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Spectrum sensing and modulation recognition using a novel CNN Deep Learning model and Learning transfer technique

Abstract. *The misuse of frequency bands leads to a spectrum shortage. The cognitive radio appears as a natural solution to this problem. A good exploitation of the frequency spectrum starts with a good detection through various techniques, each with its advantages and limitations. In this paper we worked on improving the accuracy of spectrum sensing by developing a new cnn model and the transfer learning of data, also we used the automatic modulation recognition technique to insure the previous knowledge of data witch helped in improving the quality of detection and the performance of the cnn model. our method is based on three aspects entitled aspect1, aspect2 and aspect3. In aspect1 we trained the model to preform the modulation recognition with 11 classes. In aspect2 the model was trained with tow classes an performed the spectrum sensing. In aspect 3 we used the pre-trained model from aspect1 to perform the spectrum sensing with data from aspect2.We trained the model with many types of signals from the dataset RadioML2016.10a as well as noise data that we generated. We also use transfer learning strategies to improve the performance of the sensing model. The results show that we were able to achieve maximum accuracy of 97.22% for the sensing and 99 % for the modulation classification as best accuracy which is very competitive and better than many other proposed techniques.*

Streszczenie. *Niewłaściwe wykorzystanie pasm częstotliwości prowadzi do niedoboru widma. Radio kognitywne jawi się jako naturalne rozwiązanie tego problemu. Dobra eksploatacja widma częstotliwości zaczyna się od dobrego wykrywania za pomocą różnych technik, z których każda ma swoje zalety i ograniczenia. W tym artykule pracowaliśmy nad poprawą dokładności detekcji widma poprzez opracowanie nowego modelu cnn i transferu uczenia się danych, a także wykorzystaliśmy technikę automatycznego rozpoznawania modulacji, aby upewnić się, że wcześniejsza wiedza o danych pomogła w poprawie jakości detekcji i wydajność modelu cnn. nasza metoda opiera się na trzech aspektach zatytułowanych aspekt1, aspekt2 i aspekt3. W aspekcie 1 wyszkoliliśmy model do wstępnego rozpoznawania modulacji z 11 klasami. W aspekcie 2 model został przeszkolony z klasami holowniczymi i wykonał wykrywanie widma. W aspekcie 3 wykorzystaliśmy wstępnie wytrenowany model z aspektu 1, aby przeprowadzić wykrywanie widma z danymi z aspektu 2. Wytrenowaliśmy model z wieloma typami sygnałów z zestawu danych RadioML2016.10a, a także wygenerowanymi przez nas danymi szumu. Używamy również strategii uczenia się transferu, aby poprawić wydajność modelu wykrywania. Wyniki pokazują, że byliśmy w stanie osiągnąć maksymalną dokładność 97,22% dla wykrywania i 99% dla klasyfikacji modulacji jako najlepszą dokładność, która jest bardzo konkurencyjna i lepsza niż wiele innych proponowanych technik. (**Wykrywanie widma i rozpoznawanie modulacji przy użyciu nowatorskiego modelu CNN Deep Learning i techniki transferu uczenia**)*

Keywords: Cognitive Radio, Deep Learning, Spectrum Sensing.
Słowa kluczowe: głębokie uczenie, radio kognitywne

Introduction

Due to the increasing demand for new wireless services and applications and the growing number of wireless users, available spectrum is becoming increasingly scarce [2][3]. As a conclusion, the design of new methods to ensure optimal management of radio frequency resources is a primary task for the Federal Communications Commission (FCC). Cogni tive radio (CR) is a smart radio that can be dynamically pro grammed and configured to fully utilize frequency resources that are not used by licensed users. It defines radio devices that can learn and adapt their transmission to the external ra dio environment, which means that it has some intelligence to monitor the radio environment, learn the environment and make intelligent decisions[1]. In order to solve the current spectrum management problem, new approach "dynamic ac cess radio spectrum" have been developed, where oppor tunistic access is the most widespread because it addresses the cause of the spectrum shortage. Indeed, this approach proposes a new category of users called secondary users (SUs) that can access the frequency resources allocated to primary users (PUs) when the latter are not using them[4]. Thus, the spectral efficiency is increased by allowing the transmission by the US on the frequency bands detected as free. These systems are called intelligent radio or opportunis tic radio because in addition to the autonomous detection of free bands, they must also be able to change their transmis sion parameters in order to meet, on the one hand the user's expectations, and on the other hand, to the constraints of fre quency availability and the available resource (band, signal to noise ratio (SNR)...)[5]. The concept of artificial intelligence (AI) is to make machines think "like humans". In other words, perform tasks such as reasoning, planning, learning, and un derstanding our language. The use of AI in CR is very useful, in fact, it is used in the implementation of the architecture of CR networks. These networks must be able to coexist to make the CR systems practical, which can generate interfer ence to other users[6]. In order to solve this problem, the idea of cooperation between users to detect and share spectrum without causing interference is implemented.As part of this work, we are interested to implement deep learning methods and algorithms for spectrum sensing and modulation classifi cation problem. In this work, we proposed and implemented a novel Convolutional Neural Network model for modulation classification and spectrum sensing, we examine the model with two types of inputs first one is the complex (I/Q) time domain, second one is the FFT of the signals, it's used to ob tain a real-valued classification feature matrix to feed the net work. we trained and tested the model using popula dataset.

