Technology Recognition and Traffic Characterization for Wireless Technologies in ITS Band

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ABSTRACT

The rapid advancement of wireless technologies requires efficient spectrum management considering issues such as interference management and fair coexistence between different technologies. Wireless technology recognition is one of the approaches used to enable intelligent spectrum management. This work proposes a technology classification and traffic characterization system that can recognize and characterize a wide range of wireless technologies that may coexist in the ITS 5.9 GHz band, namely LTE, Wi-Fi, 5G NR, C-V2X PC5, and ITS-G5 technologies. Compared to current state-of-the-art technology recognition solutions, a short time resolution window is selected based on the shortest possible frame duration of the considered technologies. We carried out a "complexity and accuracy trade-off" analysis for six distinct technology recognition models trained and validated at different sampling rates, including 1, 5, 10, 15, 20, and 25 Msps. In addition, the performance of the technology recognition models was evaluated under different channel conditions. For average to high SNR, a less complex CNN model with lower sampling rates (e.g., 5 Msps) can effectively distinguish the signal with 96% classification accuracy. On the other hand, high classification accuracy is obtained using complex, high sampling rate-based CNN models (e.g., 20 Msps) for low (less than 0 dB) SNR channels. A traffic characterization process is also proposed, where the output of the technology recognition is used to identify the traffic characteristics of the technologies in terms of channel occupancy time, transmission pattern, and frame count. The obtained results show that the proposed solution can be used to effectively characterize the identified traffic.

1. Introduction

The expansion of wireless network deployments, along with the rapid penetration of consumer devices such as smartphones and tablets, has resulted in an exponential increase in wireless traffic demand and spectrum usage [1]. Furthermore, the Internet of Things consumes a significant portion of the wireless spectrum, connecting an unprecedented number of intelligent devices to next-generation mobile networks. With the constantly expanding traffic demand, it is also predicted that there will be about 120 billion subscriptions by 2030 [2] and thus will create a significant impact on the spectrum usage.

As a solution to meet the rising traffic demand, spectrum sharing is proposed to be used in current and next-generation communication systems. Spectrum sharing is broadly used between Wi-Fi, private LTE, 5G New Radio Unlicensed (NR-U), Unlicensed LTE (LTE-U) or License Assisted Access (LAA), MulteFire, and others [3]. The ISM (2.4 GHz and 5 GHz) bands, the 3.5 GHz CBRS band, the mmWave bands at 60 GHz, and others are among the unlicensed or license-assisted bands where the aforementioned technologies share spectrum. Similarly, the European Commission in Europe and the Federal Communications Commission (FCC) in the United States have both begun formal investigations to determine whether unlicensed operations in the 6 GHz band are feasible. The FCC issued a Notice of Proposed Rule Making seeking comments and input on opening up the 5.925-7.125 GHz spectrum in the United States to unlicensed access [4]. According to the FCC of the US, this band has four sub-bands: U-NII-5 (5.925–6.425 GHz), U-NII-6 (6.425–6.525 GHz), U-NII-7 (6.525–6.875 GHz), and U-NII-8 (6.875–7.125 GHz). The FCC has established spectrum sharing rules for these sub-bands. Similarly, the European Commission initiated a feasibility study of unlicensed operations in the 5.945-6.425 GHz band in Europe [5]. This 6 GHz unlicensed spectrum will unlock an additional 480 MHz of spectrum in Europe and 1.2 GHz of spectrum in the US, which significantly increases the amount of unlicensed spectrum available in these regions.

Most existing spectrum sharing solutions are proposed to utilize the unlicensed spectrum efficiently. In comparison to today's static and conservative approaches, spectrum management and usage is expected to become more flexible and dynamic in the future [6, 7, 8]. As a result, a Radio Access Technology (RAT) may be able to operate in any frequency range supported by its Radio Frequency (RF) front-end, as far as it deploys efficient coexistence mechanisms with other co-located concurrent transmissions [9]. In this direction, some researchers have proposed spectrum sharing solutions between V2X technologies and Wi-Fi [10], LTE [11], and, 5G NR networks [12]. In the near future, the 5.9 GHz ITS bands could be potentially used by other RATs such as LTE, Wi-Fi, and 5G NR as long as the deployment is implemented in such a way that the RATs can harmonically coexist with the incumbent transmissions.

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The IEEE 802.11p standard is an improved version of the IEEE 802.11a standard that is designed for vehicular networking. IEEE 802.11p-based vehicular communications are known as Dedicated Short Range Communications (DSRC) in the United States [13] and Intelligent Transport Systems - G5 (ITS-G5) in Europe [14]. The "G5" in the ITS-G5 acronym comes from the frequency band (5.9GHz). The technical concepts of ITS-G5 in Europe and DSRC in the United States are very similar, although Vehicular Communications (V2X) in other regions, such as Japan's ITS communication system operating at 700 MHz, are quite different.

As an alternative to the ITS-G5/DSRC based vehicular communication solutions, the Third Generation Partnership Project (3GPP) published the first version of Cellular V2X (C-V2X) communications standard, as part of Release 14 [15]. In this release, Mode 3 and Mode 4 (C-V2X PC5) communication modes have been introduced, particularly for Vehicle-to-Vehicle (V2V) communications. In the case of Mode 3, the cellular network allocates and manages the radio resources that vehicles use for direct V2V communication. Mode 4 supports distributed congestion control and offers a distributed scheduling method for vehicles to allocate their radio resources. Mode 3 based V2V communications depend on the cellular coverage provided by the 4G/5G radio network. Mode 4, on the other hand, can work independently out of cellular coverage and is hence considered as the baseline cellular-based V2V mode, as safety applications cannot always rely on cellular coverage.

Figure 1 shows the 5.9 GHz bands designated for ITS application in Europe [16]. The bands in the frequency range of 5855-5875 MHz are used for non-safety road-ITS applications, whereas the bands in the 5875-5935 MHz range are for safety-related ITS applications. In addition, the frequency ranges 5875-5915 MHz and 5915-5925 MHz are prioritized for road-ITS and rail-ITS applications, respectively, with the frequency range 5925-5935 MHz reserved for rail-ITS solely. Similarly, the FCC of the US allocated 75 MHz of spectrum in the 5.9 GHz band, of which the 45 MHz of spectrum is unlicensed while the remaining 30 MHz of spectrum is exclusively used for DSRC and other transportation-related purposes [17]. The V2X services available in the 5.9 GHz ITS band include V2V, vehicle-to-Infrastructure (V2I), Vehicle-to-Network (V2N), Vehicle-to-Pedestrian (V2P), and Vehicle-to-Roadside unit (V2R). The use of On-Board Units (OBUs) and Road-Side Units (RSUs) in these ITS bands is permitted under the terms of a license exemption.

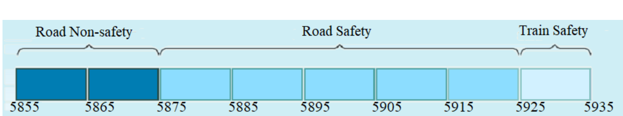


Figure 1: Spectrum bands for ITS applications at 5.9 GHz in Europe.

In the future, spectrum management is expected to become more flexible and dynamic, allowing potentially all radio access technologies to share a wide range of the spectrum, as long as this is supported by the frontend and allowed by the regulators. In this direction, smart spectrum decisions will be required, which can be aided by wireless technology recognition, allowing networks to dynamically adapt to an ever-changing environment in which fair coexistence with other wireless technologies is becoming increasingly important.

In this paper, we present a Deep Learning-based Technology Recognition and Traffic Characterization (DL-TRTC) solution that can be used to enable spectrum sharing in the 5.9 GHz ITS band. To realize this, we consider LTE, 5G NR, and Wi-Fi RATs co-located with the existing incumbent C-V2X PC5 and ITS-G5 technologies in the same 5.9 GHz ITS band. The proposed DL-TRTC comprises of two major blocks: a) technology recognition and b) traffic characterization. The technology recognition identifies the operating technology and the traffic characterization extracts characteristics of each identified technology. The main contributions of this work are summarized as follows:

- We propose a Convolutional Neural Network (CNN) based technology recognition model to identify different technologies operating in the 5.9GHz ITS band. We consider multiple RATs (LTE, 5G NR, Wi-Fi) that can coexist in the 5.9 GHz ITS band along with the incumbent C-V2X PC5 and ITS-G5 technologies.
- For the training and validation of the CNN model, we use a dataset collected from a Software Defined Radio (SDR) based testbed and Commercial off-the-shelf (COTS) hardware. In-phase and quadrature (IQ) samples are collected and the corresponding Fast Fourier Transform (FFT) frequency-domain representation is used to train and validate the developed CNN model.
- In contrast to the existing literature, a short Time Resolution Window (TRW) of only 44 μs is used for the technology recognition model. The time resolution is selected based on the shortest possible frame duration of the considered technologies.
- We analyze the performance of the technology recognition models in terms of accuracy, robustness against noise, and complexity. The complexity/accuracy analysis is obtained considering six different technology recognition models which are trained and validated using various dataset clusters collected at sampling rates of 1, 5, 10, 15, 20, and 25 Msps. The performance of the technology recognition models is evaluated for various SNR values representing different channel conditions.
- We also propose a traffic characterization scheme to determine the traffic behaviour of the technologies identified by the technology recognition model. The traffic characterization performance of the proposed

scheme is measured by Channel Occupancy Time (COT) estimation accuracy, transmission pattern characterization accuracy, and estimated frame count accuracy.

- Classification performance comparison is done between the proposed and existing technology recognition schemes. Similarly, performance comparison is done in terms of traffic characterization of the DL-TRTC using the proposed 44 μs TRW and other different TRWs adopted from related works.

- For reproducibility and bench-marking purposes, we pledge to make the training and validation dataset used in this study available as open-source[1].

The rest of this paper is structured as follows. Section 2 examines some recent studies on the coexistence of different RATs and incumbent transmissions at the 5.9 GHz ITS band. Section 3 presents the description of the system considered and the formulation of the problem addressed. The procedures of the proposed technology recognition and traffic characterization solutions are described in Section 4. Section 5 presents the performance evaluation of the proposed solution. Finally, Section 6 discusses the conclusion of this work and potential future works.

