

A Review on Internet Traffic Classification Based on Artificial Intelligence Techniques

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Abstract—Almost every industry has revolutionized with Artificial Intelligence. The telecommunication industry is one of them to improve customers' Quality of Services and Quality of Experience by enhancing networking infrastructure capabilities which could lead to much higher rates even in 5G Networks. To this end, network traffic classification methods for identifying and classifying user behavior have been used. Traditional analysis with Statistical-Based, Port-Based, Payload-Based, and Flow-Based methods was the key for these systems before the 4th industrial revolution. AI combination with such methods leads to higher accuracy and better performance. In the last few decades, numerous studies have been conducted on Machine Learning and Deep Learning, but there are still some doubts about using DL over ML or vice versa. This paper endeavors to investigate challenges in ML/DL use-cases by exploring more than 140 identical researches. We then analyze the results and visualize a practical way of classifying internet traffic for popular applications.

Keywords: Internet Traffic Classification; Network Traffic Analysis; DL; ML; Artificial intelligence.

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I. INTRODUCTION

One of the challenges in telecommunication systems has always been optimizing data transmission systems. In today's world, where a massive amount of information is transferred via the internet, some vital and sensitive information necessitates real-time communication, while others necessitate larger bandwidth and high reliability. This category is prevalent even in cellular networks, where achievement is possible through something known as QoS. Tracking the evolution of cellular networks from 1G to 5G and even 6G reveals that they all have the same goal, and that is to provide users with the best quality of services.

Several approaches were used to improve customer service delivery. Upgrade system infrastructures in high-population areas, identify communication protocols, and exchange traffic to transfer information through specific infrastructures in different regions based on priority, necessity, and security. In this survey, we attempt to examine the traffic of viral applications, which can include messengers, games, and social media, which are following the users' appetites. Accordingly, network traffic is adjusted so that the user obtains the highest satisfaction by using those applications by providing the appropriate infrastructure facilities.

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To this end, by comprehensively studying more than 140 authoritative articles and journals, we tried to find ways to solve these challenges. Among these, traditional methods were also examined. There were four approaches to traditional identification methods, but none of them works in today's world, lonely. These approaches include 1- Statistical methods which use packet length, average packet time, and other parameters to determine traffic type. This method is both costly and prone to errors due to the use of human labor. 2- Port-based methods are ineffective today due to the use of dynamic ports, changing and updating port numbers, and the use of tunnels. 3- Payload-based methods are also ineffective due to frequent updates, high costs, and encrypted data for information transfer. 4- Flow-based methods that employ a large number of packets in a timely manner. To solve the problems resulting from the high probability of error in each of these approaches, a combination of the above-mentioned methods with artificial intelligence is a useful solution for increasing accuracy, lowering costs, and improving user satisfaction. Machine learning and deep learning are examples of artificial intelligence. Features are extracted manually or using third-party software in a machine learning algorithm. In contrast, in Deep learning methods, the features in the data are automatically extracted inside the network's model, and the network itself is responsible for extracting and selecting the appropriate features. It should be noted that deep learning is a subset of machine learning and artificial intelligence, but in this article, we have treated them as separate categories due to the stated characteristics. In some cases, these new methods combine all four approaches or selected features under the subsections of each method combined with artificial intelligence; the features in the datasets include a combination of statistical features, port, IP features, or features in packets or flow traffics. [1] demonstrated that ISPs could use bandwidth and event duration as a feature to make resource allocation, routing, and QoS policies. However, when these features are combined with AI techniques, they can improve QoS performance. The key is AI structures and methods, which we will elaborate on later. This paper focuses on Network Traffic Analysis research, surveying AI-based methods in recent years, detailing their observations, and comparing their applications. Furthermore, this paper describes the limitations of ML/DL methods and briefly introduces future trends. The remainder of this paper is as follows: Section II introduces some AI-based network traffic Analysis methods, as well as classes and datasets; Section III will reveal different papers and the frequency of each ML/DL method; Section IV will be about Model Evaluations; Section V will show a general pipeline for training AI-based network traffic classification models. Conclusions are drawn in section VI.

II. NETWORK TRAFFIC ANALYSIS METHODS

To solve traffic classification problems, machine learning algorithms and deep learning models have been widely used. However, the structure and architecture of these models differ greatly, and training such models necessitates a large amount of labeled data

(dataset). In the process of creating a dataset, data tagging (labeling) is frequently a laborious and time-consuming task. The type and number of output classes are also important for data collection and network training. In some cases, the granularity of a specific application, such as WhatsApp, must be checked, which can include Voice calls, Video calls, Chat, File Sharing, and Voices, among others. In many cases, simply checking the application type, such as Map, is sufficient. Relevant solutions and outcomes will be discussed in this section.

A. Artificial Intelligence

As opposed to traditional methods, AI-based methods are used to automate the process of traffic classification and have demonstrated undeniable performance in Bigdata and high-speed connections. Traditional classification methods were primarily used for a specific application that could not be generalized, but using AI allowed for greater accuracy than superhumans. AI-based architectures benefit from model iterations for different batches of data rather than hand-crafted features extracted by humans' knowledge and expertise, which typically contain far more errors. Whereas traditional software is purposefully programmed line by line to perform a task, an AI-based algorithm is programmed to learn how to perform the task. The convergent analysis is one of the most significant advances in modern science, utilizing heterogeneous technologies from multiple and independent domains/sources to analyze and classify large amounts of data. Compared to traditional classification methods, AI is the key enabler and makes it a truly distinguishable feature. Furthermore, due to recent privacy concerns and the massive growth of connected devices, we can no longer process and classify traffic using traditional methods with the assistance of humans, and thus the best way to solve this problem is to use robots or artificial intelligence techniques for this field. One of the most substantial steps in traffic classification/identification is to use the appropriate artificial intelligence model. To solve a traffic Classification problem, we generally have two choices: one is to use machine learning methods, and the other is to use deep learning methods. As mentioned above, Deep learning is considered a subset of Machine learning. So based on that, Machine learning approaches are divided into four categories: supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning. With the studies conducted, reinforcement learning includes a very small proportion of research and practical implementation in this subject. Since we do not deal with continuous data for traffic analysis, among the subsets of **Supervised Learning** methods, which are Regression and Classification, we only explore classification methods. In [2], which is a supervised machine learning method, they firstly filter the Ip address and Protocol type of the game traffic to reduce background noise as much as possible. Then, to remove irrelevant and redundant features, the Pearson correlation coefficient and information gain ratio are used as feature selection criteria. They then analyze the traffic using the SVM algorithm. The main purpose of [3] was to introduce new traffic features to identify applications. They have Proposed a set of statistical

characteristics of traffic flow such as the number of packets in each flow, the size and time of each flow, the type of distribution in the burst, and the ideal time between different bursts, ... that can be used for C5.0 decision tree method to achieve higher accuracy in classifying web-based software traffic. As mentioned, DPI¹ is a real-time separation (filtering) method that uses packet payload to further analyze traffic alongside packet header, and it is a network traffic analysis technology. DFI² is the latest packet filtering technique that uses flow statistical features such as TBF³ and RCF⁴ and DF⁵ and APBF⁶, etc., to detect traffic types. it is worth noting that their work would cause a microsecond delay between exact service execution and packet capture time, which is not significant but should be considered. To the best of our knowledge, defining a value such as ϵ , epsilon, which is an arbitrary small sub_second value for compensating the delay, would be helpful to increase the overall accuracy, whereas the statistical features would be compromised without the delay compensation!