Background

Cognitive radio allows the use of temporally unused spectrum, which is referred to as a spectrum hole or white space.Since most of the spectrum is already as signed, the most important challenge is to share the licensed spectrum[1].

0.1 Spectrum sensing

Spectrum sensing is the process used by a cognitive radio to identify available licensed and unlicensed spectrum chan nels in order to communicate wirelessly[7]. The availability of a channel in the licensed spectrum depends on the activity of the primary user who has priority over the licensed spec trum. A Primary User has the highest priority access to the spectrum. Thus, from the observation of the radio signal y(t) received on a band B, the RC terminal determines the sta tus of this band of interest. If the terminal detects only noise b(t) then the band is said to be free. Otherwise, there is a telecommunication signal x(t), the band is declared occu pied. In detection theory, this is a hypothesis test of the type [8]:

$$H0 : y(t) = b(t) H1 : y(t) = x(t) + b(t) \quad (1)$$

with y(t) the received signal, x(t) the transmitted signal which can be random, or deterministic, but its presence is totally unknown, and b(t) the noise which is supposed to be white Gaussian (unless otherwise specified) and of zero mean with a known or unknown variance.

0.2 AMR (Automatic Modulation Recognition)

Automatic modulation recognition (AMR) plays an important role in most intelligent communication systems, especially with the emergence of Software Defined Radio (SDR). Modu lation recognition approaches can be separated into two cat egories [10]: Likelihood Based and Feature Based. A typical AMR system consists of two subsystems: the feature extrac tion subsystem and the classification subsyste

0.3 Deep Learning

Deep learning (deep structured learning, hierarchical learn ing) is a set of machine learning methods that attempt to model data with a high level of abstraction due to articulated architectures of different non-linear transformations. Deep learning depends on a network of artificial neurons inspired by the human brain. This network is created from tens or even many ”layers” of neurons, every receiving and interpret ing info from the previous layer[11].

0.4 CNN (Convolutional neural network)

Convolutional neural networks (CNNs) are models that most frequently used for image processing and computer vision. They are created to mimic the structure of the animal visual cortex. These kind of networks use a special arithmetic op eration known as convolution:

$$z(t) = x(t) * y(t) = \int_{-\infty}^{\infty} x(\tau) y(t-\tau) d\tau \quad (2)$$

Specifically, CNNs have neurons organized in three dimen sions: width, height and depth. Neurons in a given layer are connected to only a small region of the previous layer[12]. CNNs have 2 stages: feature extraction and classification. In feature extraction, a pooling layer will follow the convolutional layer. The feature matrix is convolved with totally different filters to get convolved feature map as follow

$$\mathrm{h}[i,j] = \sum_{p=1}^{m} \sum_{l=1}^{n} w_{p,l} \mathbf{X_k}[i+p-1, j+l-1] \quad (3)$$

where w_p, l is the element at p-th row and l-th column of the m × n filter matrix, andXk [·, ·] denotes the elements of fea ture matrix convolved by wp, l[18].

0.5 Transfer Learning

Transfer learning is a popular technique in Deep Learning in which a model developed for one task is reused as the start ing point of a model for a second task, reusing the weights in one or more layers of a pre-trained network model in a new model and either keeping the weights, refining them or adapting them entirely when training the model [20]. Training a CNN model from scratch (with initializations) is not recom mended because it requires a large amount of data and takes a lot of time, it is more usual to use already trained CNN mod els and readapt them for a new problem, this is called transfer learning.