Table 1 summarizes the abbreviations used in this article.

Table 1
List of abbreviations used.

Acronym	Description
BSM	Basic Safety Message
C-V2X	Cellular V2X
COT	Channel Occupancy Time
COTS	Commercial Off-the-Shelf
CNN	Convolutional Neural Network
CA	Cooperative Awareness
DEN	Decentralized Environmental Notification
DSRC	Dedicated Short Range Communications
eNB	eNodeB
EPC	Evolved Packet Core
FFT	Fast Fourier Transform
FCC	Federal Communications Commission
FPGA	Field Programmable Gate Array
IVI	Infrastructure to Vehicle Information
IQ	In-phase and quadrature
ITS-G5	Intelligent Transport Systems - G5
IOT	Internet of Things
LAA	License Assisted Access
MAP	Mobile Access Points
MCS	Modulation and Coding Scheme
NR-U	New Radio Unlicensed
OBU	On-Board Unit
pps	packets per second
RAT	Radio Access Technology
RF	Radio Frequency
RFC	Random Forest Classifier
RSSI	Received Signal Strength Identifier
RSU	Road-Side Unit
SPS	Semi-Persistent Scheduling
SDR	Software Defined Radio
SVM	Support Vector Machines
TRTC	Technology Recognition & Traffic Characterization
TRW	Time Resolution Window
LTE-U	Unlicensed LTE
UE	User Equipment
V2I	Vehicle-to-Infrastructure
V2N	Vehicle-to-Network
V2P	Vehicle-to-Pedestrian
V2R	Vehicle-to-Roadside unit
V2V	Vehicle-to-Vehicle
V2X	Vehicle-to-everything

2. Related Work

2.1. Spectrum Sensing in ITS Band

The concept of efficient spectrum sensing that can be used to enhance the spectrum efficiency of 5G NR-U, LTE LAA, Wi-Fi, MulteFire, and others in the unlicensed ISM band (2.4GHz/5GHz) is a hot research topic [3]. Similarly, spectrum sharing issues were raised for the ITS band after the FCC issued a regulation to split the 5.9 GHz band between unlicensed use (initially indoor and potentially outdoor) and its previously specified use for intelligent transportation systems [4]. As a result of this decision by FCC, concerns have been raised about the need for efficient spectrum sensing to avoid potential interference between unlicensed technologies (e.g., Wi-Fi, LTE-U, 5G NR-U) and ITS technologies (C-V2X PC5 and ITS-G5).

Energy detection based spectrum sensing is used in most existing coexistence schemes in ITS band [10, 18, 19, 20]. Devices using energy detection-based spectrum sensing measure local energy to determine channel availability. The channel is labeled as "busy" if the measured energy exceeds a predefined energy detection threshold. Otherwise, the channel is considered as idle, and the devices will be able to compete for it. Authors in [10] propose two coexistence schemes that can be used to enhance the coexistence of Wi-Fi and ITS-G5. The first scheme is called "detect and vacate", where the Wi-Fi device senses ITS-G5 transmissions and evacuates the channel. The second proposed scheme is called "detect and mitigate", where the Wi-Fi device adjusts its contention window by sensing ITS-G5 transmissions. Similarly, possible issues of coexistence between Wi-Fi and the standard vehicular communication transmissions on the ITS band are discussed in [18]. In this article, the authors propose that Wi-Fi devices should use higher receiver sensitivity to sense possible safety-critical vehicular communication. They also propose that the Wi-Fi devices operating at 5.9 GHz should use increased interframe spacing to give more transmission time to the native ITS band vehicular communication. The authors of [19] investigate co-channel interference between C-V2X PC5 and ITS-G5 in the 5.9 GHz band, where the two technologies share a 10 MHz radio channel. This article proposes new mechanisms that can be used to minimize

[1] https://gitlab.ilabt.imec.be/mgirmay/tech-rec-its-band

Table 2
Related work: technology recognition models.

Model	Considered RATs	Input	Approach	Time resolution	Traffic characterization
[22]	Wi-Fi, DVB-T, LTE	RSSI, IQ, FFT	CNN, RFC	4.096 ms	✗
[23]	LTE, Wi-Fi, 5G NR	IQ	CNN, RNN	600 ms	✗
[24]	UMTS, LTE, 5G NR	RSSI graph	CNN	Not mentioned	✗
[25]	LTE, Wi-Fi	IQ	CNN	68 μs	✗
[26]	LTE, Wi-Fi	IQ, FFT	CNN	100 μs	COT
[27]	LTE, Wi-Fi	Spectrogram	DNN	Not mentioned	✗
[28]	Sigfox, 802.11ah LoRA, 802.15.4g	IQ,FFT	CNN	244 μs	✗
[29]	GSM, WCDMA, LTE	IQ	SVM	819.2 μs	✗
[30]	ITS-G5, LTE-V2X 5G-V2X	TF features	RFC	819.2 μs	✗
Proposed	LTE, Wi-Fi, 5G NR, C-V2X PC5, ITS-G5	FFT	CNN	44 μs	COT, Frame count, Transmission pattern

the performance losses and evaluate co-channel interference between the two technologies. Similarly, the authors of [20] propose a detect and defer-based coexistence scheme for unlicensed devices co-located with ITS-G5 transmissions. The problem with energy detection is that it cannot identify operating technology, which is an important enabler for efficient spectrum decision making.

In general, several researchers have proposed different coexistence schemes that can be used for the coexistence of different RATs and the incumbent vehicular communications in the ITS band. The coexistence schemes in the literature use energy detection-based spectrum sensing to determine the medium status. However, spectrum sharing schemes in the ITS band should aim to protect safety-critical vehicular communications. For this reason, the identification of co-located transmissions is crucial to protect and prioritize the incumbent transmissions in the ITS band. The use of technology recognition is a more realistic approach to identify the concurrent transmissions as it a) replaces the need for a complex universal receiver and the architectural modification of the standard nodes required for signaling exchange, b) is a scalable solution and can easily be extended to the identification of any number of technologies, and c) does not require manual feature extraction and automatically extracts important features from the raw data. The reader can refer to [21] for a recent survey on technology recognition-based solutions.

2.2. Technology Recognition for Spectrum Sensing

The technology recognition-based spectrum sensing approach enables each active user to identify the concurrent transmissions by other technologies. This enables better coexistence between different wireless technologies operating in the same band. Hence, many researchers have proposed different technology recognition models, considering different possible combinations of RATs. Table 2 shows a summary of existing technology recognition-based spectrum sensing models in the literature [22, 23, 24, 25, 26, 27, 28, 29, 30].

The authors in [22] compare manual feature extraction and automatic feature learning algorithms for LTE, Wi-Fi, and DVB-T technologies using multiple datasets to study the complexity/accuracy trade-offs. The authors also compare the performance of classification based on Received Signal Strength Identifier (RSSI), IQ samples, and FFT of the IQ samples used as an input. The TRW used in this study is 4.096 ms. Similarly, the authors of [23] propose a model for identifying Wi-Fi, LTE LAA, and 5G NR-U signals in the unlicensed 5-6 GHz band. An optimal TRW of 600 ms is used to apply Short-time Fourier Transform to the IQ sequences to enhance the classification accuracy. In [24], deep learning neural network-based technology recognition model is proposed to classify cellular system signals, including UMTS, LTE, and 5G NR. The technology recognition model uses the RSSI graph picture as an input to classify the signals. However, the TRW used to plot each picture is not mentioned in the paper.

In [25, 26, 27], technology recognition models are also proposed to classify LTE and Wi-Fi signals. In [25], 1024 IQ samples collected at 15 Msps are used as an input to the model, which indicates a time resolution of 68 μs. In [26], IQ samples and FFT of IQ samples are used as an input to the technology recognition model. A resolution window of 100 μs with a 20 Msps sampling rate is used to generate each signal label input. The technology recognition model proposed in [27] uses spectrogram pictures of received signals as an input to classify the signals. There is, however, no mention of the TRW used in technology recognition model.

A multi-band sub-GHz technology recognition that can classify Sigfox, 802.11ah, LoRA, and 802.15.4g technologies is proposed in [28]. IQ samples and FFT of IQ samples are used to train the technology recognition model in this work. A time resolution of 244 μs is used to generate 500 IQ samples in each signal label segment.

Authors in [29] propose a Support Vector Machines (SVM) based technology recognition model that can identify GSM, WCDMA, and LTE signals. 16384 IQ samples generated at a 20 Msps sampling rate are used as an input to the model This leads to a time resolution of 819.2 μs for each labeled signal portion. The authors of [30] propose a technology recognition model based on a Random Forest Classifier (RFC) to identify ITS-G5, LTE-V2X, and 5G-V2X signals. The authors use the same number of IQ (16384) input sizes as [29], resulting in a TRW of 819.2 μs. The authors also use a simulator to generate the signal for each vehicular communication technology.

2.3. Enhancements

In the previous section, we observed that many technology recognition models have been proposed that can be used to sense the technologies available in the spectrum. The ultimate goal of technology recognition is to explicitly identify the spectrum utilized by each technology and predict traffic patterns. However, the technology recognition models in the literature use a longer TRW duration as compared to the minimum possible frame duration in the technologies they take in to account. In this case, the probability of considering multiple frames from different technologies as one label increases. Consequently, this longer TRW results in poor traffic characterization that may lead to inefficient spectrum sharing by the coexistence schemes. Such inefficient spectrum sharing with higher a probability of packet collisions makes deploying longer TRW less practical for safety-critical vehicular communications. As a solution to this, we propose a technology recognition model that uses a short TRW, selected based on the smallest possible frame duration of the considered technologies.

Additionally, the existing technology recognition solutions consider a fixed sampling rate to capture the input. However, the selection of sampling rate requires fine-tuning as it affects the number of input samples used for the model, which in turn affects the accuracy and complexity of the model. In this work, accuracy/complexity trade-off analysis is done by varying the sampling rate from 1 to 25 Msps.

