Learning-Based Approaches for Intelligent Cognitive Radio

Nada Abdel Khalek

A Thesis

in

The Department

of

Electrical and Computer Engineering

Presented in Partial Fulfillment of the Requirements

for the Degree of

Master of Applied Science (Electrical and Computer Engineering) at

Concordia University

Montréal, Québec, Canada

September 2020

CONCORDIA UNIVERSITY

School of Graduate Studies

This is to certify that the thesis prepared

By: **Nada Abdel Khalek**

Entitled: **Learning-Based Approaches for Intelligent Cognitive Radio**

and submitted in partial fulfillment of the requirements for the degree of

Master of Applied Science (Electrical and Computer Engineering)

complies with the regulations of this University and meets the accepted standards with respect to originality and quality.

Signed by the Final Examining Committee:

______________________ Chair
Dr. M.R. Soleymani

______________________ External Examiner
Dr. A. Youssef (CIISE)

______________________ Examiner
Dr. M.R. Soleymani

______________________ Supervisor
Dr. Walaa Hamouda

Approved by ______________________
Dr. Y.R. Shayan, Chair
Department of Electrical and Computer Engineering

August, 2020 ______________________
Dr. Mourad Debbabi, Interim Dean,
Gina Cody School of Engineering and
Computer Science

Abstract

Learning-Based Approaches for Intelligent Cognitive Radio

Nada Abdel Khalek

Today with the growing demand for more data transmissions and increased network capacities, cognitive radio technology is ever more relevant. Traditional static spectrum allocation is no longer a feasible option. Through dynamic spectrum access, cognitive devices are able to tap into unused licensed spectrum bands. Thus, improving the spectrum utilization efficiency and fueling spectrum scarce applications. Cognitive Radio (CR) networks consist of smart radio devices that have the ability to sense and adapt to the rapidly changing radio environment. A cognitive device goes through a process of intelligent decision-making, which intrinsically shapes them into smart devices.

Motivated by the superior performance of machine learning in various research paradigms, a cooperative Secondary Network (SN) is proposed that operates under a hybrid underlay-interweave access model. By taking advantage of both access models, the SN maximizes its throughput. A detection problem is formulated for each access model and Machine Learning (ML) techniques are applied to the SN, namely Gaussian Mixture Model (GMM), Support Vector Machine (SVM), and Naive Bayes' (NB) to classify the state of the channel. The multi-class SVM (MSVM) algorithm is reformulated and used to further classify the state of each primary user in the network. The performance of the hybrid network is evaluated based on the Receiver Operating Characteristics (ROC) and classification accuracy. In addition, we show that the accuracy of the MSVM is improved through the cooperation of the secondary users. Our results show that the proposed ML-based hybrid model is robust to low Signal-to-Noise Ratio (SNR) environments, and yields an improved performance compared with traditional cooperative sensing techniques. Moreover, we show that the Gaussian SVM surpasses other proposed learning algorithms achieving as high as an 80% detection rate with as low as 10% false alarm.

Energy detection-based spectrum sensing, relies on measuring the energy level in the spectrum, and accordingly deciding the current occupancy state of the channel. Therefore, CR devices are required to determine the corresponding channel state given a measured energy level. CR networks that use supervised learning techniques to perform the sensing task require data examples of energy levels and the corresponding channel state for training purposes , i.e., labeled data. Having readily available labeled data is a complex task for CR networks, since it requires cooperation from both primary and secondary users. Such cooperation violates the ground rules for the interweave and underlay CR access models. Tackling the problem of labeled data scarcity in practical CR applications, we propose a two-stage learning framework for cooperative spectrum sensing. The algorithm combines the superior performance of the SVM algorithm and low cost training data of the GMM. Thus, rendering the two-stage learning framework suitable for practical CR applications. Finally, a system model is proposed and the performance of the system is evaluated based on the ROC for its upper and lower performance bounds. Additionally, our results show that the two-stage learning attains a higher detection performance compared with using the GMM algorithm.

Acknowledgments

First and foremost, I would like to thank, Al-Aliym, God Almighty for giving me the strength, knowledge, and opportunity to undertake this research and to persevere and complete it satisfactorily.

Throughout my journey to pursue this degree, I found Prof. Walaa Hamouda as a pillar of support, guiding me in every step of the way and believing in me even in low moments of self doubt. He has given me all the freedom to pursue my research and non-obtrusively ensuring that I stay on track and not deviate from the core of my research. Without his able guidance, this thesis would not have been possible, and I shall eternally be grateful to him for his assistance.

I am sincerely thankful for Natural Sciences and Engineering Research Council (NSERC) for funding my research.

I would like to express my gratefulness and appreciation to have been blessed with wonderful friends and family who showered me with endless support during the course of my MASc.

My acknowledgement would be incomplete without thanking the biggest source of my strength, my mother. I can never thank you enough for helping me reach this stage in my life and becoming who I am today. Thank you for believing in me and pushing me to become the best version of myself. This would not have been possible without your unwavering and unconditional love and support.

To my beloved mother, Maha Kanz,

for her love, her patience, and her faith.

In the memory of my grandmother, Safia Hassan.

Contents

List of Figures

List of Tables

List of Acronyms

5G 5th Generation.

AI Artificial Intelligence.

ANN Artificial Neural Network.

AUC Area Under the ROC Curve.

CNN Convolutional Neural Network.

COS Channel Occupancy State.

CR Cognitive Radio.

CRN Cognitive Radio Network.

CSS Cooperative Spectrum Sensing.

DSA Dynamic Spectrum Access.

DSMF Dynamic Spectrum Management Framework.

DT Decision Tree.

EM Expectation Maximization.

FC Fusion Center.

GMM Gaussian Mixture Model.

HMM Historical Markov Model.

ICU Intelligent Cognitive User.

IoT Internet of Things.

IT Interference Temperature.

KNN K-Nearest Neighbor.

ML Machine Learning.

MSVM Multi-class Support Vector Machine.

NB Naive Bayes'.

NLOS None-Line Of Sight.

OFDM Orthogonal Frequency Division Multiplexing.

OVA One-Vs-All.

OVO One-Vs-One.

PSD Power Spectral Density.

PSK Phase Shift Keying.

PU Primary User.

QoS Quality of Service.

ROC Receiver Operating Characteristics.

SN Secondary Network.

SS-SVM Semi-Supervised Support Vector Machine.

SSL Semi-Supervised Learning.

SU Secondary User.

SVM Support Vector Machine.

WB Weighted Bayesian.

Chapter 1

Introduction

1.1 Cognitive Radio Networks

Emerging wireless technologies such as 5G, machine-to-machine communications, and Internet of Things (IoT) are calling for more data transmissions and bandwidth. With the rise of 5G networks and beyond, spectrum utilization efficiency is ever more relative as the demand for data grows rapidly. In order to satisfy the rising demand for increased network capacities and high reliability, maximizing the spectrum efficiency is a given. Technologies like Cognitive Radio (CR) create potential for enhancing flexibility of spectrum usage. The word cognitive stems from the Latin word *cognitus*, which means the act of knowing, perceiving, reasoning, and judgment. The concept of CR was first introduced in 1999 by Joseph Mitola III [1], to enable unlicensed usage of licensed spectrum bands. A CR node goes through the famous perception-action cycle to intelligently take actions according to the observed radio environment variables. Therefore, cognitive radio nodes are expected to have perception capabilities to learn and adapt to the radio environment. In order for cognitive nodes to be fully *cognitive*, they have to be equipped with learning and reasoning capabilities. To this end, machine learning techniques have been applied to CR networks, enabling the CR users to evolve into Intelligent Cognitive Users (ICUs).

1.2 Machine Learning for Smart Radio

Machine Learning (ML) is an approach that mimics a human's ability to understand and learn through the use of artificial intelligence. By giving the machine examples, it is able to draw patterns and trends that are used for future predictions and pattern identification. Motivated by the outstanding performance gains machine learning has to offer, extensive research efforts have been exerted to convert cognitive users into intelligent users. An Intelligent Cognitive User (ICU) has a better generalization functionality than the average cognitive user, it can learn radio environment patterns with incomplete or inaccurate information, track and predict environment changes, and infer a proper action to be taken [2]. Using learning techniques becomes an appealing approach when the effects of the inputs on the outputs of the system are unknown. In the context of CR networks, the cognitive node does not have any prior knowledge about the noise level, network topology, and activity of licensed users. Therefore, machine learning becomes a very appealing approach, since the wireless environment is non-ideal and may cause a lot of uncertainty. There are several machine learning techniques discussed in the literature of CR networks including, but not limited to, supervised learning, unsupervised learning, and reinforcement learning. In this thesis, we will mainly focus on supervised and unsupervised techniques for learning-based CR networks.

1.3 Motivation

The main objectives of this thesis can be summarized as:

- Study the performance of learning-based cooperative CR networks;
- Investigate learning techniques that enhance the detection performance and channel state identification of a hybrid CR network;
- Address some of the practical challenges of implementing learning-based CR networks;
- Develop simulation frameworks that assess the performance of the proposed models and techniques.

Machine learning is originally a popular research topic in the field of computer science. Nevertheless the application of machine learning to cognitive radio technology is evident. Cognitive radio is based on dynamic reconfigurability according to the rapidly changing radio environment. Hence, a CR system is intrinsically an Artificial Intelligence (AI) system. Moreover, machine learning is one of the key enablers to fully Intelligent Cognitive Users (ICUs). They are expected to play a major role in many of the future wireless communication systems such as 5G networks and beyond. Although cognitive radio technology has been extensively investigated in the literature, there is still unaddressed problems when it comes to the evolution from cognitive to intelligent cognitive devices. There is still need to investigate the performance of hybrid underlay-interweave learning-based CR networks that are able to self-configure and self-manage. Different from previous works, in this thesis, we focus on the application of learning techniques to hybrid underlay-interweave CR networks. The system takes advantage of both cooperation and learning techniques to enhance its detection performance and channel state identification compared with traditional spectrum sensing techniques.

Cognitive radio users improve the spectrum utilization efficiency through tapping into vacant licensed spectrum bands. Several works in the literature investigated the application of learning techniques to improve the detection performance of cognitive users. However, many of such works rely on supervised learning-based spectrum sensing, which requires labeled data examples, i.e., input data and its corresponding classification outcome. As a result, the performance of supervised learning techniques primarily depends on the abundance of labeled data. Most of the works in the literature assume the availability of labeled data to the ICUs, through communicating with the licensed users. Hence, there is an apparent trade-off between the detection performance of the CR network and communication between the ICUs and licensed users. Under certain CR access models such as the interweave and underlay access models, the communication between ICUs and licensed users is not possible as it violates the ground rules for the access models. Furthermore, the learning algorithm needs a large number of training data examples to perform well, which can impose a significant communication overhead between the licensed and unlicensed users. In the light of this, we believe that there is a simpler and more practical way of attaining the performance of supervised learning-based spectrum sensing without incurring the cost of communication between the ICUs and licensed users, which will be discussed in chapter 4 of this thesis.

1.4 Thesis Contribution

Motivated by open issues mentioned in the previous section. The contributions of this thesis are summarized as follows:

- Investigated the operation of a hybrid cooperative CR network that takes advantage of both the underlay and the interweave frameworks and applies machine learning techniques in both CR access models.

- Enhanced the detection performance and classification accuracy of the hybrid CR network, through the application of supervised and unsupervised machine learning techniques such as Support Vector Machine (SVM), Naive Bayes' (NB), and Gaussian Mixture Model (GMM) algorithms.

- Formulated a multiple-hypothesis problem to classify the different channel occupancy states of the primary network under the presence of multiple Primary Users (PUs). Moreover, the use of multi-class SVM (MSVM) algorithm was investigated to identify the different channel states of the primary network. In addition, the accuracy of multi-class learning was enhanced through the cooperation of Secondary Users (SUs).

- Evaluated the proposed hybrid learning-based CR network based on the Receiver Operating Characteristics (ROC), as well as the classification accuracy of the state of the primary network. Moreover, we provide extensive analysis of the system parameters and how they affect the performance of the system.

- Addressed the practical implementation of supervised-learning based spectrum sensing. We proposed an unsupervised two-stage learning-based CR network, that relies solely on unlabeled data examples, tackling the problem of labeled data scarcity in practical CR applications.

- Studied the performance of the two-stage learning framework under the joint effect of the size of the collected data at the fusion center and the cooperation size of the CR network.

1.5 Thesis Organization

The organization of this thesis is as follows:

In chapter 2, we present some of the background knowledge for cognitive radio networks. A review of various CR access models and CR network architectures is given. Furthermore, we discuss the convergence of machine learning with cognitive radio networks by providing a literature review of the state-of-the-art learning techniques in CR networks.

In chapter 3, we propose a hybrid underlay-interweave CR network that uses learning techniques to enhance its detection performance. We show that through cooperation, the classification accuracy is improved. We present a system model and extensive analysis of the hybrid CRN. Finally, we provide simulation results that prove the feasibility of our proposed network.

In chapter 4, we address the problem of labeled data scarcity, which facilitates the use of supervised learning techniques. We propose an unsupervised two-stage learning framework for CR networks. We show that through using a two-stage learning framework, the cooperative CR network attains the same detection performance as supervised learning techniques without having to incur the cost of acquiring labeled data. Finally, we present simulation results, conclusions, and discussions of the results.

In the final chapter, we conclude the thesis by discussing future research directions and challenges for learning-based CR networks.

Chapter 2

Background and Literature Review

2.1 Introduction

Cognitive Radio (CR) technology, also referred to as ”brained-powered communications”, aim to improve spectrum utilization efficiency by tapping into licensed spectrum bands that are under utilized. CR devices are able to perceive radio environment variables and adapt accordingly using a perception-action cycle, also referred to as ”cognition cycle”. In this chapter, we introduce some of the background topics for this thesis. We start by introducing the core concepts of cognitive radio networks, discussing the architectures and access models. Then we present the development from cognitive to smart radio, highlighting the role of learning in developing intelligent cognitive users. Additionally, an overview of the currently used learning techniques in CR networks is discussed, examining the convergence between learning techniques and cognitive radio networks. Given the importance of learning-based CR applications, an in-depth literature review of the current state-of-the-art smart radio applications is presented. We conclude this chapter with some of the open issues and challenges of learning-based CR networks that will be addressed in this thesis.

2.2 Cognitive Radio Networks

A Cognitive Radio (CR) network is a wireless network that consists of nodes that can sense the radio environment and intelligently take actions. The CR technology was developed to overcome the problem of spectrum under-utilization, since the wireless spectrum is a valuable resource and must be used efficiently. The Federal Communication Commission (FCC) published a report which claimed that the spectrum utilization rate is as low as 15% of the radio spectrum [3]. The CR technology is based on opportunistic spectrum access and spectrum sharing. Licensed users are called Primary Users (PUs), who can utilize the spectrum to transmit their data with no restrictions. On the other hand, there exists a secondary network, where its users are called Secondary Users (SUs). The SUs opportunistically access the medium with some restrictions depending on the access model of the CR network (to be discussed later). The allocated spectrum for the primary network might be unused for a certain time or a certain location. The unused parts of the spectrum are called spectrum "holes" or white spaces. Dynamic Spectrum Access (DSA) in CR networks was introduced to solve the problem of spectrum under-utilization. In Fig. 2.1, the concept of DSA is illustrated, where the SUs actively search for spectrum holes to send their data. Inherently, the SUs try to maximize their throughput, but at the same time try to decrease the interference caused to the PUs which are two conflicting goals that pose a trade-off. In the next subsections, a discussion of the different CR access models is presented. Fig. 2.2 summarizes the spectrum access models for cognitive radio networks.

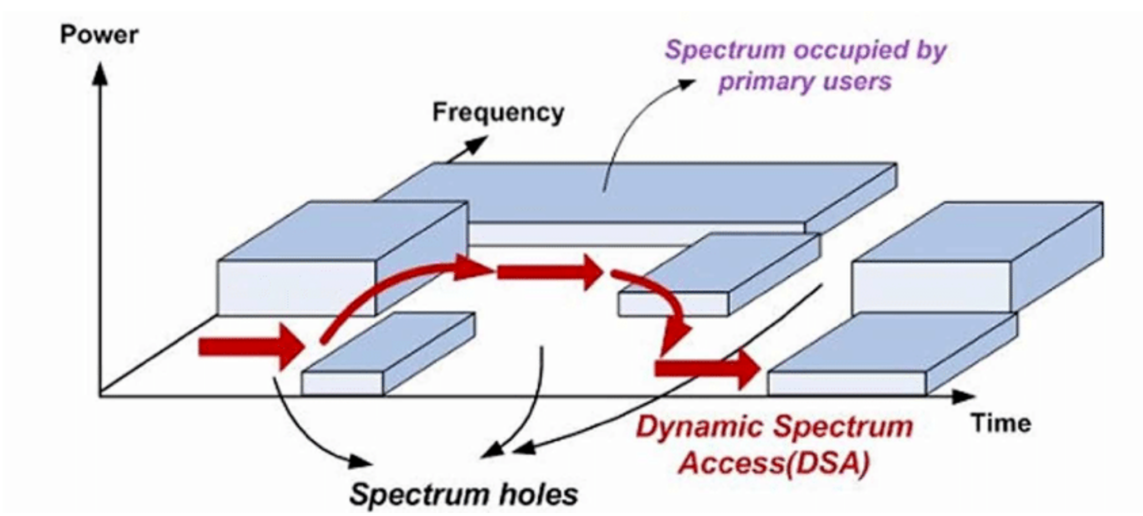

Figure 2.1: Dynamic spectrum access.

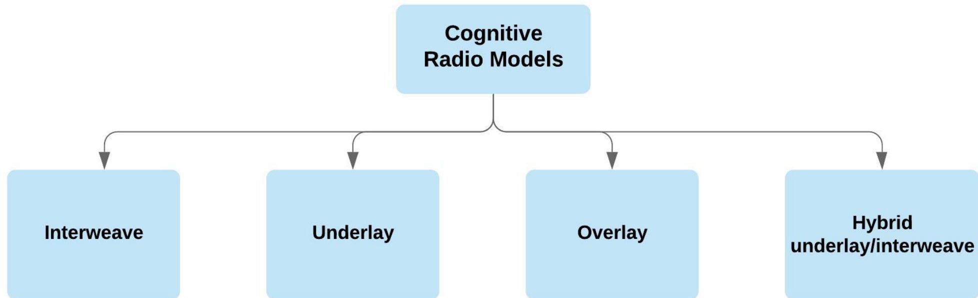

Figure 2.2: Different spectrum access models for CRNs.

2.2.1 Interweave CR Networks

The interweave access model is the first access model proposed for CR networks. Under the interweave model, the SUs actively search for spectrum holes to opportunistically transmit their data. The SUs can only access the medium if and only if the PUs are not utilizing it. Hence, for SUs operating under the interweave model, sensing the primary user activity is one of the main challenges. From the perspective of the primary network the secondary network is none-existent, meaning that the secondary network should remain invisible to the primary network. Therefore, there is no communication between the primary and secondary networks. Additionally, the SUs should not alter or affect the operation of the PUs. If the SUs misdetect the PU this could result in either causing interference to the primary network or decreasing the throughput of the secondary network. In Fig. 2.3, the concept of the interweave access model is illustrated, where the SUs only occupy frequency holes if and only if the PUs are not utilizing it.

2.2.2 Underlayed CR Networks

In underlayed CR networks, the SUs can simultaneously access the medium with the PUs under one condition that the interference caused to the primary network is below the specified interference threshold. Underlayed CR networks are also termed ”spectrum sharing networks”, as the PUs and SUs coexist in the spectrum. As a result, the SUs not only need to sense the presence of the PUs, but also maintain a transmit power level to abide by the interference threshold. In Fig. 2.3, the concept of underlayed CR transmission is illustrated, where the SUs can simultaneously transmit their data with the PUs as long as the interference caused to the PUs is below the interference threshold. The main challenge with underlay CR networks is measuring the interference caused at the PU's receiver. Therefore, underlay CR networks are mainly used for short range communications [4].

2.2.3 Overlayed CR Networks

In overlayed CR networks, not only can the SUs access the medium simultaneously with the PUs, but also they have access to the PUs' codebooks and its messages. Thus, the SUs are able to assist the PUs with their data transmissions, and mitigate the interference caused to the primary network [5]. One approach to realize the overlay model, is through relaying the PUs' messages by using a part of the power allocated for secondary transmissions [6].

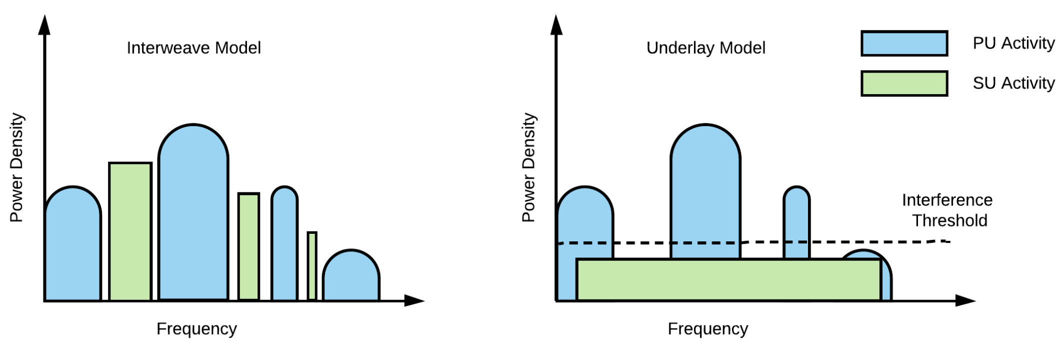

Figure 2.3: Dynamic spectrum access for the interweave and underlay CR access models.

