Network Traffic Classification Model

I. models

Byte Classification

Feature Enginneering+LSTM+CNN, a novel feature engineering approach that generalizes well for encrypted web protocols: [1]

CNN+a new discriminative objective function, apart from minimizing the empirical risk, a metric learning regularization term is also imposed on the learned features: [2]

embedding space, BLJAN embeds the packet’s bytes and all labels into a joint embedding space to capture their implicit correlations with a dual attention mechanism. It finally builds a more powerful packet representation with an enhancement from label embeddings: [3]

对比了 MLP+1D CNN+2D CNN+3D CNN, most of the existing models are created from closed-world datasets, thus they can only classify those existing classes previously sampled and labeled. In this case, unknown classes cannot be correctly classified. The core of the proposed framework consists of a DL-based classifier, a self-learned discriminator, and an autonomous self-labeling model. [4]

Multitask, Mobile traffic classification and prediction, The training of the developed MTL model is divided into two stages. The first stage consists of the training of autoencoder（MLP+LSTM）. The second stage refers to the training of both classifier（softmax layer）and predictor, known the set of feature learning representations provided by the encoder. [5]

Multimodal+XAI, With the tools of explainable artificial intelligence we analyzed an evolved multimodal- DL approach, named Mimetic-Enhanced. the generic Mimetic framework consists of P different inputs (modalities) for each traffic object to be classified. On the top of these layers, the abstract features are joined via a merge layer. Finally, the architecture is completed with a few shared-representation layers, [6]

Comparing with standard convolutional neural networks (CNN), NIN adopts a micro network after each convolution layer to enhance local modeling. Besides, NIN utilizes a global average pooling instead of traditional fully connected layers before final classification [7]

In this paper, we introduce the general framework of Deep Learning based method for network traffic classification and review recent existing work according to data preparation, pre-processing, model input design, and model architecture. [8]

1D CNN, In this paper, we propose a multi-task learning approach that predicts traffic class labels as well as bandwidth and duration of network traffic flows. In this paper, we use 1-dimensional convolutional neural network (CNN) in our multi-task learning model architecture. [9]

In this paper, we proposed a CGAN-based traffic data augmenting method called PacketCGAN to solve the class imbalance problem in the dataset. We use MLP/CNN/SAE models to verify the classification performance over different datasets. [10]

CNN, (ResNet-50 is a pre-trained deep learning model for image classification. It used a Convolutional Neural Network (CNN, or ConvNet)), the proposed approach for IoT malware traffic analysis consists of two main steps, first obtaining the corresponding visual representation of the collected network traffic, and second, processing this visual representation by the trained classification model. [11]

1D CNN [12]

CNN, we implemented and evaluated the Packet Vision, a method capable of building images from packets raw-data, considering both header and payload. Besides, we built a dataset with four traffic classes and evaluated three CNNs architectures [13]

CNN, The basic idea of the method is to convert the first few nonzero payload sizes of session to gray images, and classify the converted gray images with convolutional neural network to achieve the goal of categorizing the encrypted network traffic. [14]

1D CNN, XGBoost, In this paper, we share our experience on a commercial-grade DL traffic classification engine that combines supervised and unsupervised techniques to identify known and zero-day traffic. [15]

Since the 1D-CNN network proposed in [7] proves to have the best performance on ISCXVPN2016, it is adopted by Baseline, [16]

1D CNN [17]

DNN [18]

CNN [19]

CNN,RNN, We propose a spectrum-based procedure that uses a DL-based classifier to realize this framework. We design two DL-based classifiers, a novel Convolutional Neural Network (CNN) spectrum-based TC and a Recurrent Neural Networks (RNN) as baseline architecture [20]

The traffic classifier is designed by a residual network (ResNet), which is known as a state-of-the-art deep learning technique [20]. [21]

Convolutional Neural Network (CNN), Long Short - Term Memory Neural Network (LSTM), Residual Neural Network (ResNet) and Fusion Neural Network (FusionNet) constructed by CNN and LSTM, To testify the validness of our proposed loss function, we designed four kinds of deep neural networks to confirm. [22]