Moreover, most of the technology recognition models in the literature perform performance analysis based on the identification of signals measured in each TRW. However, identification of a signal transmitted in a single TRW cannot be useful to estimate meaningful information about the spectrum utilization of each technology. Relevant traffic predictions can be made after collecting sufficient statistics of identified technology, which can be obtained based on a signal segment measured in a certain traffic characterization time period. Therefore, the performance analysis in terms of complexity and accuracy has to be validated considering a practical characterization time window for each technology. In this work, we propose a traffic characterization process where the identified statistics of each co-located network are used to identify the traffic characteristics (frame count, COT, transmission pattern) of each technology.

To the best of our knowledge, existing wireless technology identification solutions have not considered the context of sharing ITS-G5 and C-V2X PC5 vehicular communication technologies and other RATs such as Wi-Fi, LTE and 5G NR operating in the ITS band. In this paper, we propose a DL-TRTC solution that can be used to identify and characterize LTE, 5G NR, Wi-Fi, C-V2X PC5, and ITS-G5 traffic in the 5.9 GHz ITS band. Unlike many technology recognition models in the literature, we use a dataset collected at different sampling rates using an SDR-based experimental setup and COTS devices and show their impact in terms of model accuracy and complexity.

3. Problem Definition

With the exponential growth of wireless network users, the process of making new spectrum available has become a challenge. Similarly, the concept of sharing the spectrum between different radio services continues to be a difficult task. Interference management and fair coexistence between different RATs require innovative ways to define efficient technical solutions that are feasible for practical deployment. Generally, efficient spectrum utilization in the dynamic environment of wireless networks necessitates a fast, robust, and adaptive spectrum sensing scheme that requires identification of different technologies sharing the medium.

In this work, we consider that 5G NR, LTE, and Wi-Fi RATs can be deployed in the ITS band along with the incumbent technologies (C-V2X PC5 and ITS-G5). Figure 2 shows a practical scenario where the aforementioned technologies can interfere with each other. The figure shows that C-V2X PC5 and ITS-G5 user vehicles moving on the road can get interference from each other and from nearby 5G NR, LTE, and Wi-Fi users. As a result, the C-V2X PC5 and ITS-G5 user vehicles may lose critical safety warnings that are important to minimize/avoid accidents. This scenario is more likely to happen in the near future in metropolitan areas, where a large number of RATs operate in the same ITS band.

Furthermore, 5G NR, LTE, and Wi-Fi RATs can be deployed on vehicle-based Mobile Access Points (MAPs)

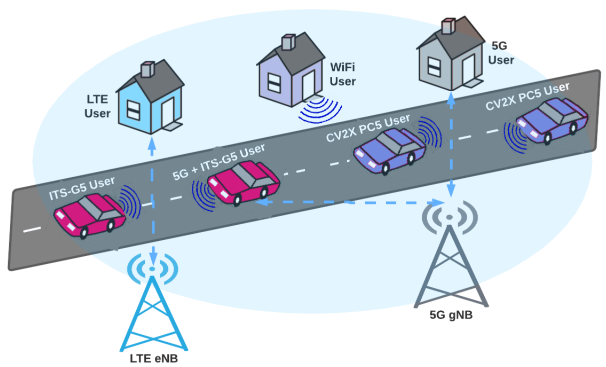


Figure 2: Interference scenarios in future networks in ITS band

Table 3
Minimum possible continuous channel occupancy duration for each technology.

Technology	Minimum signal duration
802.11n	44 μs (for the ACK frame)
LTE	0.5 ms (slot duration)
5G NR	70 μs (mini slot duration)
C-V2X PC5	643 μs (for a 193B BSM packet)
ITS-G5	120μs (for a 193B BSM packet)

[31]. In such a network, multiple MAPs with multi-RAT capabilities may be dynamically deployed in close proximity to each other, leading to higher interference. Generally, efficient spectrum sensing mechanisms must be implemented to ensure fairness and optimal sharing of spectral resources among the co-located RATs, while ensuring the protection of potential incumbents in the 5.9 GHz band.

In such heterogeneous networks, each actively transmitting node has to sense the spectrum and adapt its spectrum utilization in such a way that it minimizes collisions with other active nodes. In many coexistence solutions, the common mechanism used to sense the environment and detect a co-located active node is based on the energy detection threshold. However, multiple RATs and incumbent technologies are expected to share the same ITS band, and this makes the energy detection-based sensing inefficient to identify and protect/prioritize the incumbent transmission. In such scenarios, the identification of co-located active RATs and incumbent ITS transmissions is essential in making smart spectrum decisions. In an environment with the concurrent transmission of different technologies, a node can determine the traffic characteristics of the co-located active nodes by i) using a complex universal receiver that can decode all the possible co-located technologies, ii) introducing a signaling channel that is used to communicate between the technologies, and iii) deploying a technology recognition model. Using a universal receiver requires a complex system that decodes all possible signal types in each node, and this increases the implementation cost and the complexity, making it an unfeasible option. Similarly, introducing a coordination signaling channel to enable status communication between all the nodes requires architectural modifications in all the existing standards, which increases the overall system complexity. Technology recognition can be used to minimize this implementation complexity as it enables an active node to sense the wireless environment and identify the traffic statistics of other co-located networks [32]. The extracted information can be used to formulate coexistence decisions [33] without signaling exchange and without the need for a complex receiver.

Technology recognition is used for the identification of co-located wireless technologies. The identified statistics of each identified technology is used to characterize the traffic of each technology. The characterization process is used to estimate and predict the traffic characteristics of each technology, which can be used as an input to develop a spectrum sharing scheme [12]. In this direction, we propose a deep learning-based technology recognition and characterization solution, which we call DL-TRTC. The proposed DL-TRTC is used for identification and characterization of C-V2X PC5, ITS-G5, LTE, 5G NR, and Wi-Fi technologies.

The TRW of a technology recognition model is an important parameter in terms of traffic characterization accuracy and practicability. Using a TRW longer than the minimum possible frame duration of the considered technologies results in an increased probability of getting a label composed of portions of multiple frames from different technologies. This leads to poor traffic characterization accuracy, which in turn leads to a larger risk of packet collisions, which are uncompromised in safety-critical applications of vehicular communications. Hence, we need a technology recognition solution with a short TRW so that it can distinguish the shortest possible frame among the considered technologies, which is 44 μs in our case (Table 3).

Table 3 shows the minimum possible transmission duration of each considered technology. In the case of LTE and 5G NR networks, the resources are mapped on a resource block basis. LTE uses a 15 kHz sub-carrier spacing, which leads to a slot duration of 0.5 ms [34]. Unlike LTE, 5G NR supports multiple types of sub-carrier spacing and mini-slots used for ultra-reliable low latency communications [35]. The shortest possible mini-slot has a duration of 70 μs.

The outcome of a technology recognition model shows which technology is used for each TRW. A meaningful traffic characteristics of the technologies can be determined considering a sufficient number of TRWs. Hence, the traffic characteristics of the identified technologies have to be collected and processed based on a reasonable traffic characterization time period.

In the case of an IEEE802.11n Wi-Fi network, the shortest possible frame is the ACK frame, which has a frame duration of 44 μs [36]. The shortest possible packet for a Basic Safety Message (BSM) with a packet size of 193B [36] leads to a shortest possible frame duration of 120 μs in the ITS-G5 network when the highest possible Modulation and Coding Scheme (MCS) index 7 is used. In the case of C-V2X PC5 a 193B BSM packet requires 643 μs for MCS 20 [37].

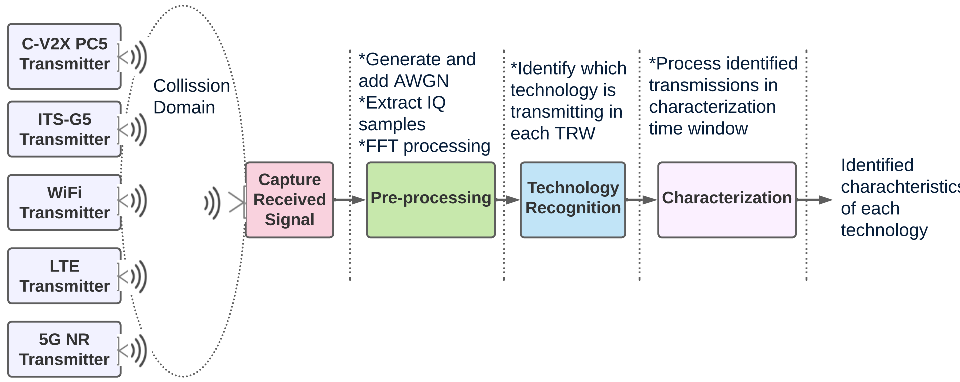


Figure 3: Architecture of proposed technology identification and characterization process.

4. Proposed Technology Recognition and Characterization Solution

In this section, the dataset collection, training, and validation process of the proposed technology recognition model are described. The main procedures of the technology recognition and characterization process are also described in this section. Figure 3 shows the execution process of technology recognition and characterization based on a trained and validated technology recognition model. The figure shows that transmissions from C-V2X PC5, ITS-G5, Wi-Fi, LTE, and 5G NR transmitters are received and pre-processed before the technology classification and characterization process.

4.1. Data Collection

In the *data collection* phase, samples of each signal type are received and collected at different sampling rates. In principle, a bandlimited continuous-time signal can be sampled and perfectly reconstructed from its samples if the waveform is sampled at least twice its highest frequency component. However, even if the signals are downsampled to a low sampling frequency, unique features of each technology can be detected using a technology recognition model. For this reason, different sampling rates ranging from low to high are used in the existing technology recognition models. As an example, a low 1 MHz sampling rate is used in [22], while a higher sampling rate of 20 MHz is used in [26]. However, these sampling rates are used without proper complexity and accuracy analysis. Hence, we perform complexity and accuracy analysis at a range of sampling rates, including 1, 5, 10, 15, 20, and 25 MHz.

The dataset for each technology is prepared in a controlled environment where only one technology transmits at a time. Once the technology recognition model is trained and validated using the dataset representing each considered technology, the model can identify and characterize the traffic from each technology when multiple technologies share the spectrum. We propose a short TRW based on the shortest possible frame size among the considered technologies. This enables efficient traffic identification and characterization when multiple technologies share the spectrum, as the chance of overlapping within a TRW will be low.