2.2.4 Hybrid Underlay-Interweave Networks

Inspired by the apparent benefits of both the underlay and interweave models, a hybrid access model that combines both was proposed in the literature. The model aims to enhance the throughput of the secondary network [5, 7, 8]. In a hybrid underlay-interweave access model, the SUs can transmit in both the presence and absence of the PUs. When the PUs are not utilizing the medium, the SUs can take advantage of the spectrum holes using the interweave approach. In case the PUs reappear, the SUs do not have to vacate the channel. The SUs adjust their transmission parameters accordingly to keep the interference to the primary network below the threshold.

2.3 Cognition Cycle

Under the Dynamic Spectrum Management Framework (DSMF), the cognition cycle begins with the SU sensing the radio environment [9]. If the SU does not sense any PU activity it takes advantage of the spectrum, otherwise it continues monitoring. While the cognitive node is using the spectrum, it continues its monitoring process in the background in case the primary user reappears. If the primary user reappears, the SU executes its spectrum mobility process and continues to monitor the spectrum for future holes to take advantage of [10]. Fig. 2.4 illustrates the different processes and transitions between each process in the cognition cycle. The processes required for a full cognition cycle are summarized as follows:

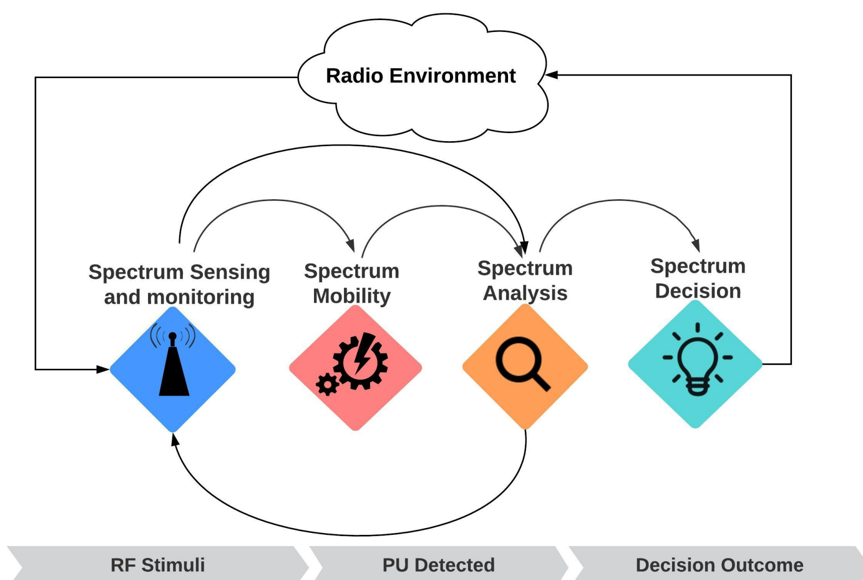

Figure 2.4: The cognition cycle.

- *Spectrum sensing and monitoring:* Spectrum sensing is the first step an SU performs. It captures the radio environment variables, such as energy level in the case of energy detection, to identify spectrum holes. If the SU is already occupying a spectrum band, then it keeps on monitoring the channel in case the PUs reappear.

- *Spectrum mobility:* If an SU is already occupying a spectrum hole and a PU reappears, it executes its spectrum mobility process to vacate the channel avoiding harmful interference to the PUs.

- *Spectrum analysis:* After capturing the radio environment variables, the SU performs its spectrum analysis process to detect the characteristics of the spectrum such as the PU activity, operating frequency, and bandwidth [10].

- *Spectrum decision:* Using the spectrum analysis obtained, the SU decides on the appropriate spectrum band to be occupied according to the user requirements and spectrum characteristics. Consequently, it determines its transmission rate, bandwidth, and mode [9].

2.4 Narrow-Band Spectrum Sensing

Narrowband sensing involves sensing a particular frequency band and determining whether it is occupied or vacant. The detection problem can be formulated as a binary hypothesis [11] or multiple hypothesis depending on the CR access model [12, 13]. Additionally, the primary users can have a single constant transmit power [14], or multiple transmit power levels [15]. For an interweave CR access model, there are mainly two hypothesis of interest, which are channel available H_0 and channel unavailable H_1. When the channel is available that means there is only noise in the medium, which can be modeled by several channel models such as Gaussian, or Rayleigh channel models. On the other hand, when the channel is unavailable that means that there is at least one PU utilizing the channel along with some noise effects. In other words:

$$\begin{aligned} H_0 &: x(n) = w(n) \\ H_1 &: x(n) = s(n) + w(n), \end{aligned} \tag{2.1}$$

where $s(n)$ is the received PU signal in the n-th time sample, and $w(n)$ is the noise. There are several narrowband sensing techniques discussed in the literature, some of the classical techniques include but not limited to: feature detection, matched filter detection, and energy detection [10]. In [16, 17] machine learning techniques were used to decrease the sensing time and energy, as well as enhance the throughput of the SUs in the CR network.

2.4.1 Energy Detection

Energy detection has been widely adopted in the literature, since it most corresponds to general purpose spectrum sensing. It also is low in terms of complexity and simpler compared to other sensing techniques. Energy detection belongs to the class of non-coherent detectors. An SU using an energy detector for spectrum sensing purposes takes N energy samples from the spectrum and computes the average through the following:

$$Y = \frac{1}{N}\sum_{n=0}^{N-1}|x_n|^2, \tag{2.2}$$

where x_n is the collected energy sample at the n-th time interval. Subsequently, the SU compares the energy statistic Y against a threshold λ to decide whether the channel is available or not. The drawbacks of using an energy detector to perform spectrum sensing is that it performs poorly in low SNR scenarios, rendering the SU unable to differentiate between the PU signal and the noise [4].

The authors in [18] minimized the cooperation overhead and complexity imposed by traditional cooperative sensing techniques by using learning-based CR networks. They investigated learning techniques such as Weighted Bayesian (WB), Naive Bayes' (NB), and Gaussian Mixture Model (GMM), and used the collected energy samples by the SUs at the fusion center as their feature vector. In [14], the authors enhanced the performance of spectrum sensing through using learning techniques such as Gaussian Mixture Model, K-means, K-Nearest Neighbor (KNN), and Support Vector Machine (SVM). Similar to [18], the authors used the energy samples collected at the fusion center as a feature vector for the learning algorithms.

Energy detection is more challenging in mobile cognitive radio networks, and often lead to detection performance loss compared with static sensing. In the literature, various sensing techniques for dynamic spectrum access in CR networks have been proposed. However, these works assume that the SUs are stationary and the PUs are assumed to be idle during the SUs' transmissions. However, in [19] the authors proposed an improved version of energy detection that takes into account the joint impact of SUs' sensing range, PUs' protection range, and SUs' mobility model on the PU activity. In addition, the authors derive a closed form expression for the probability of the PU being inside the SUs' sensing range. They obtain numerical results along with analyses which show that the new proposed model leads to superior performance. In [20], the authors formulated the detection problem in a mobile environment as a composite hypothesis testing problem. The proposed system incorporated an adaptive clustering algorithm that fuses only a subset of the energy vectors to alleviate the load on the control channel. The algorithm can also deal with incomplete energy vectors (missing data).

2.4.2 Matched Filter Detection

Matched filter detectors are one of the most conventional digital receivers. They are often referred to as optimum receivers. They work on the principle of maximizing the received SNR when making a decision regarding the received signal. Unlike energy detection, matched filter detection is a form of coherent detection. Therefore, the SU's receiver has to have perfect knowledge about the PU's signal to have accurate synchronization. This is costly to implement in a CR network, since the secondary network does not have any prior knowledge about the PUs' signals in some CR access models. Moreover, in the case of multiple PU signals the matched filter detector needs to be implemented with multiple correlators, which significantly increases the cost and complexity of implementation. Given a received signal $x(n)$ the matched filter correlates it with a known *priori* signal $s(n)$ at the receiver, and the output is sampled and compared with a threshold θ as follows

$$\Gamma(x) \triangleq \sum_{n=1}^{N} x(n) * s(n) \lessgtr_{H_1}^{H_0} \theta, \tag{2.3}$$

where $\Gamma(x)$ is the test statistic that gets sampled at the output.

2.5 Multi-Band Spectrum Sensing

Initially the SU selects a certain frequency band to be sensed at random and sends its data if the channel is found to be idle. However, if the channel is not idle, the SU performs wideband sensing. That is sensing multiple bands until a band is found to be idle. Hence, narrowband sensing is first initiated to decide if a particular band is vacant or not. If the band is not vacant the SU performs wideband sensing to determine a variety of vacant frequency bands. The main challenge of multi-band/wideband sensing is performing the sensing operation over a larger frequency range. The SUs have to scan/sense a wide range of wireless bands to determine the empty channels. Traditional multi-band sensing techniques include, but not limited to, sub-Nyquist rate sensing, FFT-based detection, and wavelet-based detection [10]. The authors in [21] optimized the energy needed for detecting multi-bands in low SNR environments with constraints on the detection performance while maximizing the sensing reliability.

The application of machine learning algorithms was not limited to single band sensing only. Works in the literature such as [15, 21, 22, 23, 24, 25, 26] have discussed the use of machine learning algorithms in multi-band sensing. In [22] the authors proposed a fully Bayesian soft assignment variational learning technique. Their algorithm enables autonomous spectrum sensing without the knowledge of how many clusters there is. Moreover, their technique is able to detect the number of PUs utilizing a wideband and is capable of determining the number of vacant sub-bands. They achieve a 90% and above detection rate with as low as 10% false alarm rate. Unlike the work done in [14] that requires prior knowledge of the number of states of the spectrum, [15] and [23] propose a non-parametric Bayesian learning algorithm for multi-band sensing in large scale heterogeneous networks. The algorithm is applied to a mobile Cooperative Spectrum Sensing (CSS) framework, in which the algorithm automatically learns the number of spectrum states. Additionally, it captures the spatio-temporal correlation in the collected spectrum data. The proposed method exploits the mobility of the SUs (low mobility) to collect spatial-temporal spectrum sensing data. Bayesian inference is then carried out to form the global spectrum occupancy picture, and predict the PUs locations with their transmission ranges. The authors claim that their algorithm surpasses the performance of the GMM algorithm. In [24], the authors investigated the performance of autonomous wideband sensing in low SNR environments and tried to enhance the performance using Support Vector Machine (SVM) learning technique. Their classification features include Smoothed Correlation of Reversed Spectrum Segments (SCRSS) and Variance of Multi-Scale Moving Averages (VMMA). They claim that using SCRSS and VMMA as classification features, the classification time is 5 times faster than Eigen learning. In addition, the computational complexity is also reduced. Their method was proven to perform really well in low SNR environments (as low as -13dB) with more than 90% detection rate. In [25], the authors propose using supervised learning techniques to determine spectrum occupancy in wideband cooperative spectrum sensing combined with weighted compressive sampling and regression techniques. In addition, they propose a prediction approach that depends on regression to provide accurate estimation of sparsity levels. They show that their model surpasses other existing models by making accurate spectrum occupancy decisions with less sensing and energy overhead. In [26], a cooperative multi-band sensing technique was proposed that improves the sensing accuracy under path-loss and shadowing environment using machine learning techniques. To reduce the classification delay, they use an Archetypal clustering scheme. They found that the Archetypal clustering yields lower classification times for the SVM algorithm. In addition, it achieves very high detection rates.

2.6 Cooperative Secondary Networks

The hidden primary user (PU) problem is a major challenge in cognitive radio networks that can lead the SUs to misinterpret the spectrum occupancy. In addition, in some scenarios, where the channel is affected by shadowing effects or fading, sensing by a single SU maybe a difficult task [27]. One of the solutions to such problems is to increase the spatial diversity of the secondary network by employing more secondary nodes to perform the sensing. This is called ”Cooperative Spectrum Sensing” (CSS). Cooperative secondary networks can be centralized or distributed networks. In the centralized models, the SUs send their sensed data to a central unit called the Fusion Center (FC). At the FC, the data gets processed and a unified decision is taken that gets transmitted to the SUs. In distributed cooperative network, the SUs exchange the sensed data among themselves. This could impose an added communication overhead, since each SU takes its own decision. There are several types of fusion rules which include, but not limited to, AND rule, OR rule, and majority rule [27]. Fig. 2.5 shows a centralized cooperative secondary network, where the secondary users send their sensed data to a centralized fusion center. In some scenarios in CR networks, sensing reports from

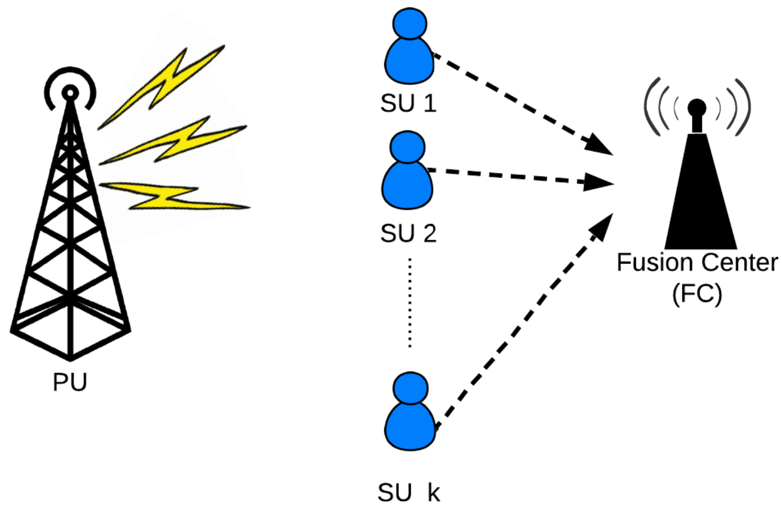

Figure 2.5: Cooperative spectrum sensing.

SUs that are close to each other are highly correlated. The combination of sensing information from all the correlated SUs will have a detrimental effect on the detection accuracy. Moreover, if all the SUs in the network send their data this could impose an overhead in some CR networks. Hence, user selection techniques are used to select particular SUs that are more spatially diverse and do not impose a cooperation overhead on the network [28].

In [7], a distributed user selection algorithm is used that adaptively selects uncorrelated SUs based on the dynamic changes in the network topology and channel conditions. The authors used joint spatial-temporal correlation in the case of soft combining to improve the CSS decision while reducing the cooperation overhead. They employed the maximum likelihood ratio to find the optimal probability of detection with respect to the spatial-temporal correlation for a given probability of false alarm. In addition, a secondary user selection problem was formulated as a double threshold optimization problem similar to [29], while considering both the sensing accuracy and stability to achieve the optimal probability of detection. Results show a sensing performance gain is attained, when a subset of SUs is selected for cooperation. They show that by employing spatial-temporal diversity, the user selection frequency is reduced.

Machine learning techniques were used to improve the detection performance and to reduce the time required to perform a reliable detection in cooperative CR networks [14, 18, 30, 31]. Supervised learning techniques such as K-Nearest Neighbor (KNN), Decision Tree (DT), Naive Bayes' (NB), and Support Vector Machine (SVM) were proven to enhance the performance of cooperative sensing through reducing the overhead on the network such as delay, energy, and operations [32]. A comparative study in [33] about different machine learning techniques such as NB Classifier (NBC), DT, SVM, and Historical Markov Model (HMM) in cooperative secondary networks was presented, showing that the SVM outperforms all other algorithms.

2.7 Learning-Based CR Networks

Over the past two decades, the application of artificial intelligence to cognitive radio networks has received a lot of attention [2]. The motivation to use learning techniques came from the fact that historical wireless data collected over time contains a lot of variations and features. Thus, the collected historical data can be used to predict future patterns. In the context of wireless cognitive radio, the network has high degrees of freedom. Therefore, deriving an input-output relation is not a simple task. Machine learning algorithms can be applied to learn and estimate the input-output function of the system through the use of data examples without complete knowledge of the system parameters. Machine learning techniques are divided into three main categories: supervised learning, unsupervised learning, and reinforcement learning. In this section we will give a brief overview of the learning techniques and their applications in cognitive radio networks.

Machine learning techniques have been widely used in the literature of CR networks to perform tasks such as feature classification, clustering, and control. The choice of the learning technique to be implemented in the CR network mainly depends on the type of data that is presented to the system , i.e., labeled or unlabeled data and the nature of the learning problem at hand (will be discussed later). Fig. 2.6 summarizes some of the machine learning techniques widely used in the context of cognitive radio networks and their corresponding learning problems.

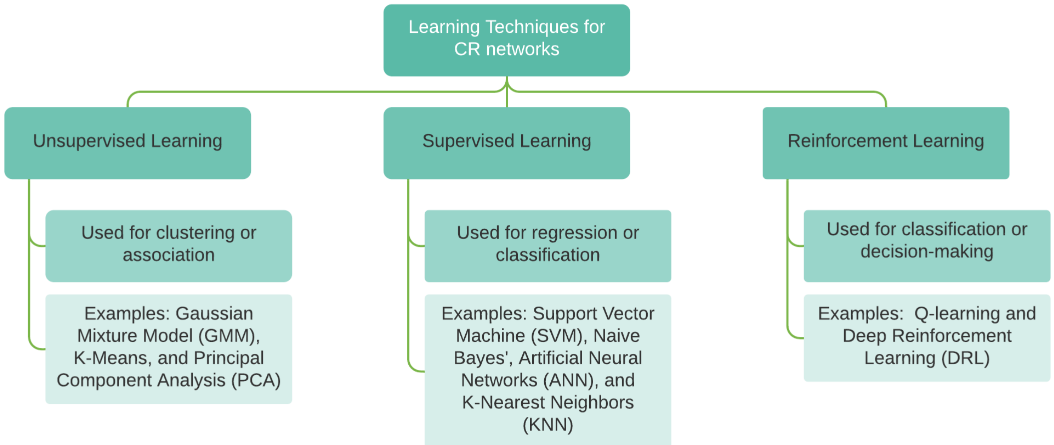

Figure 2.6: Taxonomy of learning techniques for CR networks.

2.7.1 Supervised Learning in the Radio Environment

An agent in a supervised learning algorithm, learns the features and hidden patterns through the use of labeled data. Let x_n be the n-th input and y_n is the corresponding output. A supervised learning algorithm needs to learn the mapping function $f(.)$ that maps the input x_n to the output y_n through the use of a set of x and y data points. After learning the mapping function $f(.)$, the algorithm will be able to determine the output y_n given only x_n. In the context of CR networks, the input x can correspond to the PU signal and the output y is the impact of the radio environment on x. Examples of supervised learning techniques used in the domain of CR networks, include but not limited, to Support Vector Machines (SVM), K-Nearest Neighbor (KNN), and Artificial Neural Networks (ANN) [2].

The performance of spectrum sensing for Orthogonal Frequency Division Multiplexing (OFDM) system-based machine learning was investigated in [34]. In their work, the authors formulate their spectrum sensing problem into an SNR multi-class learning problem. They also propose a class-reduction assisted Naive Bayes' classifier method to reduce the spectrum sensing time. In addition, they use the SVM classification algorithm for detecting spectrum holes. Their simulation results show high spectrum sensing accuracy specially in low SNR environments.

The use of Support Vector Machine (SVM) as a learning technique was widely used in the literature for multi-class learning in CR networks [35]. Unlike most works in the literature, which are concerned with temporal spectrum sensing, the work in [36] proposes a spatio-temporal spectrum sensing approach. The system aims to provide reliable detection of spectrum holes at a specific time and location. They formulated their detection problem as a multiple state detection problem and applied a multi-class SVM to it. They also added beamforming techniques to enhance the performance of the SVM. Their algorithm does not need prior information about the PU signal, the noise, or the channel gain. This is the first work that applies beamforming aided multi-class learning to the CR context. Their method was shown to be far more superior than proposed alternative solutions (multi antenna SU). In [37], the authors use polynomial based kernel-SVM for energy level classification in underlay CR networks. The hypothesis of primary users present is further classified into multi classes, and the SU varies its transmit power based on the output class. They claim that this technique increases the Quality of Service (QoS), since it causes low interference to the PUs. In [38], the authors propose an SVM-based spatial spectrum sensing scheme. The authors use beamspace transformation to suppress the out-of-band interference, and improve the received SNR under low SNR conditions. The beamspace technique has the ability to do spatial filtering, which in turn decreases the dimensionality of the received matrix in a multi-antenna system. Also, it can determine the angle information of the PU signal. Hence, even if the PU is utilizing the channel the SU can access it from other angles using beamforming. Aiming to determine the actual PU-SU state at any given time, the authors in [39] formulated a spectrum sensing problem under a multiple primary users scenario. Each class is comprised one or more sub-classes, and multi-class SVM was selected to perform the classification task. They prove through simulations that their proposed detector is robust to spatio-temporal detection of spectrum holes.

2.7.2 Unsupervised Learning in the Radio Environment

An agent in an unsupervised learning algorithm learns the hidden patterns and features only through input data x that does not contain any corresponding outputs, i.e., unlabeled data. Hence, using unsupervised learning eliminates the challenge of finding labeled data. On the other hand, the performance of unsupervised learning is not as well as the supervised learning. Unsupervised learning is usually used for clustering analysis or data association [40]. Fig. 2.7 shows the conceptual difference between the supervised and unsupervised learning algorithms. The supervised learning algorithm needs to be given labeled data (each color belongs to a different cluster) to perform the classification task. On the other hand, the unsupervised learning algorithm clusters the input solely based on unlabeled data (all data points are the same color). In the context of CR networks, the CR node performs blind sensing in the unknown radio environment. The secondary users are expected to use the medium at any time and at any location. Hence, this makes unsupervised learning an appealing approach for such problem. Through using unsupervised learning techniques, the SUs do not need to have any prior knowledge about the interference levels, the noise distribution, or primary user traffic profiles [40].