1D CNN, Additionally, the 1D-CNN network proposed in [15] proves to have the best performance on the ISCXVPN2016 dataset. Therefore, it is adopted by our baseline [23]

Graph Convolution and LSTM [24]

RNN, EBSNN first divides a packet into header segments and payload segments, which are then fed into encoders composed of the recurrent neural networks with the attention mechanism [25]

Network Traffic Images(a 2-dimensional (2D) formulation)+CNN, we base our primary machine learning model off of the VGG-16 CNN presented in [20] with a few modifications to make learning faster. [26]

RNN [27]

CNN [28]

NIN is a special kind of CNN. It is a deep learning model proposed by Lin [13]. NIN model consists of convolutional layer, mlpconv layer, max-pooling layer and global average pooling (GAP) layer. [29]

The network traffic classification is performed using the AlexNet, ResNet, and GoogLeNet DL models. The accuracy obtained for ResNet is 95 [30]

LSTM [31]

In TFSN, each TLS flow is input into the sequence generator and decomposed into two-dimensional sequence (i.e. time and length) of Application Data. Then, the two-dimensional vector sequence is input to the attention-guided Bi-LSTM layer. Finally, the feature is extracted and compressed through the dense layer, and the feature representation of the TLS flow is introduced into the softmax function to calculate the prediction class of the TLS flow. [32]

MLP + CNN, Two popular AI-based NTC models, i.e., MLP based and CNN based, are implemented to evaluate the proposed byte importance distillation scheme. [33]

Flow Feature Classification

Agglomerative Clustering, We design the Multiple Counter Sketch (MC Sketch) to quickly extract features from the sampled data stream in a backbone, propose the Batch Classifier based on Agglomerative Clustering (BCAC) for unsupervised clustering of traffic, and combine with the supervised machine learning method to train the labeled data in the clustering: [34]

In this paper, we introduce the general framework of Deep Learning based method for network traffic classification and review recent existing work according to data preparation, pre-processing, model input design, and model architecture. [8]

In this article, several experiments were conducted on two publicly available datasets, UNIBS and UNB, whereby the traffic traces were run through several machine learning algorithms like naïve Bayes, linear SVM, polynomial SVM, KNN, random forest, and artificial neural networks. The suitability of the extracted feature variables was validated using stepwise regression and random forest feature selection. [35]

Naive-Bayes, Sequential Forward Selection method and Naive-Bayes classifier are applied to select the best combination subset of features. [36]

binary coding tress (BCT set), First, inspired by the hash mechanism in blockchain and the learning to hash for big data, we propose a new learning-to-hash method named extension hashing. By this method, we can build the set of binary coding tress (BCT set), then generating hash table for more efficient k-nearest neighbor-based classification without complex classifier training. Then, we design a new voting-based consensus algorithm to synchronize the BCT sets and the hash tables across edge nodes, thereby providing the traffic classification service. [37]

AL, it introduces the concepts of AL, discusses it in the context of NTC, and review the literature in this field. [38]

FlowPic+CNN, We introduce a novel approach for encrypted Internet traffic classification and application identification by transforming basic flow data into an intuitive picture, a FlowPic , and then using known image classification deep learning techniques, CNNs, to identify the flow category [39]

CNN [40]

RkNN, inter-class imbalance and critical time constraints. We propose an RkNN-based correlation classification strategy to measure the distance between new flows and bag of flows training the ensemble algorithm. [41]

DNN, In this study, we build a cross-silo horizontal federated model for TC using flow-based time-related features. The model has one input layer, six hidden layers with 256 neurons and Relu activation, and an output layer with 2 neurons with softmax activation. The optimizer used is stochastic gradient descent (SGD). [42]

Decision Tree+Feature Selection, in this paper, we firstly propose a data pre-processing approach with undersampling and embedded feature selection, then, we utilize LightGBM to build an traffic classification approach [43]

Stacked Autoencoder [44]