According to [4,] P2P applications such as Facebook, WhatsApp, BitTorrent, and others generate 60-80 percent of traffic. They compared the performance of three machine learning algorithms: decision trees, SVM, and Bayesian networks with DPI and DFI. Some articles have also conducted thorough research on encrypted data. Many applications combine symmetric and asymmetric cryptography. Secure Socket Layer (SSL) and Transfer Layer Security (TLS), two encryption protocols designed to provide secure communications over the Internet, are common examples of such dual systems. SSL protocols are now deemed insecure and will be phased out. TLS protocols, on the other hand, are secure and widely used by major browsers. While their work contains a wealth of useful information, it contains some flaws, such as the effect of DPI classification over DFI classification. They did not take into account this effect in their work, and as a result, some accuracy degradation happened.

Authors in [5] believe that different encrypted software leaves distinct Footprints. So, they used a sequence of randomly selected bits by the application as a feature. They proved that when randomly generated data is encrypted in different ways, these obtained features can be used for training machine learning models to achieve acceptable accuracy in classifying the network traffic. Decision tree methods, Gaussian Naïve Bayes, SVM, and Adaboost, have been used for this purpose. A mobile device with an Asus RT-3200AC as a wireless router was required to perform such a test. It was claimed that by using specific bit sequences for each software and the aforementioned machine learning methods, achieving an average accuracy of about 95 percent was easily accessible. An important note about potential software updates or new network changes that may arise for any application is mentioned in [6]. They examined the impact of packet length changes that may occur primarily to improve a program or security issues. Various supervised machine learning algorithms were used to investigate this issue. The Random Forest,

Bagged Trees, and XGBoost algorithms achieved 90% accuracy on the original data. Increasing the length of packets (padding) reduces the accuracy of SGD and SVM algorithms but does not affect Bayesian-based network algorithms. Recall reduction is more affected by packet length change in the random forest than in Google Chrome, Google Drive, One Drive, OneNote, Spotify, and WhatsApp. Despite using one of the best-boosting algorithms to classify the traffic, they did not consider the newly generated fake data for watermarking or concealing information inside other apps' data using Autoencoders or GANs. As a result, in the case of Steganography, this method would be inaccurate. We believe that boosting the model with synthetic data requires combining their techniques with some more advanced techniques.

Two methods were explored in [7], one related to MLP, and the other was LSTM. Instead of Softmax for the last layer, which is commonly used, they defined a threshold to determine the classes. If the class probability falls below that threshold, the traffic is recognized as a VPN; if it goes above that threshold, the traffic is classified as a normal flow. This technique, known as "the distance from the class center," has the potential to improve model accuracy. A hybrid method for network router traffic classification is introduced in [9]. It uses a combination of flow-based methods with XGboost algorithms to train a model and then use it as a classifier. The method begins by sampling the original data, then classifying it using packet-based methods. The categorization process is then aided by flow-based and deep packet inspection methods. If the traffic does not fit within the available information and classes, the RULES will be updated to achieve the best results. Incoming traffic goes through the router for routing policy based on Class Aware or RULES. In addition, Flow-Based and DPI-Based classifiers are given a mirror of incoming traffic to label Packets/Flows based on their characteristics. Gradient boosted tree models such as XGBoost and LightGBM were used to design and implement an updated packet-based routing policy for the router to improve Class Aware classification on time, which is a must.

[11] studies Unsupervised Learning methods. As you may know, unsupervised methods are used only for clustering. They discussed definitions and issues related to the scope of traffic analysis in the first part and techniques for unsupervised learning methods such as data clustering, hidden variable models, and dimensional reduction in the second part. Finally, unsupervised learning applications were indexed in cases such as Internet Traffic Classification, Anomaly/Intrusion Detection, Network Operations/optimization & Analysis, Dimensionality Reduction & Visualization. Three different algorithms in [12], including K-Means, Fuzzy C Means, and Expectation Maximization, were considered as part of the proposed classification and network error detection solution. The methods attempted to improve the quality of guaranteed services by automatically preventing errors or detecting error points. Due to the increasing

¹ Deep Packet Inspection

² Deep Flow Inspection

³ Total Byte of Flow

⁴ Packet Count of Flow

⁵ Duration of each Flow

⁶ Average Packet Byte of Flow

growth of applications, especially messengers and SuperApp⁷, Various communication services and protocols had used within an application. this is only for Android traffic, but one of the concerns about this method is that it requires knowledge of a user's PII (Hardcoded identifiers) to work on, which has some privacy implications that should be taken seriously.

In [13], a study of performance and detection of granularity using the MIMD techniques, a set selector for the optimal feature selection was conducted. This is helpful and differentiable to feature selection. Using RCC, a type of K-Means could achieve in-app traffic clustering. They evaluated this on WeChat, WhatsApp, and Facebook and gained considerable accuracy.

[14] Is a **Semi-supervised Learning** approach. They come up with new ideas for classifying applications such as YouTube, Netflix, BitTorrent, Skype, DropBox, GDrive, 8 ball Pools, Treasure Hunter, Outlook, and more. They used 17-Tuple Bidirectional NetFlow Records to categorize network traffic. To accomplish this, the traffic was clustered using K-mean, and the classification was obtained using the C5.0 decision tree algorithm. Video Streaming, Video Chat/Voice, p2p Torrent, Cloud Storage, Online Gaming, and Email Clients are examples of clusters.