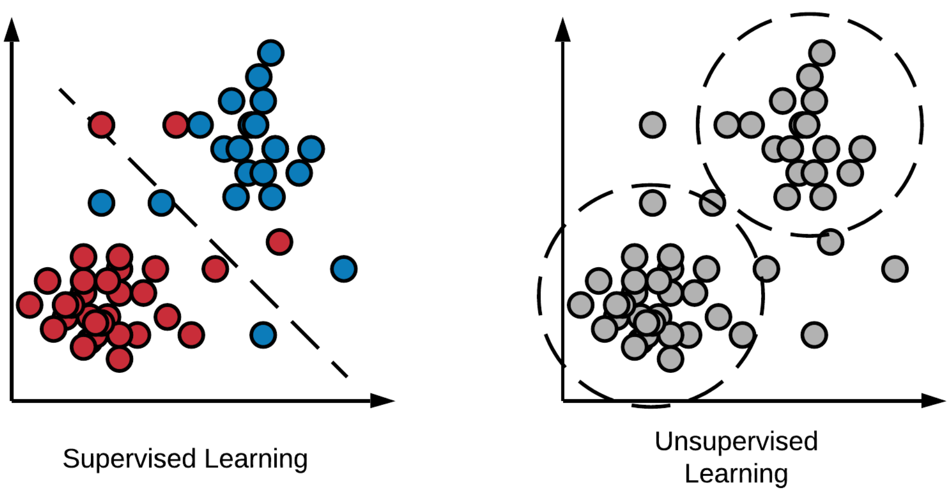

Figure 2.7: Supervised and unsupervised classification.

The performance of cooperative spectrum sensing in mobile environments was studied in [41]. The authors propose a newly derived adaptive Expectation Maximization (EM) algorithm that allows the Fusion Center (FC) to dynamically estimate the parameters of the GMM based on the most recent energy estimates from the SUs. In addition, they derived closed form expressions for the Expectation and Maximization steps. Their simulation results prove the effectiveness of the proposed method in realistic slow-fading environments. Motivated by the scarcity of labeled data in the domain of CR networks and dependence of learning algorithms' performance on model features, the authors in [42] propose an Unsupervised Deep Spectrum Sensing (UDSS) approach. The UDSS employs a neural network that relies mainly on unlabeled data for learning and a small amount of labeled data collected in the absence of the primary user. Their results show that their proposed algorithm achieves a performance close to that of the Convolutional Neural Network (CNN) based supervised learning. The authors in [43] propose using unsupervised learning algorithms for cooperative spectrum sensing, they use eigenvector and eigenvector value as classification features along with K-Means clustering and a Gaussian Mixture Model (GMM). Their results show that the proposed algorithm outperforms the system in [14].

2.8 Conclusions

In this chapter, we gave an overview of cognitive radio networks as an enabling technology to enhance the spectrum utilization efficiency. A discussion of CR access models was presented. Additionally, a variety of spectrum sensing techniques used in the literature was given. We highlighted the role of learning to facilitate the development from cognitive to intelligent radio nodes. Furthermore, we discussed the convergence of machine learning and cognitive radio. We showed how learning techniques are promising tools that enhance the sensing performance of CR networks, focusing on the most commonly used learning techniques in CR networks.

In the following chapter, we present a cooperative secondary network that operates under a hybrid underlay-interweave access model. The hybrid CR network employs learning techniques to classify the state of the channel and accordingly it can adjust its transmission parameters. By taking advantage of both access models, the secondary network maximizes its throughput. Our results show that the proposed learning-based hybrid CR network is robust to low SNR environments, and yields an enhanced performance compared with traditional cooperative sensing techniques.

In chapter 4, we address the problem of labeled data scarcity in practical CR applications. We propose an unsupervised two-stage learning framework that yields comparable detection performance to fully supervised learning algorithms. Through using an unsupervised learning framework, the cost of obtaining labeled data is eliminated. Moreover, the system enables autonomous learning in the radio environment, leading to fully intelligent cognitive nodes. A system model is proposed and the performance of the system is extensively analyzed to prove its feasibility.

Chapter 3

Learning-Based Cooperative Spectrum Sensing in Hybrid Underlay-Interweave Secondary Networks

3.1 Introduction

In the previous chapter, we discussed the role of cognitive radio technology as a solution for spectrum under-utilization. We presented an overview of the different cognitive radio access models. Finally, we reviewed some of the most common learning techniques in the context of cognitive radio networks. In this chapter, we will present a hybrid underlay-interweave CR network that employs learning techniques in both access models to enhance its detection performance.

With the emergence of the age of artificial intelligence, machine learning has been one of the key enablers of smart wireless devices. In recent years, machine learning has made its way to evolving cognitive radio into smart radio, allowing cognitive users to reach their full cognition potential. As discussed in chapter 2, a cognitive user goes through a cognition cycle through which it dynamically adapts to changing radio environment variables. Hence, cognitive users are inherently smart users. In this chapter, we propose a hybrid underlay-interweave CR network that incorporates both cooperation and learning techniques to enhance its detection performance and classification accuracy.

3.2 System Model

In the proposed Cognitive Radio (CR) network, there exists N Secondary Users (SUs) indexed from $n = 1, ..., N$, while in the primary network there exists M Primary Users (PUs) indexed from $m = 1, ..., M$. The nodes are scattered in a two-dimensional grid with coordinates C_n^{SU} and C_m^{PU}. Similar to the work in [14], all nodes are considered to be static. Each SU senses the spectrum and reports the energy level to the Fusion Center (FC), which can also be an SU or a dedicated standalone unit. The FC receives the energy levels from all the SUs and fuses them to come up with a decision to whether the spectrum is available or not. If the m-th PU is active then its occupancy state s_m is set to 1, which indicates channel unavailable. If the m-th PU is inactive then its occupancy state is $s_m = 0$. The channel occupancy state vector is denoted by **S**, which is comprised of the occupancy states of the PUs. **S** is a random variable and the probability that $\mathbf{S} = \mathbf{s}$ is given by:

$$v(\mathbf{s}) = Pr[\mathbf{S} = \mathbf{s}]. \tag{3.1}$$

Let a be the channel availability, given a channel occupancy state $\mathbf{s} = (s_1, ..., s_M)$, if at least one element of **s** is set to 1, that means the channel is not available and a= 0.

3.3 Spectrum Sensing

The channel has a bandwidth of w, the energy detector at each SU senses the channel for a duration of τ. According to the Nyquist sampling criteria, the sampling frequency is found to be $f_s = 2\omega$. Therefore, the number of samples i that need to be taken from the spectrum is $2\omega\tau$. Let $Z_n(i)$ denote the i-th sample of the channel taken by the n-th SU that is ,

$$Z_n(i) = \sum_{m=1}^{M} s_m h_{m,n} X_m(i) + N_n(i), \tag{3.2}$$

where $h_{m,n}$ is the channel gain from the m-th PU to the n-th SU, and $X_m(i)$ is the symbol sent by the m-th PU. Without loss of generality, the transmitted PU symbol is modulated using Phase Shift Keying (PSK) modulation. $N_n(i)$ is the thermal noise at the n-th SU that is normally distributed with mean $\mu_n = 0$ and variance $\sigma_n^2 = E[|N_n(i)|^2]$. Therefore, the detection problem can be formulated as a binary hypothesis test:

$$\begin{aligned} H_0 &= N_n(i), \\ H_1 &= Z_n(i). \end{aligned} \tag{3.3}$$

The energy detector estimates the energy level in the channel normalized by the Power Spectral Density (PSD) of the noise $\eta = \sigma_n^2$ from the channel samples by the following:

$$Y_n = \frac{2}{\eta} \sum_{i=1}^{w\tau} |Z_n(i)|^2. \tag{3.4}$$

All SUs report their soft data, which is the energy level that was calculated by the energy detector using (3.4) to the FC. An energy vector is formed at the FC denoted by $\mathbf{Y}$ where $\mathbf{Y} = (Y_1, ..., Y_N)$. The distribution of the energy vector follows a non-central chi distribution with $q = 2w\tau$ degrees of freedom and a non-centrality parameter ζ_n that is [14]:

$$\zeta_n = \frac{2\tau}{\eta} \sum_{m=1}^{M} s_m g_{m,n} \rho_m, \tag{3.5}$$

where $g_{m,n}$ is the power attenuation from the m-th PU to the n-th SU, such that $g_{m,n} = |h_{m,n}|^2$. The power attenuation $g_{m,n}$ is given by [14]:

$$g_{m,n} = PL(||C_m^{PU} - C_n^{SU}||).\psi_{m,n}.\nu_{m,n}, \tag{3.6}$$

where $\psi_{m,n}$ and $\nu_{m,n}$ are the shadow fading component and the multi-path fading component respectively. Similar to [14], both $\psi_{m,n}$ and $\nu_{m,n}$ are assumed to be unity and quassi-static during the time duration of interest. $||.||$ is the Euclidean distance and $PL(d) = d^{-\alpha}$, which represents the path-loss component with a relative distance d and path-loss exponent α. In this thesis, a non-line of sight (NLOS) channel environment is considered, hence α is 4. The transmit power ρ_m is given by:

$$\rho_m = \frac{\sum_{i=1}^{w\tau} E[|X_m(i)|^2]}{\tau}. \tag{3.7}$$

If the number of channel samples, i.e., $\omega\tau$ is large enough, the distribution of the energy level Y_n, reported by the n-th SU, can be approximated by a Gaussian distribution with mean $\mu_{Y_n|\mathbf{S}=\mathbf{s}}$ and variance $\sigma^2_{Y_n|\mathbf{S}=\mathbf{s}}$ which are given by:

$$\begin{aligned}\mu_{Y_n|\mathbf{S}=\mathbf{s}} &= E[Y_n|\mathbf{S}=\mathbf{s}] = q + \zeta_n \\ &= 2w\tau + \frac{2\tau}{\eta}\sum_{m=1}^{M} s_m g_{m,n}\rho_m,\end{aligned} \tag{3.8}$$

$$\begin{aligned}\sigma^2_{Y_n|\mathbf{S}=\mathbf{s}} &= E[(Y_n - \mu_{Y_n|\mathbf{S}=\mathbf{s}})^2|\mathbf{S}=\mathbf{s}] = 2(q + 2\zeta_n) \\ &= 4w\tau + \frac{8\tau}{\eta}\sum_{m=1}^{M} s_m g_{m,n}\rho_m.\end{aligned} \tag{3.9}$$

All the SUs report their soft data to the Fusion Center (FC), where an energy vector $\mathbf{Y}$ is formed, i.e., $\mathbf{Y} = (Y_1, ..., Y_N)$. Therefore, the distribution of the energy vector $\mathbf{Y}$ conditioned on the channel occupancy state $\mathbf{s}$ at the FC follows a multivariate Gaussian distribution with a mean vector $\boldsymbol{\mu}_{\mathbf{Y}|\mathbf{S}=\mathbf{s}}$ and a covariance matrix $\Sigma_{\mathbf{Y}|\mathbf{S}=\mathbf{s}}$ as follows:

$$\boldsymbol{\mu}_{\mathbf{Y}|\mathbf{S}=\mathbf{s}} = (\mu_{Y_1|\mathbf{S}=\mathbf{s}}, ..., \mu_{Y_N|\mathbf{S}=\mathbf{s}}), \tag{3.10}$$

$$\boldsymbol{\Sigma}_{\mathbf{Y}|\mathbf{S}=\mathbf{s}} = diag(\sigma^2_{Y_1|\mathbf{S}=\mathbf{s}}, ..., \sigma^2_{Y_N|\mathbf{S}=\mathbf{s}}), \tag{3.11}$$

where diag indicates a diagonal matrix whose diagonal elements are $\sigma^2_{Y_1|\mathbf{S}=\mathbf{s}}, ..., \sigma^2_{Y_N|\mathbf{S}=\mathbf{s}}$. Therefore, the sensed energy level by each SU is independent and uncorrelated from the rest of the sensed data by other SUs. Based on the binary hypothesis formulated in (3.3), the channel availability a can be obtained by comparing the energy level Y_n with a predefined threshold λ as follow:

$$a = \begin{cases} 0, & \text{if } Y_n \geq \lambda \\ 1, & \text{if } Y_n < \lambda \end{cases} \tag{3.12a}$$

$$\text{for } n = 1, ..., N. \tag{3.12b}$$

The probability of false alarm P_{fa} is defined as the probability that an SU detects the presence of a PU given that the PU was not utilizing the medium, which can be expressed as:

$$P_{fa} = P(Y_n|\mathbf{S} = \mathbf{s} \geq \lambda|H_0) = \frac{P(Y_n|\mathbf{S} = \mathbf{s} \cap H_0)}{P(H_0)}. \tag{3.13}$$

On the other hand, the probability of detection P_d is the probability that an SU detects the presence of a PU given that the PU was utilizing the spectrum. Therefore, P_d is as follows:

$$P_d = P(Y_n|\mathbf{S} = \mathbf{s} \geq \lambda|H_1) = \frac{P(Y_n|\mathbf{S} = \mathbf{s} \cap H_1)}{P(H_1)}. \tag{3.14}$$

3.4 Traditional Fusion Techniques for Cooperative CR Networks

In tradition Cooperative Spectrum Sensing (CSS), the Fusion Center (FC) forms an energy vector **Y** by collecting the energy levels from the SUs in the network. The FC then decides whether the channel is available or not based on a predefined energy threshold λ. If the received energy level by the n-th SU Y_n is greater than λ, then one or more PUs are utilizing the channel. The FC then applies fusion rules such as the AND, OR, or majority vote rules, to decide on the channel availability a based on the energy vector **Y**.

A) AND Rule:

Through using the AND rule, a channel is labeled unavailable if at least one SU sensed an energy level above the threshold. The FC applies a logical AND operation as follows:

$$a = \begin{cases} 1, & \text{if } (Y_1|\mathbf{S} = \mathbf{s} > \lambda \odot Y_2|\mathbf{S} = \mathbf{s} > \lambda ... \odot Y_N|\mathbf{S} = \mathbf{s} > \lambda) = 1 \\ 0, & \text{otherwise.} \end{cases} \tag{3.15}$$

B) OR Rule:

On the other hand, through using the OR rule a channel is labeled unavailable if all the cooperating SUs sensed an energy level above the threshold [27]. The FC applies a logical OR operation as follows:

$$a = \begin{cases} 1, & \text{if } (Y_1|\mathbf{S} = \mathbf{s} > \lambda \oplus Y_2|\mathbf{S} = \mathbf{s} > \lambda ... \oplus Y_N|\mathbf{S} = \mathbf{s} > \lambda) = 1 \\ 0, & \text{otherwise.} \end{cases} \tag{3.16}$$

C) Majority Rule:

The majority rule decides that the channel is unavailable if more than half of the cooperating SUs report energy levels above the threshold.

$$a = \begin{cases} 1, & \text{if } (Y_1|\mathbf{S} = \mathbf{s} > \lambda + Y_2|\mathbf{S} = \mathbf{s} > \lambda ... + Y_N|\mathbf{S} = \mathbf{s} > \lambda) \geq \frac{N}{2} \\ 0, & \text{otherwise.} \end{cases} \tag{3.17}$$

After applying one of the fusion rules, the FC then determines the channel availability a and passes the decision to the SUs. The OR rule performs better in terms of the probability of detection and worse in terms of the probability of false alarm. On the other hand, the AND rule performs better in terms of the probability of false alarm and worse in terms of the probability of detection [27].

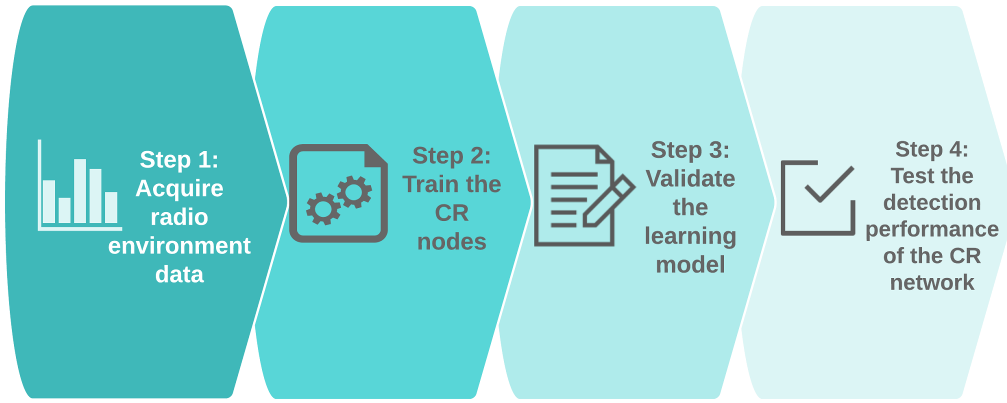

Figure 3.1: Stages of establishing a machine learning model for cooperative CR networks.

3.5 Machine Learning Framework

Motivated by the fact that SUs in CR Networks (CRNs) are adaptive and intelligent nodes that automatically detect available channels in a wireless spectrum, the use of machine learning algorithms was investigated to enhance the detection performance of CRNs. To fully realise their cognitive potential, radio nodes need to establish a three-step learning framework, that starts with perception, learning, and reasoning. Perception is achieved through sensing the radio environment variables, learning from them in order to draw patterns and trends, and finally using the acquired knowledge to achieve its goals, i.e., gain access to the radio spectrum. A learning-based classifier has two modules: the training and classification modules. Prior to classification, the Machine Learning (ML) classifier needs to go through a training phase, where it is fed with training feature vectors. Fig. 3.1 highlights the main general steps needed to establish a machine learning model for cooperative CR networks. The first step to establishing a machine learning model, is to first start by training it prior to classification. The learning process is modular, and both training and classification modules could be run in parallel, which makes the system more time efficient. The use of machine learning techniques eliminates the need to know the *a priori* probability of the channel occupancy, SNR, PU signal, or channel gain, as they will be inferred from the training phase. In addition, the learning algorithm is able to implicitly learn the topology of the network, which renders this approach suitable for practical systems as it is highly adaptive. Once the algorithm is trained, there is no need for further training until the channel changes, which significantly reduces complexity in slow fading channels [44]. Additionally, ML approaches optimize the decision region based on a feature space, which is better than the optimization used by classical techniques.

3.5.1 Training in the Radio Environment

During the training phase, the learning-based cooperating CR node is fed with the training data subset that has N features, where N is number of energy levels in an energy vector $\mathbf{Y}$. Let x_i be i-th input energy vector containing N energy levels and y_i is the corresponding channel occupancy state a of the PUs. The CR node needs to learn the mapping function $f(.)$, that maps the radio environment input x_i to the output y_i. The detection performance of the learning-based CR network is greatly affected by the quality of training data provided. Even the most prominent learning algorithms will not yield a satisfying performance if they were given poor quality data for training. Examples of poor quality data include biased data, mislabeled data, and data that lacks variety of examples. Hence, it is very crucial to provide the CR node with accurate, relevant, and sufficient data for training. After the training phase, the learning-based CR node is able to perform energy vector classification with no previous knowledge about the *a priori* probability of the channel occupancy, the SNR, and the topology of the network as they will be inferred from the training phase. This is a very appealing approach, since CR networks perform blind sensing of the primary network. Hence, through the use of learning models the challenge of obtaining information about the PUs is eliminated.

3.5.2 Radio Environment Data Collection

There are two main types of data sets used for training the learning-based CR network, namely *labeled* and *unlabeled* data sets. In a labeled data set, the features are annotated with a corresponding classification outcome, unlike unlabeled data, where the data set only has features with no labels or classification outcomes. In the context of cooperative secondary networks, the Fusion Center (FC) collects energy levels Y_n from the $n = 1, ..., N$ spatially diverse SUs, and forms an energy vector $\mathbf{Y}$ comprised of their corresponding energy levels. In this case, the dimensionality of the data set increases with the increase in the number of cooperating SUs. Based on the energy vector, the FC decides on the channel occupancy state a of the primary network, i.e., if the channel is available or not. If each **Y** corresponds to a classification outcome, i.e., a, then the data set is labeled, otherwise it is considered unlabeled. It is important to mention that the choice of features is not unique, and it depends on the data set at hand. The acquired data set is split into two main subsets, which are the subset for training and the subset for validation used to assess the detection performance of the learning-based CR network. A collection of unlabeled energy vectors is used to test the accuracy and efficiency of the network's feature classification.

The size of the training data set plays a crucial role in defining the detection performance. If an insufficient amount of training data is given to the CR network, it will produce an under-fitted learning model. An underfit model still has room for performance improvement. Another problem that may arise is over-fitting, which happens if the CR network is trained for too long, or if the collected energy vectors from the radio environment do not include all the possible examples that the network needs to learn from. That is, the learning model fits very well to the training data and does not generalize to other data points, which can negatively impact the overall detection performance of a cooperative CR network.

