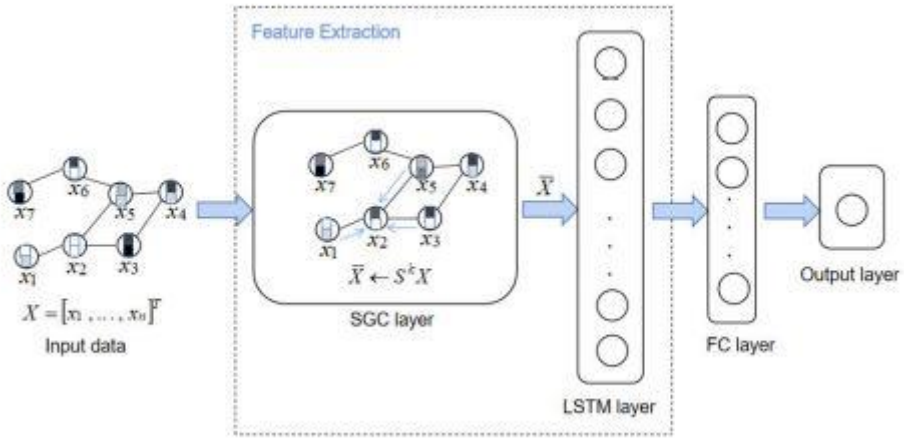


Figure 2. Framework for a GC-LSTM Model.

One Processing of Incoming Information Because various features employ different measurement techniques, it is important to normalize the data for numerical characteristics to remove the influence of measurement.

The GC-LSTM Feature Extraction Layer strongly reflects the GC layer, particularly the local smoothing of nodes and their neighbours.

Layer 3 and Training Process Interconnected Method 1 is a brief overview of the GC-LSTM model-based traffic categorization algorithm. The LSTM layer's output is sent into the fully connected layer, with 64 nodes and a similar number of connections. The major focus of this article is to determine whether aberrant traffic patterns have any discernible geographic patterns. To that end, we'll focus on a binary-classification experiment, where a sigmoid function is a viable option for the output layer's activation function.

Algorithm 1 : GC-LSTM Training

Input: Sampled UNSW-NB15 dataset, RMSProp, lr, batch_size, dropout , KDDCUP99
Output: GC-LSTM Model
load dataset
for data in training and test sets **do**
  Extract Features(X)
  Extract Labels(Y)
end
scale features with $\hat{X}_{ij} = \frac{X_{ij} - MEAN_j}{STD_j}$
establish matrix A and D based on connection rules
calculate S based on $\tilde{A}$ and $\tilde{D}$, initialize $H = S$
for i from $2 \rightarrow k$ **do**
  $H = HS$
end
get the output $\bar{X} = HX$
input $\bar{X}$ into the LSTM layer
add a fully connected layer, whose value is 32
add a dropout, whose value is 0.1
get cross-entropy loss by z_i and y_i
update parameters by RMSProp with loss

D. Analysis of the Model

Using benchmark datasets like UNSW-NB15 [27] and KDDCUP99 [28] has led to several important improvements in network security. However, recent studies have shown that these figures don't correctly reflect traffic or the incidence of risks like low-occupancy attacks in the actual world of networks. The India Cyber Security Centre gathers data sets more representative of the actual status of the Internet, such as UNSW-NB15 and KDDCUP99. This is why the UNSW-NB15 and KDDCUP99 datasets were used in the experiment reported here. Stratified sampling of 20% of the data from the UNSW-NB15 and KDDCUP99 datasets was used in the experiments; Laterobjective 20% of the data_set was sampled, and there is a decrease in the number of samples available in a particular attack class. As such, the binary-classification problem is a focal point of the experiment designed to confirm the hypothesis. Test and training set traffic flow distribution samples are shown in Table 1.

IV. IMPLEMENTATION

4.1 The Laboratory Setup

A 14-inch, full-screen, touch-enabled IPS panel that can be folded into a tablet form factor (the x360 Touchscreen 2-in-1). This endeavour used Python and a laptop equipped with a 10th-generation Core i7-10510U and a 512GB SSD. Windows 10 Home 64 Bit was the OS of choice. Distinct types of processors: There are four processing cores, with a base frequency of 1.6 GHz up to 4.9 GHz with the help of Intel's Turbo Boost Technology; the L3 cache is 8 MB, and the clock speed is 1.6 GHz. This system has HD Audio and Intel Iris Plus Graphics. HP offers the HD TrueVision camera. The approach used several Python packages, including NumPy, Pandas, SciPy, PyTorch and Plotly, Keras, and OpenCV-python.