Deep Learning has emerged as one of the most effective methods for overcoming challenges in a variety of domains in recent years. If a large amount of data is available and also powerful processors are accessible, acceptable accuracy can be achieved through these models. An innovative method for traffic analysis was presented in [16]. According to the authors, Deep Packet is the first deep learning-based traffic classification system that could identify the application and traffic using CNNs⁸ and SAE⁹. Five fully connected layers of 50 to 400 neurons were used in the SAE structure. The system described in this study first receives incoming PCAP files before performing preprocessing operations such as removing the data link layer, modifying the transport layer header, deleting irrelevant packets, truncating, normalizing, and IP masking. The output is then fed into CNN and SAE, and the expected output is displayed in the form of a specific label. It is also worth noting that they compared the results of their work with four different machine learning methods to demonstrate the promising results of deep learning models. [17] perused data collection methods and identified about 140 widely used applications using CNN, SAE, and LSTM networks. They also studied the accuracy of convolutional neural network models by increasing the number of input payload bytes, which is much higher by using the initial 300 bytes of the subsequent payloads compared to using a smaller number of payloads. They also used the Tanh activation function for SAE with the ReLU activation function for CNN & LSTM, and Adam optimization is used in all of these models. In [18], NTMA Techniques associated with network traffic analysis and monitoring were scrutinized. It delves into four broad categories of deep learning traffic classification, traffic prediction, fault management, and

network security. They looked at two common types of NTMA techniques for obtaining network information: 1- Active methods, such as traffic probe generation and injection within the network, to learn and understand how it works. The sampling is mostly done on a regular and scheduled basis. 2- Passive methods, which use logs and post-events to improve monitoring capability, error tolerance, and problem elimination, but can result in computationally expensive network traffic analysis. They also mentioned some issues with DPI-based traffic analysis methods that could jeopardize user data. Full-packet processing requires more processing capabilities than traditional methods, and they are unusable in some types of networks, such as Virtual Private Networks(VPNs). To this end, they switched to Flow-based strategies with nearly identical temporal and statistical characteristics for each App/Service and their capability to manage encrypted/normal traffic.

[15] is an online traffic classification system for network flow identification that combines CNN and DPIs to detect network traffics such as RDP, BitTorrent, SSH, eDonkey, etc. They claimed that by receiving 10 packets of each traffic stream, classes of these protocols could be identified. The idea of using a system that can extract the pattern in the packets and the patterns in the data flows using LSTM was suggested in [19]. They identified 80 applications using a laboratory dataset collected by popular tools like Wireshark and tcpdump. They only considered the payload and statistical features of the first few packets of a flow, but as previously discussed, in the case of encrypted traffic that conceals the payload, their work will not accurately classify the traffic.

Software-Defined Networks are now considered an alternative to traditional networks. Among the reviewed articles on traffic analysis for software defined-based networks, [22] addressed traffic classification using the Mininet controller and OpenVSwitch. Various machine learning methods such as decision trees, support vector machines, simple Bayesian, and deep learning methods such as AE, NN, and RNN were used to overcome some of the challenges. Federated Learning was used in [23], which is a new framework based on decentralized datasets that allow collaborative model training. This learning approach enables the use of deep learning algorithms in resource-constrained appliances as the training data is distributed among all participants use a shared model. As a result, even with limited memory and computational resources, the entire system can achieve promising results, but none of them could happen if they acted friendlessly. For this type of dataset, a new GAN-based method was used. As a result, we have a set of local servers that communicate with FOG servers, and these FOGs communicate with a central coordinator. Each of these local servers receives the data, categorizes it, and then passes it to the FOGs. There are now two options. The first possibility is that these FOGs act as discriminators while the coordinator acts as a generator. In this case, the generator generates data, and FOG attempts to distinguish between real and fake data. If the generated data looks genuinely like the true data, the discriminator

⁷ That allows a user to access several services from a single app.

⁸ Convolutional Neural Networks

⁹ Stacked Auto Encoders

is fooled, and the data is considered real. In the second possibility, generation and discrimination are done within both the FOGs and Coordinators. This decentralized method reduces security concerns, and the new data can be generated with a small dataset, so a large amount of labeled traffic is not required.

The Internet of Things (IoT), which is expected to support approximately 21 billion devices in the upcoming years, is the communication structure of devices that send and receive data. [25] introduces a new method for converting traffic flow data into video and categorizing and managing traffic flow based on the analysis of this video for IoT traffic data. The combination of CNN and LSTM was used to extract spatial and temporal information from the stream and then convert this information into a video so that they could apply Time Distributed Feature Learning with MLP to achieve 95% accuracy. They discovered that the combination of TD and MLP aids in understanding semi-temporal properties which could not be detected by LSTM. They compared the CNN + LSTM + TD + MLP structure to the CNN + LSTM + MLP structure, which is an obvious trade-off between 41 times the parameters (about 115 thousand) for a 10% increase in accuracy. It should be noted that the cost was doubling the training time. In [26], the performance of AI-based systems, including the ML and DL methods for classifying encrypted traffic has been examined while Adversarial Evasion Attacks are conducted. Adversarial Evasion attacks are a method in which noise is added to the original data in such a way that it misdiagnoses the decision boundary between normal data and manipulated data which makes traffic classification difficult. In this method, traffic generation and evaluation were performed using Zeroth Order Optimization (ZOO), Projected Gradient Descent (PGD), and DeepFool to investigate the classification performance of various algorithms for encrypted traffic. The performance had measured with and without attack, and it has shown that DL models performed better than ML in non-attack environments. In attack time, depending on the type of attack, the superiority of DL over ML models could be different. In [31], the problems of conventional AI methods for analyzing network traffic classification were addressed, and an optimal model called iCarl + was introduced. The iCarl+ algorithm was inspired by the iCarl algorithm, which is widely used in machine vision tasks for continuous learning. To add a new class or category of traffic using traditional methods, two steps must be taken: 1- Create new training data or improve and expand on existing data 2- Create a new network model from scratch using new data. However, incremental (continuous) learning methods were proposed, eliminating the need for retraining from scratch, saving time and money, and improving performance. A network that benefits from continuous or incremental learning is always looking for new ways to update the models' weights to adapt to new information needed for the best classification performance. In this case, combining the knowledge gained from previous information and available classes with the addition of new classes can result in much higher accuracy. Then they worked to resolve iCarl's ambiguities and improve the network. NMC was replaced with SoftMax, and the output layer was dynamically expanded instead of a

fixed predefined output layer size, allowing it to be compatible with new classes while improving performance without affecting error. The model consists of 1D-CNN with about 200,000 parameters.