The idea is to apply semi-unsupervised Machine Learning techniques, such as Linear Discriminant Analysis (LDA) and K-Means, with a proper customization to take into account the issues related to packet-level analysis, i.e. unbalanced distribution of traffic among classes and selection of proper IP header related features. [45]

Clustering, For this purpose, it relies on unsupervised learning, namely agglomerative hierarchical clustering. Thus, it can be applied in the absence of labeled data (seldom available in operational cellular networks) [46]

CNN, To solve these problems, this paper proposes three methods based on semi-supervised learning (SSL), transfer learning (TL) and domain adaptive (DA), respectively. The ConvLaddernet method consists of the CNN and the Laddernet. The processed training data is fed into the convolutional layer for training. After data features are extracted, the features are inputted into the Laddernet. [47]

Thus, the network data is realized as a video stream to employ time-distributed (TD) feature learning. The intra-temporal information within the network statistical data is learned using convolutional neural networks (CNN) and long short-term memory (LSTM), and the inter pseudo-temporal feature among the flows is learned by TD multi-layer perceptron (MLP) [48]

We then selected state-of-the-art machine learning algorithms based on the recent survey papers for the IoT traffic classification. We then comparatively evaluated the performance of those machine learning algorithms on the basis of classification accuracy, speed, training time, etc. [49]

RNN+CNN [50]

CNN, We apply three optimization algorithms, namely, NSGA-II, SPEA-II and MOPSO, to architecture search, which can automatically generate a set of useful CNN models. [51]

k-nearest neighbors (KNN), decision tree (DT), random forest (RF), LightGBM (LG), and multilayer perceptron (MLP). [52]

CNN, Here, we propose and validate algorithms to perform this task, at runtime , from the raw physical control channel of an operative mobile network , without having to decode and/or decrypt the transmitted flows. Towards this, we decode Downlink Control Information (DCI) messages carried within the LTE Physical Downlink Control CHannel (PDCCH). [53]

LSTM, MLP [54]

(i) Random Forests (RF) with 100 decision trees and (ii) an N x (2N+1) x 1 Multilayer Perceptron (MLP), with sigmoid activation functions [55]

The Random Forest model had maximum depth = 16 and 50 estimators. The kNN achieved best performance with 8 estimators, MLP was comprised of 100 hidden layers, while GradientBoosting classifier had 100 estimators. [56]

Integer Linear Programming (ILP) [57]

Transfer Leaning+CNN+LSTM [58]

decision tree [59]

random forest [60]

convolutional neural network (CNN) and a stacked autoencoder (SAE) [61]

we used DoHMeter to extract featuresRandom Forest (RF), Decision Tree (C4.5), Support Vector Machines (SVM), and Naive Bayes (NB), deep neural network (DNN) and convolutional neural network (CNN) [62]

In the first step, the joint deep learning model contains four components, including logistic regression (LR), recurrent neural network (RNN), convolutional neural network (CNN) and joint learning network. In the second step, the attention mechanism is adopted to reduce the computational complexity of the extra-long-time sample. [63]

Reconstruction + 1D CNN [64]

graph neural network (GNN) [65]

We test ten machine learning classifiers from the scikit learn package (https://scikit-learn.org) in Python [66]

The classification phase contains two modules: (1) feature extractor and (2) ensemble comparator [67]

two-layer Graph Convolutional Network (GCN)+ AE [68]

In this paper, we have suggested two hybrid models that combine the Convolutional Neural Network (CNN) along with the Recurrent Neural Network (RNN) models, inclusive of the Gated recurrent unit (GRU) and Long Short-Term Memory (LSTM) [69]

MNN, Multilayer perceptron classification networks are used to assign classification probabilities to the flows[26] [70]

NB+Clustering [71]

Clustering [72]

Feature Extraction+Our model ends with a global average pooling, a fully-connected layer and softmax. The loss function is the Cross Entropy. The reason why we did not use more complex network and advanced loss function to form the Classifier is to highlight the DeepFE's superior performance in feature extraction. [73]

Decision Tree, Random Forest, and Naive Bayes which are chosen based on their consistent and improved classification performance for other standard data sets. [74]

Gaussian Mixture Models (GMMs). We generate a separate GMM for each class of applications using component-wise expectation-maximization (CEM) to match the network traffic distribution generated by these applications. [75]

参考文献

[1] I. Akbari, M. A. Salahuddin, L. Ven, N. Limam, R. Boutaba, B. Mathieu, S. Moteau, and S. Tuffin, "A look behind the curtain: traffic classification in an increasingly encrypted web," *Proceedings of the ACM on Measurement and Analysis of Computing Systems*, vol. 5, no. 1, pp. 1–26, 2021.