4.2 Dataset

Table 1: Twenty percent of the datasets were randomly picked for use as training and test data, respectively.

UNSW-NB15 [27]		
	Normal	Abnormal
Training set	1,05,204	70,136
Test Set	49,399	32,932

KDDCUP99 [28]		
	Normal	Abnormal
Training set	99,436	45,326
Test Set	34,256	26,354

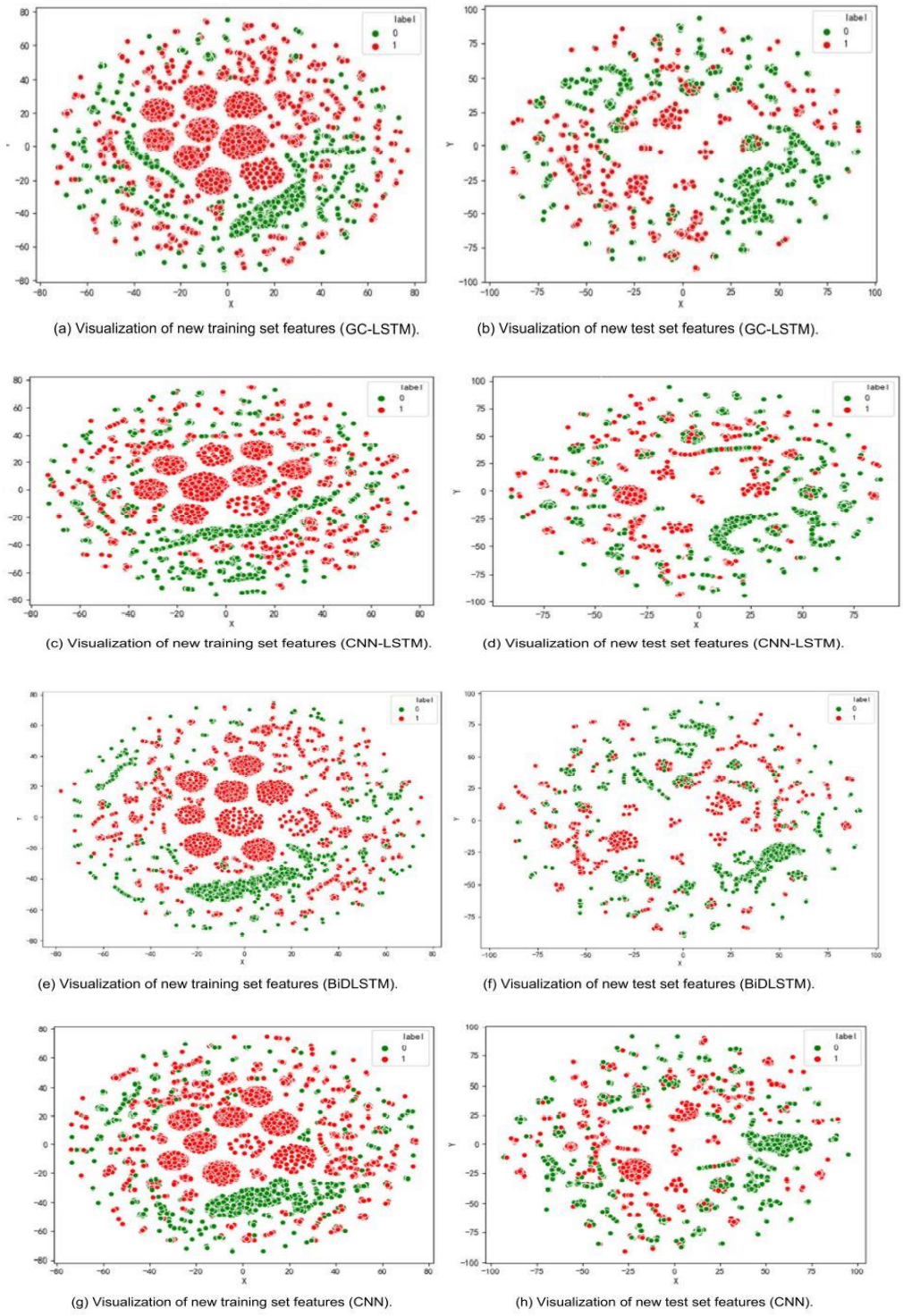
Table 2. A Look at UNSW-NB15 vs. KDD CUP 99 [12]