A synthetic dataset of each technology can be generated using simulators [30]. However, simulators make many assumptions, and the performance of a model trained with synthetic data deviates when it is evaluated in real-world applications. For this reason, we used hardware and software-based setups that are used in the real-world application of each technology. Unlike simulator-based data collection, in this data collection approach, setting up an end-to-end network of each technology and varying all possible channel conditions, network configuration, and traffic parameters of each technology is challenging. However, we used different software-based solutions to configure various MCS, traffic load, traffic type, and transmission patterns for each technology. In the following subsections, we describe the hardware and software used to collect data for each technology. For the Wi-Fi, LTE, and 5G NR network setups, a host PC connected to a USRP X310 is used to capture and store the captured IQ samples. Similarly, a host PC connected to a USRP N310 is used to capture IQ samples from ITS-G5 and C-V2X PC5 networks.

4.1.1. Wi-Fi

For the Wi-Fi dataset collection, the openWi-Fi [38] SDR solution is used. openWi-Fi is an open-source full-stack IEEE 802.11 a/g/n SDR implementation based on the Xilinx Zynq System on Chip that includes a Field Programmable Gate Array (FPGA) and an ARM processor. Figure 4 shows the equipment and set up used for the Wi-Fi dataset collection. For our dataset, we used an IEEE802.11n access point and a client connected to it. Wi-Fi traffic generated covers a wide range of traffic loads, i.e., 10–200 packets per second (pps), with packet sizes ranging from 500 to 1500 bytes. The MCS used was varied by manually configuring the MCS index value between 0 and 7.

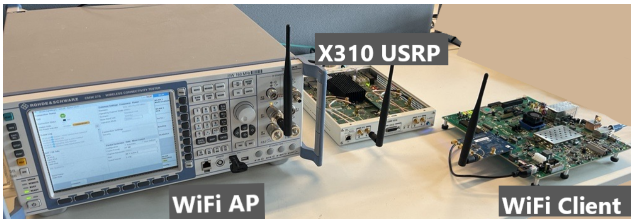


Figure 4: Setup used for Wi-Fi dataset collection.

4.1.2. LTE and 5G NR

For LTE dataset collection, srsRAN [39], an open-source SDR platform, is used. srsRAN offers a 4G LTE SDR solution that supports LTE User Equipment (UE), eNodeB (eNB), and Evolved Packet Core (EPC) implementations. This LTE SDR implementation is used to collect samples for the LTE dataset. An end-to-end srsRAN LTE SDR setup requires a minimum of two Linux host PCs, one for the UE and one for the eNB and EPC. Each host PC is connected to a single RF-frontend. The indoor testbed setup used to collect our dataset consists of one eNB host PC and one UE host PC. Each host PC is connected to a USRP X310 board, which is used as the RF front end. We use the latest srsRAN version 21.04, which is installed on each host PC. Blank subframes were introduced in some of the LTE frames to represent a varying spectrum utilization. The blank subframes are introduced by modifying the srsRAN source code based on our previous work in [40]. For the LTE dataset collection, the FDD mode with a 10 MHz bandwidth and a 5.9 GHz center frequency is used for the downlink traffic.

Similarly, the OpenAirInterface [41] SDR solution is used for 5G NR dataset collection. OpenAirInterface is an open source SDR platform that provides a 3GPP compliant implementation of eNB, UE, and EPC. The OpenAirInterface SDR solution also includes a 5G non-stand alone (NSA) mode which supports 5G networks by using existing 4G infrastructure. This SDR-based 5G network setup is used to collect the IQ samples for the 5G NR dataset. For the 5G NR dataset collection, a 1:1 static TDD configuration is used for up-link and down-link traffic in NSA mode. Numerology 1 is used at 10 MHz bandwidth and center frequency of 5.9 GHz.

For both the LTE and 5G NR datasets, the MCS used was varied by manually configuring different values ranging from MCS index 1 to 28, and the traffic load was varied between 5 and 50 Mbps. Figure 5 shows the setup used to collect LTE and 5G NR dataset. The figure shows two potable units in IDLab 5G testbed used for an end-to-end test, one used as eNB/gNB and the second used as 4G/5G UE. Each portable unit consists of a powerful computing unit which is used to test the srsRAN and OAI based open-source LTE/5G solutions. An SDR USRP X310 connected to the computing unit is used as an RF front end.

4.1.3. ITS-G5 and C-V2X PC5

The CAMINO framework [42] was used for the ITS-G5 and C-V2X PC5 dataset collection. CAMINO is a core framework for managing the V2X communication technologies, including ITS-G5, C-V2X PC5 and C-V2X Uu (5G/4G). The CAMINO framework is used to dynamically generate standardized C-ITS service packets, including Co-operative Awareness (CA), Decentralized Environmental Notification (DEN), and Infrastructure to Vehicle Information (IVI) message packets.

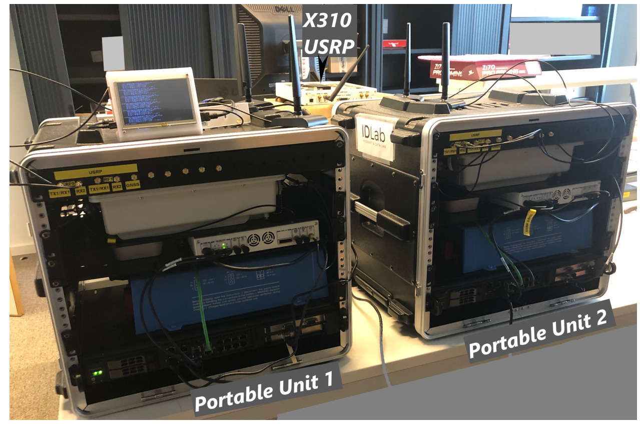
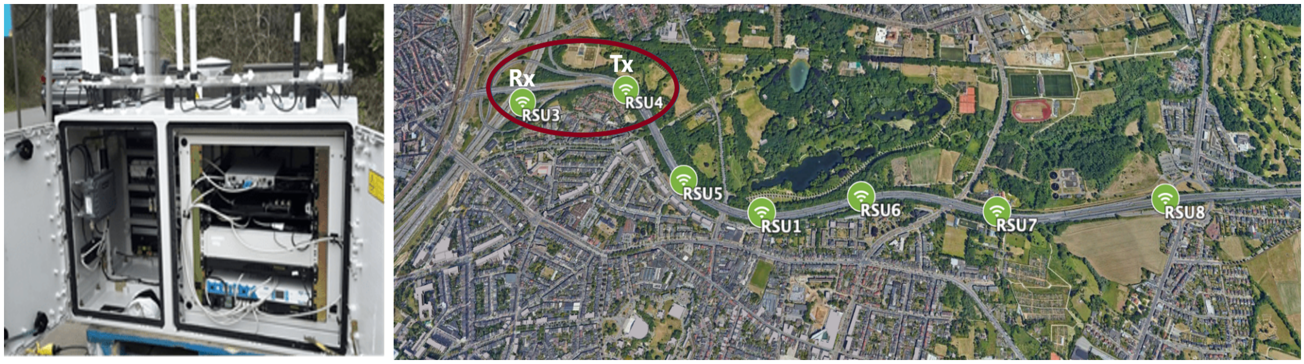


Figure 5: Setup used for LTE and 5G NR dataset collection.

The CAMINO software is implemented on the infrastructure deployed as part of the Belgian Smart Highway testbed [43]. The Smart Highway is a testbed deployed by IMEC on the E313 highway, near Antwerp, Flanders. The Smart Highway testbed consists of eight RSUs and two OBUs. Each RSU and OBU includes a general purpose CPU running the CAMINO software, and Cohda MK5 and MK6c modules, which are COTS ITS-G5 and C-V2X modules respectively. In our dataset collection, RSU4 is used as a transmitter, and a USRP N310 connected to RSU3 is used to capture and store the samples. Figure 6 shows the location of RSU3 and RSU4 on the Smart Highway testbed and the hardware components of each RSU [43]. To represent a wide range of traffic characteristics, different packet sizes of 300B for CA, 300B and 600B for DEN, and 600B for IVI packets were used at inter-packet intervals of 20, 50, 100, and 200 seconds. The MCS used in both technologies was varied by manually changing the MCS index value in the configuration files of the Cohda devices. The MCS index of ITS-G5 varied from 0 to 7. Similarly, the MCS index of C-V2X PC5 varied from 0 to 20.

4.1.4. Noise

The noise floor of the noise signal is dependent on the state and type of the hardware used to sense the spectrum. This makes using a threshold based noise detection inaccurate. Hence, we consider noise signal as an additional class in the technology recognition model along with the considered technologies. Likewise, for the other technologies, IQ samples of the noise signal were also captured for each considered sampling rate. The noise signal was captured in a clear channel where no other active transmissions were active. For generalization purposes, the noise signal was



(a) RSU Components (b) RSU location map

Figure 6: a) RSU components b) The locations of the transmitter (RSU4) and receiver (RSU3) road side units used for ITS-G5 and C-V2X PC5 dataset collection (on the E313 smart highway, near Antwerp, Belgium).

captured using USRP X310 in an indoor environment and using USRP N310 in an outdoor environment at the Smart Highway testbed.

4.2. Pre-processing Phase

In this subsection, the procedure followed during the *Pre-processing* phase is described. To evaluate the performance of the technology recognition model on different channel conditions, the collected IQ samples are pre-processed by adding White Gaussian Noise for various SNR levels in dB. The SNR levels include {-10, -5, $\cdots$, 25, 30} dB. If the received signal sample is $R[n]$, then the signal $R'[n]$ after the noise insertion becomes:

$$R'[n] = R[n] + W^n_{SNR}, \quad n = 1, 2, 3, ..., N. \tag{1}$$

where W^n_{SNR} denotes additive white Gaussian noise and N denotes the number of samples which is selected based on sampling rate.