B. Datasets and tools

As you may know, data plays a very essential and critical role in the accuracy and performance of artificial intelligence methods. Deep learning algorithms are data-hungry, which means that the more data they hit, the better their performance and accuracy will be. In the network traffic analysis field, due to the possibility of misusing data for specific purposes, the number of articles that provide up-to-date and valid data to the public for free is practically low. For this reason, the data used in this field are mainly related to the university environment (campus) or obsolete data. Of course, as shown in TABLE. I, many dataset names are no longer usable; only about 10-20 are publicly available and valid to be used for today's development. Some of the most available prominent datasets can be pointed out as follows: IP Network Traffic Flows Labeled with 75 Apps [38], Moore [39], ISCX [40], ANSM [41], ISCXVPN [52], Labeled Network Traffic Flows-141 Applications [53], USTC-TFC[54], UNIBS: Data sharing[59]. On the other hand, there are articles about dataset collection and construction, including [55], which provide tips on how to collect data for the training and test dataset. It also explains how to place the probes correctly. Are the training and test data collected from the same networks (cellular networks, home networks, or public networks)? Is the training and testing data from the same layer (L7, L3, L2)? How was the information gathered (online or offline)? A rich dataset can be collected by observing and applying these notes to achieve high-performance accuracy.

Another influential topic in dataset collection that should be considered is tools. Wireshark and Netmate were used for this purpose in [143]. NetFlow, SoftFlow, and TCPdump are mostly open-source tools used by [144], a system for detecting anomalies. By the way, some commercial tools, such as PACE, Libprotoident, and NBAR, ... that can be used in both the data collection as well as classification phases, are studied in [65]. It is also important to note in [19], which was mentioned earlier, that if you want to generate a dataset, you must pay attention to ambient traffic. According to the authors, each application generates some ambient traffic (obscure traffic) in addition to normal traffic. Shared modules between applications, such as ad-related traffic or a shared web API, can generate this traffic. They also attempted to detect this type of traffic. However, it should be noted that this type of traffic can have a similar pattern while being delivered from different apps. They also perused the effects of categorizing traffic using adjacent flows. As a result, they believe that examining ambiguous packets generated by one application may not have a distinct pattern from other applications; however, they were able to achieve sufficient accuracy by leveraging nearby traffic as well as the LSTM algorithm (the LSTM uses time-series processing so that it can manage few packets around the engaging packets). Preprocessing can cause higher accuracy and better performance in all AI-related studies. [60] examines and categorizes Anomaly traffic class, and they believe

in such a manner. They pointed out that preprocessing methods have not received enough attention, and many implementations have been done without paying much attention to these methods, even though simple items like raw data aggregation, Data Cleaning, Data Transformation, Data Normalization, and under-sampling can boost data quality and thus model accuracy. They used Under Sampling to reduce the unbalanced difference between data classes to increase the number of Benign samples from approximately 13 million to roughly one million. The main focus of [61] was on Deep Learning-based methods for studying various issues in network traffic classification and identification. However, they initially stated that the complexity of the deep learning model and training time would be increased due to the numerical dispersion of training samples for each software, operating system, device, and software version. They also grouped deep learning classes into four broad categories, including Single / Multiple Input Modalities (SM / MM) and Single / Multiple Classification Task.

C. Classes

Numerous works in network traffic analysis have been completed, ranging from intrusion detection to identifying social media, games, and messengers. Each of these includes several categories based on the dataset and the researchers' intentions. For example, [29] discusses the traffic classification of social networks such as WhatsApp, WeChat, Facebook, and Weibo. Alternatively, in [33], traffic is classified as HTTP, BitTorrent DNS, SSL, etc. Convolutional neural networks were used in [8] to classify Emails, file transfers, chat, streaming, and VoIP traffic. They obtained promising results, but they were only considered ideal for classifying the majority classes and focused on improving the performance of the model structure because their approaches lacked rebalancing strategies and thus failed to classify minority classes. The full results of these studies can be seen in TABLE I. In [3], which was mentioned earlier, the output classes include Facebook, Google, YouTube, Gmail, Amazon, BBC News, and Bing, which are considered from a very general perspective. Also, in [19], 80 applications from different contexts were categorized. I.e., Social media's subcategories include traffic detection on Instagram, WhatsApp, Telegram, LinkedIn, Skype, Twitter, etc. Other contexts such as Download, Store, Maps, News, and Music have also been studied. The classes used in [60] related to IDS include Benign, BruteForce, DDos, Web Attack, and Infiltration, built using a model based on LightGBM.

III. FINDINGS

After numerous and time-consuming studies, more than 140 articles in which at least one artificial intelligence method was used had studied, and the results have shown in TABLE I.

The Table starts with the name of the article's author, the reference number, and the publication year. The columns that follow are about Machine Learning or Deep Learning methods, and the last two columns are about Datasets and Classes. In ML algorithms, If the exact header, such as Bayesian Networks, was used and no details were provided, the green checkbox would be

present as the possible article methods. If the exact method of Bayesian Networks was mentioned in their articles, that is written in the Table. For example, [5] compares their self-collected datasets using gaussian bayesian networks with other ML methods. As mentioned earlier, the majority of the articles collected their datasets (written as Self-collected), while the others used public datasets. The classes cover a wide range of use-cases, such as encrypted traffic, VPNs, social media, and various protocols such as FTP, TCP, UDP, SCTP, and so on.

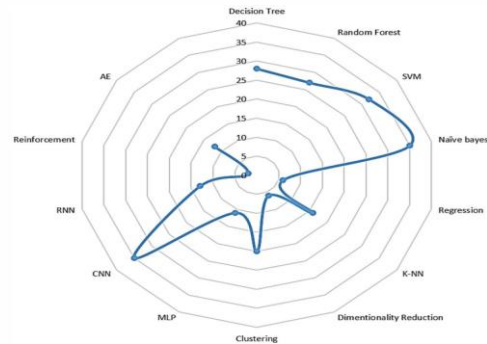


Figure 1. Most Frequently used AI/ML Techniques in reviewed Network Traffic Classification papers

According to studies and investigations, the frequency of methods is shown in Fig.1. As can be seen, if we consider the left side of the figure as deep learning models and the right side of the figure as machine learning-based algorithms, it can be argued that for machine learning methods, algorithms based on Bayesian networks are at the forefront and they are the most widely used machine learning algorithms for traffic analysis. Also, convolutional neural networks or a combination of convolutional networks with other networks such as LSTM are known as the most widely used type of implementation for models based on deep learning.