Parameters	**KDDCUP99 [28]**	**UNSW-NB15 [27]**
No. of networks	2	3
No. of distinct ip address	11	45
Simulation	Yes	Yes
The duration of data collected	5 weeks	16 hours, 15 hours
Format of data collected	3 types (tcpdump, BSM and dump files)	Pcap files
Attack families	4	9
Feature Extraction tools	Bro-IDS tool	Argus, Bro-IDS and new tools
No. of features extraction	42	49

In Table 2 [32], we see a comparison between KDDCUP99 and UNSW-NB15 data. In the table below, we can see eight characteristics that differentiate each data set: the number of

networks, the number of unique IP addresses, the kind of data, the time of data production, the output format, the attack vectors, the tools used to extract the features, and the number of features. In the UNSW-NB15 data set, we can identify several different attack families typical of modern, low-footprint attacks.

4.3 Visualization



(a) Visualization of new training set features (GC-LSTM). (b) Visualization of new test set features (GC-LSTM).

(c) Visualization of new training set features (CNN-LSTM). (d) Visualization of new test set features (CNN-LSTM).

(e) Visualization of new training set features (BiDLSTM). (f) Visualization of new test set features (BiDLSTM).

(g) Visualization of new training set features (CNN). (h) Visualization of new test set features (CNN).

Figure 3. Displaying the features collected by each deep learning model during training and testing using t-SNE.

Each model extracted novel structures from the unique preparation and examination sets, and the outcomes of this process are shown in Figure 3 using the t-SNE approach. There is no obvious way to tell how well any of the four feature extraction models perform just by looking at the picture; instead, we will use several different categorization criteria to evaluate their effectiveness.

From the image above, it is clear that the GC-LSTM model performs worse than the CNN-LSTM model in terms of recall and accuracy for the abnormal class. Still, it outperforms the additional three representations in terms of additional metrics. The CNN with LSTM approach outperforms the CNN approach and the BiDLSTM approach across the board. Although there isn't much difference, the BIDLSTM model outperforms the CNN model overall.

V. RESULT

A confusion matrix is a common tool in classification issues [31] because it represents the proportion of data samples that were properly and wrongly labelled by the classifier. Think of the atypical group as a plus and the typical group as a minus. Then Table 3 displays the confusion matrix in its form:

Table 3. The mess of Confusion Matrix

		Predict	
		abnormal class (Positive)	normal class (Negative)
Actual	abnormal class (Positive)	**TP**	**FN**
	normal class (Negative)	**FP**	**TN**

The percentage of correctly labelled samples measures the accuracy of a prediction.

$$accuracy = \frac{TP + TN}{TP + FP + FN + TN}$$

In the equation below, r denotes the percentage of legitimately abnormal samples relative to total anomalous traffic records, which is a measure of abnormal class accuracy:

$$precision = \frac{TP}{TP + FP}$$

Measured as a percentage of all abnormal samples, recall of abnormal class indicates how many records were properly identified as abnormal. Another name for this is Detection Rate (DR), and it is calculated using the following formula:

$$DR = recall = \frac{TP}{TP + FN}$$

An all-encompassing measure of accuracy and recall, the f 1 score is written as follows:

$$f1 - score = \frac{2 * precision * recall}{precision + recall}$$

An equation describing the false alarm rate may be found below:

