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Enhancing the Coexistence of LTE and Wi-Fi in Unlicensed Spectrum Through Convolutional Neural Networks

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ABSTRACT Over the last years, the ever-growing wireless traffic has pushed the mobile community to investigate solutions that can assist in more efficient management of the wireless spectrum. Towards this direction, the long-term evolution (LTE) operation in the unlicensed spectrum has been proposed. Targeting a global solution that respects the regional requirements, 3GPP announced the standard of LTE licensed assisted access (LAA). However, LTE LAA may result in unfair coexistence with Wi-Fi, especially when Wi-Fi does not use frame aggregation. Targeting a technique that enables fair channel access, the mLTE-U scheme has been proposed. According to mLTE-U, LTE uses a variable transmission opportunity, followed by a variable muting period that can be exploited by other networks to transmit. For the selection of the appropriate mLTE-U configuration, information about the dynamically changing wireless environment is required. To this end, this paper proposes a convolutional neural network (CNN) that is trained to perform identification of LTE and Wi-Fi transmissions. In addition, it can identify the hidden terminal effect caused by multiple LTE transmissions, multiple Wi-Fi transmissions, or concurrent LTE and Wi-Fi transmissions. The designed CNN has been trained and validated using commercial off-the-shelf LTE and Wi-Fi hardware equipment and for two wireless signal representations, namely, in-phase and quadrature samples and frequency domain representation through fast Fourier transform. The classification accuracy of the two resulting CNNs is tested for different signal to noise ratio values. The experimentation results show that the data representation affects the accuracy of CNN. The obtained information from CNN can be exploited by the mLTE-U scheme in order to provide fair coexistence between the two wireless technologies.

INDEX TERMS Convolutional neural network, LTE, Wi-Fi, coexistence, spectral efficiency, unlicensed spectrum.

I. INTRODUCTION

Over the last years, the wireless transmitted traffic has been increased tremendously, as a result of the unparalleled technological growth. Mobile communications have transformed the way people communicate, exchange information and experience entertainment. According to the International Telecommunication Union Radiocommunication Sector (ITU-R), in May 2015, over the world's population of 7.3 billion, there were about 7.5 billion mobile subscriptions worldwide and about 3.7 billion people connected [1]. It is estimated that the mobile traffic will grow at an annual rate of around 54% between 2020 and 2030. Additionally, Huawei predicts that by 2025 consumers worldwide will collectively be using 40 billion connected devices [2]. This massive amount of devices communicate using different types of wireless technologies such as Long Term Evolution (LTE), IEEE 802.11 (Wi-Fi), IEEE 802.15.4 and Bluetooth. Recently, high frequency bands (mmWave) are used for multi-gigabit speeds (IEEE 802.11ad), while sub-GHz bands are exploited by technologies that target low power and wide range communications such as LORA and SIGFOX. It becomes clear that soon the wireless network capacity will become a bottleneck for serving the wireless traffic.

The LTE operation in the unlicensed spectrum has emerged as a promising and effective solution that can assist in

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exploiting the wireless spectrum in a more efficient way [3]. Hence, it has attracted significant attention from the wireless community that has introduced several techniques aiming to enable harmonious coexistence between LTE and other well-established technologies in the unlicensed spectrum, such as Wi-Fi [4]. There are three dominant approaches for LTE operation in unlicensed spectrum according to the regional regulations and the desired deployment scenario. In regions where a Listen Before Talk (LBT) procedure before a transmission is not mandatory by the regional regulations, such as in U.S.A. or in China, it has been proposed that LTE can transmit in unlicensed frequencies using a duty-cycle technique. Carrier Sense Adaptive Transmission (CSAT) [5] is the most prominent technique of this nature and it has been proposed by Qualcomm. This technique builds on elements of LTE Release 12 [6] and exploits duty-cycle periods in order to give transmission opportunities (TXOP) to other co-located networks.

On the other hand, 3GPP published the LTE Licensed Assisted Access (LTE LAA) standards as part of the Release 13 [7]. Through LTE LAA, 3GPP aims for a coexistence technique that respects the regional regulations worldwide, including regions where an LBT procedure before a transmission in the unlicensed spectrum is mandatory, such as in Europe and in Japan. The standard defines that an LBT procedure, also known as Clear Channel Assessment (CCA) must precede any transmission in the unlicensed spectrum. Initially and according to Release 13, LTE LAA is designed to be used only for downlink (DL) traffic in the 5-GHz unlicensed band. Within Release 14, LTE LAA may be used for both DL and uplink (UL) traffic [8]. According to LTE LAA standard, the evolved NodeB (eNB) is able to opportunistically activate and deactivate a secondary cell in unlicensed spectrum that operates next to the primary cell in the licensed band owned by the operator. This way and according to Release 13, an operator can offload the LTE network by transmitting DL data traffic through the Physical DL Shared Channel (PDSCH), while the LTE control signals together with the UL traffic will be transmitted via the licensed anchor, which can guarantee interference-free and timely transmission.

Both the aforementioned solutions require that an operator owns a licensed frequency band and opportunistically offloads LTE traffic in the unlicensed spectrum. In order to decouple LTE from the operators and enable the LTE operation solely in the unlicensed spectrum, leading wireless stakeholders formed the MulteFire Alliance [9]. MulteFire LTE builds on elements of LTE LAA and combines the high performance of LTE with the simple deployment of Wi-Fi. Thus, MulteFire LTE can be deployed by cable companies, Internet Service Providers (ISPs), operators, building owners and enterprises.

In [10], we observed that the LTE LAA standard defines that a CCA procedure must be performed before any transmission in the unlicensed spectrum; this is being done according to four channel access priority classes. Each of these classes defines among others the transmission duration in the unlicensed channel after it has been accessed as idle. This duration varies from 2 ms up to 10 ms. This behavior can cause unfair coexistence with a typical Wi-Fi transmission that lasts for a few hundreds of μs when frame aggregation is not enabled or supported by the 802.11 standard [11]. Based on this observation and in order to enable harmonious and fair coexistence between LTE and Wi-Fi, we proposed a novel coexistence mechanism named mLTE-U. mLTE-U builds on elements of LTE Release 13 and requires an LBT procedure before a transmission in unlicensed spectrum. mLTE-U is an adaptive LTE transmission scheme according to which LTE can transmit in the unlicensed spectrum for a variable TXOP period, after the medium has been assessed as idle. The TXOP is followed by a variable muting period. This muting period can give channel access opportunities to other co-located networks such as Wi-Fi. The selection of the appropriate combinations of TXOPs and muting periods must be done in a way that the co-located networks share the medium in a fair manner. In [12], we further extended our previous work by introducing a Q-learning procedure that is able to provide automatic and autonomous selection of the appropriate TXOP and muting period combinations that can enable fair coexistence between the co-located networks.

However, the wireless environment by its nature is non-deterministic as it changes dynamically and continuously. The users of the networks change frequently, new networks may be deployed and operating networks may always be abolished. Additionally, the amount of data each wireless node has to transmit and the load on the network varies. It becomes clear that a technique that aims to provide fair coexistence to different wireless technologies in unlicensed spectrum must take into consideration potential changes to the wireless environment. Towards this direction, this article introduces a Convolutional Neural Network (CNN) [13] that can be used to enable the transmission identification of co-located LTE and Wi-Fi networks. The trained CNN can be used to identify in real-time LTE and Wi-Fi transmissions. Additionally, it can identify hidden terminal effect that is caused by multiple LTE transmissions, multiple Wi-Fi transmissions and concurrent LTE and Wi-Fi transmissions. The designed CNN has been trained and validated for the following two wireless signal representations: In-phase and Quadrature (I/Q) samples and frequency domain representation through Fast Fourier Transform (FFT). The classification accuracy is tested for variable Signal to Noise Ratio (SNR) values. For the purposes of this study, Commercial Off-The-Shelf (COTS) LTE and Wi-Fi hardware equipment has been used. The transmission identification can be exploited in order to compute the channel access occupancy of each technology and select the appropriate mLTE-U configurations that offer fair coexistence in the unlicensed spectrum.