IV. MODEL EVALUATION

After we've trained our model on a dataset, it's time to see how accurately it can classify unknown data. The "Confusion Matrix" concept will be conducted when the accuracy of predicting a category is more important than the accuracy of the overall diagnosis. Each data point will eventually be assigned to one of these Classes. Therefore, each data sample contains four candidates:

- The data is a member of a Positive category and predicted to be a member of the same Class (TP)
- The sample is a member of the Positive Class, but the model predicts it as a Negative Class (FN)
- The sample is a member of a Negative class and predicted to be a member of the same Class (TN)
- Finally, the sample is a member of the Negative Class, but the model has predicted to Positive Class (FP)

TABLE I. COMPREHENSIVE REVIEW ON MORE THAN 140 PAPERS ON NETWORK TRAFFIC CLASSIFICATIONS FOR ML/DL TECHNIQUES, CLASSES AND DATASETS

Name/Algorithm	Reference	Year	Decision Tree	Random Forest	SVM	Regression	Bayesian Networks	KNN	Dimensionality Reduction	Clustering	Deep Learning	Dataset	Classes
Shahbaz	1	2020									CNN	QUIC Dataset, ISCX VPN-nonVPN Dataset	VPN-non-VPN, GoogleDns (1251 flows), GoogleDrive (1664 flows), Google Music (622 flows), Youtube (1107 flows), Google Search (1945 flows)
Yuning	2	2018			✓							Self Collected	GAME: Fantasy Westward Journey, against the war, furnace stone legend, LOL, DOTA2 and DOTA
Hussein	3	2019	✓									Self Collected	Encrypted TLS, Ciphering Algorithms, ARP, DNS, ICMP, ICMP, NTP, DHCP, DNS
Sanaul	5	2019	✓	✓	✓	Logistic	Gaussian	✓			MLP	Self Collected	Google Chrome, Google Drive, Microsoft One Drive, WhatsApp, Microsoft OneNote, and Spotify
Sina	6	2019	Bagged Trees, Decision Trees	✓	✓		AdaBoost, Bernoulli NB, Gaussian NB, XGBoost				MLP	Self Collected: The total generated dataset consists of about 11 million TCP packets	Alipay, Baidu, Billibili, CNTV, JD, Kingou, QQ, QQMail, QQMusic, Taobao, Wechat, Weibo
D. Li	7	2017									MLP, VAE	Self Collected :IMTD17	Web browsing Firefox and Chrome mail SMTPS, POP3S and IMAPS Chat ICQ, AIM, Skype, Facebook and Hangouts, Video Vimeo and Youtube, File Transfer Skype, FTP over SSH (SFTP) and FTP over SSL (FTPS), VoIP Facebook, Skype and Hangouts voice calls, P2P iTorrent
All Safari	8	2019	✓	✓		ridge regression	Bernoulli, Multinomial, Complement, Linear	✓				UNB2015, NIMS2018	SSH services as Shell login, X11: Local tunneling; Remote tunneling; SCP and SFTP, DNS, HTTP, FTP, P2P (torrent) and voice
L. Vu, C. T. Bui	9	2017									GAN	NIMS	Protocols: BT, DNS, ERUBDY, EDON, KEY, FTP, HTTP, IMAP, MSN, POP3, RSP, RTSP, SMB, SMTP, SSH, SSL2, SSL, XMP, and YAHOOIM
Yuanzhan	10	2018								Kmeans		ISP	HTTP and HTTPS, VPN, Non-VPN, Entertainment, Media & Video, Social, Music & Audio, Communication, News & Magazines, System, Travel & Local, Other
A. Le	12	2015			Linear SVM							self Collected	HTTP/HTTPS, run time app identification
H. F. Alan	13	2016					Gaussian & Multinomial					Self Collected	Video streaming YouTube, Netflix, Dailymotion, Video chat VoIP Skype, Club Facebook Messenger, P2P torrent VIZIE, BitTorrent, Cloud storage Dropbox, Google Drive, ChatGin: Online games 8-Ball Pool, Treasure Hunt, Email client: Thunderbird, Outlook, "RDP", "BitTorrent", "SSH", "SSL", "XMP", and "NTP"
Taimar	14	2016	C-4.5	J-48			✓			K means		Self Collected using Netflow	Video streaming YouTube, Netflix, Dailymotion, Video chat VoIP Skype, Club Facebook Messenger, P2P torrent VIZIE, BitTorrent, Cloud storage Dropbox, Google Drive, ChatGin: Online games 8-Ball Pool, Treasure Hunt, Email client: Thunderbird, Outlook, "RDP", "BitTorrent", "SSH", "SSL", "XMP", and "NTP"
Qing	15	2019					✓				CNN, RNN, FC	UNBIS traces, UPC traces	AIM chat, Email, Facebook, FTPS, Gmail, Hangouts, ICQ, Netflix, SCP, SFTP, Skype, Spotify, Torrent, Tor, VoIP, Baidu, Vimeo, YouTube
Mohammad	16	2019									CNN, SAE	UNB ISCX VPN-nonVPN	TLS encryption, WeChat, JingDong
Xin	17	2020									SIMAE, CNN, RNN, LSTM	Self Collected: Used NetLog	Google Map, Google Music, Hangouts, Gmail, Google Earth, YouTube, and Google Play, Google Commons, Google Analytics, Google Search, Google AdSense, TCP Connect, HTTP, and HTTPS
SHAHBAZ	19	2019		✓							CNN + LSTM	Self Collected: Our dataset is comprised of 80 apps from a wide range of categories, including streaming, messaging, news, navigation, etc.	encrypted protocols, QQ, Sina, googletags, hotspots, shield, broom, pureVPN, QQReader, HiromanVPN, Baidu, google+, 8taMovie, googleMaps, private Tunnel VPN, GoogleTalk, Hangouts, Enterprise, NetTalk, Fsecure VPN, Shadowsocks, Smart Voip, 360 Security, Google Photos, Hadoop, Minicrafts
Giuseppe	20	2018	cart	Tay_RF	Tay_SVC		Multinomial NB, Hcr_Pare, Hcr_FF				CNN, LSTM	dataset collected by a global mobile solutions provider. Due to NDA with the provider we can not report its name, details of its network, detailed information on the data set, nor release the data set	Asymmetric standard definition videos Asymmetric high definition videos HTTP-download HTTP-download videos QQ Interactive video communication class Xunlei P2P video data sharing Sponset Network live TV
Yu-ning	21	2017	c4.5	✓	✓		✓	✓			MLP	MIT KDD 1999	Wikipedia, World Bank data
Ays,e	22	2019	✓	✓	✓	Linear, Polynomial	✓	✓			K-means	SAE, CNN, RNN, LSTM	5 Self Collected Dataset using different devices
Vincent	24	2017	✓	✓	✓						Reinforcement Learning		SSL/TLS, HTTP/HTTPS
Bogdan	27	2014				logistic	✓						Social Media, StockMarket
Lichi	28	2015	NBTree	✓	✓	Logistic	NaiveBayes, BayesNet, AdaBoost, ...					UNBIStraces, UNBTraces, AwklandTraces	fb, fb-data, http, imap, pop3, smp, ssh, telnet, bittorrent, edonkey, http, imap, pop3, skype, smp, ssh, Webbrowser, Chat, Cloud disk, Liveupdate, Streammedia, Mail, P2P
Zhen	29	2018	c4.5	✓			AdaBoost, Bagging				NN	Self Collected	Social WeChat, Weibo, Facebook, WhatsApp Streaming Youku, Mi Video, Web Browser, AppStore, VipShop Service Downloads, Mail Yahoo mail, QQ mail, Gmail