The In-phase ($I[n]$) and Quadrature phase ($Q[n]$) components of each sample are also extracted in the pre-processing phase. The values of $I[n]$ and $Q[n]$ respectively, represent the real and imaginary parts of each sample signal $R'[n]$.

Previous studies have shown that using IQ values as an input of a technology recognition model leads to lower classification accuracy for lower SNR values as compared to using the FFT of the IQ values as an input [22, 26]. This happens due to the fact that FFT representation has frequency domain features and are more distinguishable for low SNR as compared to their IQ representation. This accuracy gain is in fact obtained at the cost of additional complexity prepended due to FFT computation. As we aim for ITS band application, where safety-critical information is transmitted, classification accuracy is of paramount importance. As a result, the FFT of the collected IQ values is computed and labeled in such a way that it will be used as an input, initially for training of the neural network and later for real-time identification and characterization of co-located wireless technologies.

We compute M point FFT computation of the M IQ samples collected in a TRW duration as follows:

$$R''[k] = \sum_{i=1}^{M} (I[i] + jQ[i]) W_M^{(i-1)(k-1)}, \quad k = 1, 2, ..., M. \tag{2}$$

where $W_M = e^{(2\pi j)/M}$ and the value of M is selected based on the sampling rate and time resolution used. In our technology recognition model, a TRW of 44 μs is selected based on the shortest possible frame duration among the considered technologies, as shown in Table 3. For the selected TRW of 44 μs, the value of M can be 44, 220, 440, 660, 880, and 1100 for a sampling rate of 1, 5, 10, 15, 20, and 25 Msps, respectively.

4.3. CNN based Technology Recognition

After the captured samples are pre-processed, the FFT of the IQ samples is used to train and validate a CNN based technology recognition model. The structure of the CNN model and the implementation details are described in the next subsections.

4.3.1. CNN Structure

Figure 7 shows the CNN structure used in the proposed technology recognition model. The datasets collected from each technology are grouped on a resolution time window basis and given as an input to the CNN model. As shown in the figure, the input to the CNN model has a 2 X M dimension, where M indicates the number of samples captured in the selected TRW. At a certain sampling rate, the 2 X M input matrix (I_t) obtained by computing the real and imaginary parts of the FFT of the IQ samples captured at the t^{th} TRW. The input matrix can be expressed as:

$$I_t = \begin{bmatrix} real(R''[1]) & real(R''[2]) & ... & real(R''[M]) \\ imag(R''[1]) & imag(R''[2]) & ... & imag(R''[M]) \end{bmatrix}. \tag{3}$$

where t is the TRW counter and $R''[K]$ is the FFT computed for K= *1, 2, ...,* M using eq. 2.

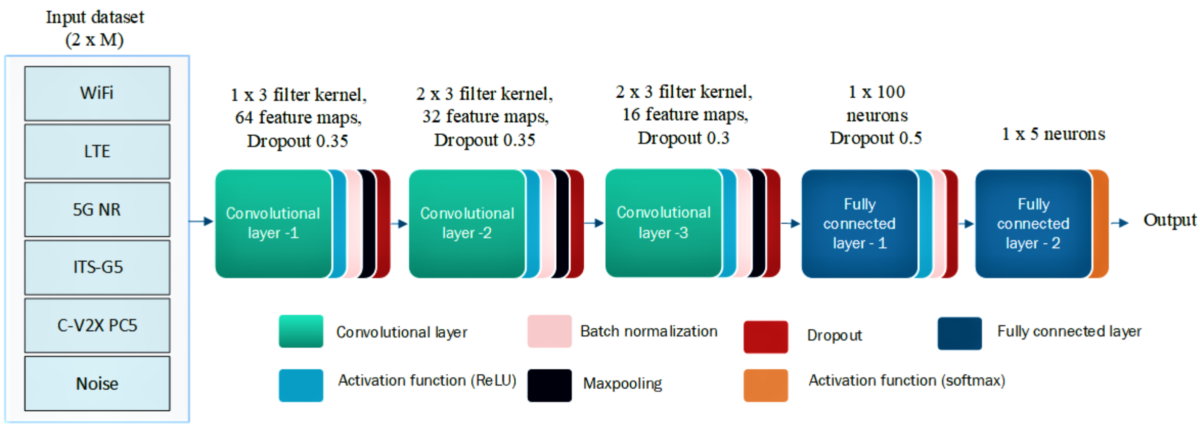


Figure 7: Proposed CNN structure.

Three convolutional layers are used in the feature extraction part of the network. The convolutional layers are used to extract high-level features of each signal from the input samples. The first convolutional layer, *Convolutional layer-1*, is composed of 64 stacked filters with dimensions of 1 x 3 that convolve with the input. As a result, 64 feature maps with dimensions of 5 x (M+2) are created. Similarly, *Convolutional layer-2*, the second convolutional layer, is made up of 32 stacked 2 x 3 filters. These first and second convolutional filters, in convolution with the layer's input, produce 32 feature maps with dimensions of 6 x (M+3), where is M is number of IQ samples for a given sampling rate. They both have zero padding of size 2 on their input. *Convolutional layer-3*, is made up of 16 stacked 2 x 3 filters. The filters are convolved with a stride of 1.

A ReLu activation function follows each convolutional layer. As the parameters of the previous layers change, the distribution of inputs for each layer can change during training. To address this issue, a batch normalization [44] is performed after each ReLu function. As a result, while the training rate increases, the activations are properly adjusted and scaled. The first two convolutional layers employ regularization with a dropout of 0.35 in conjunction with the L2 kernel regularizer to reduce overfitting. For the third convolutional layer, a dropout of 0.3 is used for the regularization. The L2 regularizer is designed to penalize weights of large magnitudes. Each convolutional layer is followed by a pooling layer that performs Max Pooling.

The classification phase, which consists of two FC layers, comes after the feature extraction phase. The input to the classification part is flattened first, and then FC layer-1 is added. This layer is made up of 100 neurons. It employs the ReLu activation function, batch normalization, a 0.5 dropout, and an L2 kernel regularizer. This layer's output is fed into FC layer-2. FC layer-2 is a softmax classifier used to estimate the probability of correctly classified inputs for each class.

4.3.2. *Training and Validation Process*

From the collected dataset, 70% randomly selected samples are used for training, while the remaining 30% are equally split for validation and testing of the model. The random selection was made at a batch size of 256. To ensure convergence, a default learning rate (α) value of 0.001 was used for the learning process. The number of training epochs used was set at 2000, with a patience of 20 consecutive epochs to stop the training process if the accuracy of the CNN model stays unchanged without improvement. The parameters of the CNN structure are estimated based on the Adaptive moment estimation (Adam) optimizer [45]. Using this approach, a total of six different CNN models have been trained and validated for the different dataset clusters collected using sampling rates of 1, 5, 10, 15, 20, and 25 Msps.

4.3.3. *Implementation Details*

The proposed CNN network used in this work was trained and validated using the Keras software library [46]. Keras is a Python-based high-level API for neural networks. This API can run on top of a variety of deep learning frameworks, including TensorFlow [47], on top of a Central Processing Unit (CPU), or Graphics Processing Unit (GPU). The model training and validation was done in our in-house built JupyterHub which provides access to high-end GPUs [48].

4.4. Technology Characterization Process

In the previous section, we described the CNN model that is used to identify a signal captured in a TRW of 44 μs. However, the spectrum utilization and transmission pattern of each technology can be estimated after sensing the spectrum for a longer duration. After collecting a sufficient set of statistics over a certain period of time, the traffic characteristics of each technology can be estimated. In our solution, we use 22,727 consecutive TRWs to characterize the traffic and spectrum utilization of each technology. Considering the 44 μs time resolution used in the technology recognition models, the characterization duration occupied

Table 4
Characterization parameters used for each technology.

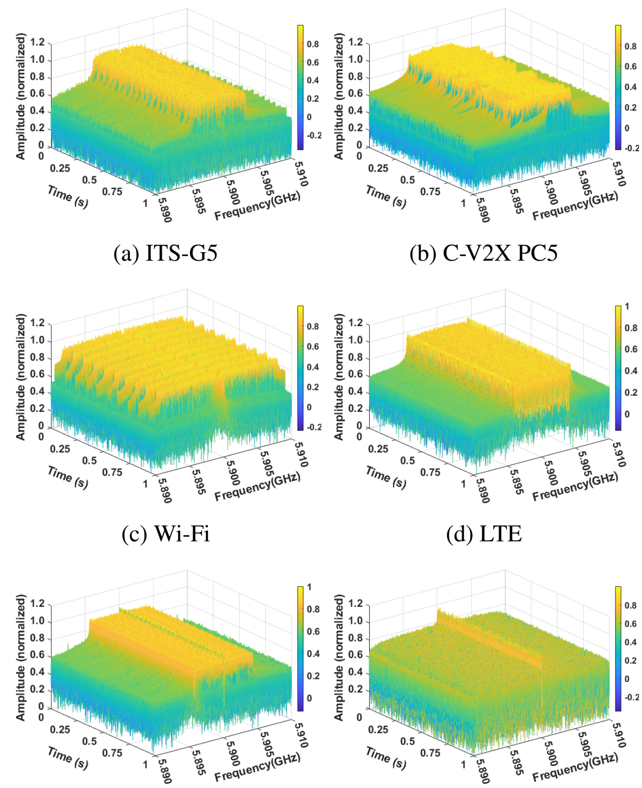
Technology	Characterization parameters
802.11n	Traffic pattern, pps, COT
LTE	Traffic pattern, COT
5G NR	Traffic pattern, COT
C-V2X PC5	Traffic pattern, pps, COT
ITS-G5	Traffic pattern, pps, COT

by 22,727 TRWs equals to 0.999988 s. We refer to this period of time as the characterization window and it was selected as it is the closest possible window as compared to the typical sensing window of Semi-Persistent Scheduling (SPS) in C-V2X PC5, which is 1 s [49]. This sensing window of SPS is used as a reference to select the characterization period as the other considered vehicular technology (ITS-G5) has a short clear channel assessment duration (42-131 μs) which is the arbitrary inter-frame space duration of the enhanced distributed channel access mechanism used in its medium access control protocol [50].