[2] L. Zhao, L. Cai, A. Yu, Z. Xu, and D. Meng, "A novel network traffic classification approach via discriminative feature learning," in *Proc. of SAC*, 2020.

[3] K. Mao, X. Xiao, G. Hu, X. Luo, B. Zhang, and S. Xia, "Byte-label joint attention learning for packet-grained network traffic classification," in *Proc. of IWQOS*, 2021.

[4] J. Zhang, F. Li, F. Ye, and H. Wu, "Autonomous unknown-application filtering and labeling for dl-based traffic classifier update," in *Proc. of INFOCOM*, 2020.

[5] A. Rago, G. Piro, G. Boggia, and P. Dini, "Multi-task learning at the mobile edge: An effective way to combine traffic classification and prediction," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 9, pp. 10 362–10 374, 2020.

[6] A. Nascita, A. Montieri, G. Aceto, D. Ciuonzo, V. Persico, and A. Pescapé, "Xai meets mobile traffic classification: Understanding and improving multimodal deep learning architectures," *IEEE Transactions on Network and Service Management*, vol. 18, no. 4, pp. 4225–4246, 2021.

[7] Z. Bu, B. Zhou, P. Cheng, K. Zhang, and Z.-H. Ling, "Encrypted network traffic classification using deep and parallel network-in-network models," *IEEE Access*, vol. 8, pp. 132 950–132 959, 2020.

[8] L. Hota, B. P. Nayak, A. Kumar, G. Ali, P. H. J. Chong *et al.*, "An analysis on contemporary mac layer protocols in vehicular networks: State-of-the-art and future directions," *Future Internet*, vol. 13, no. 11, p. 287, 2021.

[9] S. Rezaei and X. Liu, "Multitask learning for network traffic classification," in *Proc. of ICCCN*, 2020.

[10] P. Wang, S. Li, F. Ye, Z. Wang, and M. Zhang, "Packetcgan: Exploratory study of class imbalance for encrypted traffic classification using cgan," in *Proc. of ICC*, 2020.

[11] G. Bendiab, S. Shiaeles, A. Alruban, and N. Kolokotronis, "Iot malware network traffic classification using visual representation and deep learning," in *Proc. of NetSoft*, 2020.

[12] A. M. Sadeghzadeh, S. Shiravi, and R. Jalili, "Adversarial network traffic: Towards evaluating the robustness of deep-learning-based network traffic classification," *IEEE Transactions on Network and Service Management*, vol. 18, no. 2, pp. 1962–1976, 2021.

[13] R. Moreira, L. F. Rodrigues, P. F. Rosa, R. L. Aguiar, and F. de Oliveira Silva, "Packet vision: a convolutional neural network approach for network traffic classification," in *Proc. of SIBGRAPI*, 2020.

[14] Y. He and W. Li, "Image-based encrypted traffic classification with convolution neural networks," in *Proc. of DSC*, 2020.

[15] L. Yang, A. Finamore, F. Jun, and D. Rossi, "Deep learning and zero-day traffic classification: Lessons learned from a commercial-grade dataset," *IEEE Transactions on Network and Service Management*, vol. 18, no. 4, pp. 4103–4118, 2021.

[16] Y. Guo, G. Xiong, Z. Li, J. Shi, M. Cui, and G. Gou, "Ta-gan: Gan based traffic augmentation for imbalanced network traffic classification," in *Proc. of IJCNN*, 2021.

[17] A. Telikani, A. H. Gandomi, K.-K. R. Choo, and J. Shen, "A cost-sensitive deep learning based approach for network traffic classification," *IEEE Transactions on Network and Service Management*, 2021.