State of the art

- During this paper [13],a completely unique convolutional neural network (CNN) classifier model is planned to classify modulation categories in terms of their types. The proposed classifier is robust against realistic wire less channel impairments, it’s seen that during this pa per, a completely unique dataset, named as Hisar Mod2019.1, is introduced, it includes twenty six mod ulation categories passing through the channels with five different fading types and several number of taps for classification.it’s shown that the planned model per forms higher than the existing models in terms of each accuracy and training time underneath additional realis tic conditions.
- [14] This paper propose a deep learning primarily based unified pipeline for real-time WSS and modulation clas sification for sparse wideband signal. The performance of the planned SenseNet model is valid for different datasets.They additionally show that the model gives 78 percent accuracy on raw wideband samples at high SNR(0-20dB). Furthermore,they also show the perfor mance of the proposed model on IQ samples and AP samples.
- Authors in [15] propose a deep learning method-based passive signal detection.They used a convolution neural network (CNN) and and therefore the long short-term memory (LSTM) approach to extract the frequency and time domain features of the signal. This method can de tect signal when little to none prior information exists. A verification of the probability of detection was performed and the results showed that this method is about 4.5–5.5 dB better than a traditional blind detection algorithm un der different SNR environments.
- A deep learning primarily based model, “DLSenseNet”, was proposed in [16], which exploits structural informa tion of received modulated signals for spectrum sens ing. They performed there experiments using Ra dioML2016.10b dataset and the outcome was studied. The performance of the models was tested with custom ary metrics of spectrum sensing. This model demon strates higher performance within the same the grade of services of the probability of detection and probabil ity of false alarm. The results shoes that “DLSenseNet” provides better spectrum detection than other sensing model.

Method

The dynamic communications surroundings of next gen eration wireless networks need quick, study and adaptational sensing and identification of the multi-dimensional commu nications medium to utilize the resources quickly and with efficiency [19]. For this context, spectrum sensing and sig nal identification becomes important means of achieving ef fective resource utilization. To that end, we propose an ap proach for the problems of sensing and identification via DL from three aspects: aspect 1: : In this aspect, first a novel CNN classifier is trained with all 11 classes from the dataset. For each signal the FFT is extracted then fed to the model classifier. Finally, the classification is made. aspect 2: In this aspect we will use the same model to achieve the spectrum sensing by using the data of signals in the dataset after the extraction of the FFT of each signal and generating awgn data then fed the classifier. Finally the sensing is made. case3: In this aspect in order to improve the accuracy of sensing we will use the pre-traiend model from case one to do the detection, first we will import the pre-trained model from aspect 1 then we'll freeze the layers after that retrain the model with the dataset used in the aspect 2, Finally a new detection model is generated and the sensing is made. . The three aspects are illustrated in Fig 1, Fig2 and Fig3 respectively.

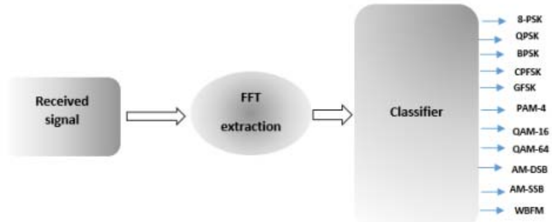

Fig. 1. Aspect 1 modulation classification.

Fig. 2. Aspect2 Spectrum sensing

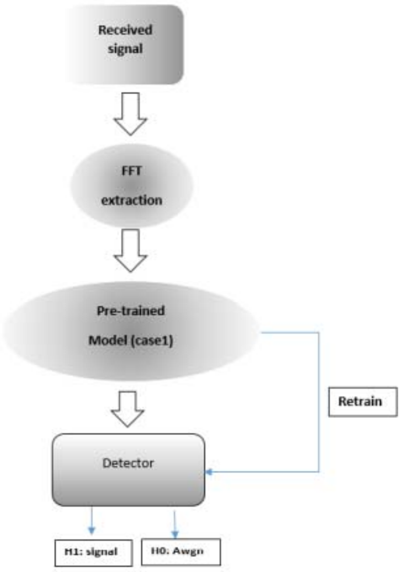

Fig. 3. Aspect3 spectrum sensing using learning transfer.