In each characterization window, different traffic characteristic parameters are extracted based on the type of identified technologies. The characterization process starts by determining the transmission pattern for each technology. The continuous transmission duration of each identified technology is calculated by concatenating consecutive TRWs identified as one technology. The traffic characterization parameters used for each considered technology are shown in Table 4. For C-V2X PC5 and ITS-G5, the number of pps and the duration of each identified frame are used to characterize the traffic. With the knowledge of these parameters, a RAT operating in the ITS band can avoid potential interference with transmissions from the incumbent C-V2X PC5 and ITS-G5 technologies. For Wi-Fi, the traffic characterization is carried out by calculating the number of Wi-Fi frames and the duration of each frame in the characterization window. Similarly, transmission patterns are estimated to characterize LTE and 5G NR traffic. For all the considered technologies, the COT is computed using the aggregate frame duration determined in the characterization window.

5. Experimentation Results

Based on the data collection procedure described in subsection 4.1, 6 different dataset bunches are collected at sampling rates of 1, 5, 10, 15, 20, and 25 Msps. The dataset size at each considered sampling rate is 7500 X M, where M can be 44, 220, 440, 660, 880, and 1100 for a sampling rate of 1, 5, 10, 15, 20, and 25 Msps, respectively. Figure 8 shows a spectrogram plot of sample signals used for the dataset of each class at a 20 Msps sampling rate for a 1 s duration. The figure shows the spectrogram of sample signals from each considered technology and a sample noise signal from the USRP used to capture the dataset of each technology. Figure 8f shows the spectrogram of the noise on a USRP N310 in a 20 MHz bandwidth at a center frequency of 5.9 GHz. Any non-zero value over the whole bandwidth shows the level of the noise signal, while the sharp values at the center frequency show the DC component of the noise signal from the USRP. In the next section, the obtained results are presented in terms of a) technology recognition performance and b) traffic characterization performance.



(a) ITS-G5 (b) C-V2X PC5 (c) Wi-Fi (d) LTE (e) 5G NR (f) Noise

Figure 8: Spectrogram plot of sample signals used for the dataset of each class at a 20 Msps sampling rate for a 1 s duration.

5.1. Technology Recognition Performance

In this section, the performance of the CNN-based technology recognition model is presented in terms of model training/validation loss, classification performance, and model complexity. The performance of the proposed technology recognition solution is also compared with other existing technology recognition schemes.

5.1.1. Model Loss

Figure 9 shows the training and validation loss curves of the proposed CNN model. The validation and training loss curves are obtained in a complete CNN training process by testing the performance of the model on the 30% of the total dataset samples that are used to validate the CNN model. These validation and training loss curves are specifically for a 20 Msps sampling rate and a 44 μs. Similar loss curves were observed for the other sampling rates and TRWs used in the performance analysis. The loss curves show that there is no overfitting in the training and validation processes, and we used an early stopping criterion in model training, which is used for better generalization performance.

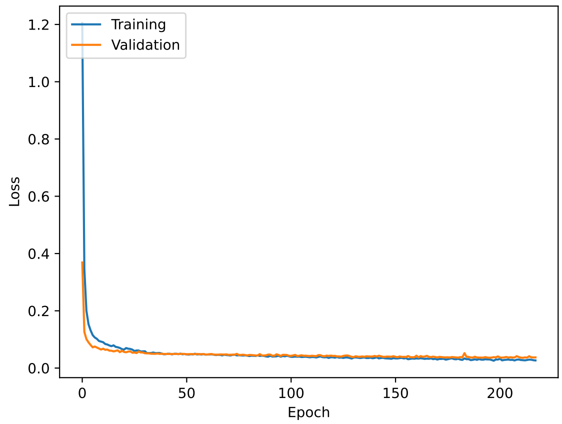


Figure 9: Training and validation loss.

5.1.2. Classification Performance

Once the technology recognition model is trained and validated, the classification performance of the proposed technology recognition model is computed to evaluate the performance of the CNN model as it identifies the captured samples from the considered wireless technologies. The classification performance is presented in terms of precision, recall, F1-score, and accuracy metrics.

To assess the model's effectiveness in different SNR conditions, various levels of noise ranging from -15 to 30 dB are introduced. Figure 10 shows the confusion matrix of the proposed technology recognition models with different sampling rates at 0 dB SNR. Each column in this figure represents the true label, and each row represents the predicted labels. The confusion matrix in Figure 10 shows the true positive (ϑ), false positive (δ), and false negative (ξ) values of each class at 0 dB SNR and 44 μs TRW. This is used to compute the precision (Π) , recall (Ω), and F1-score (Ψ) metrics using:

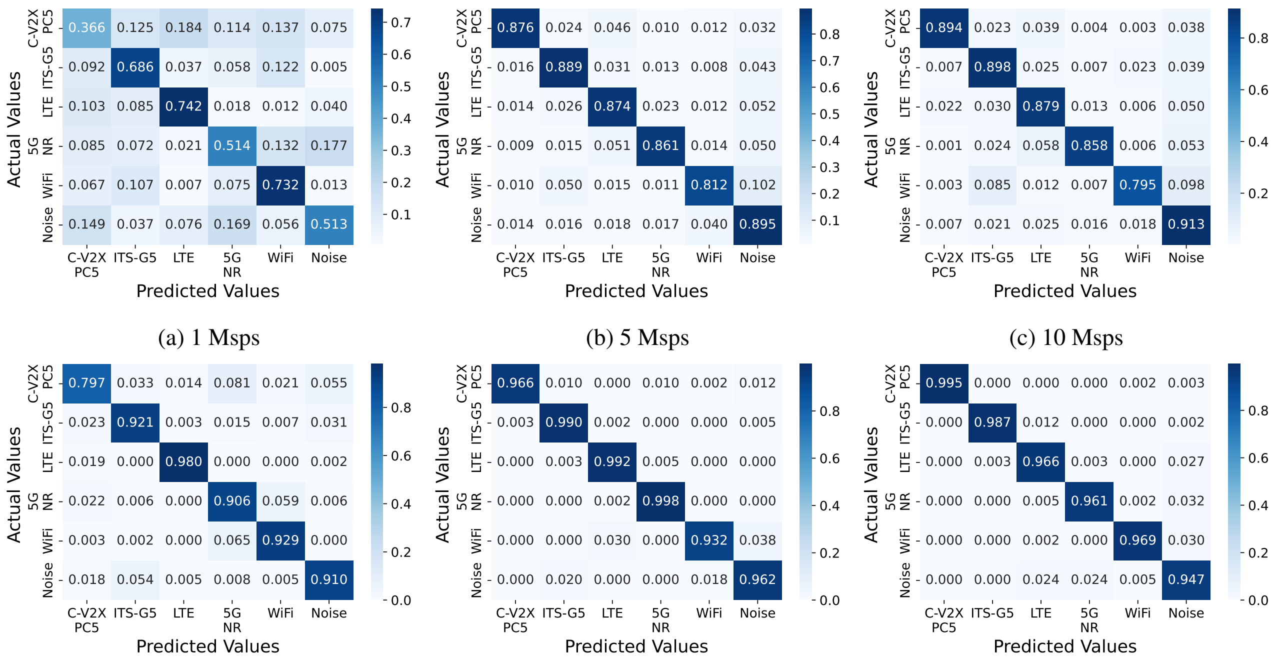
$$\Pi = \frac{\vartheta}{\vartheta + \delta}, \quad \Omega = \frac{\vartheta}{\vartheta + \xi}, \quad \Psi = 2 \times \frac{\Pi \times \Omega}{\Pi + \Omega}. \tag{4}$$

The precision metric quantifies the proportion of positive outcomes that are actually positive, whereas the recall metric indicates the proportion of true positives that are accurately identified as positive. The F1-score measures the overall accuracy of a classifier model as it is the harmonic mean of precision and recall. The results in Table 5 show that the precision, recall, and F1-score of the proposed CNN models increase as the sampling rate used increases.

Figure 11 shows the accuracy of the proposed technology recognition model at different sampling rates. The classification accuracy results are obtained by assessing the model's performance on the 30% of the total dataset samples that are used to validate and test the CNN model. The figure shows the classification accuracy of the technology recognition models at different sampling rates as the SNR of the received signal varies from -15 to 30 dB. For higher SNR, the signal is less distorted and high above the noise floor, and the features of each signal are still representative enough to be well classified by CNN. However, with lower SNR, the signal may be corrupted, and some unique features may be distorted, which results in wrong classification by the CNN. The Figure illustrates that the CNN model's classification accuracy increases when a higher sampling rate is used. The number of IQ samples captured in each TRW increases as the sampling rate increases. As an example, for a fixed 44 μs TRW, each signal sample will be represented by 220 and 880 IQ samples for a sampling rate of 5 and 20 Msps, respectively. With a higher number of IQ samples in each TRW, the unique features of each technology are

Table 5
Precision, Recall, and F1-Score of the proposed technology recognition model for different sampling rates.