The main contribution of this work is summarized as follows:

- A CNN has been designed and trained to be able to identify LTE and Wi-Fi transmissions.

- Interfering LTE and Wi-Fi transmissions, as the result of a hidden terminal, can be identified. These interfering transmissions include concurrent LTE transmissions, concurrent Wi-Fi transmissions and simultaneous LTE and Wi-Fi transmissions.
- For the training and validation of the CNN, COTS hardware and open-source software have been used. The designed CNN has been trained and validated using two wireless signal representations: I/Q samples and frequency domain representation through FFT.
- The classification accuracy of the trained CNNs is tested for various SNR values.
- The real-time classification capability of the trained CNN is analyzed.
- The extracted information by the CNN is exploited by mLTE-U scheme to enhance the coexistence between LTE and Wi-Fi in unlicensed spectrum.

The remainder of the article is organized as follows. Section II gives an overview of the current literature on the coexistence of LTE and Wi-Fi. Additionally, it presents several use-cases of deep learning on wireless networks. In Section III, we give a brief introduction to CNN, their constituent elements and the relevant terminology. Then, Section IV describes the hardware and software equipment that has been used to train and validate the designed CNN, as well as the CNN implementation details. Section V presents the structure of the CNN network and the performance metrics that have been used in the context of this article. Furthermore, the section evaluates the performance of the designed CNN for each signal representation and discusses the obtained experimentation results. In Section VI, we discuss the capability of the trained CNN to perform identification of the co-located networks in real-time. Section VII presents how the CNN can be exploited by mLTE-U scheme in order to enhance the coexistence between co-located LTE and Wi-Fi networks. Finally, Section VIII concludes the article and discusses plans for future work.

II. RELATED WORK

A. LTE and Wi-Fi COEXISTENCE

When the idea of LTE operating in unlicensed spectrum was initially introduced, there were serious concerns about unfair coexistence between LTE and other well-established technologies in unlicensed spectrum, such as Wi-Fi. These concerns lie in the fact that LTE has been designed to be a scheduled technology operating in a licensed band, meaning that it does not estimate the availability of the wireless channel before a transmission. As a result, arbitrary transmissions could force the networks in its proximity to continuously backoff. In [14], we investigated the impact of a traditional LTE network operating in unlicensed spectrum on Wi-Fi. For the purposes of this study COTS hardware has been used at the LTE testbed of IMEC [15]. The study examines three different levels of LTE signal power, each one representing different possible levels of LTE impact on Wi-Fi. The results show that the performance of Wi-Fi can be significantly affected by LTE. This has been verified by several other studies [16]–[18] that evaluate the impact of LTE on Wi-Fi through experiments, mathematical analysis and simulations. The results make clear that coexistence mechanisms are required in order to enable fair and harmonious spectral sharing between LTE and other co-located technologies such as Wi-Fi.

Over the last years, several coexistence mechanisms have been proposed, aiming to enable the desired coexistence between LTE and Wi-Fi. A detailed survey of the coexistence between LTE and Wi-Fi on 5 GHz together with the corresponding deployment scenarios is given in [19]. The survey describes in detail the coexistence-related features of LTE and Wi-Fi, the coexistence challenges, the differences in performance between the two wireless technologies and co-channel interference. The authors present in detail the coexistence techniques that have been proposed in the literature and they analyze the concept of scenario oriented coexistence. According to this concept, coexistence related problems can be solved based on different deployment scenarios.

In [20], the LTE operation in unlicensed spectrum has been extensively studied. The article provides a detailed analysis of the current state-of-the-art of LTE and Wi-Fi coexistence. Additionally, it introduces a classification of techniques that can be applied between co-located LTE and Wi-Fi networks. The study of the literature together with the classification revealed the lack of cooperation schemes between LTE and Wi-Fi that can lead to more optimal use of the wireless resources. In order to fill this gap, we proposed several concepts of cooperation techniques that can enhance the spectral efficiency of co-located LTE and Wi-Fi networks. The proposed methods are compared between each other in terms of complexity and performance.

Similar to the CSAT mechanism as described in Section I, Almeida *et al.* [21] describe a coexistence mechanism that exploits periodically blank subframes during an LTE frame. These frames can be used by Wi-Fi to gain access to the medium. Simulation results show that the number and the order of the black subframes have an impact on the performance of the provided coexistence.

A coexistence scheme in order to be applicable globally must incorporate, among others, a channel estimation mechanism that will be used to ensure the availability of the wireless medium before a transmission. Following this approach and as it has been described in Section I, 3GPP announced the LTE LAA as part of Release 13 [7]. According to the LTE LAA standard, a CCA procedure must be performed before every transmission in the unlicensed spectrum.

The concept of a channel estimation procedure by LTE as a coexistence enabler mechanism has been proposed in several works. Kim *et al.* [22] propose an LBT scheme for LTE that comprises of two parts, named on-off adaptation for channel occupancy time and short-long adaptation for idle time. According to the first part, the LTE occupancy time is adapted based on the load of the network. Concerning the second part, the idle period is adapted based on the Contention Window (CW) duration of Wi-Fi. Hao *et al.* [23] propose an LBT Category 4 (Cat 4) channel access scheme for LTE. The proposed LBT scheme uses an adaptive CW size for LTE LAA. The simulation results show that it can achieve higher performance compared to the fixed CW size approach.

B. DEEP LEARNING FOR WIRELESS NETWORKS

Over the last years, deep learning has been widely used in the domains of computer vision (image recognition and image classification) [24] and language processing (speech recognition and translation) [25], [26]. Importantly, the performance of the deep learning algorithms in these applications has become remarkable, reaching or even surpassing human levels of accuracy [27]. Inspired by that, wireless communication engineers have started adopting neural networks in order to enhance applications in wireless networks such as channel prediction, decoding, quantization, modulation recognition, technology recognition and more [28].

The work presented in [29] was one of the first approaches in this domain. The authors propose a CNN trained based on I/Q data for radio modulation classification. The proposed solution is compared with traditional methods based on expert features such as cyclic-moment based features and conventional classifiers, such as Decision Tree, K=1-Nearest Neighbor, Gaussian Naive Bayes, Support Vector Machines (SVM) as well as a deep neural network consisting only of fully connected (FC) layers. They show how the proposed solution outperforms the traditional methods especially at low SNR.

Zhang *et al.* [30] propose a CNN system that is able to identify eight different kinds of signals. They describe the appropriate architecture that renders the CNN classifier effective for the proposed system. Choi-Williams time-frequency distribution (CWD) transformation is used in order to obtain the image features into the CNN. Simulations are used to measure the identification performance of the proposed framework. The simulations results show that the overall ratio of successful recognition (RSR) is 93.7% when the SNR is higher or equal to -2 *dB*.

Kulin *et al.* [31] present a framework for end-to-end learning from spectrum data, which is a deep learning based unified approach that enables various wireless signal identification tasks. The article gives a brief overview of machine learning, deep learning and CNNs and proposes a reference model for their application for spectrum monitoring. The authors discuss the importance of the choice of wireless data representation that can have a big impact on the classification performance. The presented methodology was validated on two wireless signal identification research problems named modulation recognition and wireless interference identification. For each of the two research problems, three wireless signal representations were examined. Hence, six different CNNs were trained using massive and complex datasets. The results show the importance of choosing both the correct data representation and the machine learning approach.

The article in [32] discusses several applications of deep learning for the physical layer. Most importantly, the authors interpret a communication system as an autoencoder and introduce an end-to-end reconstruction optimization task that targets to jointly optimize the transmitter and the receiver side in a single process. Next, they extend the idea to multiple transmitters and receivers and describe the concept of radio transformer networks (RTNs) on raw I/Q samples for modulation classifications. The article concludes by discussing the open research challenges in the domain of deep learning and machine learning for wireless communications.