For comparison purposes in the following subsections, a network in a two-dimensional grid is constructed to compare the classification performance of the different proposed machine learning algorithms. In Scenario-I, there are two fixed PUs at (500m,0m) and (0m,-500m), in addition to two fixed SUs at (0m,0m) and (1000m,0m). In Scenario-II, an additional SU is added to scenario-I at (1000m,-500m) and an additional PU at (1000m,500m). All the PUs are activated with a probability p and are independent of one another. The SUs sense a bandwidth ω= 5 MHz for a sensing duration of τ= 100 μs. The noise spectral density in the medium is η= -174 dBm.

3.5.3 Unsupervised Learning in Cooperative CR Networks

An agent in an unsupervised learning algorithm learns the main features and hidden patterns through unlabeled data. The main purposes of using an unsupervised machine learning algorithm is for clustering or data compression [2]. The performance of unsupervised algorithms is lower than the supervised learning, since it does not learn from ”ground truths”, i.e., labeled data. It is evident that there is a trade-off between the availability of labeled data and the performance of the learning algorithm.

Before the classifier is able to operate, it has to be trained first through a set of energy vectors $\bar{\mathbf{y}}$ of size L, where the l-th energy vector is $\mathbf{y}^{(l)}$ (i.e, $\bar{\mathbf{y}} = \{\mathbf{y}^{(1)}, ..., \mathbf{y}^{(L)}\}$). The distribution of the energy vector $\mathbf{Y}$ at the FC is a multivariate Gaussian distribution with a mean vector $\boldsymbol{\mu}_{\mathbf{Y}|\mathbf{S}=\mathbf{s}}$ and a covariance matrix $\boldsymbol{\Sigma}_{\mathbf{Y}|\mathbf{S}=\mathbf{s}}$ given by (3.10) and (3.11). Energy vectors that belong to cluster "channel available" are samples taken from a multivariate Gaussian distribution that has a mean vector $\boldsymbol{\mu}_{\mathbf{Y}|\mathbf{S}=0}$ and a covariance matrix $\boldsymbol{\Sigma}_{\mathbf{Y}|\mathbf{S}=0}$. On the other hand, the energy vectors that form cluster "Channel unavailable" are samples taken from a multivariate Gaussian distribution with a mean vector $\boldsymbol{\mu}_{\mathbf{Y}|\mathbf{S}=\mathbf{s}}$ and a covariance matrix $\boldsymbol{\Sigma}_{\mathbf{Y}|\mathbf{S}=\mathbf{s}}$ which are unknown.

The Gaussian Mixture Model

A Gaussian Mixture Model (GMM) is a model-based clustering algorithm [2], which means that the data in each cluster follows a certain distribution. The GMM algorithm is a mixture of multivariate Gaussian distributions with different mixing coefficients which is given by:

$$f(\mathbf{x}|\boldsymbol{\theta}) = \sum_{k=1}^{K} \upsilon_k.\phi(\mathbf{x}|\boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k), \tag{3.18}$$

where $\boldsymbol{\theta}$ is the collection of all the variables that define the GMM. $\boldsymbol{\theta}$ includes variables such as $\boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k$, and υ_k for $k = 1, ..., K$, where K is the total number of Gaussian densities in the mixture model. The GMM perfectly fits the distribution of the energy vectors received at the FC, since each energy vector is a sample taken from either a multivariate Gaussian distribution with a mean vector $\boldsymbol{\mu}_{\mathbf{Y}|\mathbf{S}=0}$ and a covariance matrix $\boldsymbol{\Sigma}_{\mathbf{Y}|\mathbf{S}=0}$ or with a mean vector $\boldsymbol{\mu}_{\mathbf{Y}|\mathbf{S}=s}$ and a covariance matrix $\boldsymbol{\Sigma}_{\mathbf{Y}|\mathbf{S}=s}$.The parameters $\boldsymbol{\mu}_{\mathbf{Y}|\mathbf{S}=0}$ and $\boldsymbol{\Sigma}_{\mathbf{Y}|\mathbf{S}=0}$ are known to the CR network in advance, since they correspond to the distribution of the noise in the channel. However, $\boldsymbol{\mu}_{\mathbf{Y}|\mathbf{S}=\mathbf{s}}$ and $\boldsymbol{\Sigma}_{\mathbf{Y}|\mathbf{S}=\mathbf{s}}$ which are the mean vector and covariance matrix of the k-th Gaussian density are unknown. In addition, the mixing coefficients υ_k, where $k = 1, .., K$ are also unknown. Under the interweave model, there are namely two clusters that need be learnt by the algorithm, therefore there are exactly two Gaussian densities in the mixture model. To estimate the set of parameters $\boldsymbol{\theta}^{*}$, the Expectation Maximization (EM) algorithm is fed with a set of training data $\bar{\mathbf{y}}$, then it calculates the maximum likelihood of the mixtures' parameters. Algorithm. 1 converges to a local optimal solution over several iterations of calculating the expectation and maximization steps [45].

Algorithm 1: EM algorithm used for GMM Training

1. **Set** $\boldsymbol{\mu}_1(1) \leftarrow \boldsymbol{\mu}_{\mathbf{Y}|\mathbf{S}=0}$ and $\boldsymbol{\Sigma}_1(1) \leftarrow \boldsymbol{\Sigma}_{\mathbf{Y}|\mathbf{S}=0}$
2. **Initialize** $v_k(1)$ for $k = 1, ..., K$ and $\boldsymbol{\mu}_k(1)$ and $\boldsymbol{\Sigma}_k(1)$
for $k = 2, ..., K$.
3. $j \leftarrow 1$
4. **Repeat**
5. Expectation step

$$u_k^{(l)} \leftarrow \frac{v_k(j).\phi(\mathbf{y}^{(l)}|\boldsymbol{\mu}_k(j),\boldsymbol{\Sigma}_k(j))}{\sum_{i=1}^{K} v_i(j).\phi(\mathbf{y}^{(l)}|\boldsymbol{\mu}_i(j),\boldsymbol{\Sigma}_i(j))},$$

for $l = 1, ..., L$ for $k = 1, ..., K$.

6. Maximization step

$$v_k(j+1) \leftarrow \frac{\sum_{l=1}^{L} u_k^{(l)}}{L}, \text{ for } k = 1, ..., K.$$
$$\boldsymbol{\mu}_k(j+1) \leftarrow \frac{\sum_{l=1}^{L} u_k^{(l)} \mathbf{y}^{(l)}}{\sum_{l=1}^{L} u_k^{(l)}}, \text{ for } k = 2, ..., K.$$
$$\boldsymbol{\Sigma}_k(j+1) \leftarrow \frac{\sum_{l=1}^{L} u_k^{(l)} \{diag(\mathbf{y}^{(l)} - \boldsymbol{\mu}_k(j+1))\}^2}{\sum_{l=1}^{L} u_k^{(l)}},$$

for $k = 2, ..., K$.

7. $j \leftarrow j+1$
8. **Until** $\boldsymbol{\theta}(j)$ converges
9. **Obtain** $f(x|\theta)$

To classify a test energy vector $\mathbf{y}^*$ to determine whether it belongs to cluster one or two, i.e., H_0 and H_1. The GMM calculates the log-likelihood that $\mathbf{y}^*$ belongs to cluster one or two. Consequently, the channel is classified as available $\hat{a}$= 1 if and only if for a predefined threshold δ its satisfies the following [14]:

$$\ln(v_2^*.\phi(\mathbf{y}^*|\boldsymbol{\mu}_2^*, \boldsymbol{\Sigma}_2^*)) - \ln(v_1^*.\phi(\mathbf{y}^*|\boldsymbol{\mu}_1^*, \boldsymbol{\Sigma}_1^*)) \geq \delta. \tag{3.19}$$

If δ increases, that means that $\mathbf{y}^*$ is more likely to be classified as channel available. In Fig. 3.2, the raw energy vectors collected at the FC are plotted as the "Unclustered data" before the GMM is trained. From Fig. 3.2 it can be observed that the two clusters are overlapping, however the GMM is able to establish a clear cut boundary between the two clusters. The same data is applied to the classifier after training and the results are plotted as "Clustered data".

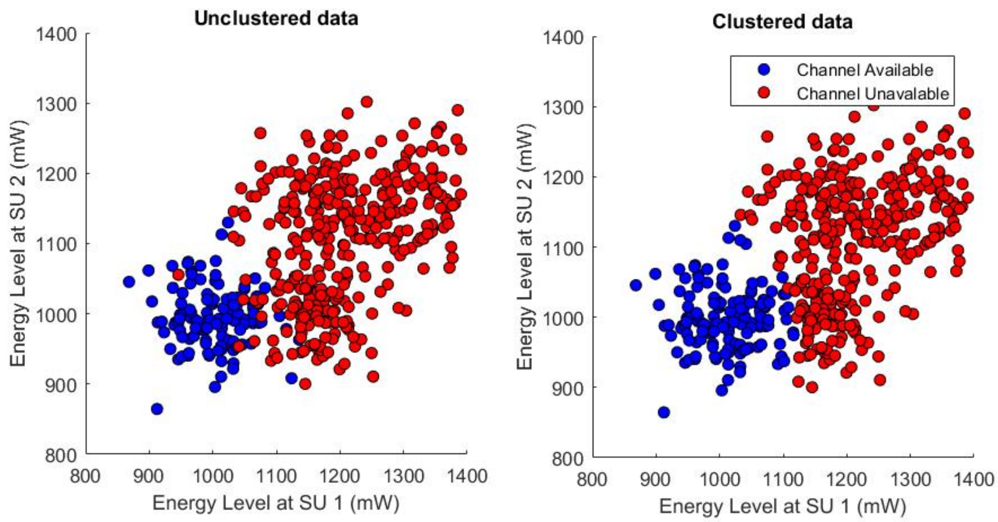

Figure 3.2: Classification using the GMM algorithm for scenario-I.

3.5.4 Supervised Learning in Cooperative CR Networks

An agent/user in a supervised learning algorithm must be provided with labeled data. The algorithm infers the classification pattern through a labeled data set also known as the ”ground truth”. In cooperative secondary networks, the labeled data set should have the feature vector, i.e., the energy vector $\mathbf{Y}$ at the FC, and the corresponding channel occupancy state a. Supervised learning has been proven powerful for applications with historical data [2]. Therefore, its application in cognitive radio networks has a great potential for improving the detection accuracy of SUs. Similar to the work in [14], it is assumed that occasionally such information is transmitted by the primary network to the secondary network.

Naive Bayes’ Classifier

A Naive Bayes’ Classifier (NBC) is based on the principle of Bayes’ theorem, where the conditional probability is used to find the probability that an event will occur given the knowledge of prior events. An NBC is also known as the ”independent feature model” [33], as it does not take into account the dependence of features by making a ”Naive” assumption. That is the presence of a certain feature in a class is independent of the presence of any other feature. In the context of co-operative secondary networks, the assumption would be that the estimated energy levels $Y_n|\mathbf{S} = \mathbf{s}$, where $n = 1...N$ are mutually independent. The joint conditional probability distribution could be written as follows:

$$f(\boldsymbol{Y}|\mathbf{S}=\mathbf{s}|H_j) = \prod_{n=1}^{N} f(Y_n|\mathbf{S}=\mathbf{s}|H_j), \quad \text{for } j = 0, 1, \tag{3.20}$$

with $f(Y_n|\mathbf{S}=\mathbf{s}|H_j)$ Gaussian distributed, $f(\boldsymbol{Y}|\mathbf{S}=\mathbf{s}|H_j)$ becomes a multi-variate Gaussian distribution. After the training period, the NB algorithm can estimate the probability density function parameters of each hypothesis as:

$$\begin{gathered} \mu_{Y_n|\mathbf{S}=\mathbf{s},H_j} = \frac{1}{L^{H_{1,0}}} \sum_{l=1}^{L^{H_{1,0}}} Y_n|\mathbf{S}=\mathbf{s}, H_j[l], \\ \text{for } j = 0, 1, \end{gathered} \tag{3.21}$$

$$\begin{gathered} \sigma^2_{Y_n|\mathbf{S}=\mathbf{s},H_j} = \frac{1}{L^{H_{1,0}} - 1} \sum_{l=1}^{L^{H_{1,0}}} (Y_n|\mathbf{S}=\mathbf{s}, H_j[l] - \mu_{Y_n|\mathbf{S}=\mathbf{s},H_j})^2, \\ \text{for } j = 0, 1, \end{gathered} \tag{3.22}$$

where $L^{H_{1,0}}$ is the subset of the training data L corresponding to hypothesis H_1 or H_0. The Naive Bayes' classifier estimates an *a posteriori* probability, which is the channel occupancy, in the CR network model, based on Bayes' Theorem:

$$\begin{aligned} &P(H_1|\mathbf{Y}|\mathbf{S}=\mathbf{s}) = \\ &\frac{f(\mathbf{Y}|\mathbf{S}=\mathbf{s}|H_1)P(H_1)}{f(\mathbf{Y}|\mathbf{S}=\mathbf{s}|H_1)P(H_1) + f(\mathbf{Y}|\mathbf{S}=\mathbf{s}|H_0)P(H_0)}, \end{aligned} \tag{3.23}$$

where $P(H_1)$ and $P(H_0)$ are the a *priori* probabilities for the channel occupancy state.

Binary Support Vector Machine (SVM)

The Support Vector Machine (SVM) classifier has been used in a variety of applications due to its robustness to high-dimensional data, noise, and outliers. In cooperative cognitive networks, increasing the number of cooperating SUs increases the dimensionality of the data. Thus, the SVM would be best suited to perform the classification tasks in such scenarios. Moreover, since the

SVM algorithm is based on structural risk minimization, it is less prone to over-fitting problems for small training data sets [46]. The primary task of an SVM algorithm is to find a linearly separable hyperplane h, even if the training data may not be linearly separable, through the help of support vectors. It does so by maximizing the margin of the classifier while minimizing the sum of errors [14]. Hence, the goal is to find a linear separable hyperplane h such that the gap between the two margins on both sides of h needs to be maximized [33]. In the proposed Cognitive Radio (CR) network, the training energy vectors may not be linearly separable because of overlapping clusters as a result of the noise. To overcome this, the data is mapped to a higher dimensional feature space. This is done through applying a non-linear mapping function $\phi(.)$ to the input energy vectors to get a feature space. Support vectors are the energy vectors that are closer to the classifier's hyperplane, which are the data points that are the most difficult to classify. If some of the support vectors are removed, the position of the hyperplane will change. Given a training set of energy vectors of size L, i.e, ($\overline{\mathbf{y}} = \{\mathbf{y}^{(1)}, ..., \mathbf{y}^{(L)}\}$) and its corresponding labels $\overline{\mathbf{a}} = \{a^{(1)}, ..., a^{(L)}\}$, i.e., whether the channel is occupied or not, the decision surface becomes as follows [47]:

$$h(\mathbf{y}^{(l)}) = \Psi.\phi(\mathbf{y}^{(l)}) + \psi_0 = 0, \quad \text{for } l = 1, ..., L, \tag{3.24}$$

where $\mathbf{y}^{(l)}$ is a training energy vector. The goal is to find the weighting vector Ψ, and the bias ψ_0 used for shifting the hyperplane from the origin. Therefore, the classifier should satisfy the following:

$$\begin{aligned} \Psi.\phi(\mathbf{y}^{(l)}) + \psi_0 \geq 1, \quad \text{if } a^{(l)} = 1, \\ \Psi.\phi(\mathbf{y}^{(l)}) + \psi_0 \leq -1, \quad \text{if } a^{(l)} = -1, \end{aligned} \tag{3.25}$$

Fig. 3.3 shows the mapped energy vectors in the higher dimensional feature space, and the separating hyperplane h with its margins on each side. The conditions in (3.25) assume that the energy vectors will become perfect linearly separable. However, in the proposed practical cognitive network the energy vectors may still not be perfect linearly separable since the clusters may still

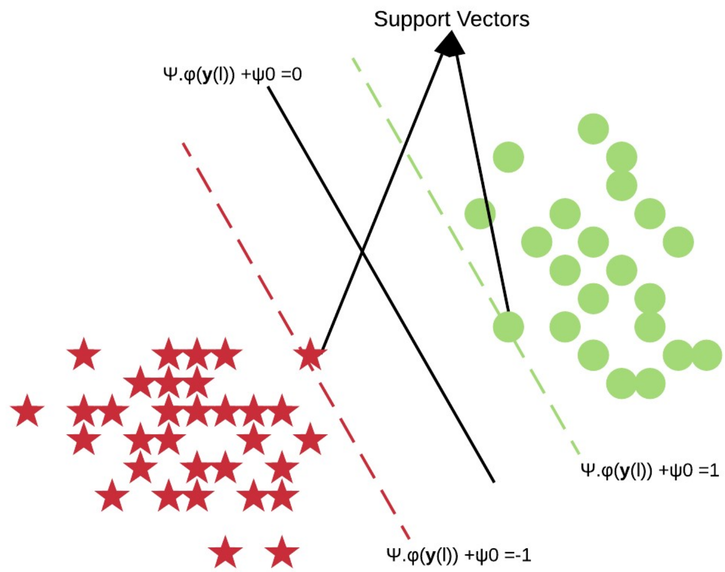

Figure 3.3: SVM Classification model.

overlap. Therefore, a slack variable $\epsilon^{(l)}$ is introduced to modify the conditions in (3.25) for possible classification errors. Hence, it becomes [47]:

$$a^{(l)}[\Psi.\phi(\mathbf{y}^{(l)}) + \psi_0] \geq 1 - \epsilon^{(l)}, \tag{3.26}$$

where $\epsilon^{(l)} \geq 0$ for $l = 1...L$. $\epsilon^{(l)}$ lies in $0 \leq \epsilon^{(l)} \leq 1$ for marginal classification errors, and greater than 1 $\epsilon^{(l)} > 1$ for misclassification. The optimization problem for finding the linearly separable hyperplane becomes:

$$\underset{\Psi,\psi_0}{\text{minimize:}} \quad \frac{1}{2}||\Psi||^2 + \zeta \sum_{l=1}^{L} I_{\{\epsilon^{(l)}>1\}}, \tag{3.27}$$

$$\text{subject to:} \quad a^{(l)}[\Psi.\phi(\mathbf{y}^{(l)}) + \psi_0] \geq 1 - \epsilon^{(l)}, \tag{3.28}$$

$$\text{for} \quad l = 1, ..., L, \tag{3.29}$$

$$\epsilon^{(l)} \geq 0, \quad \text{for} \quad l = 1, ..., L, \tag{3.30}$$

where $||\Psi||^2 = \Psi.\Psi$, ζ is a soft margin constant used to control the trade-off between minimizing the classification errors and the model complexity [47], and $I_{\{.\}}$ is the indicator function when the condition inside it is true the output is 1 and when it is false the output is zero. Larger values of ζ mean a higher penalty to errors [48]. The proposed optimization problem is a non-convex problem, since the indicator function is in the objective function. $\sum_{l=1}^{L} \epsilon^{(l)}$ gives a bound on the number of misclassified training data as $\epsilon^{(l)} > 1$ is for misclassification by the decision surface defined in (3.24). Therefore, $\sum_{l=1}^{L} \epsilon^{(l)}$ can be used to measure the number of misclassified energy vectors, as well as the correctly classified energy vectors that lie in $-1 < \Psi.\phi(\mathbf{y}^{(l)}) + \psi_0 < 1$. Hence, the optimization problem can be reformulated as [47]:

$$\underset{\Psi,\psi_0,\epsilon^{(l)}\geq 0}{\text{minimize:}} \quad \frac{1}{2}||\Psi||^2 + \zeta\sum_{l=1}^{L}\epsilon^{(l)} \tag{3.31}$$

$$\text{subject to:} \quad a^{(l)}[\Psi.\phi(\mathbf{y}^{(l)}) + \psi_0] \geq 1 - \epsilon^{(l)}, \tag{3.32}$$

$$\text{for} \;\; l = 1, ..., L, \tag{3.33}$$

$$\epsilon^{(l)} \geq 0, \quad \text{for} \;\; l = 1, ..., L. \tag{3.34}$$

Minimizing $\frac{1}{2}||\Psi||^2$ is equivalent to minimizing $2/||\Psi||$, which is the margin between the two clusters [47]. Let $\tilde{\beta}^{(l)}$ be the solution to the optimization problem above. The final non-linear decision function could be obtained as follows:

$$d(\mathbf{x}) = sgn(\sum_{l=1}^{L}\tilde{\beta}^{(l)}a^{(l)}\kappa(\mathbf{x}, \mathbf{y}^{(l)}) + \psi_0), \tag{3.35}$$

where $\kappa(\mathbf{x}, \mathbf{y})$ is $\phi(\mathbf{x}).\phi(\mathbf{y})$ is the kernel function that computes the inner product of $\phi(\mathbf{x})$ and $\phi(\mathbf{y})$ produced in the feature space. Kernel function types include linear, polynomial, and Gaussian also known as the radial basis function [49]. It is crucial to select a kernel function that minimizes the number of support vectors, since using a smaller number of support vectors leads to decreasing the expected number of errors. Note that the bias ψ_0 could be obtained through solving the optimization problem in (3.31)-(3.33) after finding the optimal Ψ. However, in our model we chose to adjust ψ_0 to control the trade-off between the probabilities of false alarm and detection. The decision function could be viewed as the summation of weighted distances from the test energy sample $\mathbf{y}^*$ to the support vectors that define the separating hyperplane [50]. After the classifier obtains the decision function in (3.35), it can classify the test energy vector $\mathbf{y}^*$ as $\hat{a} = d(\mathbf{y}^*)$.