$$FAR = \frac{FP}{FP + TN}$$

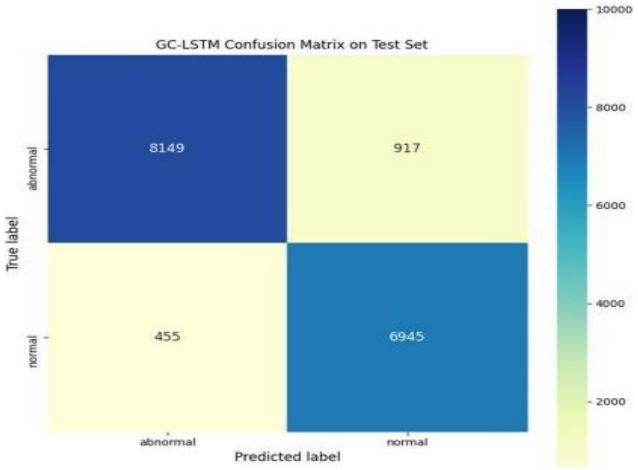
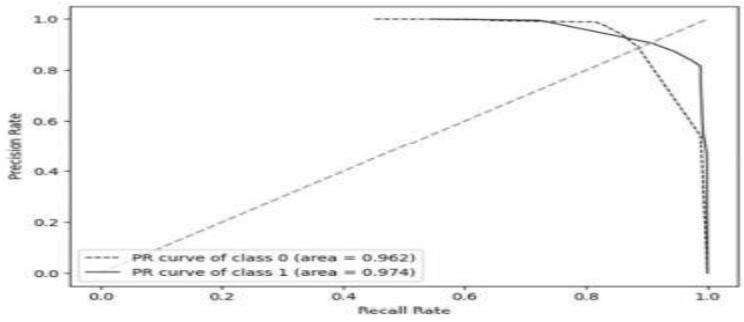
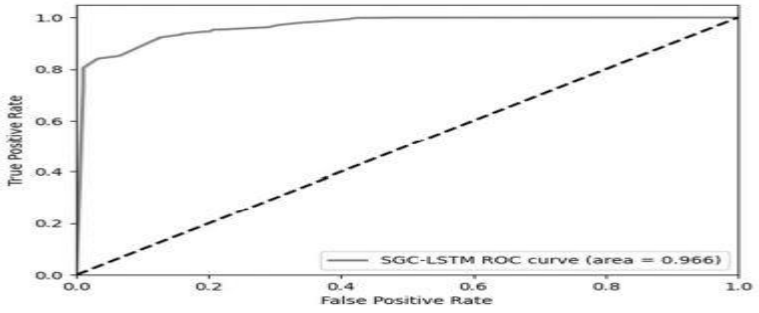


Figure 4. Xgboost's new test set data was collected using GC-LSTM, including its confusion matrix.

Figure 4 displays the metrics, and Table 4 displays the confusion matrix for the Xgboost model applied to the new test set retrieved using GC-LSTM.



(a) PR curve and AUCPRC value on each class.



(b) ROC curve and AUCROC value.

Figure 5. Xgboost's GC-LSTM-extracted evaluation curves for a fresh test dataset.

The ROC_curve of the Xgboost method on the novelexaminationestablished retrieved using GC_LSTM (a) and the PR_curve of each class (b) are shown above.

You can see that the model's AUCPRC score is more than 0.95 across the board in Fig.5 (a), albeit it excels at class 1 data (abnormal class). Later in this paper, we'll conduct experimental comparisons.The proposed approach is evaluated by first comparing the SC-LSTM model's retrieved features with those selected by the feature selection method. The outcomes are then contrasted with those produced using other deep learning methods.

Table 4: Measurements of the Xgboost method using the novelexamination data gathered with the help of the proposed GC-LSTM.

UNSW-NB15 Dataset			
Class	**Precision**	**Recall**	**F1-Score**
normal(0)	0.91	0.96	0.94
abnormal(1)	0.98	0.92	0.93
macro avg	0.95	0.95	0.95
weighted avg	0.95	0.95	0.95

KDDCUP99 Dataset			
Class	**Precision**	**Recall**	**F1-Score**
normal(0)	0.89	0.96	0.92
abnormal(1)	0.96	0.91	0.9
macro avg	0.93	0.93	0.93
weighted avg	0.93	0.93	0.93

Table 4 shows that there is minimal difference between both the normal class and the abnormal class present in the sample setfollowing GC-LSTM feature extraction.

Table 5: Performance Evaluation of the Proposed GC-LSTM and Feature_Selection Approach using the below Metrics.