Jeon *et al.* [33] inspired by supervised learning present two novel blind data symbol detection techniques for Multiple-Input Multiple-Output (MIMO) systems with low-resolution Analog-to-Digital converters (ADCs). In contrast to traditional MIMO detection techniques that require explicit channel state information at a receiver (CSIR), the proposed techniques learn a nonlinear function that characterizes the input-output relation of the system together with the effects of the channel matrix and the quantization at the ADCs. The authors also provide an analytical expression for the symbol-vector-error probability of the MIMO systems with one-bit ADCs when employing the proposed framework. Simulation results show that the proposed approach improves the symbol-error-rates (SERs) and is effective to use with ADCs with arbitrary number of precision levels.

Schmidt *et al.* [34] propose a method for interference identification between different wireless technologies in 2.4 *GHz* industrial, scientific and medical (ISM) bands using CNN trained on frequency domain. The proposed CNN can identify transmissions of IEEE 802.11 b/g, IEEE 802.15.4 and IEEE 802.15.1 with overlapping frequency channels. The trained CNN can distinguish between 15 classes that represent the allocated frequency channel and the wireless technology. The experimentation results show that the proposed CNN outperforms proposed classifiers and can achieve a high classification accuracy that is greater than 95% for SNR values of at least -5 *dB*.

C. ENHANCING THE COEXISTENCE OF LTE AND Wi-Fi BY USING CNN

As it has been mentioned in Section I, in our previous work we have proposed an adaptive LTE scheme named mLTE-U that can enable fair coexistence between LTE and Wi-Fi in a flexible way [10]. mLTE-U can offer balanced spectrum access even when Wi-Fi does not support or use frame aggregation. mLTE-U builds on elements of LTE LAA. Hence, the eNB uses an anchor channel in licensed band together with a secondary channel in unlicensed spectrum wherein it can transmit DL traffic. After the eNB estimates the channel in unlicensed spectrum as idle, it transmits for a variable TXOP followed by an adaptable muting period. This muting period can be exploited by other co-located networks, such as Wi-Fi to gain access to the medium. It becomes clear that the performance of the provided coexistence depends on the selection of TXOP and muting period duration. In [12],

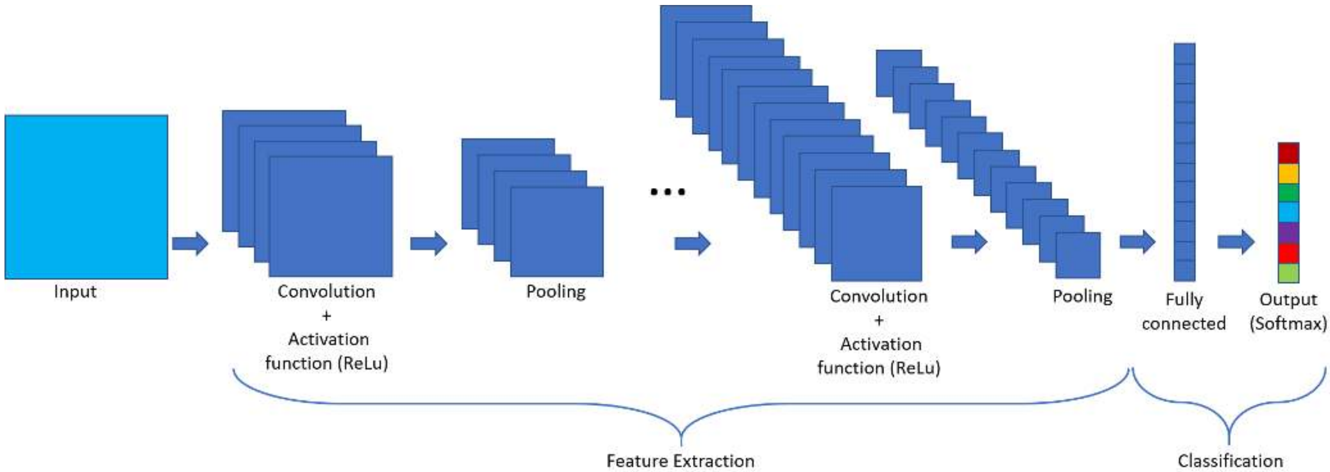

FIGURE 1. Structure of a CNN network. The input is processed by a series of convolutional layers, activated functions and pooling layers, ending up to a FC layer and a softmax classifier that gives the probability of the input belonging to each class.

we further extended this work by introducing a Q-learning technique that enables autonomous selection of the optimal TXOP and muting period. In order to do so, the Q-learning scheme learns the TXOP and muting period combinations that allow LTE to achieve a targeted fair throughput.

In [10] and [12], we assumed that the information of the wireless environment is known. This article goes a step further and with the assistance of deep learning and more specifically using CCN, it attempts to identify the type of the co-located networks. The CNN is trained and validated using COTS hardware for both the LTE and Wi-Fi networks. The learned information can be exploited by mLTE-U in order to select the appropriate TXOP and muting period.

III. CNN IN A NUTSHELL

During the last years, CNNs have been widely used by applications to perform image recognition and image classification. A CNN takes as input an image, it processes and classifies it into certain categories (e.g. dog, cat, horse, etc.).

In computer language, an image is translated as an array of pixel values. The dimensions of the array depend on the resolution of the image. For instance an array of $1920 \times 1080 \times 3$ corresponds to an image with *Width* of 1920 pixels and *Height* of 1080 pixels, while the *Depth* of 3 refers to the RGB values (the color of the pixel).

CNNs are inspired by biology and more specifically by neuroscience. When an eye looks at an object, individual neuronal cells are fired in the presence of curves and edges of specific orientation. Similarly to this, a computer identifies an object by investigating low level features (curves and edges) and by building up to more abstract concepts through consecutive convolution layers.

Figure 1 presents the typical structure of a CNN. As can be seen, the CNN takes an image as an input, it passes it through a series of hidden layers and gets an output that is the probability of the input belonging into a certain class. The hidden layers consist of a series of convolution, pooling and FC layers that aim to extract several abstract features.

Convolution layer is the first layer that is used to extract features from the input. This is being done by using a set of *filters* (also known as *kernels*) that perform a convolution over the input and are activated when a special feature is detected. These filters are small in terms of *Width* and *Height* compared to the original image but they extend through the full *Depth* of the input. During the convolution procedure, each filter is convolved across the *Width* and *Height* of its input and computes dot products between the values of the filter and the values of the input at every position. This procedure produces an *activation* or *feature map* that holds the responses of that filter at every position. The number of pixels that a filter shifts over the input matrix is given by the *stride*. For instance, when the *stride* equals to one, then the filter slides one pixel at a time, when the *stride* is two, then the filter slides two pixels at a time and so on and so forth. According to the filter size and the *stride*, it is possible that the filter does not fit totally in the input image. In that case the input is *padding* with zeros until the filter fits, or the part of the image where the filter does not fit is dropped. In the end, the output of every convolution layer is a set of *feature maps*, one for every filter that is convolved across the input of the layer. The filters of the first convolution layer detect low level features such as edges and curves of specific orientation. As we go deeper in the network, the output of a layer becomes the input of the next one. Hence, the consecutive convolution layers detect more complex and high level features. The convolution between a two-dimensional input x and a two-dimensional filter f can be computed as a discrete convolution and is expressed as:

$$\begin{aligned}(x * f)_{i,j} &= x[i,j] * f[i,j] \\ &= \sum_{m}\sum_{n} x[m,n]f[i-m][j-n] \qquad (1)\end{aligned}$$

where m and n correspond to the *Height* and *Width* of the filter respectively. After the convolution, a *bias* term (b) is added.

The convolution layer is followed by a *rectifier activation function* that introduces non-linearity to the CNN. Typically, Rectified Linear Unit (ReLU) function is used that is defined as:

$$h(x) = max(0, x) \tag{2}$$

There are other common non-linear activation functions such as the hyperbolic tangent function (tanh) and the sigmoid activation function that are defined respectively as:

$$h_{tanh}(x) = \frac{2}{1 + e^{-2x}} - 1 \tag{3}$$

and

$$h_{sigmoid}(x) = \frac{1}{1 + e^{-x}} \tag{4}$$

For the k-th neuron the output Y_k will be:

$$Y_k = h((x * f)_{i,j} + b_k) \tag{5}$$

where $x * f$ is the convolution between the input and the filter, b_k is the shared value for the bias and h is the activation function.