[18] A. Malik, R. de Fréin, M. Al-Zeyadi, and J. Andreu-Perez, "Intelligent sdn traffic classification using deep learning: Deep-sdn," in *Proc. of ICCCI*, 2020.

[19] S. Soleymanpour, H. Sadr, and H. Beheshti, "An efficient deep learning method for encrypted traffic classification on the web," in *Proc. of ICWR*, 2020.

[20] M. Camelo, P. Soto, and S. Latré, "A general approach for traffic classification in wireless networks using deep learning," *IEEE Transactions on Network and Service Management*, 2021.

[21] S. Ahn, J. Kim, S. Y. Park, and S. Cho, "Explaining deep learning-based traffic classification using a genetic algorithm," *IEEE Access*, vol. 9, pp. 4738–4751, 2020.

[22] L. Xu, X. Zhou, X. Lin, Y. Ren, Y. Qin, and J. Liu, "A new loss function for traffic classification task on dramatic imbalanced datasets," in *Proc. of ICC*, 2020.

[23] Y. Guo, G. Xiong, Z. Li, J. Shi, M. Cui, and G. Gou, "Combating imbalance in network traffic classification using gan based oversampling," in *Proc. of IFIP Networking*, 2021.

[24] Y. Pan, X. Zhang, H. Jiang, and C. Li, "A network traffic classification method based on graph convolution and lstm," *IEEE Access*, vol. 9, pp. 158 261–158 272, 2021.

[25] X. Xiao, W. Xiao, R. Li, X. Luo, H.-T. Zheng, and S.-T. Xia, "Ebsnn: Extended byte segment neural network for network traffic classification," *IEEE Transactions on Dependable and Secure Computing*, 2021.

[26] I. Saleh and H. Ji, "Network traffic images: A deep learning approach to the challenge of internet traffic classification," in *Proc. of CCWC*, 2020.

[27] K. Zhu, G. Shen, Y. Jiang, J. Lv, Q. Li, and M. Xu, "Differentiated transmission based on traffic classification with deep learning in datacenter," in *Proc. of IFIP NETWORKING*, 2020.

[28] G. Aceto, D. Ciuonzo, A. Montieri, A. Nascita, and A. Pescapé, "Encrypted multitask traffic classification via multimodal deep learning," in *Proc. of ICC*, 2021.

[29] M. Lu, B. Zhou, Z. Bu, K. Zhang, and Z. Ling, "Compressed network in network models for traffic classification," in *Proc. of WCNC*, 2021.

[30] M. M. Raikar, "Phd forum: Data traffic classification using deep learning models," in *Proc. of WoWMoM*, 2021.

[31] W. Chen, F. Lyu, F. Wu, P. Yang, G. Xue, and M. Li, "Sequential message characterization for early classification of encrypted internet traffic," *IEEE Transactions on Vehicular Technology*, vol. 70, no. 4, pp. 3746–3760, 2021.

[32] H. Wu, L. Wang, G. Cheng, and X. Hu, "Mobile application encryption traffic classification based on tls flow sequence network," in *Proc. of ICC*, 2021.

[33] F. Li and F. Ye, "Simplifying data traffic classification with byte importance distillation," in *Proc. of ICC*, 2021.

[34] H. Wu, X. Chen, G. Cheng, X. Hu, and Y. Zhuang, "Bcac:

Batch classifier based on agglomerative clustering for traffic classification in a backbone network," in *Proc. of IWQOS*, 2021.

[35] M. Elnawawy, A. Sagahyroon, and T. Shanableh, "Fpga-based network traffic classification using machine learning," *IEEE Access*, vol. 8, pp. 175 637–175 650, 2020.

[36] B. Mohammed, M. Hamdan, J. S. Bassi, H. A. Jamil, S. Khan, A. Elhigazi, D. B. Rawat, I. B. Ismail, and M. N. Marsono, "Edge computing intelligence using robust feature selection for network traffic classification in internet-of-things," *IEEE Access*, vol. 8, pp. 224 059–224 070, 2020.