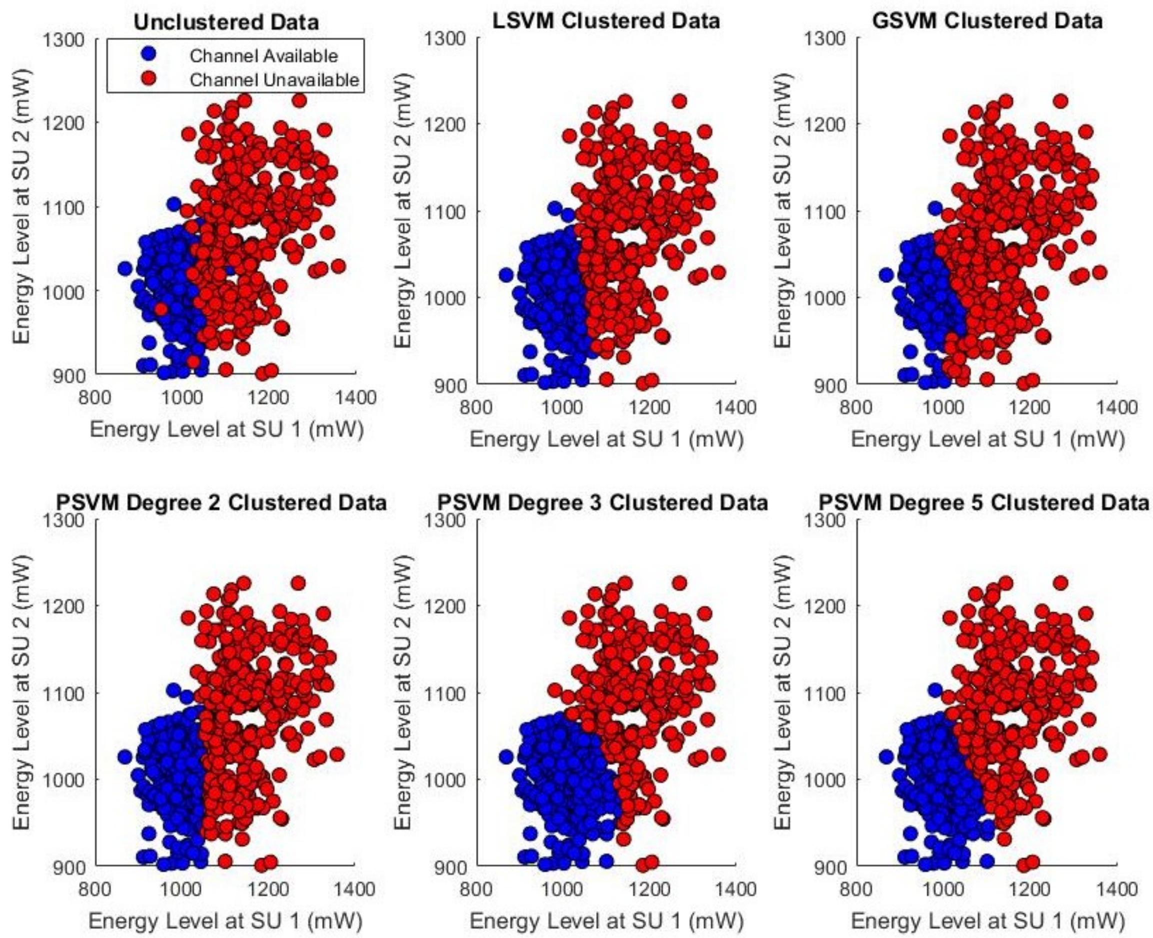

Figure 3.4: Comparison between classification boundary shapes for a target probability of false alarm of 0.25 at $\rho_m = 150$ mW for scenario-I.

Considering scenario-I which consists of two SUs and two PUs, where each PU transmits independently with a transmit power of 150 mW. The degree of the SVM based polynomial kernel was manipulated to achieve the best energy vector classification performance. In Fig. 3.4, the energy vectors that arrive at the fusion center prior to learning are plotted as "unclustered data". It can be observed that the clusters are overlapping as a result of the noise in the radio spectrum. In addition, the energy vectors are plotted in two dimensions owing to the presence of only two SUs reporting energy levels. Fig. 3.4 highlights the importance of the choice of the SVM kernel, as it greatly affects the shape of the classification boundary, which in turn affects the detection performance of the secondary network. Furthermore, we noted that increasing the order of the kernel does not always lead to a better performance in our CR interweave model, as it is sensitive to the energy vectors collected at the FC. Hence, it is not only crucial to select the appropriate kernel that best fits our model, but also the order of the kernel so that the performance of the CRN does not suffer.

3.6 Multi-class Learning in Underlay CR Networks

Multi-class learning is a sub-branch of classification techniques, in which the classifier is trained to identify more than two classes. In underlayed cognitive radio networks, both the secondary and primary users can simultaneously access the radio spectrum under the condition that the SUs' transmissions' do not exceed the interference threshold. Hence, the SUs under such networks are not only concerned with whether the primary user is available in the medium or not, but also interested in the current Channel Occupancy State (COS) of each PU. If the secondary network has knowledge about the current COS, it can adjust its transmission parameters accordingly thereby reducing the interference to the PUs. The number of channel occupancy states of the primary network, i.e., the clusters, is dependent on the number of PUs, i.e., for M PUs there are 2^M clusters. Hence, by using MSVM hypothesis H_1 is further classified into several clusters each pointing to a certain channel occupancy state of the PUs. Thus, the algorithm learns k-hypotheses, where $k = 1, ..., 2^M$. The detection problem under the presence of multiple PUs is reformulated as follows:

$$H_1 \triangleq \begin{cases} H_1^{\mathbf{S}=\mathbf{s}_1} \\ H_1^{\mathbf{S}=\mathbf{s}_2} \\ \vdots \\ H_1^{\mathbf{S}=\mathbf{s}_k} \end{cases} \tag{3.36}$$

where $\mathbf{s}_k = (s_1, .., s_M)$ is the channel occupancy state vector of the primary network. As an example, in Table. 3.1 shows the number of possible channel occupancy states for the case where m = 3.

	S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8
PU1	0	1	0	0	1	1	0	1
PU2	0	0	1	0	1	0	1	1
PU3	0	0	0	1	0	1	1	1

Table 3.1: The different channel occupancy states for m= 3 PUs.

There are several approaches of extending binary SVM to k-class SVM. The most popular are the One-vs-All (OVA) and One-vs-One (OVO) [46]. In our work, the OVO approach was used in constructing the k-class SVM classifier. In the OVO approach, $k(k-1)/2$ binary SVM classifiers are constructed, where each classifier trains on data from two classes. To construct a linearly separable hyperplane for training data from class i and class j, the optimization problem in (3.31)-(3.33) is reformulated as follows:

$$\underset{\Psi^{ij},\psi_0^{ij},\epsilon_{ij}^{(l)}\geq 0}{\text{minimize:}} \quad \frac{1}{2}||\Psi^{ij}||^2+\zeta\sum_{l=1}^{L}\epsilon_{ij}^{(l)} \tag{3.37}$$

$$\begin{aligned} \text{subject to: } & (\Psi^{ij})^T\phi(\mathbf{y}^{(l)})+\psi_0^{ij}\geq 1-\epsilon_{ij}^{(l)}, \quad \text{if } k_l=i \\ & (\Psi^{ij})^T\phi(\mathbf{y}^{(l)})+\psi_0^{ij}\leq -1+\epsilon_{ij}^{(l)}, \quad \text{if } k_l=j \end{aligned} \tag{3.38}$$

where k_l is the class that $\mathbf{y}^{(l)}$ belongs to. The final classification decision is obtained through a voting approach called ”Max-Wins” [46]. For example, if the decision function decides that a test energy vector belongs to cluster i, then the vote for cluster i increases by one, otherwise the vote for cluster j increases by one. In Fig. 3.5, the raw energy vectors at the FC are plotted before the MSVM classifier is trained for scenario-II. Since the network has m = 3 PUs, there are eight clusters that need to be classified. In addition, the network had three cooperating SUs, therefore the classification becomes three-dimensional. As shown, the clusters are completely overlapping, because the transmit power of the PUs is low. Nevertheless, the MSVM algorithm is able to identify the different clusters and form clear cut boundaries among them. That is the MSVM is able to perform well in low SNRs.

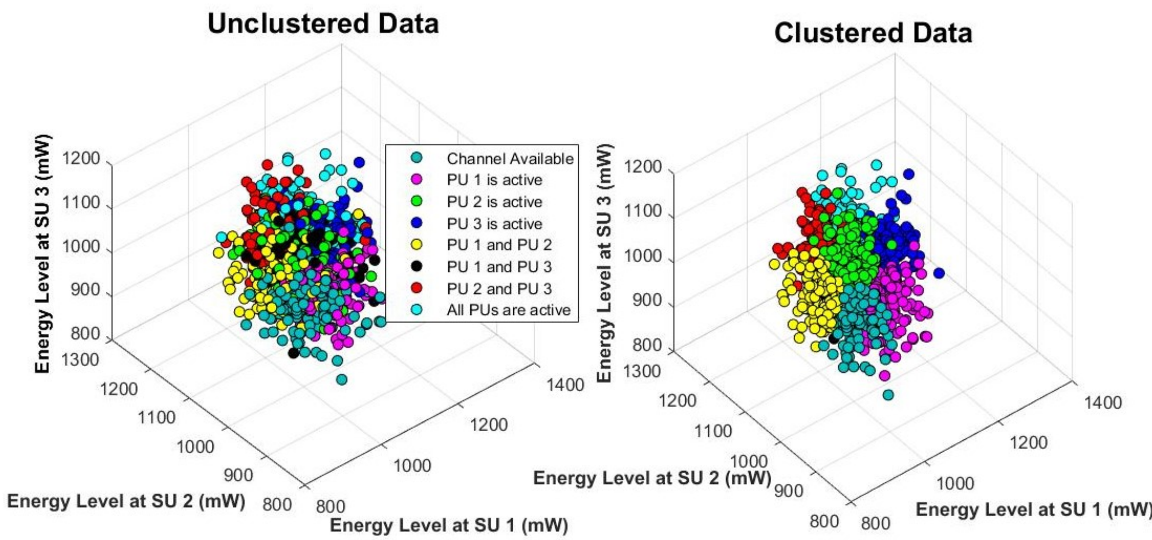

Figure 3.5: Multi-class SVM before and after training for scenario-II for a PU transmit power ρ_m= 80 mW.

3.7 Simulation Model and Results

In this section, we present simulations to investigate the performance of a hybrid underlay-interweave cooperative network that employs learning techniques to determine the channel occupancy state of the primary network under the presence of multiple PUs. After determining the state of the primary network, the secondary network adjusts its transmission parameters accordingly to operate in an interweave or underlay fashion. The network was constructed in a two-dimensional grid of area 4000 m x 4000 m with 25 equally spaced cooperating SUs. The performance was evaluated for scenario-I when there are two PUs at (500m,500m) and (-1500m,0m) and for scenario-II when there is a single PU at (500m,500m). Fig. 3.6 shows the node deployment for scenario-I. Without loss of generality, it is assumed that the data of the PU's signal is PSK modulated. The SUs sense the medium for a duration of τ = 100 μs in a bandwidth of ω = 5 MHz. The noise spectral density was taken as η = -174 dBm. A non-line of sight (NLOS) channel environment is considered with a path-loss exponent α= 4. The PUs are activated with equal probability p and are activated independently from each other. The training module was given 1000 training vectors, and the classifier was given 1000 test vectors. Table. 3.2 summarizes the simulation parameters used in the proposed model.

1:

Parameter	Value
PU Transmit Power ρ_m	200 mW
Noise PSD η	-174 dBm
Sensing Duration of SU δ	100 μs
Bandwidth ω	5 MHz
Area	16 Km^2
Path-loss Exponent α	4
Shadow Fading Component $\psi_{m,n}$	1
Multi-path Fading Component $\nu_{m,n}$	1

Table 3.2: Simulation parameters

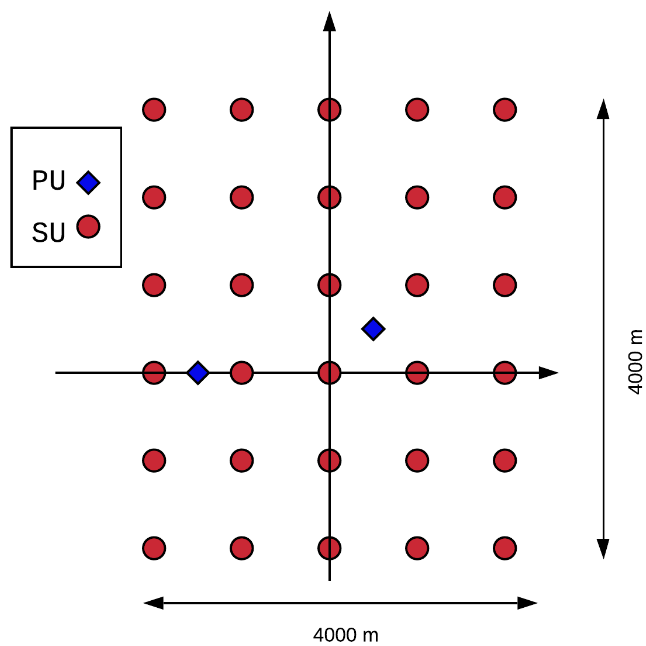

Figure 3.6: The node deployment in the proposed CR network in scenario-I.

The performance of the proposed cooperative secondary network was evaluated using the Receiver Operating Characteristics (ROC). The degree of the SVM kernel was manipulated to achieve the best detection performance. As seen in Fig. 3.7, the Gaussian SVM (GSVM) outperforms all other algorithms in scenario-I. That is the GSVM is able to form a classification boundary that minimizes errors for the hybrid CR network operating in an interweave fashion. This proves that the relationship between the energy vectors from each cluster is non-linear. Increasing the degree of the polynomial SVM kernel does not lead to an enhanced detection performance and that is because it is sensitive to the energy vectors collected at the FC. Additionally, a clear difference in performance is seen between the supervised learning algorithms (i.e., NB, LSVM, PSVM, and GSVM) and the unsupervised learning, namely the GMM. Since supervised learning algorithms are trained with labeled data, i.e., ground truth , they are able to perform better than unsupervised learning algorithms. Also, supervised learning algorithms such as the SVM are robust to high dimensional feature data unlike the GMM algorithm.

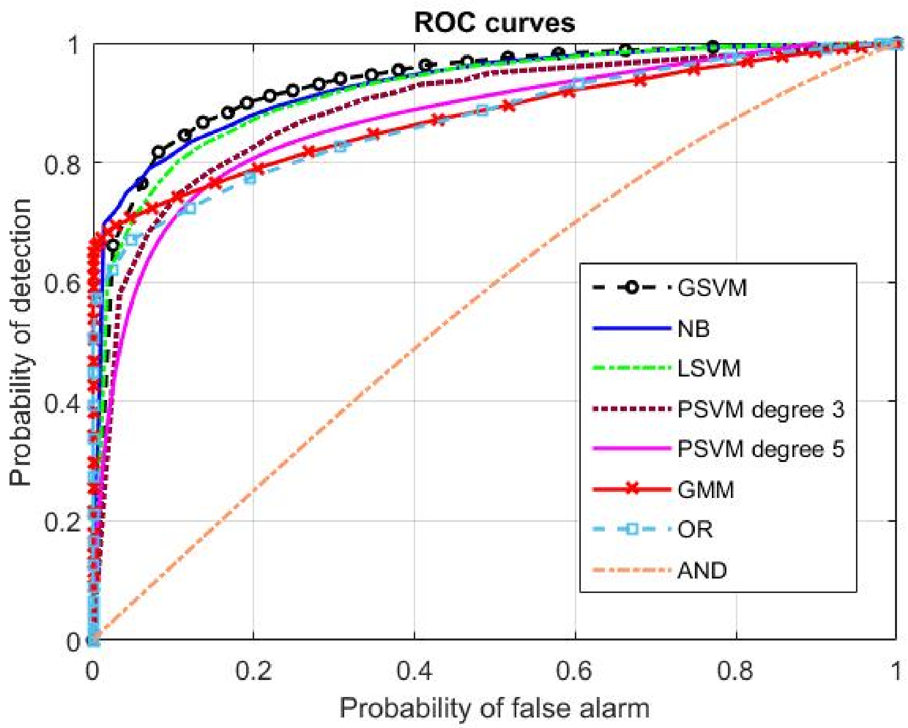

Figure 3.7: The ROC curves at $\rho_m = 200$ mW.

The performance of the learning-based cooperative network is compared with the performance of traditional cooperative sensing fusion techniques such as the AND rule and the OR rule. The detection performance of the CR network in scenario-II is plotted in Fig. 3.8 for different values of PU transmit power ρ_m for a probability of false alarm of 0.1. Even though the OR rule offers very close performance to the GMM, Fig 3.8 shows how the GMM can improve the CR network's detection performance with a slight increase in the PU transmit power ρ_m unlike the OR rule.

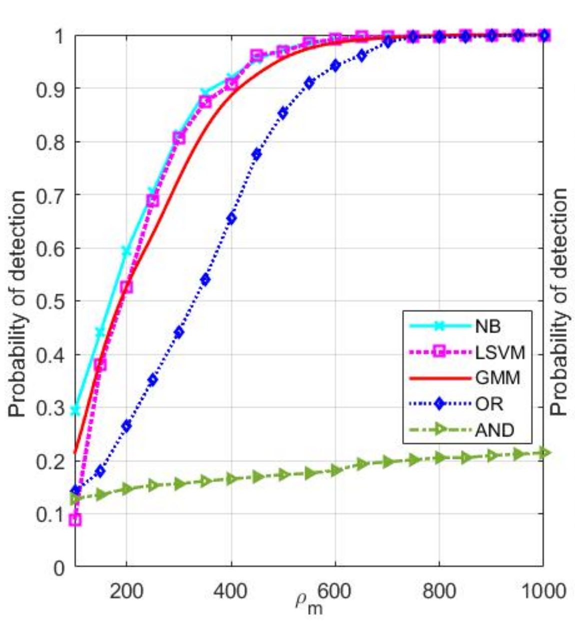

Figure 3.8: The probability of detection for different values of ρ_m at a probability of false alarm of 0.1 and the corresponding ROC curves.

To examine the effect of increasing the number of PUs in the primary network, the ROC curves in Fig. 3.7 and Fig. 3.8 are combined in Fig. 3.9. It is apparent that increasing the number of PUs leads to an enhanced detection performance. That is because the power in the medium has increased. Instead of having a single PU transmitting at 200 mW, there are two PUs each transmitting with 200 mW. Thus, the classification clusters move further from each other rendering them more distinguishable. It is also important to point out that increasing the number of PUs is not equivalent to increasing the transmit power of a single PU. In the case where there is a single PU, the learning algorithm trains on energy vectors that correspond to only two channel occupancy states, i.e., PU is on or off. However, in the case where there are two PUs there are four different channel states.

Under the interweave model, three of those channel states indicate channel unavailable and one indicates channel available. Thus, it is expected that the performance of a single PU transmitting with ρ_m= 400 mW to perform better than a network with two PUs each transmitting with ρ_m= 200 mW.

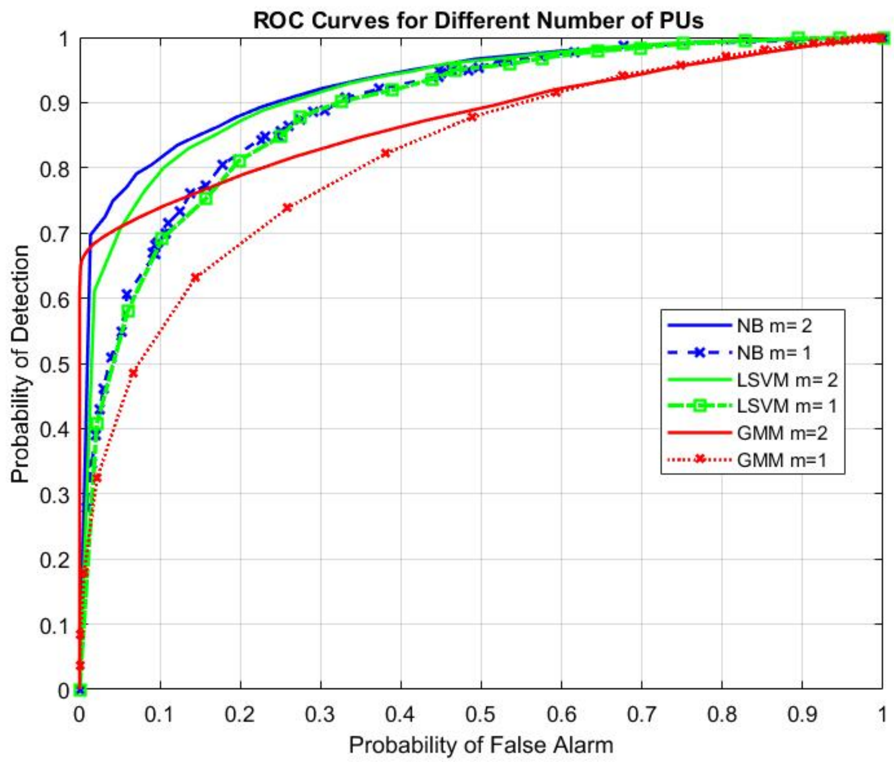

Figure 3.9: Examining the effect of increasing the number of PUs m, each transmitting with ρ_m= 200 mW.