A stack of few convolution and ReLU layers is followed by a pooling layer. The pooling layers are responsible to downsample the spatial dimensions of their input. The spatial pooling reduces the dimensions of each map but retains the important information. The most common type is a pooling layer that uses filters of size 2×2 that are applied with a stride of 2, discarding this way the 75% of the activations, while the depth dimension remains unchanged. There are several types of spatial pooling such as *Max Pooling*, *Average Pooling* and *Sum Pooling*. Max Pooling selects the element with the highest value, the Average Pooling uses the average value of the elements and the Sum Pooling uses the summary value of the elements.

After a series of convolution, ReLU and pooling layers and towards the end of the CNN, we have the FC layer similar to a traditional neural network. The last feature map matrix is flattened into a vector and is fed into the *neurons* of the FC layer. These neurons have connections to all activations in the previous layer.

The last layer of the CNN is a *softmax classifier* that computes the probability of the input belonging to each class.

A common problem of the neural networks is overfitting, where after training, the weights of the network are very tuned to the training examples. As a result, the neural network does not perform well during the verification phase when new, untagged examples are used. In order to deal with this problem, *dropout* is used [35]. With this technique, a specific percentage of a random set of activations in a layer is set to zero. This way the network becomes more redundant and is able to give the right classification even if some of the activations are dropped out. This layer is used only during the training process and not during the verification process.

IV. EQUIPMENT AND EXPERIMENTATION SETUP

A. NETWORKING EQUIPMENT

For the purpose of this study, COTS LTE and Wi-Fi hardware equipment has been used in a fully controlled environment. The LTE network has been deployed and configured to operate in the unlicensed spectrum, next to a Wi-Fi network that is configured to operate in the same frequency channel. The experiments were performed at the LTE and Wi-Fi infrastructure of the W-iLab.t testbed of IMEC [15].

The radio part of the LTE network consists of software-defined radio (SDR) platforms and more specifically the Universal Software Radio Peripheral (USRPs) B210 boards [36]. This is a two-channel device that supports continuous radio frequency (RF) coverage that ranges from 70 *MHz* up to 6 *GHz*. This allows us to configure the operational frequency in the unlicensed spectrum (2.4 *GHz* or 5 *GHz*). The USRP boards are connected to Gigabyte BRIX Compact PCs [37] that are used as host nodes, on which the LTE software runs. The LTE software that has been used is the srsLTE [38] open-source software suite. srsLTE is a highly modular LTE software framework developed by SRS and includes complete SDR LTE applications for the eNB, the UE and the Evolved Packet Core (EPC) side. The srsLTE framework is LTE Release 8 compliant with selected features of Release 9. Frequency Division Duplex (FDD) mode has been selected, similar to what is being used in LTE LAA. In order to operate LTE in unlicensed spectrum, the srsLTE software was configured to use the same center frequency as Wi-Fi channel 6 at 2.437 *GHz* for the DL. The bandwidth has been set to 10 *MHz* that is one of the most usable bandwidth configurations of LTE network deployments.

The Wi-Fi network consists of Zotac nodes [15] configured in infrastructure mode. One node operates as Access Point (AP) and it can have multiple associated stations. All the Wi-Fi nodes use a Qualcomm Atheros AR928X wireless network adapter together with the ath9k driver [39]. The Wi-Fi network has been set to operate in channel 6 of the 2.4 *GHz* band, overlapping this way with LTE. Additionally, it has been configured to use the 802.11g mode. This mode has been selected as it does not support frame aggregation and MIMO and it provides relatively low data rate compared to the newest Wi-Fi standards (e.g. 802.11n/ac). Being able to identify 802.11g transmissions would permit our model to identify also standards that support higher data rates, MIMO and carrier aggregation. This way, the proposed model can be used for identification of a wide range of Wi-Fi standards.

Targeting a clean and controlled environment without any interference from other co-located networks, both the LTE and the Wi-Fi equipment were interconnected with each other using COAX cables through combiner and splitter units. Furthermore, remotely programmable attenuators have been used in order to control the power of each signal and create different coexistence scenarios (e.g. hidden terminal scenario). In order to train and verify the CNN network I/Q samples are collected from a USRP device that is interposed between the transmitting devices. The USRP has been

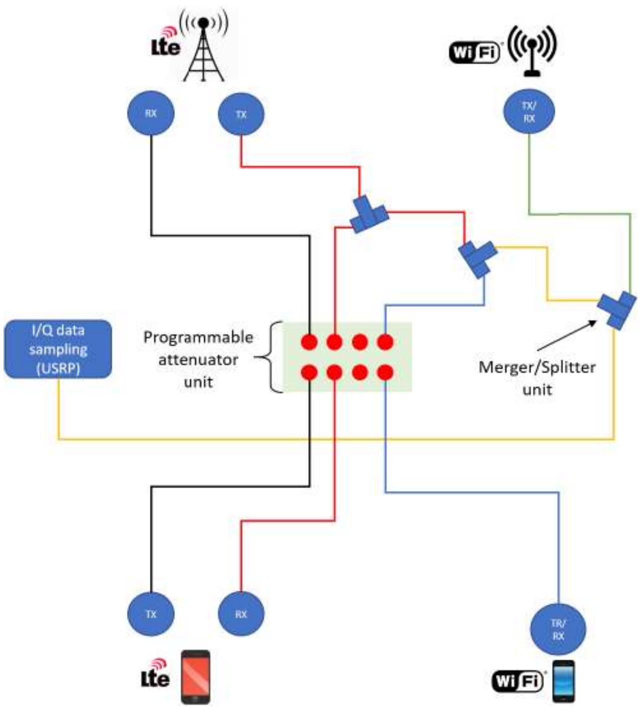

FIGURE 2. Indicative coexistence scenario between LTE and Wi-Fi. Each network consists of one end-devices connected to one base station.

configured to use the same center frequency as LTE and Wi-Fi (2.437 GHz) and bandwidth of 20 MHz.

Figure 2 illustrates an indicative coexistence scenario of an LTE network consisting of one eNB and one UE operating next to a Wi-Fi network consisting of one AP and one station.

B. CNN IMPLEMENTATION DETAILS

The CNN network that have been used in this work has been trained and validated using the Keras software library [40]. Keras is a high-level API for neural networks written in Python. This API is able to run on top of several deep learning frameworks such as TensorFlow [41], Theano [42] and CNTK [43]. It is designed to run seamlessly on top of both Central Processing Unit (CPU) and Graphics Processing Unit (GPU). In our setup, we have used a NVIDIA GTX 1080 Ti GPU that incorporates 3584 NVIDIA Cuda cores.

In order to train and validate our CNN, 125, 000 examples, each one consisting of 4000 I/Q samples, have been collected over the air and have been labeled properly with the corresponding wireless technologies. The collected samples have been post-processed by including noise of different SNR values. This can be considered as a way of applying data augmentation techniques to I/Q samples. The SNR values range from 0 dB to +45 dB with a step of 5 dB. As a result, the original data set size has been increased by a factor of 10. From the new data set, 70% randomly selected examples are used for training in batch sizes of 64. The rest 30% are used for validation of the model.

Additionally, the Adaptive moment estimation (Adam) optimizer [44] has been selected to estimate the parameters of the CNN. The learning rate of the algorithm has been chosen to be the default value $\alpha = 0.001$ in order to ensure convergence. The CNN has been trained for 200 epochs. However, an early stop of the training can be triggered when the accuracy of the network is not improved for 20 consecutive epochs.

In total, two CNNs have been trained. The one has been trained by using I/Q samples and the other by using their FFT representation in the frequency domain.