Sampling Rate	Class	Precision	Recall	F1-Score
1 Msps	C-V2X PC5	0.37	0.43	0.39
	ITS-G5	0.69	0.62	0.65
	LTE	0.74	0.70	0.72
	5G-NR	0.51	0.54	0.53
	WiFi	0.73	0.61	0.67
	Noise	0.51	0.62	0.56
5 Msps	C-V2X PC5	0.88	0.93	0.90
	ITS-G5	0.89	0.87	0.88
	LTE	0.87	0.84	0.86
	5G-NR	0.86	0.92	0.89
	WiFi	0.81	0.90	0.86
	Noise	0.90	0.76	0.82
10 Msps	C-V2X PC5	0.89	0.96	0.92
	ITS-G5	0.90	0.83	0.86
	LTE	0.88	0.85	0.86
	5G-NR	0.86	0.95	0.90
	WiFi	0.80	0.93	0.86
	Noise	0.91	0.77	0.83
15 Msps	C-V2X PC5	0.80	0.90	0.85
	ITS-G5	0.92	0.91	0.91
	LTE	0.98	0.98	0.98
	5G-NR	0.91	0.84	0.87
	WiFi	0.93	0.91	0.92
	Noise	0.91	0.91	0.91
20 Msps	C-V2X PC5	0.97	1.00	0.98
	ITS-G5	0.99	0.97	0.98
	LTE	0.99	0.97	0.98
	5G-NR	1.00	0.99	0.99
	WiFi	0.93	0.98	0.96
	Noise	0.96	0.95	0.95
25 Msps	C-V2X PC5	1.00	1.00	1.00
	ITS-G5	0.99	1.00	0.99
	LTE	0.97	0.96	0.96
	5G-NR	0.96	0.97	0.97
	WiFi	0.97	0.99	0.98
	Noise	0.95	0.91	0.93



(a) 1 Msps (b) 5 Msps (c) 10 Msps

(d) 15 Msps (e) 20 Msps (f) 25 Msps

Figure 10: Confusion matrices for CNN models using different sampling rates at 0 dB SNR.

more representable, which is then used by the CNN for extracting good features. Therefore, the classification accuracy increases as the sampling rate increases. For an SNR of 0 dB, we can clearly observe that setting the sampling rate to 15 Msps or higher leads to a classification accuracy of more than 90%. More precisely, using the CNN model that uses the highest considered sampling rate (25 Msps) offers an excellent accuracy of 97.5% as compared to the lower classification accuracy of 48.5% for the CNN model that employs the lowest considered sampling rate (1 Msps).

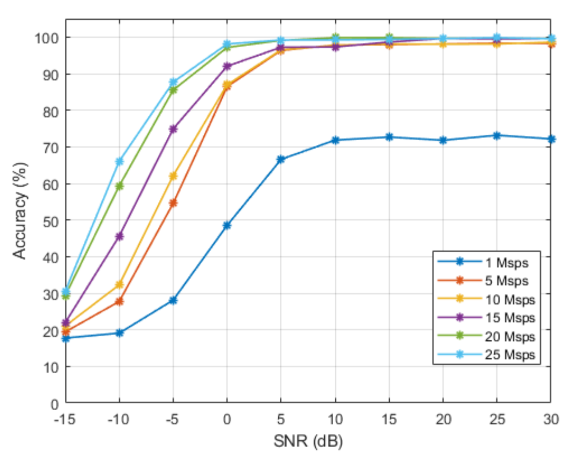


Figure 11: Classification accuracy in relation to SNR for the proposed technology recognition model using 44 μs TRW and different sampling rates.

For SNR values higher than 5 dB, the classification accuracy can reach up to 73.2% when the CNN model trained and validated with 1 Msps sampling rate. For the rest of the CNN models, the classification accuracy obtained is higher than 98%. However, the classification accuracy of the CNN model with 1 Msps sampling rate drops to 28% if the SNR of the received signal drops to -5 dB, while a classification accuracy of 86% is achieved with the CNN model that employs a 20 Msps sampling rate. For SNR values higher than 10 dB, an excellent classification accuracy (higher than 90%) is achieved with a lower sampling rate of 5 Msps.

5.1.3. Model Complexity

The complexity analysis of the proposed technology recognition models in terms of model parameters is presented in Table 6. The table shows the input dimensions and model parameters used for the CNN models trained and validated with different sampling rates and TRWs. To illustrate the complexity/accuracy trade-off, the table also presents the classification accuracy of each CNN model at 0 and 10 dB SNR.

For the proposed 44 μs TRW, it can be observed that the lower sampling rate (5 Msps) based CNN model can be used to develop a less complex CNN model which can effectively distinguish the signal. Hence, for average to high SNR values, lower sampling rates can be used to accurately classify the signal with lower complexity compared to the CNN models that use the higher sampling rates. However, bad channel conditions with an SNR lower than 0 dB require the more complex, high sampling rate-based CNN models to achieve excellent classification accuracy.

Table 6
Complexity vs accuracy analysis in terms of input, model parameters, and accuracy: i) using different sampling rates with proposed TRW (44 μs) ii) using different TRWs with fixed sampling rate (20 Msps).

Varying sampling rate with proposed TRW (44 μs)				
Sampling rate	Input dimension	Model parameters	Accuracy at 0 dB	Accuracy at 10 dB
1 Msps	2 X 44	53,696	48.52%	71.26%
5 Msps	2 X 220	159,296	86.14%	98.12%
10 Msps	2 X 440	293,696	86.67%	98.24%
15 Msps	2 X 660	423,296	92.43%	98.67%
20 Msps	2 X 880	557,696	97.48%	99.26%
25 Msps	2 X 1,100	687,296	98.21%	99.67%
Different TRWs with fixed sampling rate (20 Msps)				
TRW	Input dimension	Model parameters	Accuracy at 0 dB	Accuracy at 10 dB
44 μs	2 X 880	557,696	97.48%	99.26%
68 μs	2 X 1,635	845,696	97.44%	99.34%
100 μs	2 X 2,000	1,229,696	98.34%	99.46%
244 μs	2 X 4,880	2,957,696	98.21%	99.51%

Additionally, Table 6 shows the accuracy/complexity trade-off for 68 μs, 100 μs, and 244 μs TRWs, which are adopted from [25], [26], and [28], respectively. The results are compared with the proposed 44 μs TRW based model. Increasing the TRW (for a fixed sampling rate) leads to a higher number of IQ samples captured in each sample signal. For a fixed 20 Msps sampling rate, 220 and 4,880 IQ samples will be captured in TRW of 44 and 244 μs, respectively. With a higher number of IQ samples in each TRW, the unique features of each technology are more representable, which is then used by the CNN for extracting good features automatically. This results in increasing the classification accuracy. The results show that using a longer TRW leads to a marginally better accuracy at a cost of increased complexity. If a longer TRW is employed, more features will be included in each TRW, resulting in enhanced accuracy, as long as only one technology transmits its traffic within the TRW. In practice, different technologies can transmit their traffic within a short window, and this makes using longer TRWs impractical.

Generally, CNN models have a significantly high arithmetic intensity, resulting in increased inference time, energy consumption, and memory bandwidth. This may create additional processing overhead for real-time systems employing models running on the edge and embedded devices. Model quantization can be used to reduce the complexity of the proposed CNN models so that they can execute on embedded and edge devices. Model quantization is an approach used to reduce latency, memory requirements, and energy per inference with minimal accuracy changes [51].

5.1.4. Comparison with Existing Technology Recognition Schemes

Figure 12 shows the comparison of classification accuracy between i) RFC based on manual feature extraction from RSSI histogram [22] , ii) CNN based on IQ samples [25], and iii) the proposed CNN model that uses FFT of IQ samples as input. The comparison is made for a 20 Msps sampling rate and a 44 μs TRW. For higher SNR channels, the RFC that uses RSSI histogram-based manual feature extraction has a good classification accuracy (>80%). But this RFC-based TR has generally lower accuracy as compared to the proposed CNN-based technology recognition. The accuracy gain in the proposed CNN-based technology recognition is obtained at the cost of additional complexity for the automated feature extraction of the neural network.

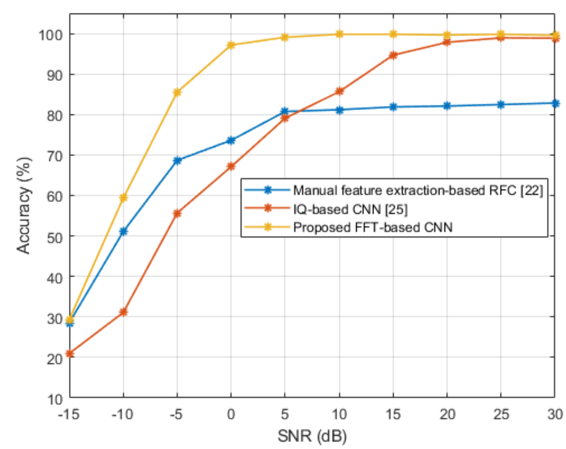


Figure 12: Comparison of Classification accuracy at 44 μs TRW and 20 Msps sampling rate for i) RFC based on manual feature extraction from RSSI histogram [22] , ii) CNN based on IQ samples [25], iii) CNN based on FFT of IQ samples (proposed model).

On the other hand, the IQ sample-based CNN has excellent classification accuracy, reaching up to 99% for the higher SNR channel. However, using IQ values as an input of a technology recognition model leads to lower classification accuracy for lower SNR values as compared to the proposed mode. This happens due to the fact that the proposed model uses the FFT of the IQ values as an input. The FFT representation has frequency domain features that are less corrupted by noise as compared to the corresponding IQ representation. This accuracy gain is also achieved at the cost of additional computational complexity for the FFT computation. In general, it can be seen that the proposed approach offers greater accuracy at the expense of increased complexity. However, classification accuracy is crucial as we aim for technologies in the ITS band in which safety-critical information is transmitted. Thus, the proposed solution becomes a more feasible approach.

Table 7
Traffic characterization performance comparison in terms of the estimated number of frames (N_f), estimated COT, and transmission pattern characterization accuracy for technology recognition models using 44 μs (proposed), 68 μs [25], 100 μs [26], and 244 μs [28] TRWs for 20 Msps sampling rate and 0 dB SNR channel.

	Actual	Characterized N_f at TRW(μs)				Actual	Characterized COT(%) at TRW(μs)				TP_{acc} (%) at TRW(μs)			
Technology	N_f	44	68	100	244	COT(%)	44	68	100	244	44	68	100	244
ITS-G5	250	250	250	250	250	0.75	0.75	0.78	0.83	0.95	97.54	91.03	87.23	84.2
C-V2X PC5	500	500	500	500	500	1.49	1.50	1.54	1.63	1.71	96.25	93.41	86.11	79.34
Wi-Fi	500	505	494	482	468	0.26	0.26	0.34	0.45	0.52	-	-	-	-
LTE	-	-	-	-	-	15.97	15.98	16.80	21.03	22.12	-	-	-	-
5G NR	-	-	-	-	-	10.03	10.04	11.32	12.89	14.78	-	-	-	-

5.2. Traffic Characterization Performance

The characterization process starts with the determination of the transmission pattern of each identified signal. The transmission pattern of an identified signal represents the T_{ON} and T_{OFF} duration statistics within each characterization window. The T_{ON} indicates the time duration where an identified technology occupies the channel continuously, whereas and T_{OFF} represents the silent duration in between the transmissions. For ITS-G5 and C-V2X PC5 technologies, the minimum possible frame duration (minimum possible T_{ON}) is greater than two consecutive TRWs (Table 3). Hence, a resolution window identified as a different technology in between two resolution windows identified as ITS-G5 or C-V2X PC5 is changed to match the bounding resolution windows. This process was introduced to reduce the effect of miss-classification on the frame characterization process for the high-priority safety-critical ITS-G5 and C-V2X PC5 technologies. Figure 13a shows an example of the transmission pattern of an actual received signal from the ITS-G5 transmitter with 50 pps for a 0.15 s duration. On the other hand, Figure 13c shows the characterized ITS-G5 transmission pattern using technology recognition.