Fig. 3.10 examines the effect of increasing the cooperation size n in the presence of a single PU. It is evident that increasing the cooperation size leads to enhancing the detection performance. That is because the secondary network takes advantage of the increased spatial diversity of the added SUs. Additionally, it can be concluded that the supervised learning techniques such as Naive Bayes' and Support Vector Machine are able to deal better with high dimensional data. Therefore, there is a higher performance gain when the cooperation size is increased compared with the GMM algorithm. Nevertheless, the learning-based secondary network using the GMM experiences a performance increase when the cooperation size is increased.

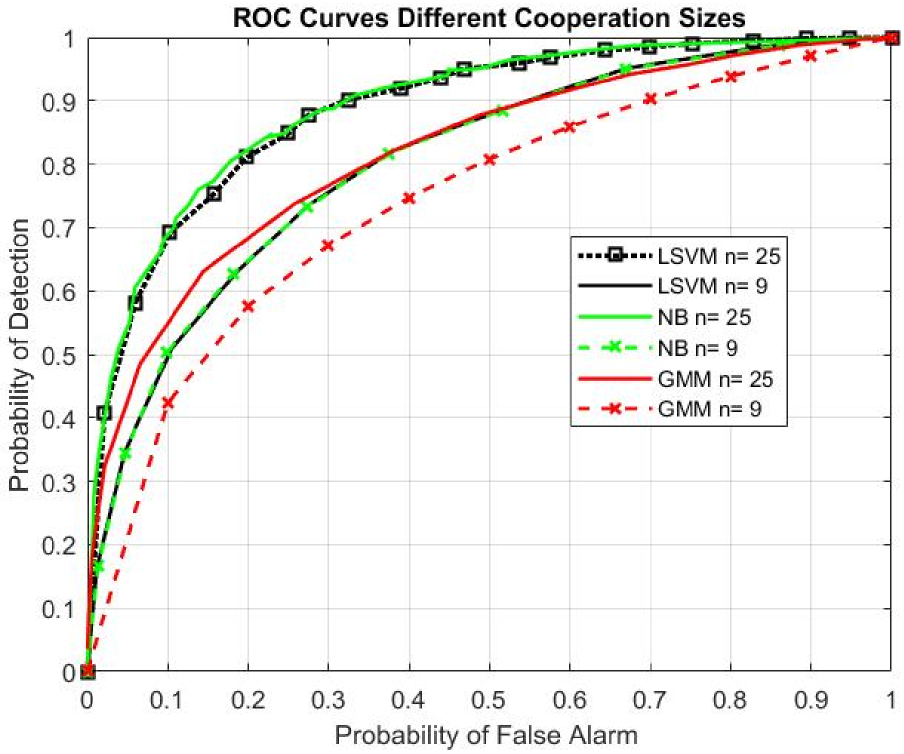

Figure 3.10: Examining the effect of increasing the cooperation size n while sensing a single PU with ρ_m= 200 mW.

Fig. 3.11 examines the effect of increasing the transmit power ρ_m of a single PU from 80 mW to 200 mW, while keeping the same number of cooperating SUs at n= 9. It it obvious that increasing ρ_m leads to a better detection performance. This is because increasing the transmit power renders the clusters more distinguishable, which increases the detection performance.

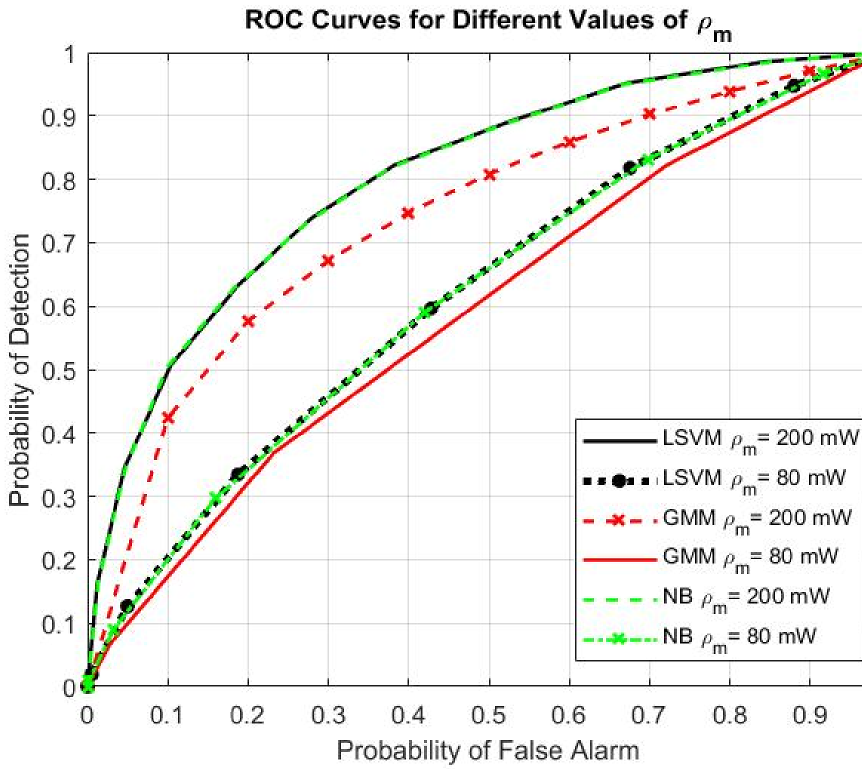

Figure 3.11: Examining the effect of increasing ρ_m while keeping the cooperation size at n= 9.

The performance of the hybrid underlay-interweave CR network that employs Multi-class SVM (MSVM) to classify the state of the channel is evaluated. Accuracy is used as an evaluation metric to assess the accuracy of channel state classification. The accuracy is defined as the ratio of the number of true classifications to the number of all test samples. It can be concluded from Fig. 3.12 that the accuracy of classification of the MSVM increases as the transmit power of the PUs increases. This is because the clusters move away from each other as the transmit power increases, making them more recognizable. Moreover, for low transmit power levels, networks with different cooperation sizes perform the same. As ρ_m increases, the accuracy improves as the number of cooperating SUs n increases. However, increasing n in our scenario leads to increasing the distance between the SUs and the PUs up to a point where the data sensed by far SUs does not lead to enhancing the accuracy of the MSVM.

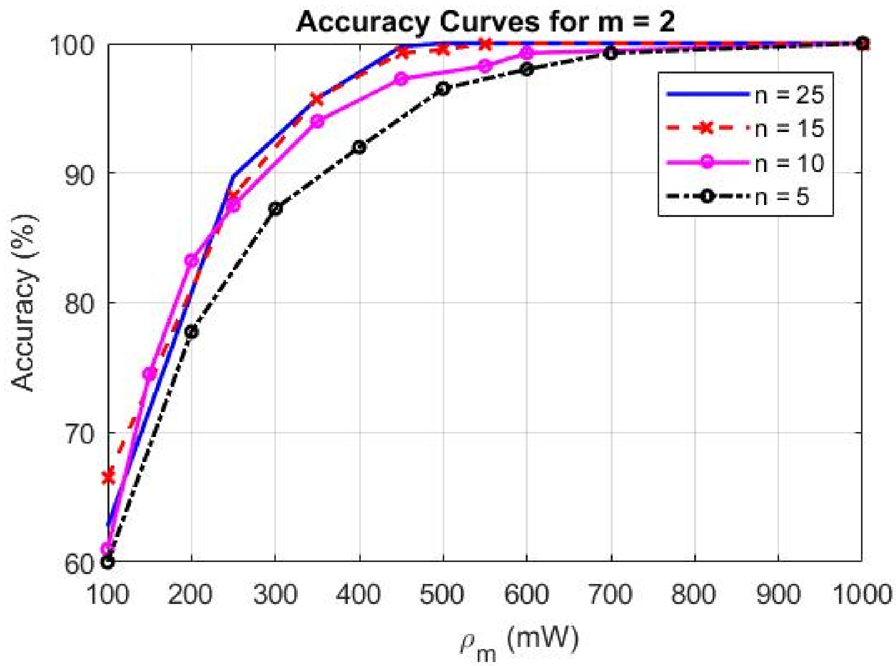

Figure 3.12: Accuracy of multi-class SVM for different cooperation sizes.

3.8 Conclusions and Discussion

In this chapter, an enhanced hybrid underlay-interweave CR system was proposed that employs both cooperation and learning techniques. The hybrid system is able to use learning techniques such as GMM, SVM, and NB to classify the availability of the channel under the interweave access model. The MSVM classifier was constructed using the OVO approach to perform multi-class learning under the presence of multiple PUs. The system is able to use multi-class learning to classify the channel occupancy state, and accordingly the SUs adjust their transmission parameters to abide by the interference threshold specified by the underlay access model. Consequently, the SUs opportunistically maximize their transmission throughput and enhance their performance. Through cooperation the hybrid network is able to enhance its classification accuracy. Furthermore, the cooperation also enhances the detection performance by taking advantage of the spatially diverse SUs. Our results show that a non-linear relation exists between the energy vectors collected at the FC. Hence, the GSVM algorithm was proven to be the most suitable for the proposed hybrid model with an 80% detection rate with as low as 10% false alarm. Moreover, the algorithm was able to implicitly learn the surrounding radio environment variables, and correctly classify the channel occupancy states. The MSVM was proven to be robust to low SNR environments.

Chapter 4

Two-Stage Learning-Based Cooperative Secondary Networks

4.1 Introduction

In chapter 3, we discussed learning-based Cognitive Radio (CR) networks which use supervised or unsupervised learning to determine the channel occupancy state of the primary network. In this chapter, we address the problem of labeled data scarcity in practical CR applications and how it can be overcome through using an unsupervised two-stage learning framework. Most works in the literature that use supervised learning techniques to enhance the detection performance of CR networks assume that their labeled data, i.e., ground truths, are obtained through cooperation with the primary network. That is, the primary network occasionally transmits such information to the secondary network. Having communication between the primary and secondary networks violates the foundation of both the interweave and underlay CR access models. Additionally, the superiority of the supervised learning is dependent on acquiring a massive amount of labeled training data, which is a difficult task as the communication between the SUs and PUs will impose a significant overhead on the network. Motivated by this, in this chapter an unsupervised two-stage learning-based spectrum sensing framework is established. The CR network performs full blind spectrum sensing that relies on unlabeled data to determine the channel occupancy state of the primary network and achieves the same performance of the supervised learning techniques. We believe that introducing two layers of learning will result in a higher spectral utilization efficiency compared with existing supervised learning-based CR networks.

4.2 Semi-Supervised Support Vector Machine (SS-SVM)

Semi-Supervised Learning (SSL) is a branch of learning approaches that combines both supervised and unsupervised learning. SSL uses both supervised learning along with unlabeled data. The training data set X which consists of two subsets; X_1 and X_2. The first subset X_1 is comprised of the labeled training energy vectors $\bar{\mathbf{y}}$ with the channel availability $\bar{a}$, whereas X_2 is the set of unlabeled energy vectors $\bar{\mathbf{y}}$. The two subsets are as follows

$$X_1 = \{(\mathbf{y}^{(1)}, a^{(1)}), (\mathbf{y}^{(2)}, a^{(2)}), ..., (\mathbf{y}^{(L)}, a^{(L)})\}, \tag{4.1}$$

$$X_2 = \{(\mathbf{y}^{(L+1)}), (\mathbf{y}^{(L+2)}), ..., (\mathbf{y}^{(L+K)})\}, \tag{4.2}$$

where L and K are the sizes of the labeled data and unlabeled data sets, respectively.

In Fig. 4.1, the energy vectors in the training data set are mapped to a higher dimensional feature space using a the mapping function $\phi(.)$ discussed in chapter 3 and a decision boundary h is obtained that linearly separates the mapped feature vectors. The green dots represent the unlabeled energy vectors and the red and blue dots represent labeled energy vectors from the two hypotheses H_0 and H_1 respectively.

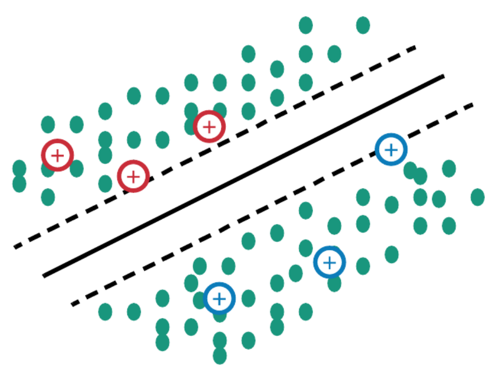

Figure 4.1: Semi-Supervised SVM decision boundary.

In semi-supervised learning, the majority of the training energy vectors are unlabeled. Hence, the original SVM problem in (3.31)-(3.34) must be reformulated to account for this change. Besides calculating the misclassification error ϵ for labeled data, two constraints will be added. The first one that calculates the misclassification error as if all the unlabeled energy vectors belong to class ”channel unavailable”. The second one calculates the misclassification error as if all unlabeled energy vectors belong to class ”channel available”. The objective function calculates the minimum of the two and the final classification decision will be based on the smallest misclassification error. Using K raw energy vectors along with a labeled set of energy vectors of size L where $L < K$, the optimization problem in (3.31)-(3.34) becomes [51]

$$\underset{\Psi,\psi_0,\epsilon^{(l)},v^{(k)},\sigma^{(k)}}{\text{minimize:}} \quad \frac{1}{2}||\Psi||^2+\zeta[\sum_{l=1}^{L}\epsilon^{(l)}+\sum_{k=L+1}^{L+K}\min(v^{(k)},\sigma^{(k)})], \tag{4.3}$$

$$\text{subject to:} \quad a^{(l)}[\Psi.\phi(\mathbf{y}^{(l)})+\psi_0] \geq 1-\epsilon^{(l)} \quad \epsilon^{(l)} \geq 0 \quad l=1,...,L, \tag{4.4}$$

$$\Psi.\phi(\mathbf{y}^{(k)})+\psi_0 \geq 1-v^{(k)} \quad v^{(k)} \geq 0 \quad k=L,...,L+K, \tag{4.5}$$

$$-1[\Psi.\phi(\mathbf{y}^{(k)})+\psi_0] \geq 1-\sigma^{(k)} \quad \sigma^{(k)} \geq 0 \quad k=L,...,L+K, \tag{4.6}$$

where $v^{(k)}$ is the misclassification error for class ”channel unavailable”, i.e., H_1, and $\sigma^{(k)}$ is the misclassification error for class ”channel available”, i.e., H_0.

The learning-based CR network is constructed in a two-dimensional grid with n= 25 SUs equally spaced, and m= 2 PUs each transmitting with ρ_m= 235 mW. The network deployment is shown in Fig. 4.2. A semi-supervised SVM (SS-SVM) algorithm is used for primary user detection. The algorithm is given a training data set consists of two subsets. One being the ground truth data presumably obtained through cooperation between the primary and secondary networks, i.e., the energy vectors and the corresponding state of the primary network. The other subset is the raw energy vectors and their obtained labels through using the Gaussian Mixture Model. Both subsets are combined to form the training data for the SS-SVM algorithm.

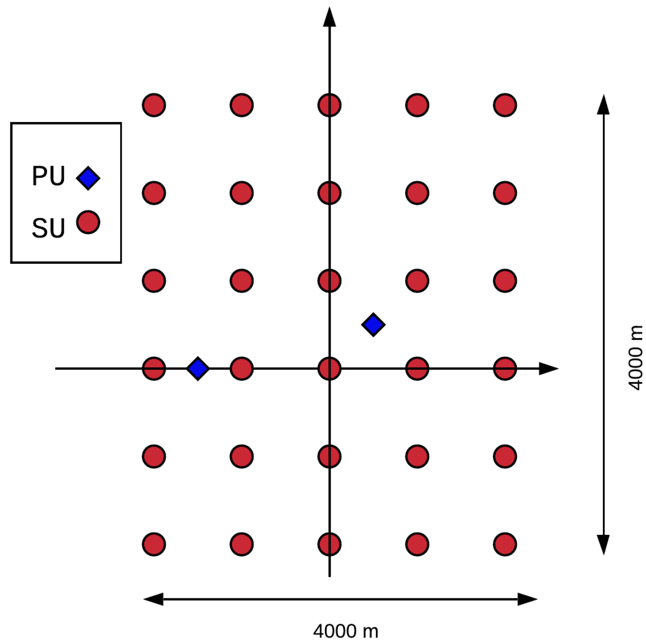

Figure 4.2: The proposed network deployment for the two-stage learning-based CR network.

The percentage of supervision γ is defined as the ratio of the labeled energy vectors to the total size of the training data set. The SUs sense a bandwidth of ω= 5 MHz for a duration of τ= 100 μs. The noise spectral density η= -174 dBm. A NLOS environment is considered with a path-loss exponent α= 4. Using the previously mentioned parameters, the effect of increasing γ on the performance of the SS-SVM is investigated in Fig. 4.3. It is evident that γ plays a crucial role in determining the detection performance of the SS-SVM. As the value of γ increases, the detection performance of the learning-based CR network approaches that of the CR network that uses a fully supervised SVM algorithm. A value of γ= 100% signifies a fully supervised SVM algorithm. Hence, there is a clear trade-off between the availability of labeled data and the detection performance of the CR network. Additionally, we conclude that as γ increases the probability of detection also increases. This motivates us to propose a two-stage learning framework that enhances the performance of the learning-based CR network when labeled data is unavailable, i.e., γ= 0%.

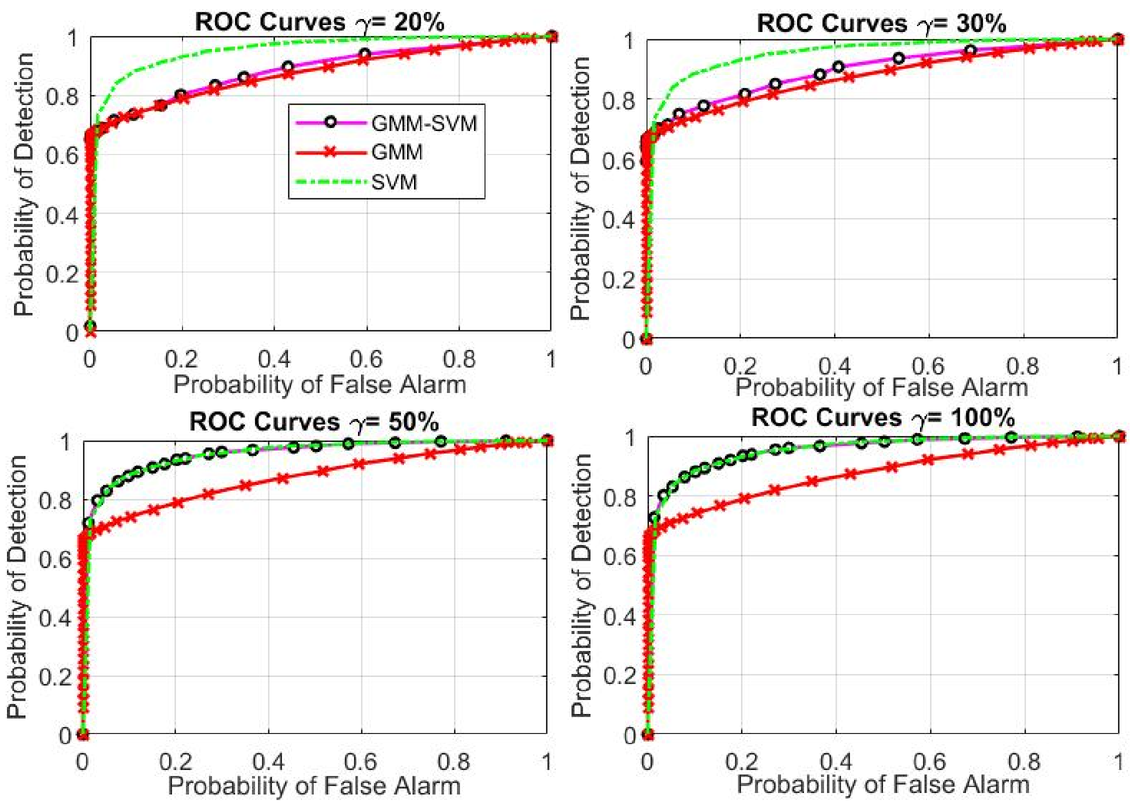

Figure 4.3: The effect of the percentage of supervision γ on the performance of semi-supervised SVM (SS-SVM).

4.3 Two-Stage Learning-Based Spectrum Sensing

In this section, we will focus on the case where γ= 0%, i.e., all the labeled data is generated through using an unsupervised learning algorithm. The learning-based system is composed of two phases; the first phase is the two-stage training phase and the second is the real-time detection of the PUs, i.e., the classification phase. As it was concluded in the previous section, the performance of the SS-SVM depended mainly on the number of labeled energy vectors used in the training. The main challenge to establish an unsupervised learning framework that achieves the same performance as the supervised learning is the training module. As it is one of the key determining factors of the detection performance of the CR network. In the next sections, we will show how using a two-stage training phase enhances the detection performance compared with the classical one-stage unsupervised learning. Furthermore, we prove that the unsupervised two-stage learning-based CR network is able to achieve a comparable performance to fully supervised learning-based CR systems.