According to the selected data representation, the respective CNN network takes as input either I/Q samples or their FFT representation in frequency domain and gives as output the identified class where the input belongs to. Such identification can be single LTE transmission, single Wi-Fi transmission, concurrent LTE and Wi-Fi transmissions, concurrent LTE transmissions and concurrent Wi-Fi transmissions.

V. EXPERIMENTAL EVALUATION

A. CNN STRUCTURE

The CNN structure that has been used in this study is illustrated in Figure 3. The input of the network, also known as the visible layer, has a size of 2×2000 and it corresponds to either I/Q samples or the FFT of them. The I/Q samples are collected from a USRP device that is interposed between all the transmitted devices, as indicatively is shown in Figure 2.

The feature extraction part of the network consists of two hidden convolutional layers. These layers are used to extract high-level features from the input representation of the wireless signal. The first convolutional layer (convolutional layer-1) consists of 64 stacked filters, each one having dimensions 2×3 that convolve with the input. As a result, 64 feature maps are created with dimensions 5×2002. The second convolutional layer (convolutional layer-2) consists of 32 stacked filters of size 1×3. These filters perform a convolution with the input of the layer, creating 32 feature maps with dimensions 6×1003. For both convolutional layers, a zero padding of size 2 is applied to their input and a stride of 1 is used while convolving the filters.

Each convolutional layer is followed by a ReLu activation function. The distribution of the inputs for each layer can change during training, as the parameters of the previous layers change. To overcome this issue, a batch normalization [45] is applied after every ReLu function. Hence, the activations are properly adjusted and scaled, while the training rate increases. To reduce overfitting, each layer uses regularization with Dropout of 0.35 together with the L2 kernel regularizer. The L2 regularizer aims to penalize weights with large magnitudes A pooling layer follows each convolutional layer, performing *Max Pooling*.

After the feature extraction part, the classification part follows and consists of two FC layers. First the input to the classification part is flattened and a FC layer is added (FC layer-1). This layer consists of 100 neurons. It uses a ReLu activation function, batch normalization, dropout of 0.5. and L2 kernel regularizer. The output of this layer is fed

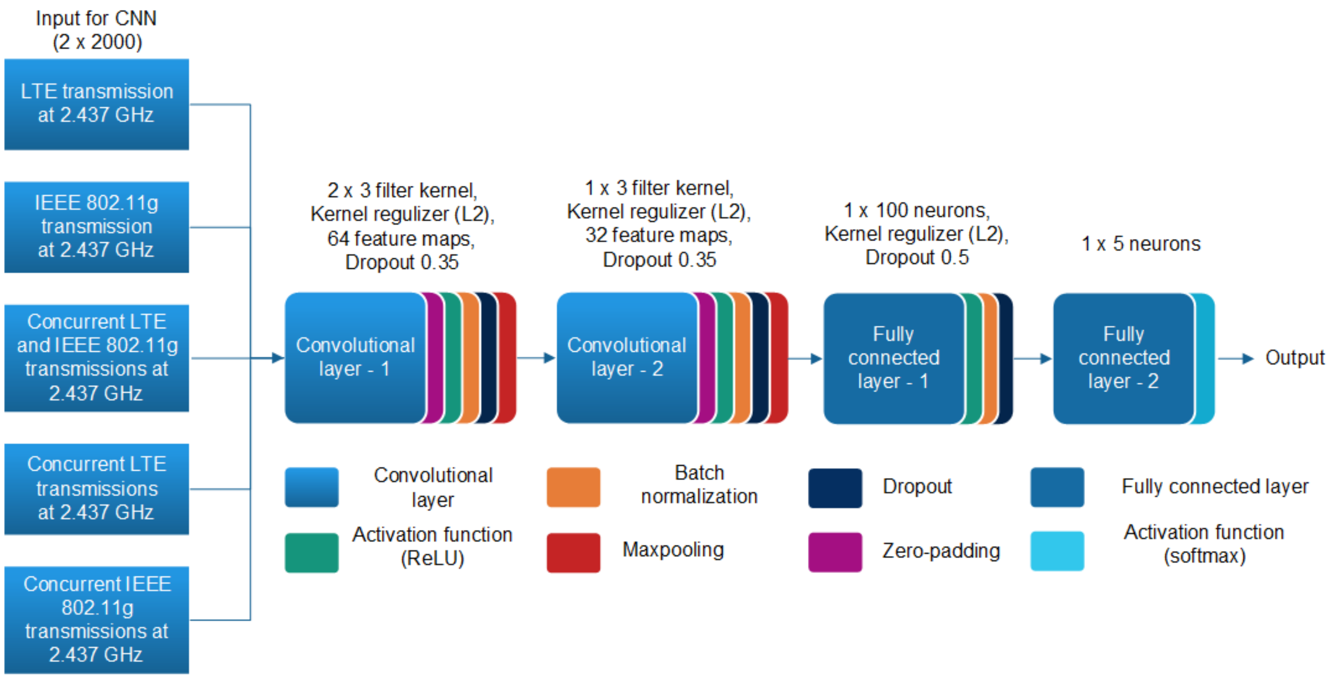

FIGURE 3. **Structure of the proposed CNN network.**

to a softmax classifier (FC layer-2) in order to estimate the probability of the input belonging to each class.

B. CLASSIFICATION ACCURACY

In order to evaluate the performance of the designed CNN that identifies the co-located LTE and Wi-Fi wireless technologies, it is necessary to compute the classification accuracy of the CNN. The classification accuracy corresponds to the fraction of predictions that the CNN identified correctly and it is defined as:

$$Class\_acc = \frac{N_{correct}}{Tot_{predictions}} \tag{6}$$

where $N_{correct}$ is the number of samples that have been classified correctly, while $Tot_{predictions}$ is the total number of predictions.

For the computation of the $N_{correct}$ and $Tot_{predictions}$, intermediate statistics of positive and negative predictions are required. These statistics correspond to:

- *True Positive (TP)* meaning that a wireless signal has been identified as belonging to a specific class and according to its label, it correctly belongs to that class.
- *True Negative (TN)* meaning that a wireless signal has not been identified as part of a specific class and according to its label, it does not belong to that class.
- *False Positive (FP)* meaning that a wireless signal has been identified as being part of a specific class, but according to its label, it does not belong to that class.
- *False Negative (FN)* meaning that a wireless signal has not been identified as belonging to a specific class, but according to its label, it does belong to that class.

Hence, function (6) can also be represented as:

$$Class\_acc = \frac{TP + TN}{TP + TN + FP + FN} \tag{7}$$

C. EXPERIMENTATION RESULTS

The CNN network that is described in Section V-A has been trained for two different data representations. The first representation corresponds to the collected over-the-air I/Q samples, while the second corresponds to their transformation in frequency-domain through FFT. In the rest of the section, we refer to the trained CNN using I/Q samples as $CNN_{I/Q}$ and to the trained CNN using FFT as CNN_{FFT}.

The training accuracy indicates the percentage according to which the CNN can correctly identify a signal during the training phase. The validation accuracy shows the percentage of correct signal identifications during the validation phase (after the training has been completed). On the other hand, the identification error during the training phase is referred as training loss, while the error during the validation phase is referred as validation loss. The validation and training accuracy in relation to the number of epochs for both the I/Q and the FFT cases is presented in Figure 4. Additionally, Figure 5 presents the validation and training loss in relation to the number of epochs for both CNNs. The training and the validation of the networks have been done using the entire data set, including the different SNR values. As can be seen, both CNNs converge after approximately 40 epochs.

It can be observed that the validation accuracy of the CNN_{FFT} is slightly higher than its training accuracy. This means that the CNN_{FFT} has been trained on worse data than

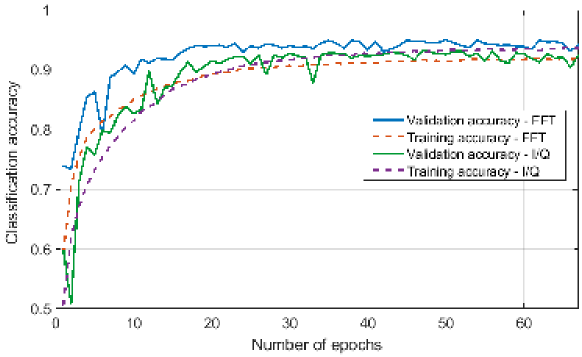

FIGURE 4. Validation and training accuracy in relation to the number of epochs for both I/Q and FFT data representations.