UNSW-NB15 Dataset			
Methods	**AUCPRC_0**	**AUCPRC_1**	**AUCROC**
Proposed GC-LSTM	0.984	0.995	0.989
Feature Selection [35]	0.922	0.959	0.957

KDDCUP99 Dataset			
Methods	**AUCPRC_0**	**AUCPRC_1**	**AUCROC**
Proposed GC-LSTM	0.961	0.974	0.963
Feature Selection [35]	0.893	0.943	0.948

Here, the xgboost model is used to assess the newly recovered features via the usage of GC-LSTM and the feature subset generated through the feature selection approach. The recommended GC-LSTM and the technique for feature selection were evaluated using AUCPRC and AUCROC, and the results of these evaluations are shown in Table 5.

Table 6: Accuracy, Detection Rate, and Fault-Tolerance of the Proposed GC-LSTM vs a Feature Selection Approach

UNSW-NB15 Dataset			
Methods	**Accuracy (%)**	**DR (%)**	**FAR (%)**
Proposed GC-LSTM	96.45	91.85	3.8
Feature Selection [35]	89.31	84.38	18.65

KDDCUP99 Dataset			
Methods	**Accuracy (%)**	**DR (%)**	**FAR (%)**
Proposed GC-LSTM	94.36	87.42	5.2
Feature Selection [35]	87.29	81.94	22.68

Table 6 displays the results of a comparison between GC-LSTM and a feature selection approach in terms of accuracy, DR, and FAR. The table clearly shows that the GC-LSTM model is more accurate than the feature selection approach by roughly 7%. Regarding DR, the two approaches are almost identical. However, the GC-LSTM technique is 60% more efficient than the feature selection approach.

Table 7: Evaluation of the Proposed GC-LSTM compared to various deep learning approaches based on the AUCPRC and AUCROC measures.

UNSW-NB15 Dataset			
Methods	**AUCPRC_0**	**AUCPRC_1**	**AUCROC**
CNN [32]	0.984	0.981	0.984
BiDLSTM [33]	0.983	0.987	0.981
CNN-LSTM [34]	0.986	0.989	0.983
Proposed GC-LSTM	0.993	0.998	0.994

KDDCUP99 Dataset			
Methods	**AUCPRC_0**	**AUCPRC_1**	**AUCROC**
CNN [32]	0.961	0.958	0.953
BiDLSTM [33]	0.964	0.967	0.963
CNN-LSTM [34]	0.968	0.972	0.971
Proposed GC-LSTM	0.985	0.988	0.985

Tabletop 7 displays the results of AUCPRC and AUCROC comparisons for all models. Limited spatial aspects of movement flows are extracted by the CNN algorithm using multiple convolution kernels, while temporal features are extracted by the BiDLSTM model using the memory unit. The two models' results on the three benchmarks in the table are quite similar. Both the spatial feature extraction skills of CNN and the temporal feature extraction capabilities of LSTM are included in the CNN-LSTM model. CNN-LSTM outperforms CNN and BiDLSTM by around 0.2% across the board. Although effective in extracting features related to visual structure, the CNN model has its limits. The GC-LSTM model outperforms the CNN-LSTM model on three criteria, with an average 0.2% improvement.

Table 8: The accuracy, DR, and FAR of the proposed GC-LSTM compared to those of existing deep learning techniques.

UNSW-NB15 Dataset			
Methods	**Accuracy (%)**	**DR (%)**	**FAR (%)**
CNN [32]	89.52	89.98	19.65
BiDLSTM [33]	91.36	91.68	17.82
CNN-LSTM [34]	94.85	95.36	13.68
Proposed GC-LSTM	98.56	97.28	4.26

KDDCUP99 Dataset			
Methods	**Accuracy (%)**	**DR (%)**	**FAR (%)**
CNN [32]	85.82	86.79	21.53
BiDLSTM [33]	89.73	90.28	18.69
CNN-LSTM [34]	92.69	91.63	15.27
Proposed GC-LSTM	97.12	96.83	5.83

On the test set, these four feature extraction models are compared in terms of accuracy, DR, and FAR in Table 8. The CNN-LSTM approach outperforms both CNN and the BiDLSTM technique. With a DR of 98.56%, the CNN-LSTM approach outperforms the other three

models by around 4.43% compared to the GC-LSTM approach. The GC-LSTM technique, on the other hand, outperforms the CNN-LSTM approach in terms of accuracy and FAR, with a 9.44% reduction in FAR.