[37] H. Qi, J. Wang, W. Li, Y. Wang, and T. Qiu, "A blockchain-driven iiot traffic classification service for edge computing," *IEEE Internet of Things Journal*, vol. 8, no. 4, pp. 2124–2134, 2020.

[38] A. Shahraki, M. Abbasi, A. Taherkordi, and A. D. Jurcut, "Active learning for network traffic classification: a technical study," *Proc. of TCCN*, 2021.

[39] T. Shapira and Y. Shavitt, "Flowpic: A generic representation for encrypted traffic classification and applications identification," *IEEE Transactions on Network and Service Management*, vol. 18, no. 2, pp. 1218–1232, 2021.

[40] C. Beliard, A. Finamore, and D. Rossi, "Opening the deep pandora box: Explainable traffic classification," in *Proc. of INFOCOM*, 2020.

[41] M. A. S. Saber, M. Ghorbani, A. Bayati, K.-K. Nguyen, and M. Cheriet, "Online data center traffic classification based on inter-flow correlations," *IEEE Access*, vol. 8, pp. 60 401–60 416, 2020.

[42] U. Majeed, L. U. Khan, and C. S. Hong, "Cross-silo horizontal federated learning for flow-based time-related-features oriented traffic classification," in *Proc. of APNOMS*, 2020.

[43] Y. Hua, "An efficient traffic classification scheme using embedded feature selection and lightgbm," in *Proc. of ICTC*, 2020.

[44] O. Aouedi, K. Piamrat, and D. Bagadthey, "A semi-supervised stacked autoencoder approach for network traffic classification," in *Proc. of ICNP*, 2020.

[45] D. Aureli, A. Cianfrani, A. Diamanti, J. M. S. Vilchez, and S. Secci, "Going beyond diffserv in ip traffic classification," in *Proc. of NOMS*, 2020.

[46] C. Gijón, M. Toril, M. Solera, S. Luna-Ramírez, and L. R. Jiménez, "Encrypted traffic classification based on unsupervised learning in cellular radio access networks," *IEEE Access*, vol. 8, pp. 167 252–167 263, 2020.

[47] J. Ning, G. Gui, Y. Wang, J. Yang, B. Adebisi, S. Ci, H. Gacanin, and F. Adachi, "Malware traffic classification using domain adaptation and ladder network for secure industrial internet of things," *IEEE Internet of Things Journal*, 2021.

[48] Y. S. K. Manjunath, S. Zhao, and X.-P. Zhang, "Time-distributed feature learning in network traffic classification for internet of things."

[49] R. Kumar, M. Swarnkar, G. Singal, and N. Kumar, "Iot network traffic classification using machine learning algorithms: An experimental analysis," *IEEE Internet of Things Journal*, 2021.

[50] X. Wang, S. Chen, and J. Su, "App-net: a hybrid neural network for encrypted mobile traffic classification," in *Proc. of INFOCOM*, 2020.

[51] X. Wang, X. Wang, L. Jin, R. Lv, B. Dai, M. He, and T. Lv, "Evolutionary algorithm-based and network architecture search-enabled multiobjective traffic classification," *IEEE Access*, vol. 9, pp. 52 310–52 325, 2021.

[52] H.-Y. Chen and T.-N. Lin, "The challenge of only one flow problem for traffic classification in identity obfuscation environments," *IEEE Access*, vol. 9, pp. 84 110–84 121, 2021.

[53] H. D. Trinh, A. F. Gambin, L. Giupponi, M. Rossi, and P. Dini, "Mobile traffic classification through physical control channel fingerprinting: a deep learning approach," *IEEE Transactions on Network and Service Management*, vol. 18, no. 2, pp. 1946–1961, 2020.

[54] M. Dicks and J. Chavula, "Deep learning traffic classification in resource-constrained community networks," in *Proc. of AFRICON*, 2021.

[55] M. Dimolianis, A. Pavlidis, and V. Maglaris, "Signature-based traffic classification and mitigation for ddos attacks using programmable network data planes," *IEEE Access*, vol. 9, pp. 113 061–113 076, 2021.