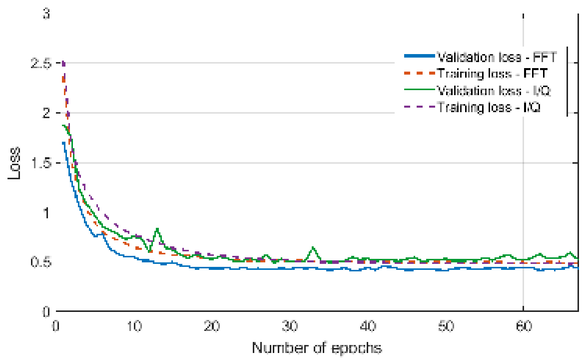

FIGURE 5. Validation and training loss in relation to the number of epochs for both I/Q and FFT data representations.

the ones that it identifies during the validation process. This may happen as the training data are randomly selected (70%) from the complete dataset. Additionally, the FFT representation has more information gaining features, as LTE and Wi-Fi have more distinguishable differences in the frequency domain. As a result, the dropout has bigger impact on the FFT than on the I/Q representation. The validation accuracy of CNN_{FFT} is higher than the validation accuracy of the $CNN_{I/Q}$. The same results were noticed in [31] and [34] where the authors have used both I/Q and FFT data representations for interference identification through CNN. Respectively, the validation loss of the CNN_{FFT} is slightly lower than the validation loss of the $CNN_{I/Q}$. It can be concluded that the CNN that has been trained based on FFT data representation performs better than the CNN that has been trained using I/Q samples. Consequently, the LTE and Wi-Fi signals can be identified easier in frequency domain. This can be explained by the significant differences that the two wireless technologies have in this domain. According to the Orthogonal Frequency-Division Multiple Access (OFDMA) digital modulation scheme that is used by LTE, the LTE scheduler is able to schedule simultaneously multiple users in the frequency domain. On the other hand, Wi-Fi is a packet-based technology using Orthogonal Frequency Division Multiplexing (OFDM) digital modulation scheme. Hence, it allocates all the subcarriers to a single user.

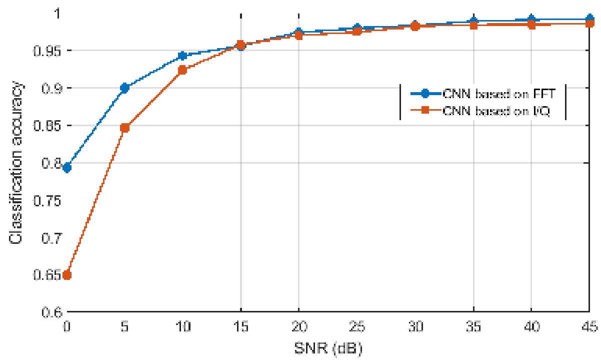

FIGURE 6. Classification accuracy for FFT and I/Q data representation in relation to SNR.

Figure 6 presents the classification accuracy of both CNN in relation to the SNR. As can be seen, the CNN_{FFT} outperforms the $CNN_{I/Q}$ especially in low SNR values. More precisely, for 0 dB of SNR, CNN_{FFT} offers an accuracy of approximately 80% compared to the accuracy of $CNN_{I/Q}$ that is 65%. For SNR values higher than 15 dB the classification accuracy of both networks is similar. Especially for SNR values higher than 40 dB, the classification accuracy of $CNN_{I/Q}$ and CNN_{FFT} approaches 98% and 99% respectively. Hence, for average to high SNR values, I/Q samples offer high accuracy with lower complexity compared to the FFT case, as the identification can be done based on I/Q samples, without required the extra step of the FFT.

Figure 7 shows the confusion matrices for both CNNs with regard to different SNR scenarios. More specifically, Figure 7a and Figure 7d show the respective confusion matrices of $CNN_{I/Q}$ and CNN_{FFT} for all the SNR values. It can be observed that the CNN_{FFT} can identify the different transmitting networks slightly more accurate than the $CNN_{I/Q}$. Both CNNs identify less accurately single IEEE 802.11 and multiple LTE transmissions, while both of them achieve the highest classification accuracy by identifying single LTE transmissions.

Figure 7b and Figure 7e present the confusion matrices of $CNN_{I/Q}$ and CNN_{FFT} respectively for the lowest SNR value that corresponds to 0 dB. Here, it can be observed the superiority of FFT representation compared to I/Q. $CNN_{I/Q}$ classifies best single LTE transmissions, while it struggles to identify the other classes. More precisely, 35% of concurrent LTE and IEEE 802.11g transmissions, 31% of multiple LTE transmissions and 29% of IEEE 802.11g transmissions are identified as multiple IEEE 802.11g transmissions. On the contrary, CNN_{FFT} is much more accurate identifying best simultaneous LTE and IEEE 802.11g transmissions. Additionally, it lacks to identify 46% of single IEEE 802.11g transmissions that for 34%, they are identified as multiple IEEE 802.11g transmissions.

Finally, Figure 7c and Figure 7f illustrate the corresponding confusion matrices for the highest SNR value of 45 dB. In this case, both networks are able to identify with excellent accuracy the different wireless transmissions. Again, the CNN_{FFT} is slightly better than the $CNN_{I/Q}$.