Zhen	30	2018		✓								Self Collected	Web Browsing Firefox and Chrome, Email SMTPS, POP3S and IMAPS, Chat ICQ, AIM, Skype, Facebook and Hangouts, Streaming Video and Youtube, File Transfer Skype, FTPS and SFTP using Filezilla and an external service, VoIP Facebook, Skype and Hangouts voice calls (H), P2P iTorrent and Transmission (BitTorrent) HTTP, BitTorrent, DNS, SSL, ICMP, Apple, HTTP Proxy, Qbit, and iDCE, IRC
Gerard	32	2016	c4.5								✓	Self Collected	News & Politics, Personal Health, Social, Dating, Travel & Local, Shopping, Communication, Media Streaming
Lei	33	2017		J48		logistic	✓					Self Collected	Benign, Malware
Brendan	35	2016					multi-class support vector machine					NetScope Dataset	Instant messaging apps, WeChat and WhatsApp, Alipay app, Ti Tok, Weibo, Taobao, Weishi
Anish	36	2019		✓	Linear, RBF, Polynomial		XGBoost	✓				CTU-13, The Malware Capture Facility project	WEB, P2P, DATA, FTP, Network Management, Mail, Chat, Streaming and Gaming, Skype, QQ, SSH, SSL, MSN, IMAP, POP3, SMTP, Telnet, BitTorrent, IPSEC
Yaru	37	2019		✓			AdaBoost, XGBoost					Self Collected: using wieshark	WWW, DNS, FTP, P2P, FTP Data, FTP, SSH, Telnet, SMTP, DNS, HTTP, POP3, NTP, SNMP, W-W
per	42	2015	C-4.5	✓	✓		✓	✓			Reinforcement Learning	Not Mentioned	RDP, BitTorrent, Web, SSH, eDonkey
Muhammad	43	2016	C-4.5	✓	✓		✓				CNN	Self Collected : from WEKA	Video Streaming - Youku SD, Youku HD, Youku CD
Q. Liao	45	2019					Bayes Network	✓				CNN	CAMPUS, ISP
Yang	46	2019					Bayes Network	✓				Self Collected	Skype, Voip
BONFGLKO	47	2007										Self Collected	Live video: g. Chat 1: Web browsing (e.g. Baidu), Online audio (QQMusic), Web browsing (sina), Voice chat (skype), Video Streaming (Youku)
Y. Dong	48	2019										Self Collected	FORENSICS
Giuseppe Aceto	50	2019		✓								Self Collected	WWW, Skype
Zou	51	2018		✓								Self Collected	Yahoo Mahjong, Gtubebus, QQ Game, Club Marlin, and FashionDash
Hanca	55	2016		✓								Self Collected	SEN
Zhang	57	2012	c4.5		Linear, RBF, Polynomial and Stigmid							WEKA	SEN
Kandara	58	2019	✓	✓							K means	IP Network Traffic Flows, Labeled 75 Apps Kaggle	SEN
Raouf	62	2017		✓							CNN	Self Collected	SSL, SSH, SMTP, HTTP, GVSP, FTP, DNS, SKYPE, WOW, POP3 MSN, BITTORRENT, MYSOQL
Shuang	63	2019		✓								Self Collected	Wechat, TencentVideo, BILIBILI, Souyou Pinyin, Taobao, Baidu Browser, QQ
Zhanqi	66	2015									CNN, Deep Belief Networks (DBN) and Stacked, SAE	Self Collected	SSL, HTTP, Proxy, MySQL, SMB, HTTP, Connect, Whois, DNS, Redis, SSH, Apple, Kerberos, iDCE, IRC, NetSoc, Socialchat (SN) FTP, CONTROL, DNS, Skype, LDAP, Apple/Cloud, Apple/Time, MSN, Gmail, BitTorrent, TDS, IMAPS, SMTP, RSTNC
Hongtao	67	2018	C-4.5	✓	✓		✓				Recurrent Neural Networks, CNN, Deep Belief Networks	Cambridge and UNBIS	WWW, http, https, MAIL, imap, pop3, smp, FTP, CONTROL, ftp control, FTP, PASV, ftp passive mode ATTACK Internet worm and virus attacks P2P KuduA, BitTorrent, Gnutella, FTP, DATA, ftp data DATABASE Postgres, sqlnet oracle, Ingres MULTIMEDIA Windows Media Player, Real SERVICES X11, dns, ident, ldap, sip, web, P2P vs. VoIP
Z. A. Qazi	68	2013	C5.0									self Collected	Browsing Chrome(CB) Loading text, pictures and streaming Garing Room Beak(BB) Gaming action Multimedia YouTube (UTB), Song(SO) Streaming Online, Chatting Facebook Message (FBM), Text(QQ), NetSoc (SN) Sending and receiving text (Network Facebook (FB), Twitter (TW) Posting, messaging, adding contact, loading text, pictures, Dating Trader (TD) Loading pictures Facebook Mail (MT) Configuring account, loading text, pictures Medical CDC News (CDC), Medscape (MED) Loading text, pictures
Q. Wang	70	2015		✓								self Collected	Facebook, Line, Skype, Youtube, web
Mongkolksamee	72	2016		✓								Self Collected	SEN
E. Serkani	73	2019	C5.0		LS-SVM						Neural Network	Self Collected	SEN
Z. Fallah	74	2017									Neural Network	Self Collected	Intrusion Detection -DoS, Probe, U2R, DoS, Proh, R2L
E. Hods, X. Bellekens	75	2017										Self Collected	SEN
H. Gharaee	76	2018										Self Collected	Intrusion Detection -DoS, Probe, U2R, DoS, Proh, R2L
W. Wang	77	2017									CNN	KDD CUP1999 & NSL-KDD	BitTorrent P2P Outlook Email/WeChat Facetime Voice/Video Skype Chat/IM FTP Data Transfer/SMB Data Transfer Gmail Email/WhatsApp Weibo/Social Network MySQL Database WorldOf Warcraft Game
M. Yousefi-Azar	78	2017										Self Collected	NSL-KDD
X. Xie	79	2012										Self Collected	Intrusion Detection
M. Adda	80	2012									K-means	Self Collected	IoT traffic
A. H'adot, u	81	2017									Disimilarity Based clustering	Self Collected	Intrusion Detection
J. Liu, Y	82	2017										Self Collected	SSH or HTTPS, FTP, POP, IMAP, and SMTP, HTTP Video Enterprise, HTTP Enterprise, SSH Enterprise, Oracle Enterprise, Raw UDP Enterprise, Raw Enterprise, BitTorrent Enterprise, Flash Enterprise, HTTPS Simulated Enterprise, SBR Enterprise, SMTP Enterprise, P2P Enterprise, FTP Enterprise, YouTube Enterprise
T. Wiraditana	83	2016									PCA	Self Collected	Wechat WhatsApp Facebook
H. Shi	84	2017									PCA	Self Collected	WWW, MAIL, FTP, CONTROL, FTP, PASV (FP), ATTACK, P2P, DATABASE (DB, FTP, DATA (FD), MULTIMEDIA (MM), SERVICES (SV), INTERACTIVE (INT), GAMES (GM)
S. Liu	85	2016									Mixture Distribution	Self Collected	VOIP, P2P-LD, SMTP, WWW, P2P-IM and HTTP+FLASH, TEL, FAX, TEL, Net and TLS5 WWW, MAIL, FTP, CONTROL (FC), FTP, PASV (FP), ATTACK, P2P, DATABASE (DB, FTP, DATA (FD), SERVICES (SV), MULTIMEDIA (MM), INTERACTIVE (INT), GAMES (GM)
J. Cao	86	2017									PCA	Self Collected	WWW Mail FTP control FTP pass Attack P2P Database FTP data Multimedia Services, HTTP and HTTPS, Pop3, smp, and Inmap FTP worm and virus Kazaa, BitTorrent, and Gnutella Postgres, sqlnet, oracle, and Ingres FTP Voice and video streaming X11, dns, ident, and sip
S. Rajendran	87	2017									t-SNE	Self Collected	Signal Detector WFM, Tetra, DVB, RADAR, LTE, GSM