[56] L. A. Iliadis and T. Kaifas, "Darknet traffic classification using machine learning techniques," in *Proc. of MOCAST*, 2021.

[57] M. Polverini, J. Galán-Jiménez, F. G. Lavacca, A. Cianfrani, and V. Eramo, "A scalable and offloading-based traffic classification solution in nfv/sdn network architectures," *IEEE Transactions on Network and Service Management*, vol. 18, no. 2, pp. 1445–1460, 2020.

[58] X. Hu, C. Gu, Y. Chen, and F. Wei, "tcld-net: A transfer learning internet encrypted traffic classification scheme based on convolution neural network and long short-term memory network," in *Proc. of CCCI*, 2021.

[59] D. Perepelkin and M. Ivanchikova, "Problem of network traffic classification in multiprovider cloud infrastructures based on machine learning methods," in *Proc. of MECO*, 2021.

[60] A. I. Owusu and A. Nayak, "An intelligent traffic classification in sdn-iot: A machine learning approach," in *Proc. of BlackSeaCom*, 2020.

[61] M. Wang, K. Zheng, D. Luo, Y. Yang, and X. Wang, "An encrypted traffic classification framework based on convolutional neural networks and stacked autoencoders," in *Proc. of ICCC*, 2020.

[62] M. MontazeriShatoori, L. Davidson, G. Kaur, and A. H. Lashkari, "Detection of doh tunnels using time-series classification of encrypted traffic," in *Proc. of DASC/PiCom/CBDCom/CyberSciTech*, 2020.

[63] C. Li, C. Dong, K. Niu, and Z. Zhang, "Mobile service traffic classification based on joint deep learning with attention mechanism," *IEEE Access*, vol. 9, pp. 74 729–74 738, 2021.

[64] Q. Ma, W. Huang, Y. Jin, and J. Mao, "Encrypted traffic classification based on traffic reconstruction," in *Proc. of ICAIBD*. IEEE, 2021, pp. 572–576.

[65] T.-L. Huoh, Y. Luo, and T. Zhang, "Encrypted network traffic classification using a geometric learning model," in *Proc. of IM*, 2021.

[66] B. Charyyev and M. H. Gunes, "Iot event classification based on network traffic," in *Proc. of INFOCOM*, 2020.

[67] Z. Zhao, Y. Lai, Y. Wang, W. Jia, and H. He, "A few-shot

learning based approach to iot traffic classification," *IEEE Communications Letters*, 2021.

[68] B. Sun, W. Yang, M. Yan, D. Wu, Y. Zhu, and Z. Bai, "An encrypted traffic classification method combining graph convolutional network and autoencoder," in *Proc. of IPCCC*, 2020.

[69] F. Sarhangian, R. Kashef, and M. Jaseemuddin, "Efficient traffic classification using hybrid deep learning," in *Proc. of SysCon*, 2021.

[70] A. A. Mohamed, A. H. Osman, and A. Motwakel, "Classification of unknown internet traffic applications using multiple neural network algorithm," in *Proc. of ICCIS*, 2020.

[71] A. Gupta, "Vpn-nonvpn traffic classification using deep reinforced naive bayes and fuzzy k-means clustering," in *Proc. of ICDCSW*, 2021.

[72] A. F. Diallo and P. Patras, "Adaptive clustering-based malicious traffic classification at the network edge," in *Proc. of INFOCOM*, 2021.

[73] Y. Guo, G. Gou, G. Xiong, M. Jiang, J. Shi, and W. Xia, "Let imbalance have nowhere to hide: Class-sensitive feature extraction for imbalanced traffic classification," in *Proc. of IJCNN*, 2021.

[74] S. Panda and G. Panda, "Intelligent classification of iot traffic in healthcare using machine learning techniques," in *Proc. of ICCAR*, 2020.

[75] H. Alizadeh, H. Vranken, A. Zúquete, and A. Miri, "Timely classification and verification of network traffic using gaussian mixture models," *IEEE Access*, vol. 8, pp. 91 287–91 302, 2020.