The T_{ON} duration of each identified technology is calculated by concatenating consecutive TRWs identified as one technology. Based on these statistics, the number of frames is also calculated for Wi-Fi, ITS-G5 and C-V2X PC5 technologies. For the incumbent ITS-G5 and C-V2X PC5 technologies, the correct transmission pattern characterization probability TP_{acc} for each technology is calculated using:

$$TP_{acc} = 1 - \frac{1}{N_f}\sum_{k=1}^{N_f}\Bigg[\frac{|t_{start}[k] - t^*_{start}[k]|}{t_{start}[k]} + \frac{|t_{stop}[k] - t^*_{stop}[k]|}{t_{stop}[k]}\Bigg]. \quad (5)$$

where N_f is the number of frames (for Wi-Fi, ITSG-5, and C-V2X PC5) and number of continuous transmission spells (for LTE and 5G NR), which is determined from the statistics of consecutive TRWs identified as one technology in the characterization window. As shown in Figure 13, t_{start}

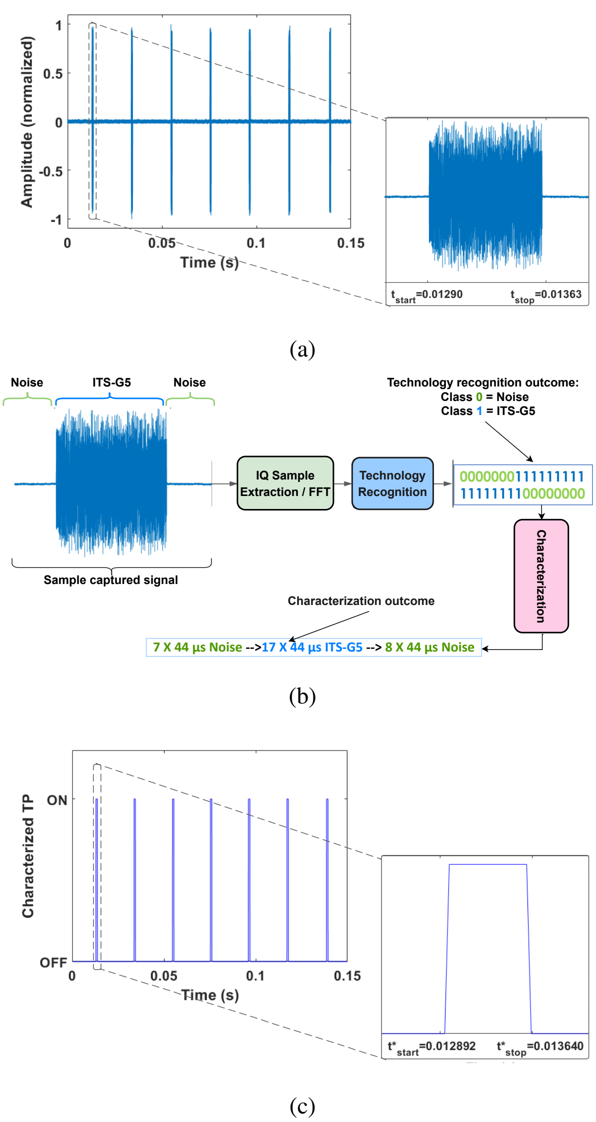


Figure 13: a) Actual transmitted IVI frames from ITS-G5 transmitter (with 50 pps transmission) in 0.15 s duration b) characterization process c) corresponding Transmission Pattern (TP) characterized using the proposed technology recognition and characterization solution.

and t_{stop} represent the actual starting and stopping points of an active transmission interval by a certain technology. Similarly, t^*_{start} and t^*_{stop} represent the starting and stopping points of an active transmission interval identified and characterized as one technology. An active transmission interval identified as one technology is composed of consecutive TRWs classified into one class of technology. For each active transmission interval identified as one technology, the starting point of the first TRW is t^*_{start}, while the ending point of last the TRW is t^*_{stop}. Figure 13b shows the characterization process for a sample captured signal in a certain time window. Consecutive TRWs identified as class 0 and class 1 are used to determine the time windows used by noise and ITS-G5 signal, respectively.

The accuracy of the number of frames determined by the characterization process was also determined using the ratio of the number of actually transmitted frames and the number of frames estimated in the characterization process. Similarly, the accuracy of number of TRWs and COT determined from the characterized signal was calculated by taking the actual transmitted number of TRWs and COT of the transmitted signal as a reference. The COT of each characterized technology is computed by using the cumulative sum of T_{ON} of each identified frame over a characterization time period.

For characterization accuracy evaluation, we used controlled medium access for each considered technology, so that we have a useful base reference to compute the accuracy of the characterization process. Table 7 shows the characterization performance of the proposed model for a signal received for 25 s, where C-V2X PC5, ITS-G5, Wi-Fi, LTE, and 5G NR occupy 5 s each. For validation purposes, transmissions from only one technology are received every 5 s. This enables us to label the signal received every 5 s and use it for characterization accuracy computation. The characterization performance is presented in terms of resolution window, COT, transmission pattern accuracy, and the number of frames determined.

The results illustrated in Table 7 are obtained using a 20 Msps sampling rate based CNN model for technology recognition. In the characterization process, a 0 dB SNR channel is considered where each technology exclusively uses the medium for 5 s. The traffic used in each 5 s is generated from the five considered technologies as follows: i) ITS-G5 transmitter with 50 pps IVI message traffic with a 20 ms inter packet interval (with no packet re-transmission), ii) C-V2X PC5 transmitter with 50 pps IVI message traffic with a 20 ms inter packet interval (with 1 packet re-transmission), iii) Wi-Fi transmitter with 100 pps traffic and 500 byte packet size, iv) 10 Mbps traffic load on LTE user (with 2 blank sub-frames in each frame), and v) 5 Mbps traffic load on 5G NR user. The results depicted in Table 7 show that the proposed technology recognition model can be used to accurately characterize the traffic characteristics of each considered technology.

The results in the table also show that the proposed TRW (44 μs) leads to a higher characterization accuracy as compared to the longer TRWs adopted from [25], [26], and [28]. As an example, it can be observed that the proposed model characterizes the ITS-G5 signal with slightly shifted starting and stopping time of the frames (TP_{acc} of 97.54%) while the number of frames and COT are accurately characterized. The slight characterization errors on the starting and stopping points of each frame lead to a drop in the TP_{acc} but this doesn't directly affect the frame count and COT. This improvement in characterization accuracy is the result of using shorter TRW, which reduces the likelihood of mixing up multiple frames from different technologies in a single label.

Generally, it can be observed that the proposed technology recognition model followed by the traffic characterization process can be used to accurately classify and characterize the traffic from each technology. The estimated traffic characteristics can be used to develop spectrum sharing schemes aiming to protect the incumbent ITS-G5 and C-V2X PC5 transmissions.

6. Conclusion and Future Works

The expansion of wireless mobile network deployments, along with the rapid penetration of the Internet of Things, has resulted in an exponential increase in wireless traffic demand. As a solution to meet the rising traffic demand, spectrum sharing approaches are proposed to be used in current and next-generation wireless communication systems. Spectrum management is anticipated to become more flexible and dynamic in the future, potentially allowing all radio access technologies to share a large portion of the spectrum. In this direction, it will be necessary to make intelligent spectrum decisions, which will be aided by wireless technology recognition, allowing networks to dynamically adapt to an environment in which fair coexistence with other wireless technologies is becoming increasingly important. In this direction, this work has proposed a CNN-based technology recognition and characterization model for enabling spectrum sharing in the ITS band. We have presented a CNN model-based technology identification and traffic characterization solution for ITS-G5, C-V2X PC5, Wi-Fi, LTE, and 5G NR technologies. As compared to current state-of-the-art solutions, a short time resolution window of 44 μs is selected for the technology recognition model. The TRW is selected based on the shortest possible frame duration in the considered technologies. The complexity/accuracy trade-off has been illustrated by collecting six dataset clusters with sampling rates of 1, 5, 10, 15, 20, and 25 Msps. To evaluate the technology recognition model's performance on various channels, the collected IQ samples are pre-processed by adding noise of various SNR values. Then, the FFT of the IQ samples is used as an input to train and validate the technology recognition model. Furthermore, a traffic characterization method has been proposed to estimate the characteristics of the traffic identified by the technology recognition process.

The classification accuracy of the technology recognition model is determined using the correct classification probability, and the technology characterization performance is determined in terms of COT, transmission pattern characterization accuracy, and accuracy of the estimated number of frames. For SNR values of 5 dB or higher, we observed that a comparatively less complex CNN model with lower sampling rates (5 Msps) can effectively distinguish the signal type, exceeding a classification accuracy of 96%. However, low SNR channels require more complex, high sampling rate (20 Msps) based CNN models to achieve high classification accuracy.

In the near future, this work will be validated by implementing the technology recognition and characterization process on edge and embedded devices. Adaptive model quantization will be used to reduce latency, memory requirements, and energy consumption per inference time with minimal changes in accuracy. This model complexity minimization is required to enable a near real-time execution of the technology recognition and characterization process on edge and embedded devices. Moreover, the traffic characteristics estimated in our solution can be utilized to develop efficient spectrum-sharing schemes in the ITS band.

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