Table 9: Metrics comparing the proposed GC-LSTM to various normal class models.

UNSW-NB15 Dataset			
	Precision	**Recall**	**F1-Score**
CNN [32]	0.91	0.91	0.91
BiDLSTM [33]	0.94	0.93	0.94
CNN-LSTM [34]	0.96	0.96	0.95
Proposed GC-LSTM	0.99	0.97	0.96

KDDCUP99 Dataset			
	Precision	**Recall**	**F1-Score**
CNN [32]	0.89	0.91	0.91
BiDLSTM [33]	0.92	0.92	0.92
CNN-LSTM [34]	0.95	0.94	0.94
Proposed GC-LSTM	0.98	0.97	0.97

Table top10: Evaluation of the Proposed GC-LSTM Model against Competing Models for the Abnormal Class.

UNSW-NB15 Dataset			
Class	**Precision**	**Recall**	**F1-Score**
CNN [32]	0.88	0.91	0.91
BiDLSTM [33]	0.92	0.91	0.92
CNN-LSTM [34]	0.94	0.93	0.92
Proposed GC-LSTM	0.98	0.96	0.94

KDDCUP99 Dataset			
Class	**Precision**	**Recall**	**F1-Score**
CNN [32]	0.86	0.88	0.89
BiDLSTM [33]	0.89	0.91	0.91
CNN-LSTM [34]	0.92	0.91	0.89
Proposed GC-LSTM	0.98	0.95	0.91

Tables 9 and 10 provide measurements of four feature extraction models for the typical and pathological classes, whereas Table 8 displays the metrics of the basic classifier, Xgboost.

VI. CONCLUSION

This study investigates the problem of traffic categorization, makes suggestions for how to set up the topological graph structure of network traffic, and offers a solution based on the proposed GC-LSTM. The GC layer is used to analyze the input and extract spatial characteristics, and then the LSTM model is used to extract probable temporal information. A portion of the UNSW-NB15 and KDDCUP99 data sets are used to compare the performance and efficacy of the proposed method to feature selection and other well-known deep learning techniques,including Convolutional Neural Networks, Bidirectional LSTM, and Convolutional Neural Network-LSTM. The experiment has certain flaws and room for improvement as well. For network traffic data, creating a topological graph with many nodes places a heavy load on the system's resources due to the increased number of undirected edges that must be constructed. Future research into the correlations between traffic flows and their normal and abnormal counterparts may be informed by this article's proposal of applying a graph convolution model in a network traffic environment.

References

[1] A. M. Sadeghzadeh, S. Shiravi and R. Jalili, "Adversarial Network Traffic: Towards Evaluating the Robustness of Deep-Learning-Based Network Traffic Classification," in IEEE Transactions on Network and Service Management, vol. 18, no. 2, pp. 1962-1976, June 2021, doi: 10.1109/TNSM.2021.3052888.

[2] Z. Bu, B. Zhou, P. Cheng, K. Zhang and Z. -H. Ling, "Encrypted Network Traffic Classification Using Deep and Parallel Network-in-Network Models," in IEEE Access, vol. 8, pp. 132950-132959, 2020, doi: 10.1109/ACCESS.2020.3010637.

[3] S. S. Sepasgozar and S. Pierre, "Network Traffic Prediction Model Considering Road Traffic Parameters Using Artificial Intelligence Methods in VANET," in IEEE Access, vol. 10, pp. 8227-8242, 2022, doi: 10.1109/ACCESS.2022.3144112.

[4] Y. Wang, X. Yun, Y. Zhang, C. Zhao and X. Liu, "A Multi-Scale Feature Attention Approach to Network Traffic Classification and Its Model Explanation," in IEEE Transactions on Network and Service Management, vol. 19, no. 2, pp. 875-889, June 2022, doi: 10.1109/TNSM.2022.3149933.

[5] S. Fathi-Kazerooni and R. Rojas-Cessa, "GAN Tunnel: Network Traffic Steganography by Using GANs to Counter Internet Traffic Classifiers," in IEEE Access, vol. 8, pp. 125345-125359, 2020, doi: 10.1109/ACCESS.2020.3007577.