Dataset

To evaluate our deep learning architecture, we chose the RdioML2016.10a it was generated by Not Unix (GNU) Ra dio and it includes eight digital modulations and three analog ones. 220k signals for 20 different SNRs were generated and divided as 1k signals per modulation per SNR [21] . in order to implement the different transmitters. The 11 modulation types are listed as follows: BPSK, QPSK, 8PSK, 16QAM, 64QAM, GFSK, 4PAM, WB-FM, AM-SSB and AM-DSB[21]. The second dataset includes the 220k from the rml dataset plus 220k AWGN data generated using python labeled 'sig' for signals and 'awgn' for noise data. For the evaluation of the performance of our method, we divided the datasets into 80% for training 10% for test and 10% for validation for both datasets.The goal is to use a 128-sample complex (I/Q) time-domain vector to identify the modulation scheme out of 11 possible classes for case1 and 2 classes for case2 and case3. The 128 samples are fed into the network in a 2x128 vector, next the FFT of the signals is used to obtain a real valued classification feature matrix to be also used as inputs for the network to perform the classification and the sensing.

Proposed CNN model

As mentioned in section 4 we are proposing a Novel CNN model designed and implemented for signal classifica tion and identification, this model was conducted via an open source machine learning library, Keras [21]. The CNN model used includes four convolution layers, four pooling and the RELU function as an activation function, which is employed in each convolution layer. Indeed, for optimal performance, we used 256 filters in the first layer, while the last layer had 16 filters. a Batch-nomalization layer was involved after each layer and before the maxpooling to make the training more stable and faster also to use higher learning rates,the max pooling was used in order to reduce the computational cost by reducing the number of parameters to learn. We also used a dropout by the end of each layer to prevent overfitting on the training data. The first dense layer is formed by 128 neurons and the ReLU activation function. The dense layer is followed by a softmax activation function that calculates the probabili ties for each class. In addition, the ADAM (Adaptive Moment Estimation) optimizer is used to estimate the model parame ters with a learning rate of 10-4. In addition, the architecture of the proposed CNN model is given in Fig 4. During the training process, we use early termination to end the process if the validation loss converges to a sufficient level. For as pect1 the classification layer contain 11 class while aspect2 and aspect3 contains 2 classes.

Model: "sequential_1"

Layer (type)	Output Shape	Param #
reshape_1 (Reshape)	(None, 1, 2, 128)	0
conv2d_4 (Conv2D)	(None, 256, 2, 128)	6656
max_pooling2d_4 (MaxPooling2	(None, 256, 2, 128)	0
batch_normalization_3 (Batch	(None, 256, 2, 128)	512
dropout_4 (Dropout)	(None, 256, 2, 128)	0
conv2d_5 (Conv2D)	(None, 128, 2, 128)	819328
max_pooling2d_5 (MaxPooling2	(None, 128, 2, 128)	0
dropout_5 (Dropout)	(None, 128, 2, 128)	0
conv2d_6 (Conv2D)	(None, 64, 2, 128)	204864
max_pooling2d_6 (MaxPooling2	(None, 64, 2, 128)	0
batch_normalization_4 (Batch	(None, 64, 2, 128)	512
dropout_6 (Dropout)	(None, 64, 2, 128)	0
conv2d_7 (Conv2D)	(None, 16, 2, 128)	25616
max_pooling2d_7 (MaxPooling2	(None, 16, 2, 128)	0
batch_normalization_5 (Batch	(None, 16, 2, 128)	512
dropout_7 (Dropout)	(None, 16, 2, 128)	0
flatten_1 (Flatten)	(None, 6144)	0
dense_2 (Dense)	(None, 256)	1573120
dense_3 (Dense)	(None, 11)	2827

Fig. 4. The proposed CNN.

Results and Discussion

The proposed model is tested using the Ra dioML2016.10a datasets and our data. The test results are provided below.

• For aspect1 using the I/Q data of the dataset Ra dioML2016.10a to feed the model, we were able to achieve a maximum accuracy of 99.19% at snr =18 and for the hole dataset the accuracy was 67.82% also for the FFT feature we achieved 98.74% as maximum ac curacy at snr = 18 and 66.29% for all the data. The confusion matrices for the classification results of the proposed model with RadioML2016.10a are depicted in Figure 5 , 6,7 and 8.

• For aspect 2 and aspect 3 the results are shown in the Figure 9 and Figure 10 we observed that the detection accuracy exceeds 93% for aspect 2 and 97.30% in as pect3.