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Author	Year	Method	Dataset	Application	Target
L. Yinggu	88 2007			K-means	WWW, MAIL, P2P, FTP, CONTROL, FTP-PASV, ATTACK, DATABASE, FTP-DATA, SERVICES, INTERACTIVE, MULTIMEDIA, and GAMES
J. Zhang	89 2013			Non-parametric Neural Network	BT, DNS, eBuddy, FTP, HTTP, IMAP, MSN, POP3, RSP, SMTP, SSH, SSL, SFTP, and Yahoo!Bg
A. McGregor	90 2004			EM Based	IMAP, HTTP, DNS, SMTP, FTP
J. Erman	91 2006			EM Based	http, smtp, dns, socks, irc, ftp (control), pop3, lmewire, ftp (data)
T. J. O'Shea, J. Corgam, Eswaradass A	94 2016			Convolutional Auto-Encoder	Radio Communication
Chen Z	95 2006			MLP, Neural Network	NSF TeraGrid dataset
	96 2016			RNN (LSTM)	Network traffic volume and flow count collected every 5 min over a 24 week period (public)
Haffner P	97 2005			Naive bayes, AdaBoost	Proprietary
Ma J, Levchenko K	98 2006			HCA	Proprietary: U.cambridge, UCSD
Finamore A	99 2010				Proprietary: U.cambridge, UCSD
Schatzmann D	100 2010				Proprietary: ISP network
Bermolen P	101 2011				Proprietary: campus network, ISP network
Roughan M	102 2004				Proprietary: univ. networks, streaming service
Zhang J	103 2013			BOF-NB	WIDE, Proprietary: ISP network
Zhang J	104 2015			BOF-NB	KEIO, WIDE, proprietary: ISP network
Este A	105 2009				LBNI, CADA, proprietary campus network
Jing	106 2011			TF-SVM	proprietary
Wang	107 2006			multiclass SVM, Binary SVM	proprietary: univ. network
Liu	108 2007				Proprietary: campus network
Zander	109 2005			AutoClass	NLANR
Erman	110 2006			AutoClass	Univ. Auckland
Erman	111 2006			Density Based	Univ. Auckland, proprietary: Univ. Calgary
Erman	112 2007			K means	proprietary: univ. network
Bernaile et al.	113 2006			K means	Proprietary: univ. network
TIE	114 2011	Random Tree	j48		Proprietary: Univ. Napoli campus network
Nguyen et al.	115 2012	C-4.5			Proprietary: home network, univ. network, game server
Li et al.	116 2007	C-4.5		AdaBoost	Proprietary
Alshammari	117 2009	C-4.5		AdaBoost, Naive bayes	AMP MAWI, DARPA99, Univ. Dalhousie
Shbair et al	118 2016	C-4.5			Synthetic trace
He et al	119 2016			Linear SVM, Radial SVM	KDD
Wang et al.	120 2016			Laplacian SVM	Proprietary: univ network
El Khayat et al.	121 2005	Boosting DT			Synthetic data: Simulation in: ns-2, BRUTE 0-1K random topologies Data distribution: Training=23k Testing=10k
Hyun-Kyo	122 2019				MLP-Neural Network
P. Wang	123 2018				CNN-LSTM
M. Lofollahi	124 2017				MLP, SAE, CNN
W. Wang	125 2017				MLP, SAE, CNN
M. Lopez-Martin	126 2017				CNN, LSTM
G. Aceto, D. Ciano	127 2018				CNN, LSTM, SAE, MLP
S. Rezaei and X. Liu	128 2018				CNN, LSTM
V. Tong	129 2018				SAE, CNN
H. Zhou	130 2017				CNN
Z. Chen	131 2017				CNN
Antonello	133 2015	Random Tree			MIN MAX algorithm
Jing	134 2017				GSAAE, LSTM, LSAE
Zhangyi	135 2014				CNN, SAE
Peng Li	136 2018				Bayesian auto-encoder
P. Xiao	137 2015				
J. Sa'arez-Varela	138 2018				
L. He	139 2016				AdaBoost
Z. Fan	140 2017				K-means
A. S. da Silva	141 2016				K-means
P. Wang	142 2016				Laplacian SVM
					K-means

Following the implementation of the classification algorithm, according to the mentioned explanations and definitions, the classifier's performance can be examined using a table as shown Fig. 2.