4.3.1 Radio Environment Data Collection

The goal of a learning-based cooperative CR network is to generate a channel availability label $a \in \mathcal{A}$ for an energy feature vector $\mathbf{y} \in \mathbf{Y}$. A supervised learning algorithm needs data points $(\mathbf{y}, a)$. Obtaining the channel availability label a for every energy vector collected at the FC would require cooperating with the primary network. On the other hand, an unsupervised learning algorithm only needs energy vectors $\overline{\mathbf{y}}$ to generate the labels $\overline{a}$. This gives rise to the concept of using low cost unsupervised learning to generate labeled data sets to be used by supervised learning algorithms. The cooperating SUs send their sensed energy levels to the FC across L sensing periods, where $\overline{\mathbf{y}} = \{\mathbf{y}^{(1)}, ..., \mathbf{y}^{(L)}\}$ is the unlabeled data set comprised of the energy vectors collected. In the proposed two-stage learning framework, the training phase is comprised of two stages; stage-I and stage-II that will be discussed in the next subsections.

4.3.2 Training Phase: Stage-I

In the first stage, an unsupervised learning algorithm is trained and used to label the raw energy vectors $\bar{\mathbf{y}}$ at the Fusion Center (FC). This way, acquiring labels for the energy vectors will not incur any SU-PU communication overhead. In Fig. 4.4, the training module for the two-stage learning-based CR network is shown. The training starts with feeding the GMM stage with the energy vectors $\bar{\mathbf{y}}$ collected at the FC. The GMM stage runs the Expectation Maximization (EM) algorithm (discussed in chapter 3) to find the mixture parameters $\boldsymbol{\theta}$ to form the Gaussian Mixture Model.

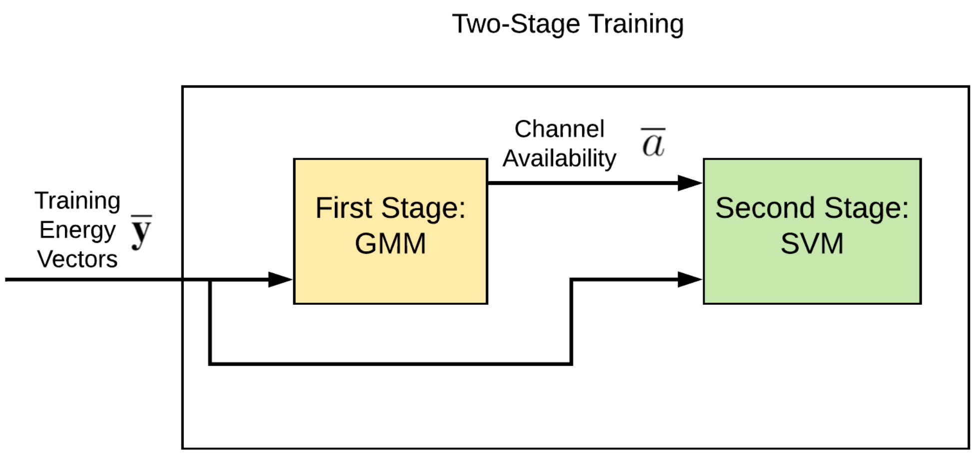

Figure 4.4: Two-Stage Training Module at the FC.

After obtaining $\boldsymbol{\theta}$, the GMM stage computes the log-likelihood of the set of training energy vectors as follows

$$\omega(\mathbf{y}^{(l)}|\boldsymbol{\theta}) = \begin{cases} \ln\left(v_2.\phi(\mathbf{y}^{(l)}|\mu_2, \Sigma_2) - \ln v_1.\phi(\mathbf{y}^{(l)}|\mu_1, \Sigma_1)\right) \geq \delta, & \hat{a}^{(l)} = 0, \\ \ln\left(v_2.\phi(\mathbf{y}^{(l)}|\mu_2, \Sigma_2) - \ln v_1.\phi(\mathbf{y}^{(l)}|\mu_1, \Sigma_1)\right) < \delta, & \hat{a}^{(l)} = 1, \end{cases} \quad For \;\; l = 1, ..., L, \tag{4.7}$$

where $\ln(v_2.\phi(\mathbf{y}^{(l)}|\mu_2, \Sigma_2)$ is the log-likelihood that the l-th training energy vector $\mathbf{y}^{(l)}$ belongs to class H_1, i.e., "channel unavailable". Similarly, $\ln(v_1.\phi(\mathbf{y}^{(l)}|\mu_1, \Sigma_1))$ is the log-likelihood that the l-th training energy vector $\mathbf{y}^{(l)}$ belongs to class H_0, i.e., "channel available". δ is the decision threshold. At the end of the first stage, each training energy vector $\mathbf{y}^{(l)}$ has been given a channel availability label $\hat{a}^{(l)}$.

4.3.3 Training Phase: Stage-II

In the second stage of the training, the labels, i.e., the channel availability $\overline{a} = \{\hat{a}^{(1)}, ..., \hat{a}^{(L)}\}$ generated by the GMM algorithm are combined with their corresponding energy vectors $\overline{\mathbf{y}}$ and they are fed to the SVM algorithm for training. The SVM algorithm finds a hyperplane h that linearly separates the data as follows

$$h(\mathbf{y}^{(l)}) = \Psi.\phi(\mathbf{y}^{(l)}) + \psi_0, \quad For\ l = 1, ..., L, \tag{4.8}$$

where $\phi(.)$ is the mapping function that maps the energy vectors to a higher dimensional feature space and ψ_0 is the bias responsible for shifting the hyperplane h from the origin. The hyperplane h is obtained through solving the optimization problem in (3.31)-(3.34) using standard techniques to solve a quadratic program [14].

4.3.4 The classifier

Let $\tilde{\lambda}$ be the solution to the optimization problem (3.31)-(3.34). The decision function of the two-stage learning CR network is formulated as follows

$$d(\mathbf{y}^*) = sgn(\sum_{l=1}^{L} \tilde{\lambda}^{(l)} \hat{a}^{(l)} \phi(\mathbf{y}^*).\phi(\mathbf{y}^{(l)}) + \psi_0) = a^*, \tag{4.9}$$

where sgn is the sign function and $\phi(\mathbf{y}^*).\ \phi(\mathbf{y}^{(l)})$ is the dot product of the support vector $\mathbf{y}^{(l)}$ and the test energy vector $\mathbf{y}^*$ in the higher feature space. After executing the two-stage training phase, the CR network will be able to perform feature classification on raw energy vectors collected at the FC with no coordination between the SUs and PUs. As shown in Fig. 4.5, applying a test energy vector $\mathbf{y}^*$ to the two-stage trained SVM, the channel availability a^* will be determined solely based on unlabeled data.

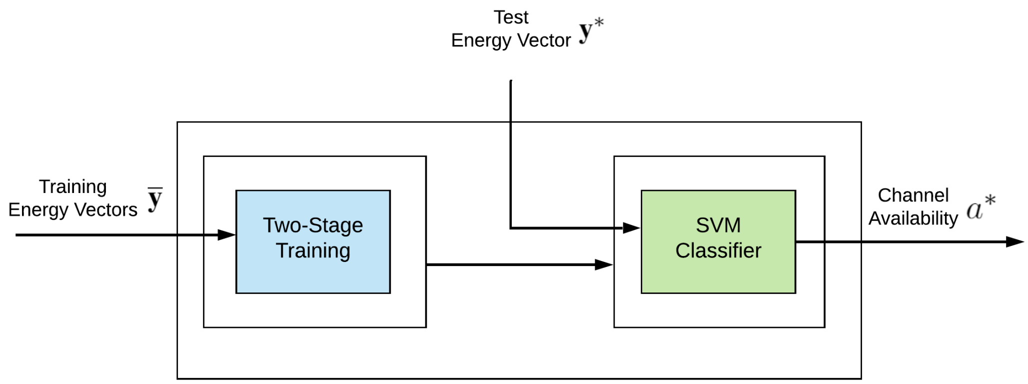

Figure 4.5: Two-Stage learning-based spectrum sensing block diagram.

4.4 Simulation Model and Results

In this section, we present extensive simulations to investigate the performance of the two-stage learning-based cooperative CR network and prove its feasibility. We introduce a new performance metric, which is the Area Under the ROC Curve (AUC). The joint effect of the number of energy vectors used as training data and the cooperation size of the network, i.e., data dimensionality on the detection performance is examined. Considering the simulation parameters in Table. 4.1, a secondary cooperative network is constructed in a two-dimensional grid, where the SUs are equally spaced. The cooperation size n is varied from 9 SUs up to 36 SUs. Two scenarios are considered for the primary network: scenario-I the primary network consists of a single PU at (500m,500m), whereas scenario-II the primary network consists of two PUs at (500m,500m) and (-1500m,0m). In both scenarios, the PUs are activated with equal probability p and are activated independently from each other. As an example, Fig. 4.6 shows the network deployment for a Secondary Network (SN) of size n= 9 for scenario-II.

Parameter	Value
PU Transmit Power ρ_m	200 mW
Noise PSD η	-174 dBm
Sensing Duration of SU δ	100 μs
Bandwidth ω	5 MHz
Area	[2-16] Km^2
Cooperation Size n	[9-36]
Path-loss Exponent α	4
Shadow Fading Component $\psi_{m,n}$	1
Multi-path Fading Component $\nu_{m,n}$	1
Number of Testing Vectors	1000
Number of Training Vectors σ	[100-2000]

Table 4.1: Simulation parameters

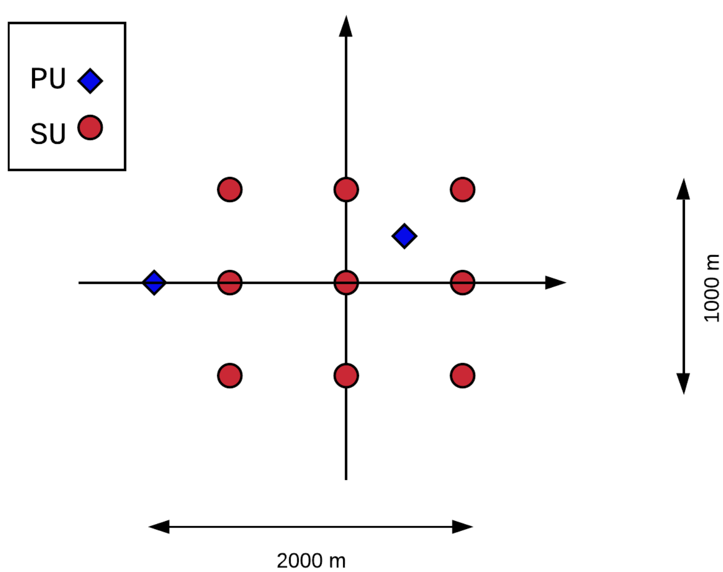

Figure 4.6: The network deployment for the n= 9 cooperation size and m= 2 PUs.

The GMM algorithm is a low-cost learning algorithm that does not need labeled data to perform feature classification. However, it does not perform well when given high dimensional data for training. On the other hand, the SVM algorithm is a supervised learning algorithm that yields a higher classification accuracy, however it needs labeled data to operate. Hence, the detection performance of the two-stage learning-based CR network is dependent on the performance of both the GMM and SVM algorithms. Consequently, the detection performance is modeled as function in both the size of the training energy vectors and the cooperation size, i.e., data dimensionality.

In Fig. 4.7 a set of three surfaces are plotted in three-dimensions, since the performance of the two-stage learning-based SN is dependent on both the size and dimensionality of the training energy vectors. For a high cooperation size, i.e., 36 cooperating SUs, as the number of training energy vectors increases, the AUC increases which means that the detection performance is improved. That is, for small values of training vectors and a high cooperation size, the formed learning model is under-fitted and needs more energy vectors to form a better classification model. Increasing the cooperation size starting from n= 9 for a small training data size, it can be observed that the AUC, i.e., the performance, increases up to a point where the model becomes under-fitted as a result of increasing the data dimensionality. Keeping the cooperation size constant at n= 9 and increasing the number of training energy vectors, the AUC increases and then it plateaus. That is because for low dimensionality, increasing the training data size leads to a performance enhancement. At a large number of training energy vectors, i.e., 2000 energy vectors, increasing the cooperation size leads to a performance increase up to a point where additional SUs do not lead to a performance increase. In this case, adding more cooperating SUs does not lead to any performance gains, it adds an overhead on the network.

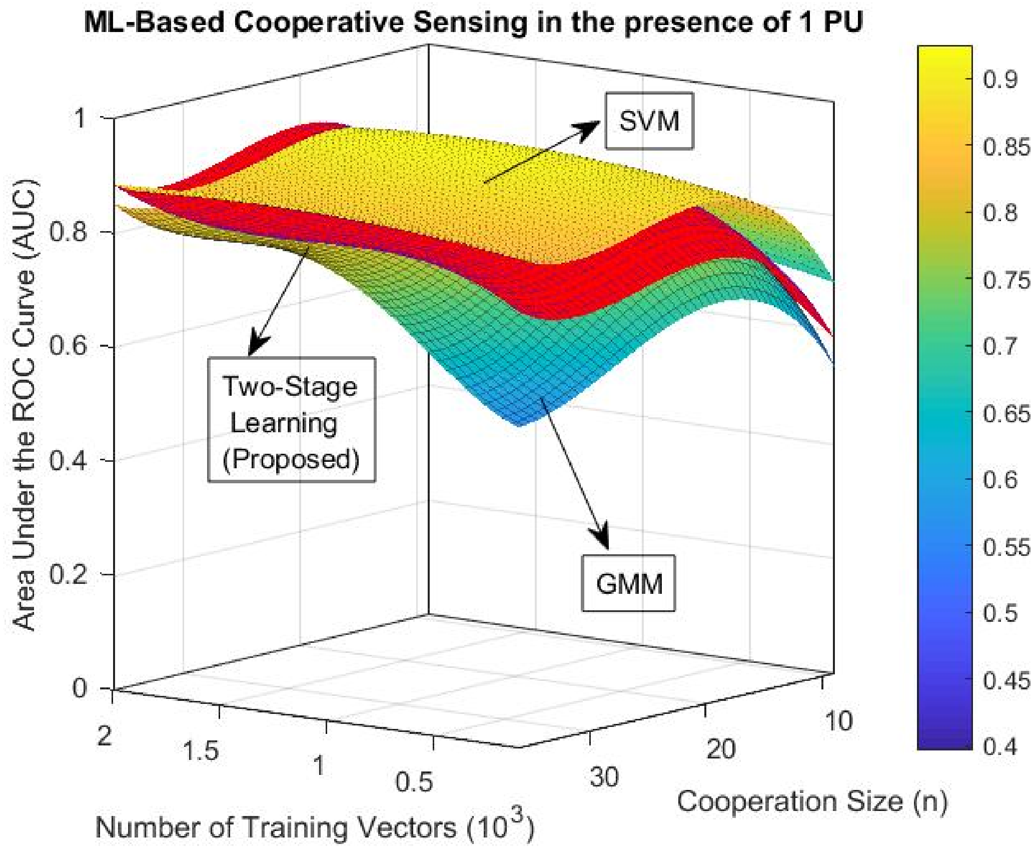

Figure 4.7: The joint effect of the number of training vectors and the size of the secondary network when $m = 1$.

Comparing the performance of the two-stage learning-based secondary network with the supervised learning and unsupervised learning, it can be observed from Fig. 4.7 through using the two-stage learning-based sensing there is a performance gain. The goal is to determine the cooperation size and the number of energy vectors that lead to a detection performance closer to the supervised-based learning than the unsupervised learning. That is maximizing the distance between the GMM and the two-stage surfaces and minimizing the distance between the SVM and the two-stage surfaces. Examining the best and worst cases in terms of the performance, Table. 4.2 and Table. 4.3 summarizes the global minima and maxima of each surface.

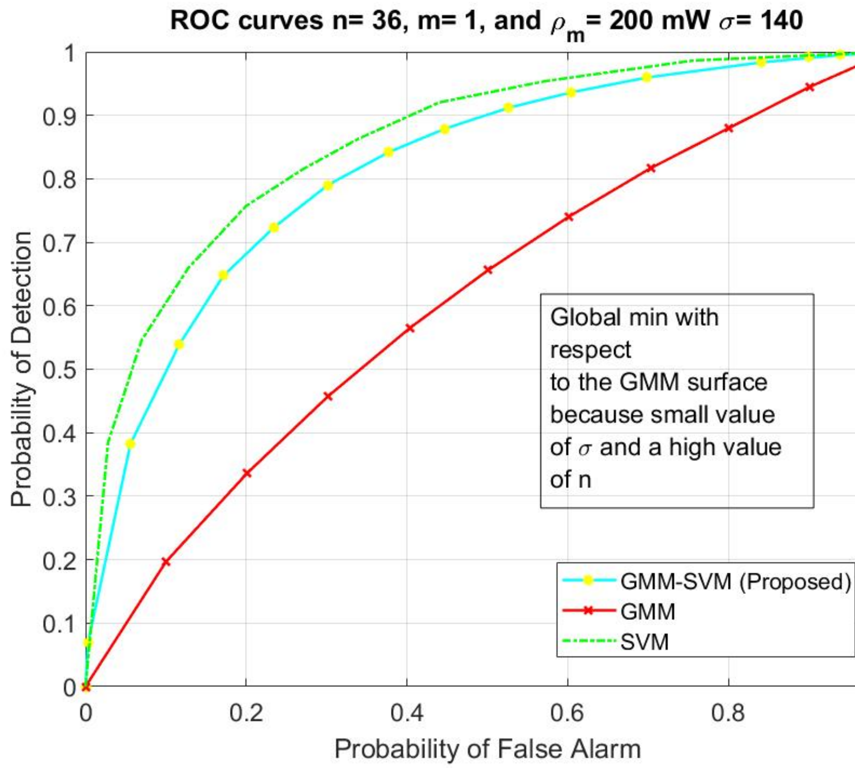

Figure 4.8: Performance analysis in the case where the GMM surface achieves a global minima.

	m= 1 PU	m= 2 PUs
GMM	(σ= 140, n= 9, AUC= 0.5769) (σ= 140, n= 36, AUC= 0.5682)	(σ= 140, n= 36, AUC= 0.7991)
GMM-SVM (Proposed)	(σ= 140, n= 9, AUC= 0.615) (σ= 140, n= 36, AUC= 0.767)	(σ= 140, n= 36, AUC= 0.827)
SVM	(σ= 140, n= 9, AUC= 0.7043)	(σ= 140, n= 9, AUC= 0.888)

Table 4.2: Global minima for the set of surfaces in Fig. 4.7 and Fig. 4.10.

Analyzing the performance of the three learning techniques at the global minima with respect to the GMM surface, in Fig. 4.8 it can be observed that the two-stage learning-based sensing performs very closely to the SVM. At the global minima of the GMM surface for $m = 1$, the cooperation size is high (n= 36) and the number of training energy vectors is low $\sigma = 140$. Hence, the GMM is under-fitted. Nevertheless, the two-stage learning is able to enhance the detection performance. That is because the SVM is robust to high dimensional data. There is a second global minima for the GMM surface, as the cooperation size is low (n= 9) and the cooperative network needs more spatially diverse SUs to enhance its detection performance.

Analyzing the performance at the global maxima of the GMM surface, in Fig. 4.9 the two-stage learning-based sensing is able to perform as well as the supervised learning. That is because in this case the GMM forms a well-fit classification model, since it has enough training energy vectors σ= 1000 and the dimensionality of the data is not very high n= 19. Furthermore, the SVM stage boosts the detection performance as it is performs better when given high dimensional data. Hence, combining these two advantages we see that the two-stage learning attains the same performance as the supervised learning.

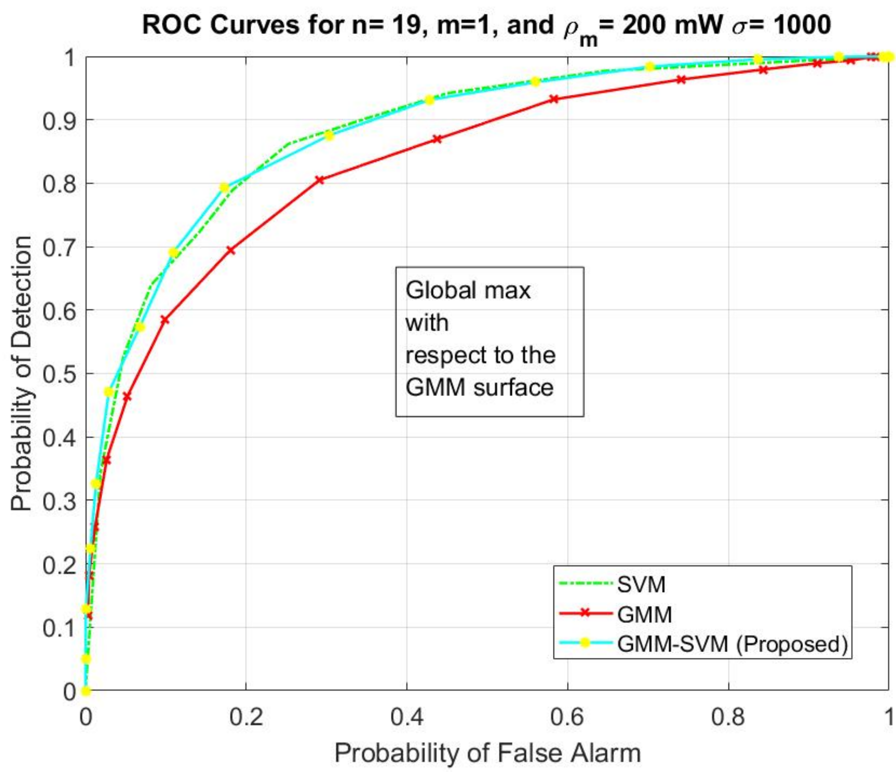

Figure 4.9: Performance analysis in the case where the GMM surface achieves a global maxima.

	m= 1 PU	m= 2 PUs
GMM	(σ= 1000, n= 19, AUC= 0.88)	(σ= 1964 , n= 23, AUC= 0.897)
GMM-SVM (Proposed)	(σ= 1000, n= 19, AUC= 0.901)	(σ= 1964 , n= 23, AUC= 0.9459)
SVM	(σ= 992, n= 19, AUC= 0.905)	(σ= 1960 , n= 23, AUC= 0.9534)

Table 4.3: Global maxima for the set of surfaces in Fig. 4.7 and Fig. 4.10.