[6] S. Fathi-Kazerooni and R. Rojas-Cessa, "Countering Machine-Learning Classification of Applications by Equalising Network Traffic Statistics," in IEEE Transactions on Network Science and Engineering, vol. 8, no. 4, pp. 3392-3403, 1 Oct.-Dec. 2021, doi: 10.1109/TNSE.2021.3113656.

[7] M. S. Sheikh and Y. Peng, "Procedures, Criteria, and Machine Learning Techniques for Network Traffic Classification: A Survey," in IEEE Access, vol. 10, pp. 61135-61158, 2022, doi: 10.1109/ACCESS.2022.3181135.

[8] A. Galal and X. Hesselbach, "Machine Learning Models for Traffic Classification in Electromagnetic Nano-Networks," in IEEE Access, vol. 10, pp. 38089-38103, 2022, doi: 10.1109/ACCESS.2022.3165013.

[9] K. -H. N. Bui, H. Oh and H. Yi, "Traffic Density Classification Using Sound Datasets: An Empirical Study on Traffic Flow at Asymmetric Roads," in IEEE Access, vol. 8, pp. 125671-125679, 2020, doi: 10.1109/ACCESS.2020.3007917.

[10] B. Mareri, G. Owusu Boateng, R. Ou, G. Sun, Y. Pang and G. Liu, "MANTA: Multi-Lane Capsule Network Assisted Traffic Classification for 5G Network Slicing," in IEEE Wireless Communications Letters, vol. 11, no. 9, pp. 1905-1909, Sept. 2022, doi: 10.1109/LWC.2022.3186529.

[11] D. Shamsimukhametov, A. Kurapov, M. Liubogoshchev and E. Khorov, "Is Encrypted ClientHello a Challenge for Traffic Classification?," in IEEE Access, vol. 10, pp. 77883-77897, 2022, doi: 10.1109/ACCESS.2022.3191431.

[12] F. U. Islam, G. Liu, J. Zhai and W. Liu, "VoIP Traffic Detection in Tunneled and Anonymous Networks Using Deep Learning," in IEEE Access, vol. 9, pp. 59783-59799, 2021, doi: 10.1109/ACCESS.2021.3073967.

[13] Q. Liu, M. Li, N. Cao, Z. Zhang and G. Yang, "Improved Harris Combined With Clustering Algorithm for Data Traffic Classification," in IEEE Access, vol. 10, pp.

72815-72824, 2022, doi: 10.1109/ACCESS.2022.3188866.

[14] Y. Pan, X. Zhang, H. Jiang and C. Li, "A Network Traffic Classification Method Based on Graph Convolution and LSTM," in IEEE Access, vol. 9, pp. 158261-158272, 2021, doi: 10.1109/ACCESS.2021.3128181.

[15] H. D. Trinh, Á. Fernández Gambín, L. Giupponi, M. Rossi and P. Dini, "Mobile Traffic Classification Through Physical Control Channel Fingerprinting: A Deep Learning Approach," in IEEE Transactions on Network and Service Management, vol. 18, no. 2, pp. 1946-1961, June 2021, doi: 10.1109/TNSM.2020.3028197.

[16] A. Shahraki, M. Abbasi, A. Taherkordi and A. D. Jurcut, "Active Learning for Network Traffic Classification: A Technical Study," in IEEE Transactions on Cognitive Communications and Networking, vol. 8, no. 1, pp. 422-439, March 2022, doi: 10.1109/TCCN.2021.3119062.

[17] A. Telikani, A. H. Gandomi, K. -K. R. Choo and J. Shen, "A Cost-Sensitive Deep Learning-Based Approach for Network Traffic Classification," in IEEE Transactions on Network and Service Management, vol. 19, no. 1, pp. 661-670, March 2022, doi: 10.1109/TNSM.2021.3112283.

[18] R. Kumar, M. Swarnkar, G. Singal and N. Kumar, "IoT Network Traffic Classification Using Machine Learning Algorithms: An Experimental Analysis," in IEEE Internet of Things Journal, vol. 9, no. 2, pp. 989-1008, 15 Jan.15, 2022, doi: 10.1109/JIOT.2021.3121517.