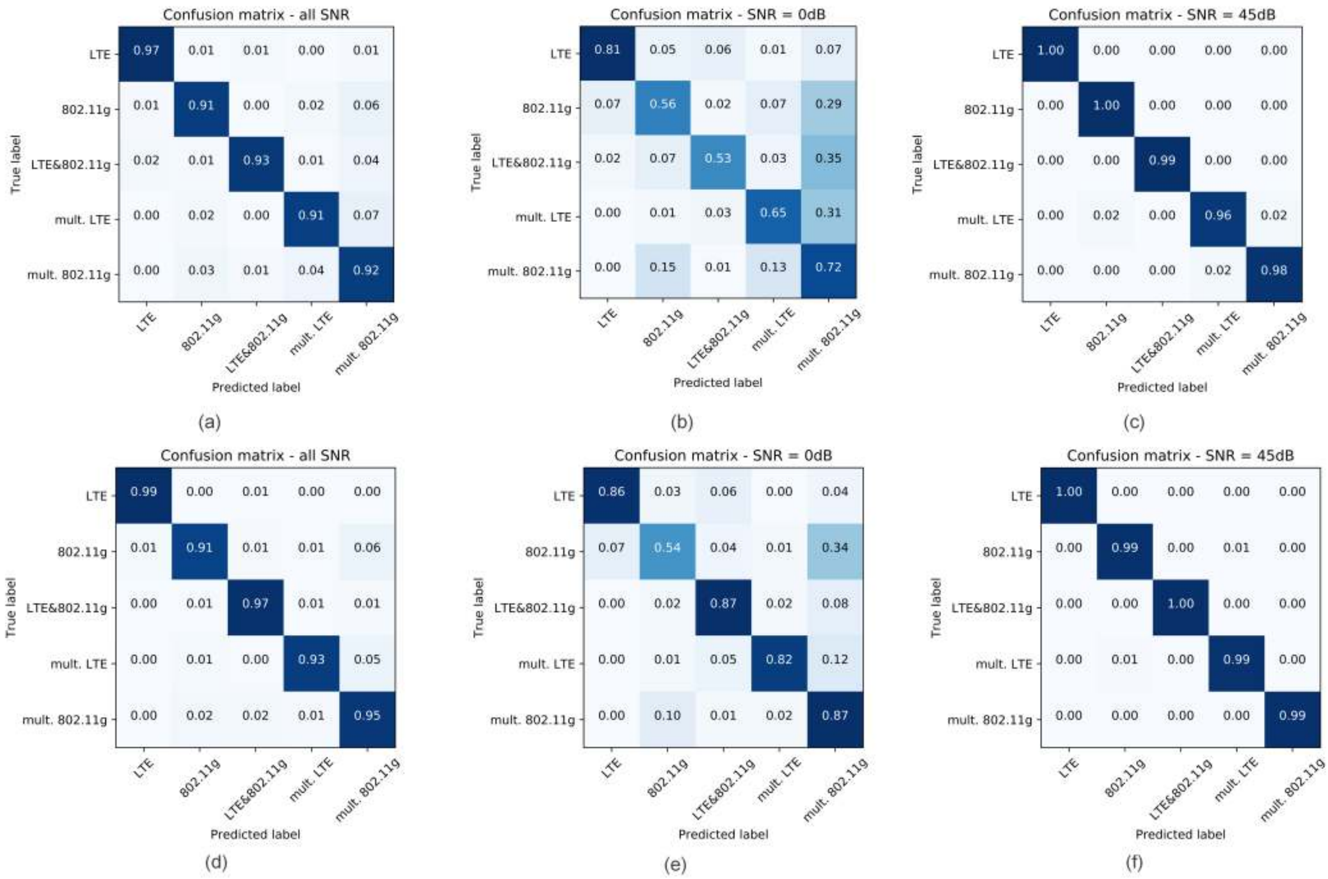

FIGURE 7. **Confusion matrices for both I/Q and FFT data representations and for different SNR values: a) $CNN_{I/Q}$ for all SNR values, b) $CNN_{I/Q}$ for SNR of 0 *dB*, c) $CNN_{I/Q}$ for SNR of 45 *dB*, d) CNN_{FFT} for all SNR values, e) CNN_{FFT} for SNR of 0 *dB*, f) CNN_{FFT} for SNR of 45 *dB*.**

The experimentation results have shown that the performance of the CNN depends on the data representation that is used to train the network. Hence, it is important to investigate different data representations in order to have enhanced accuracy for a specific task. Furthermore, the classification accuracy can be improved by tuning the hyper-parameters of the CNN. The hyper-parameters are the variables that define the structure of the network (e.g. number of convolutional layers) and variables that determine the training of the network (e.g. the learning rate). Finally, an advanced training that uses a rich dataset can further increase the performance of the CNN.

VI. REAL-TIME PERFORMANCE

When the designed CNN has been trained, it is able to perform identification of co-located technologies in real-time. In order to achieve this, the processing time which includes a) the capturing and transformation of I/Q samples and b) decision-making time by the trained model, must be smaller than the smallest transmission duration of the technologies that the system can identify. The transmission duration depends on the transmission time resolution of the technologies under consideration. For instance, LTE transmissions are slot-based, while Wi-Fi transmissions are frame-based. This way, it is guaranteed that the CNN will not miss potential transmissions due to restrictions in time (e.g. low sampling rate).

As it has been discussed in Section V-A, the CNN network is trained to identify LTE and IEEE 802.11g transmissions. The identification of a technology is being done based on 2000 I/Q samples that are collected by using a sampling frequency of 20 MHz. This means that 100μs sampling time is required before the classification for the collection of the 2000 I/Q samples. LTE is a scheduled technology that transmits in resource block base. One resource block occupies 12 subcarriers (180 *kHz*) in the frequency domain and 1 slot (0.5 *ms*) in the time domain. Hence, the LTE transmission time resolution is 0.5 *ms*. However, Wi-Fi may transmit in much lower time resolution, based on the used data rate. The IEEE 802.11g data-rate ranges from 1 *Mbps* up to 54 *Mbps* (the specified minimum data rate for 802.11g is 6 *Mbps*, in practice a 802.11g radio may use a minimum rate of 1 *Mbps* for the sake of backward compatibility with older clients). The data rate depends on the modulation type (e.g. QPSK, 64-QAM, etc.) and the coding rate (e.g. 1/2, 3/4, etc.) that is also known as Modulation and Coding Scheme (MCS). As a result, the higher the data rate the shorter the data transmission time. For the highest possible data rate of 54 *Mbps*, the required time for data transmission is 282μs and the required time for the transmission of the acknowledgement is 44μs. Thus, in total an IEEE 802.11g frame transmission time together with the acknowledgement require a minimum time of 326μs. It is clear that the sampling time resolution is smaller than the Wi-Fi transmission duration. The transformation of I/Q samples step is required to make them compatible with the CNN model. Both the transformation time and decision-making time of the collected samples can be considered to have negligible impact on the required classification time. The trained CNN can be seen as a function that maps the input (collected samples) to the output (corresponding class). Therefore, the proposed CNN is able to perform identification of co-located LTE and Wi-Fi networks in real-time.

It is important to note that the sampling time resolution of 100μs allows us to feed multiple sampling bunches to the CNN in order to enhance even more the classification accuracy. Hence, if for instance the number of collected samples is doubled (4000 I/Q samples) then, the sampling time will be doubled, without however surpassing the required transmission time of Wi-Fi.

VII. ENHANCEMENT OF mLTE-U SCHEME WITH CNN

As we mentioned in Section II-C, the designed CNN that has been trained to identify transmissions from co-located LTE and Wi-Fi networks, can be exploited by the proposed mLTE-U scheme in order to enhance the coexistence between the two wireless technologies. According to the mLTE-U scheme, LTE can transmit in the unlicensed spectrum for an adaptive TXOP that is followed by an adaptive muting period. During this muting period, other co-located networks (e.g. mLTE-U or Wi-Fi) can gain access to the wireless resources in order to transmit. Hence, every eNB that operates in unlicensed spectrum and deploys the mLTE-U scheme can use the trained CNN in order to identify the channel occupancy of each technology and adjust the mLTE-U parameters, aiming to enable fair coexistence.

Initially, when Wi-Fi transmissions are identified by the CCN, an eNB selects the TXOP and muting period configurations. Altruistically, the TXOP may be the shortest possible (e.g. 2 *ms*), while the muting period may be the longest possible (e.g. 20 *ms*). Subsequently, it should periodically monitor the potential LTE and Wi-Fi transmissions as reported by the CNN in order to adjust the mLTE-U parameters and to maintain a balanced access to the wireless resources for the two technologies.

Figure 8 demonstrates the exploitation of the CNN's output by mLTE-U in order to enhance the coexistence between LTE and Wi-Fi. The coexistence scenario is similar to the one illustrated in Figure 2, where one LTE network consisting of one eNB and one UE coexists with one Wi-Fi network consisting of one AP and one station. Both networks transmit only DL traffic in unlicensed spectrum and both networks aim to transmit as much as possible. For the purposes of this study, iperf tool [46] has been used to generate UDP traffic and measure the achieved throughput for both LTE and Wi-Fi.