		+ Predicted -	
Real	+	TP True Positives	FN False Negatives Type II error
	-	FP False Positives Type I error	TN True Negatives

Figure 2. Confusion Matrix

The Confusion Matrix displays classification results based on the currently available information. The

Confusion Matrix can be used to define various evaluation criteria such as Accuracy, Precision, Recall, Specificity, and F1-score. Accuracy is the most common, fundamental, and straightforward criterion for assessing prediction quality. This parameter represents the number of patterns that were correctly predicted and formulated as

$$Accuracy = (TP+TN) / (TP+FN+FP+TN) \quad (1)$$

Precision or Positive Predictive Value expresses the "ratio of correct replies in each category." it shows what percentage of the data has truly categorized as the Positive class and is formulated as follows:

$$Precision (PPV) = TP / (TP+FP) \quad (2)$$

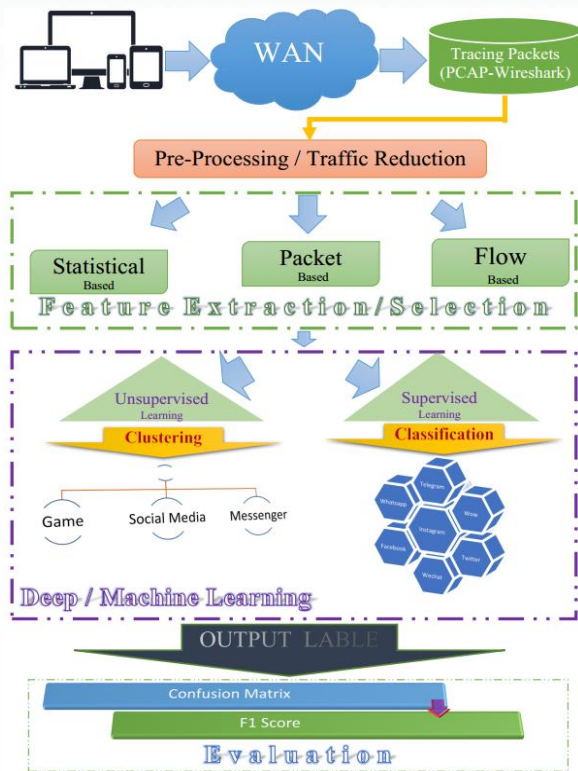


Figure 3. General Perspective of Network Traffic Classification system based on different Methodologies

V. GENERAL PERSPECTIVE

In the previous sections, disassembled information about the classification of network traffic was pointed out. Fig. 3 shows the general operational structure of a system in which the traffic of connected devices to the WAN network is first captured by Wireshark or other network traffic tracking tools. The traffic is then subjected to preprocessing operations such as Datalink Header Removal, Transport Header Modification, Irrelevant Packet Rejection, Byte Conversion, Truncation, Normalization, and IP Masking, among others. Machine learning algorithms are then utilized to select and extract features using statistical-based, packet-based, and flow-based approaches (this step for DL is done automatically within the model). Now it's time to pick an artificial intelligence learning type. At this point, extracted features can be used to train the network using Supervised Learning, Unsupervised Learning, or Semi-supervised Learning. Clustering is a subcategory of Unsupervised Learning. Some of these clusters include Games, Social Media, Messenger, and so on. Furthermore, WhatsApp, Facebook, and Telegram, among others, can be categorized as Supervised Learning algorithms in network traffic classification. After training the network, various evaluation criteria, such as the Confusion Matrix, can be used to calculate Accuracy, Recall, Precision, Specificity, etc. Other criteria, such as the F1 Score, are also computable. Following model evaluation, various techniques such as dropout can be conducted to improve the final model's result and performance. Nowadays, the majority of internet traffic transmitted via satellites/lane lines/cellular networks is encrypted to protect the user's

privacy (encrypted payload contents) while providing promising quality of service. The data rates, packet sizes, and delays remain unchanged while the payload is encrypted. As a result, we can use this information to classify traffic without having to inspect the payload of the packets. We also believe that using correlations between neighbor flows could be an important feature to extract to gain a few percent accuracies.

We discovered that many of the techniques investigated paid little attention to the balance of the dataset or the enrichment of its classes. The emphasis was primarily on providing a new model with various features. It is necessary to improve and enrich the dataset regardless of whether you are using ML-based models or DL techniques, especially when part of the traffic can be generated by new or unconventional methods such as DeepFool, where deep learning techniques generate the traffic, and they are not real. However, they look like real data to fool the model by not accurately learning features from the ground truth. The use of cloud computing for data processing and analysis, as well as edge processing, has gained traction and enabled low-cost training using a vast majority of devices and testbeds with varying devices, operating systems, topology, and protocols, and this is an open challenge to have a better and more accurate classifier even though heterogeneity and decentralized processing and traffic transfers are two of the domain's most difficult challenges.

VI. CONCLUSION AND FUTURE WORKS

A Comprehensive Comparison of AI techniques was needed to determine which methods were frequently used and which are the most suitable for different datasets of varying sizes and features. To this end, we investigated some of the limitations of DL and ML-based algorithms used to classify internet traffic for over 140 identical state-of-the-art Algorithms and articles. The routing policies can be updated to make the best/most effective use of resources by classifying the internet traffic. Knowing the best method would also enable us to apply it to the telco infrastructure/industry to ensure that users receive promising QoS and QOE. The traffic Classification algorithm can also be used in 5G network slicing to provide eMBB, MMTC, or URLLC slices to users and IoT devices.

We believe that Machine Learning algorithms are far better than Deep Learning Methods for Datasets with low sparsity in Classes and low volume of Data, while deep learning methods are better for the high volume of normalized data and a wide variety of classes in the Network Traffic Classification Domain. Considering network growth and rapid security/feature updates for various applications (e.g., social media, games, ...), the new continuous learning approaches based on deep learning, which can learn through inference time, are more efficient in all aspects. After all, we analyzed different approaches to find the best/most suitable workflow for using AI in network traffic classification (Fig. 3).

Although there are some other novel approaches to Internet traffic classification, artificial intelligence has

gained tremendous popularity in the modern era. Recent advances in Computer Vision / Deep Learning research, such as Attention Networks or Capsule networks, may draw attention to internet traffic classification in the coming years.

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