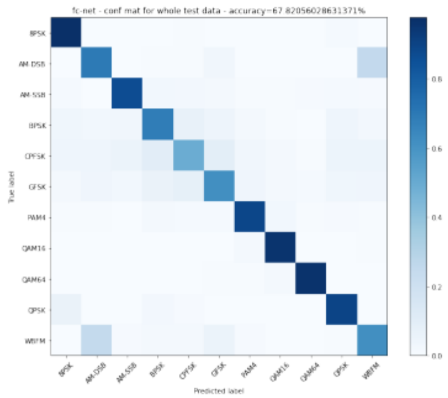

Fig. 5. Confusion matrix for all I/Q data aspect 1

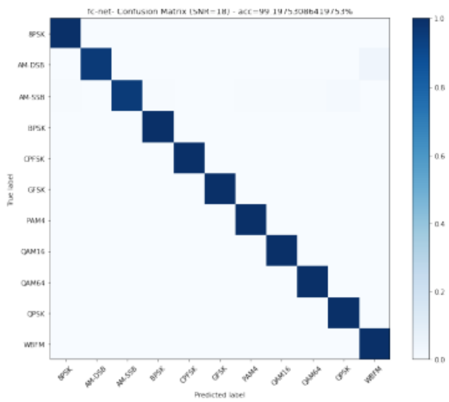

Fig. 6. Confusion matrix for snr=18 I/Q data aspect 1

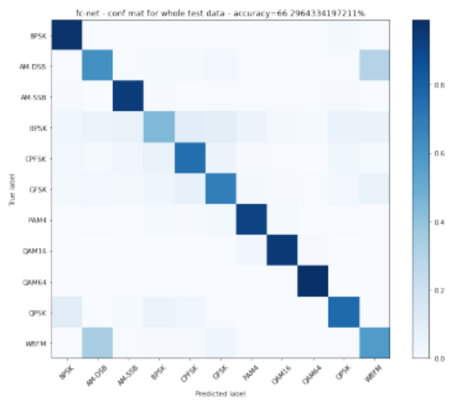

Fig. 7. Confusion matrix for all FFT data aspect 1

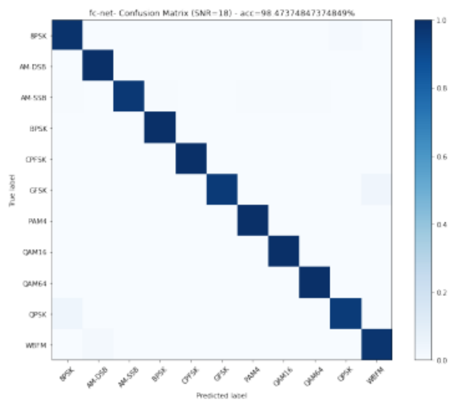

Fig. 8. Confusion matrix for snr=1

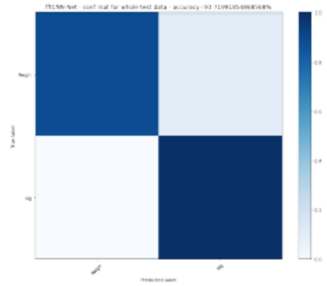

Fig. 9. Confusion matrix for sensing aspect 2

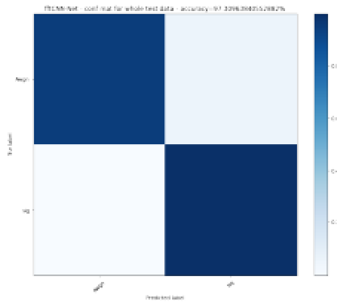

Fig. 10. Confusion matrix for sensing aspect 3

from the results given above we observe that the detec tion using a model pre-trained has given the best accuracy comparing to the other aspects. Comparing our results to the table of accuracy's in the [17] we were able to achieve better results then all the articles mentioned.

Table 1. Comparison between different aspects accuracy's.

aspect	aspect1	aspect2	aspect3
accuracy	98,47%	93.71%	97,30%

Table 2. Comparison between different models accuracy's and our proposed model.

Architecture	Best Accuracy	inputs
Proposed CNN [18]	93%	SCF
CLDNN [18]	93%	SCF
Resnet [18]	72%	SCF
LSTM [18]	68%	SCF
Proposed CNN [18]	36%	FFT
proposed inception[17]	93.22%	I/Q
proposed inception[17]	88.27	FFT
aspect1	99.19	I/Q
aspect1	98.47	FFT
aspect2	93.71	FFT
aspect3	97.30	FFT

Conclusion

The objective of this project was to develop a model for detecting radio spectrum signals using deep learning.The experimental results obtained are very interesting. The use of CNN model with transfer learning presents a better po tential and compromise (quality, robustness).The proposed classifier accuracy exceeds 97% for sensing and 99% for the modulation classification with a very small time of calculation which is very interesting compared to other methods. In the perspectives of work, we intend to develop and compare other deep learning techniques like the reinforcement learning and the unsupervised learning with new types of telecommunication data like 5G and 6G.

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