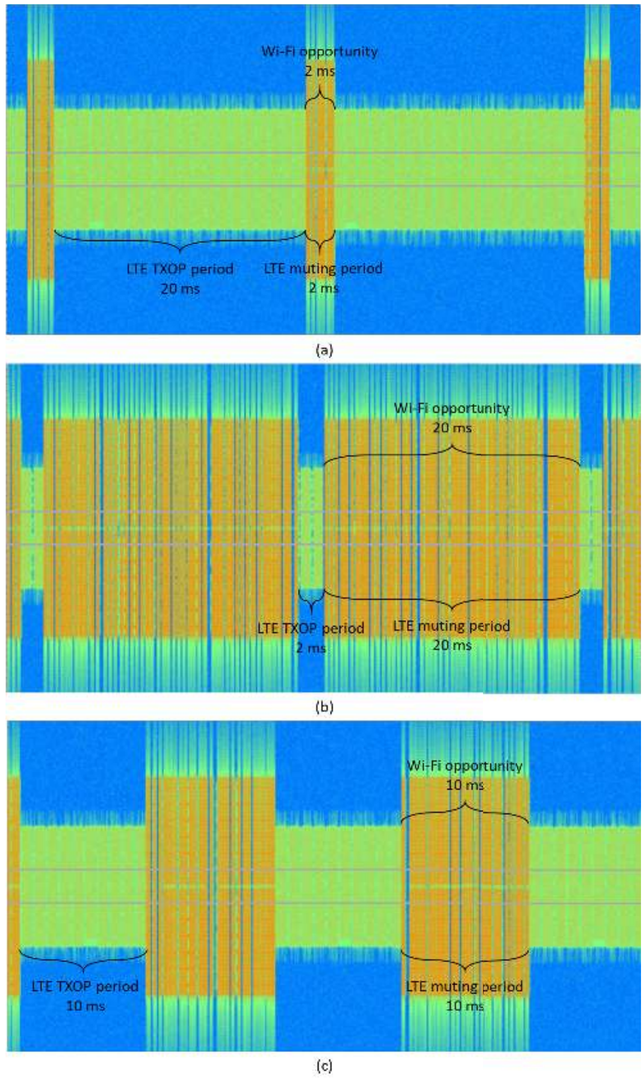

FIGURE 8. Enhancement of mLTE-U scheme with CNN. a) Spectrogram showing the unfair coexistence between LTE and Wi-Fi before the activation of the CNN. b) Spectrogram showing how LTE initializes the mLTE-U parameters after the trained CNN is activated. c) Spectrogram showing the fair coexistence between mLTE-U and Wi-Fi after the configuration of the mLTE-U scheme based on the CNN reports.

The respective standalone DL throughput of LTE and Wi-Fi are $Thr^{mLTE-U}_{standalone} = 30.9\,Mbps$ and $Thr^{Wi-Fi}_{standalone} = 28.1\,Mbps$.

Wi-Fi is a packet-based technology that estimates the availability of the channel prior to every packet transmission. On the other hand, LTE is a scheduled technology that manages the assigned spectrum very efficiently. Hence, after it assesses the availability of the medium, it can transmit optimally during a TXOP. In [10], we saw that during the standalone operation, Wi-Fi occupies the channel for 70.10% of the time, meaning that Wi-Fi spends a high percentage of time sensing the medium. The corresponding LTE channel occupancy during a TXOP is optimal approaching 99.47%. In order to ensure fair access to the wireless resources when both networks are present, the CNN should ensure that the LTE channel occupancy is maintained close to 50%. If the

CNN wants to increase the LTE channel occupancy, then it may increase the TXOP or decrease the muting period. Accordingly, if the CNN wants to give more opportunities to Wi-Fi, it may decrease the TXOP or increase the muting period. This decision can be made based on the traffic that the eNB needs to transmit. For instance, if the eNB transmits delay-sensitive traffic and the LTE occupancy time may be increased, then the eNB can use a shorter muting period in order to decrease the transmission delay. Additionally, LTE can give periodically longer channel opportunity to Wi-Fi. The CNN can compute the new channel occupancy of Wi-Fi in order to estimate if Wi-Fi exploits it or not. Further analysis of the way that the TXOP and muting period can be adjusted is not in the scope of this article.

As shown in Figure 8a, before the activation of the CNN, mLTE-U is configured to use a long TXOP of 20 *ms* that is followed by a short muting period of 2 *ms*. As result, LTE can achieve a high throughput corresponding to $Thr_{DL}^{mLTE-U} = 26.9\ Mbps$. In contrast, Wi-Fi can transmit only during the short muting period achieving a low throughput that corresponds to $Thr_{DL}^{Wi-Fi} = 1.88\ Mbps$.

After CNN is activated, it can identify the LTE and Wi-Fi transmissions in the unlicensed spectrum. Then, the eNB adjusts the mLTE-U parameters so that the shortest TXOP is used, followed by the longest muting period, as it is shown in Figure 8b. According to the CNN report, the eNB can estimate the channel use of each technology. Hence, it can compute that LTE transmits for approximately 9.1% of the time, while Wi-Fi transmissions occur during the rest 90.9% of the time. This channel access division among the two networks corresponds to $Thr_{DL}^{mLTE-U} = 2.18\ Mbps$ and $Thr_{DL}^{Wi-Fi} = 23.9\ Mbps$.

Afterwards, the eNB will attempt to adjust the mLTE-U parameters based on the reports of the CNN targeting to achieve fair coexistence of the two technologies. Eventually, this can be achieved by selecting a TXOP of 10 *ms*, followed by a muting period of 10 *ms*, as it is demonstrated in Figure 8c. In this case, LTE occupies the channel of approximately 50% of the time. In this case, the DL throughput of the mLTE-U network is $Thr_{DL}^{mLTE-U} = 15.4\ Mbps$ and the DL throughput of the Wi-Fi network is $Thr_{DL}^{Wi-Fi} = 14\ Mbps$.

It becomes clear that CNN can be exploited by the mLTE-U system in order to enhance the coexistence of LTE and Wi-Fi in unlicensed spectrum. However, as we discussed in [10], several other parameters can be obtained by the wireless environment and can be used to provide fair spectrum sharing. Such parameters can be the number of the active nodes in the unlicensed spectrum and the load of each node. As active, we consider the nodes that have traffic to transmit. By knowing this information, the mLTE-U scheme can be configured so that every active node in the unlicensed spectrum gets spectrum access opportunities proportional to the load of traffic that it needs to transmit, taking into account the provisioning of fairness within the limited spectrum. Obtaining information about the number of co-located active nodes, as well as the load of each network is a very interesting and complicated research topic that will be considered in our future work.

VIII. CONCLUSIONS AND FUTURE WORK

Recently, the operation of LTE in unlicensed spectrum has been proposed as a method that can assist in dealing with the increasing wireless traffic. Towards a solution that can enable fair coexistence between LTE and other well-established wireless technologies in unlicensed spectrum, such as Wi-Fi, 3GPP announced the standard of LTE LAA. However, this mechanism may cause unbalanced coexistence between LTE and Wi-Fi when the latter does not support or use frame aggregation. In order to deal with this issue and enable fair coexistence, mLTE-U scheme has been proposed. In order to configure properly the mLTE-U scheme, information about the dynamically changing wireless environment is required. Among others, an essential and important information is the type of the co-located wireless technologies and their respective channel occupancy.

This article has exploited the use of CNN in order to identify transmissions from co-located LTE and Wi-Fi technologies in unlicensed spectrum. The CNN has been trained to identify in real-time LTE and Wi-Fi transmissions. Furthermore, the CNN can identify multiple LTE transmissions, multiple Wi-Fi transmissions and concurrent LTE and Wi-Fi transmissions that can be the result of hidden terminal effect. The designed CNN has been trained and validated using COTS LTE and Wi-Fi hardware equipment and for the following two wireless signals representations: I/Q samples and frequency domain representation through FFT. The classification accuracy of the trained CNNs has been tested for different SNR values. The experimentation results have shown that the performance of the CNN is impacted by the data representation that is used to train the network. More specifically, we saw that the FFT representation offers higher classification accuracy compared to I/Q samples, especially for low SNR values. On the other hand, for average to high SNR values, I/Q samples offer similar performance to FFT with lower complexity, as the identification can be done based on I/Q samples without requiring the additional step of the FFT. The obtained information can be used to compute the channel occupancy time of each wireless technology. Based on the channel occupancy time, the mLTE-U scheme can be configured properly in order to enhance the coexistence between co-located mLTE-U and Wi-Fi networks. For the purpose of this study and in order to train and verify the CNNs, COTS equipment has been used for both LTE and Wi-Fi network.

In the near future, several other parameters of the wireless environment, such as the active nodes and the load of traffic that each node needs to transmit will be investigated in order to enhance the fair coexistence in the unlicensed spectrum. Furthermore, this work can be extended by investigating the use of unsupervised learning for obtaining the necessary information. Unlike in supervised learning, labeled data input is not required. This makes unsupervised learning less complex to be implemented. As a result, the algorithm can act without human guidance making the proposed system fully autonomous.

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