[19] X. Xiao, W. Xiao, R. Li, X. Luo, H. Zheng and S. Xia, "EBSNN: Extended Byte Segment Neural Network for Network Traffic Classification," in IEEE Transactions on Dependable and Secure Computing, vol. 19, no. 5, pp. 3521-3538, 1 Sept.-Oct. 2022, doi: 10.1109/TDSC.2021.3101311.

[20] H. Alizadeh, H. Vranken, A. Zúquete and A. Miri, "Timely Classification and Verification of Network Traffic Using Gaussian Mixture Models," in IEEE Access, vol. 8, pp. 91287-91302, 2020, doi: 10.1109/ACCESS.2020.2992556.

[21] C. Yao, Y. Yang, K. Yin and J. Yang, "Traffic Anomaly Detection in Wireless Sensor Networks Based on Principal Component Analysis and Deep Convolution Neural Network," in IEEE Access, vol. 10, pp. 103136-103149, 2022, doi: 10.1109/ACCESS.2022.3210189.

[22] N. Khan, U. Chaudhuri, B. Banerjee, and S. Chaudhuri, "Graph convolutional network for multi-label VHR remote sensing scene recognition," Neurocomputing, vol. 357, pp. 36–46, May 2019.

[23] J. Wu, S.-H. Zhong, and Y. Liu, "Dynamic graph convolutional network for multi-video summarisation," Pattern Recognit., vol. 107, Nov. 2020, Art. no. 107382

[24] F. Wu, A. Souza, T. Zhang, C. Fifty, T. Yu, and K. Weinberger, "Simplifying graph convolutional networks," in Proc. 36th Int. Conf. Mach. Learn., vol. 97, Jun. 2019, pp. 6861–6871

[25] Y. Imrana, Y. Xiang, L. Ali, and Z. Abdul-Rauf, "A bidirectional LSTM deep learning approach for intrusion detection," Expert Syst. Appl., vol. 185, Dec. 2021, Art. no. 115524.

[26] X. Zhou, Y. Hu, W. Liang, J. Ma, and Q. Jin, "Variational LSTM enhanced anomaly

detection for industrial big data," IEEE Trans. Ind. Informat., vol. 17, no. 5, pp. 3469–3477, May 2021.

[27] https://www.kaggle.com/datasets/mrwellsdavid/unsw-nb15?resource=download

[28] https://kdd.ics.uci.edu/databases/kddcup99/task.html

[29] P. Singh and A. Tiwari, "A review intrusion detection system using KDD'99 dataset," Int. J. Eng. Res. Technol., vol. 3, no. 11, pp. 1103–1108, 2014

[30] J. Liu, B. Kantarci, and C. Adams, "Machine learning-driven intrusion detection for Contiki-NG-based IoT networks exposed to NSL-KDD dataset," in Proc. ACM Workshop Wireless Secur. Mach. Learn., 2020, pp. 25–30.

[31] A. A. Salih and I. Duhok, "Evaluation of classification algorithms for intrusion detection system: A review," J. Soft Comput. Data Mining, vol. 2, no. 1, pp. 31–40, Apr. 2021.

[32] M. Azizjon, A. Jumabek, and W. Kim, "1D CNN based network intrusion detection with normalization on imbalanced data," in Proc. Int. Conf. Artif. Intell. Inf. Commun. (ICAIIC), Feb. 2020, pp. 218–224

[33] Y. Imrana, Y. Xiang, L. Ali, and Z. Abdul-Rauf, "A bidirectional LSTM deep learning approach for intrusion detection," Expert Syst. Appl., vol. 185, Dec. 2021, Art. no. 115524.

[34] P. Sun, P. Liu, Q. Li, C. Liu, X. Lu, R. Hao, and J. Chen, "DL-IDS: Extracting features using CNN-LSTM hybrid network for intrusion detection system," Secur. Commun. Netw., vol. 2020, pp. 1–11, Aug. 20

[35] H. Alazzam, A. Sharieh, and K. E. Sabri, "A feature selection algorithm for intrusion detection system based on pigeon inspired optimizer," Expert Syst. Appl., vol. 148, Jun. 2020, Art. no. 113249.