Investigating the detection performance for scenario-II, it can be observed from Figs. 4.10- 4.11 that the set of surfaces when m= 2 are higher than the set of surfaces when $m = 1$. That is, increasing the number of PUs m leads to an increase in the energy level of the spectrum. Therefore, it becomes an easier task for the classifier to detect the presence of the PUs. Additionally, comparing all the three learning techniques in Fig. 4.10, it can be observed that the fluctuations in the performance is not very large owing to the fact that the energy in the spectrum is increased and hence the detection performance is enhanced. Nevertheless, the same trends are observed for the three surfaces as in Fig. 4.7.

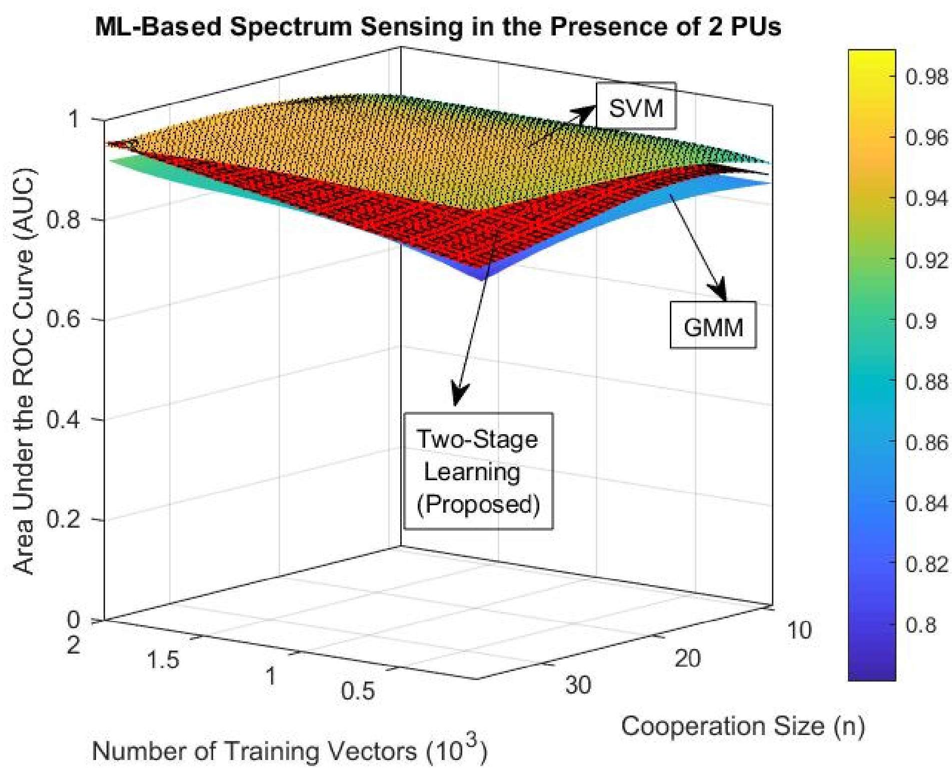

Figure 4.10: The joint effect of the number of training vectors and the size of the secondary network when $m = 2$.

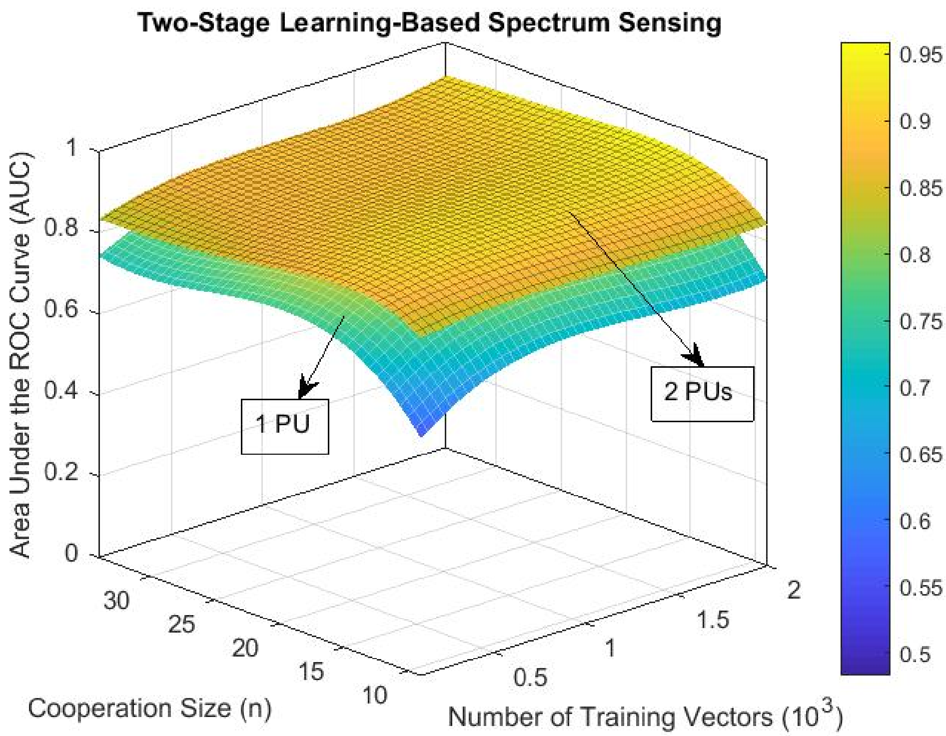

Figure 4.11: Performance comparison for the proposed two-stage learning under different values of m.

4.5 Conclusions and Discussion

In this chapter, we addressed the problem of labeled data scarcity in practical applications of CR networks, since most works in the literature assume the availability of labeled data to the CR network. An unsupervised two-stage learning-based cooperative CR network was proposed. The system uses unlabeled data only to perform channel sensing. Since the proposed two-stage learning system is dependent on both the GMM and SVM algorithms which each have different advantages and disadvantages, the performance was found to be dependent on both the dimensionality and size of the training data, i.e., the cooperation size and the number of training energy vectors. Through examining the joint effect of the cooperation size and the number of training energy vectors, the system was found to have an enhanced performance compared with the unsupervised learning GMM algorithm. That is because the second stage in the training is the SVM, which is robust to high dimensional data unlike the GMM. When the GMM was unable to deal with high dimensional data (high cooperation size), the second stage SVM was able to enhance the detection performance of the overall system. Thus, attaining the same performance as the supervised learning SVM alone without using any labeled data. Additionally, the effect of increasing the size of the primary network on the performance of the cooperative secondary network was examined. We concluded that as the number of PUs increases this increases the energy in the spectrum and thus makes the classification task at the FC easier, and as a result the detection performance of the CR network improves.

Chapter 5

Conclusions, and Future Works

5.1 Conclusions

Cognitive radio networks are defined to be ”intelligent” wireless communication systems. To attain their full cognitive potential, learning should be part of its cognition cycle. In this thesis, we showed how radio nodes evolved from being cognitive to intelligent through employing learning techniques. Learning-based CR networks are able to use accumulated knowledge through spectrum observations to enhance their cognitive ability. The main focus in this thesis was on feature classification and clustering algorithms, that allow the CR node to learn and organize observations collected from the radio environment. In chapter 2, we presented an overview of cognitive radio networks, and the role of machine learning in enhancing their performance. Additionally, an overview of the currently used learning techniques in CR networks was presented, examining the convergence between learning techniques and cognitive radio networks.

In chapter 3, an enhanced hybrid underlay-interweave CR system was proposed that employs both cooperation and learning techniques. Thus, maximizing its throughput, and enhancing its performance and classification accuracy. We have characterized two main classification problems, namely binary classification and multi-class classification. Our results show that a non-linear relation exists between the energy vectors collected at the FC. Hence, the GSVM algorithm was proven to be the most suitable for the proposed hybrid model with an 80% detection rate with as low as 10% false alarm. The MSVM classifier was constructed using the OVO approach to perform multi-class clustering under the presence of multiple PUs. Moreover, the algorithm was able to implicitly learn the surrounding radio environment variables, and accordingly classifying the channel occupancy states. Additionally, the MSVM proved to be robust to low SNRs.

In chapter 4, an unsupervised two-stage learning framework was established for cooperative secondary networks. The system uses the Gaussian mixture model to generate labels for the raw energy vectors that get collected at the FC. Then, the SVM algorithm is trained with the generated labeled data. Since the system is comprised of two stages that each has its own unique parameters, the system performance was dependent on both the cooperation size and the number of training energy vectors at the FC. Hence, the joint effect of these two factors was examined to determine the parameters that maximize the performance of the cooperative secondary network. It was found that the performance of the two-stage learning-based cooperative sensing is be equal to the supervised learning without using any labeled data.

As stated before the two-stage learning framework is based on both the GMM and SVM algorithms. Each of these algorithms are better equipped with certain scenarios. For the GMM algorithm, it is a low cost learning algorithm as it does not require any labeled data to perform feature classification, as well as the distribution of the energy vectors at the FC closely match the GMM distribution. On the other hand, the GMM needs a higher number of training vectors in order to perform well with high dimensional data. As for the LSVM, it is a supervised learning algorithm that is robust to high dimensional data. However, it needs labeled data to perform feature classification. Therefore, combining these two learning algorithms to form a two-stage learning framework combines their individual benefits and results in a performance gain compared with unsupervised learning.

5.2 Future Work

In chapter 3, we proposed a hybrid underlay-interweave CR network that uses the spectrum in both cases when the licensed user is present or absent. The network uses multi-class learning to determine the exact channel occupancy state of the primary network, and consequently it can adjust its transmission parameters to enhance its throughput while abiding by the interference constraints.

This work could be extended to further classify the state of each primary user under a multiple transmit power framework. Additionally, we investigated the system in the case where there is no mobility in the network. Therefore, this could be another extension to our work, where we study the performance of the system under a mobile framework.

In chapter 4, we proposed an unsupervised two-stage learning approach that can be further enhanced through a feedback mechanism. Through employing a feedback system, the classification accuracy of the algorithm is expected to either improve the performance of the system or keep it the same. Hence, the system requires investigations to verify its feasibility. Additionally, we expect the adaptive learning to enhance the detection performance in the cases where the fusion center has a limited number of raw energy vectors.

5.3 Key Challenges for Learning-Based CR Networks

There is no doubt that machine learning brings endless room of improvement to cognitive radio networks. However, there are certain aspects that need to be considered carefully before designing a learning-based CR network.

Mobility: Spectrum availability in mobile environments is highly dependent on the speed and the presence of the PUs. Hence, spectrum availability is highly dynamic in mobile environments, which poses a major challenge for learning based mobile cognitive networks. Moreover, the radio environment variables such as noise or interference levels change with mobility, which would require a change in the CR model parameters such as testing threshold. A learning-based cognitive radio node in a fast changing radio environment would require frequent retraining as radio environment variables change. Thereby, adding extra complexities and delays to the learning-based CR system.

5G and beyond: The use of cognitive radio technology is encouraged when it comes to simple and predictable radio environments. However, for environments such as 5G networks and beyond, the radio environment becomes much more complicated due to the large-scale heterogeneous network topologies, highly dynamic radio traffic models, and various demand services for different users [2]. Thus, it would be much more challenging for SUs to accurately learn the radio environment.

Commercialization and deployment: There is no doubt that the standardization of the CR technology is well established across standardization bodies such as IEEE, ITU, ETSI, and ECMA [2]. However, spectrum resources are government owned by nature. This poses a barrier for commercialization and deployment. There is still a long way to establishing compatibility with existing standards and technologies.

Appendix A

List of Publications

- **N. Abdel Khalek**, and W. Hamouda, ”Learning-Based Cooperative Spectrum Sensing in Hybrid Underlay-Interweave Secondary Networks”, *2020 IEEE Global Communications Conference (GLOBECOM)*, Accepted.
- **N. Abdel Khalek**, and W. Hamouda, ”From Cognitive to Intelligent Secondary Cooperative Networks for the Future Internet: Design, Advances, and Challenges”, *in IEEE Network*, Major Revision.

Bibliography

[1] J. Mitola and G. Q. Maguire, "Cognitive radio: making software radios more personal," *IEEE Personal Communications*, vol. 6, no. 4, pp. 13–18, Aug 1999.

[2] Z. Qin, X. Zhou, L. Zhang, Y. Gao, Y. Liang, and G. Y. Li, "20 Years of Evolution From Cognitive to Intelligent Communications," *IEEE Transactions on Cognitive Communications and Networking*, vol. 6, no. 1, pp. 6–20, March 2020.

[3] P. Kolodzy and I. Avoidance, "Spectrum policy task force," *Federal Commun. Comm., Washington, DC, Rep. ET Docket*, vol. 40, no. 4, pp. 147–158, 2002.

[4] A. Ali and W. Hamouda, "Power-Efficient Wideband Spectrum Sensing for Cognitive Radio Systems," *IEEE Transactions on Vehicular Technology*, vol. 67, no. 4, pp. 3269–3283, 2018.

[5] T. M. C. Chu, H. Phan, and H. Zepernick, "Hybrid Interweave-Underlay Spectrum Access for Cognitive Cooperative Radio Networks," *IEEE Transactions on Communications*, vol. 62, no. 7, pp. 2183–2197, 2014.

[6] S. Sun, Y. Ju, and Y. Yamao, "Overlay cognitive radio OFDM system for 4G cellular networks," *IEEE Wireless Communications*, vol. 20, no. 2, pp. 68–73, 2013.

[7] X. Li, T. Song, Y. Zhang, G. Chen, and J. Hu, "A Hybrid Cooperative Spectrum Sensing Scheme Based on Spatial-Temporal Correlation for CR-VANET," in *2018 IEEE 87th Vehicular Technology Conference (VTC Spring)*, June 2018, pp. 1–6.

[8] M. Karimi, S. M. S. Sadough, and M. Torabi, "Robust spectrum access for hybrid interweave-underlay cognitive radio systems using probabilistic spectrum access," *IET Signal Processing*, vol. 13, no. 9, pp. 806–813, 2019.

[9] M. T. Masonta, M. Mzyece, and N. Ntlatlapa, "Spectrum Decision in Cognitive Radio Networks: A Survey," *IEEE Communications Surveys Tutorials*, vol. 15, no. 3, pp. 1088–1107, Third 2013.

[10] A. Ali and W. Hamouda, "Advances on Spectrum Sensing for Cognitive Radio Networks: Theory and Applications," *IEEE Communications Surveys Tutorials*, vol. 19, no. 2, pp. 1277–1304, Secondquarter 2017.

[11] X. Chen, F. Hou, H. Huang, and X. Jing, "Principle component analysis based cooperative spectrum sensing in cognitive radio," in *2016 16th International Symposium on Communications and Information Technologies (ISCIT)*, 2016.

[12] F. Gao, J. Li, T. Jiang, and W. Chen, "Sensing and Recognition When Primary User Has Multiple Transmit Power Levels," *IEEE Transactions on Signal Processing*, vol. 63, no. 10, pp. 2704–2717, May 2015.

[13] X. Ma, S. Ning, X. Liu, H. Kuang, and Y. Hong, "Cooperative Spectrum Sensing using Extreme Learning Machine for Cognitive Radio Networks with Multiple Primary Users," in *2018 IEEE 3rd Advanced Information Technology, Electronic and Automation Control Conference (IAEAC)*, Oct 2018, pp. 536–540.

[14] K. M. Thilina, K. W. Choi, N. Saquib, and E. Hossain, "Machine Learning Techniques for Cooperative Spectrum Sensing in Cognitive Radio Networks," *IEEE Journal on Selected Areas in Communications*, vol. 31, no. 11, pp. 2209–2221, November 2013.

[15] Y. Xu, P. Cheng, Z. Chen, Y. Li, and B. Vucetic, "Mobile Collaborative Spectrum Sensing for Heterogeneous Networks: A Bayesian Machine Learning Approach," *IEEE Transactions on Signal Processing*, vol. 66, no. 21, pp. 5634–5647, Nov 2018.

[16] H. V. Dang and W. Kinsner, “An analytical multiobjective optimization of joint spectrum sensing and power control in cognitive radio networks,” in *2015 IEEE 14th International Conference on Cognitive Informatics Cognitive Computing (ICCI*CC)*, July 2015, pp. 39–48.

[17] Y. Lu, P. Zhu, D. Wang, and M. Fattouche, “Machine learning techniques with probability vector for cooperative spectrum sensing in cognitive radio networks,” in *2016 IEEE Wireless Communications and Networking Conference*, April 2016, pp. 1–6.

[18] C. H. A. Tavares and T. Abrão, “Bayesian estimators for cooperative spectrum sensing in cognitive radio networks,” in *2017 IEEE URUCON*, Oct 2017, pp. 1–4.

[19] O. Thakkar, D. K. Patel, Y. L. Guan, S. Sun, Y. C. Chang, and J. M. Lim, “On the Joint Impact of SU Mobility and PU Activity in Cognitive Vehicular Networks with Improved Energy Detection,” in *2019 IEEE 89th Vehicular Technology Conference (VTC2019-Spring)*, April 2019, pp. 1–6.

[20] J. Perez and I. Santamaria, “Adaptive clustering algorithm for cooperative spectrum sensing in mobile environments,” in *2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, April 2018, pp. 2611–2615.

[21] L. Arienzo and D. Tarchi, “Stochastic Optimization of Cognitive Networks,” *IEEE Transactions on Green Communications and Networking*, vol. 1, no. 1, pp. 40–58, March 2017.

[22] O. P. Awe, S. M. Naqvi, and S. Lambotharan, “Variational Bayesian learning technique for spectrum sensing in cognitive radio networks,” in *2014 IEEE Global Conference on Signal and Information Processing (GlobalSIP)*, Dec 2014, pp. 1185–1189.

[23] Y. Xu, P. Cheng, Z. Chen, Y. Hu, Y. Li, and B. Vucetic, “Mobile Bayesian Spectrum Learning for Heterogeneous Networks,” in *2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, April 2018, pp. 2631–2635.

[24] A. K. Varma and D. Mitra, “Statistical Feature-Based SVM Wideband Sensing,” *IEEE Communications Letters*, vol. 24, no. 3, pp. 581–584, March 2020.

[25] B. Khalfi, A. Zaid, and B. Hamdaoui, “When machine learning meets compressive sampling for wideband spectrum sensing,” in *2017 13th International Wireless Communications and Mobile Computing Conference (IWCMC)*, June 2017, pp. 1120–1125.

[26] Balaji V, T. Nagendra, C. Hota, and G. Raghurama, “Cooperative spectrum sensing in cognitive radio: An archetypal clustering approach,” in *2016 International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET)*, March 2016, pp. 1137–1143.

[27] H. Wang, G. Noh, D. Kim, S. Kim, and D. Hong, “Advanced sensing techniques of energy detection in cognitive radios,” *Journal of Communications and Networks*, vol. 12, no. 1, pp. 19–29, Feb 2010.

[28] Tai-Lin Chin and Cheng-Chia Huang, “Fusion-based sensing for uncertain primary user signal in cognitive ratio networks,” in *2015 11th International Conference on Heterogeneous Networking for Quality, Reliability, Security and Robustness (QSHINE)*, Aug 2015, pp. 85–91.

[29] E. Hill and H. Sun, “Double threshold spectrum sensing methods in spectrum-scarce vehicular communications,” *IEEE Transactions on Industrial Informatics*, vol. 14, no. 9, pp. 4072–4080, Sep. 2018.

[30] F. Benedetto, A. Tedeschi, and G. Giunta, “Cooperative spectrum sensing for positioning in cognitive radios,” in *2014 11th International Symposium on Wireless Communications Systems (ISWCS)*, Aug 2014, pp. 670–674.

[31] C. Sun, Y. Wang, P. Wan, and Y. Du, “A cooperative spectrum sensing algorithm based on principal component analysis and K-medoids clustering,” in *2018 33rd Youth Academic Annual Conference of Chinese Association of Automation (YAC)*, May 2018, pp. 835–839.

[32] A. M. Mikaeil, B. Guo, and Z. Wang, “Machine Learning to Data Fusion Approach for Cooperative Spectrum Sensing,” in *2014 International Conference on Cyber-Enabled Distributed Computing and Knowledge Discovery*, Oct 2014, pp. 429–434.

[33] F. Azmat, Y. Chen, and N. Stocks, "Analysis of Spectrum Occupancy Using Machine Learning Algorithms," *IEEE Transactions on Vehicular Technology*, vol. 65, no. 9, pp. 6853–6860, Sep. 2016.

[34] J. Tian, P. Cheng, Z. Chen, M. Li, H. Hu, Y. Li, and B. Vucetic, "A Machine Learning-Enabled Spectrum Sensing Method for OFDM Systems," *IEEE Transactions on Vehicular Technology*, vol. 68, no. 11, pp. 11 374–11 378, Nov 2019.

[35] A. Coluccia, A. Fascista, and G. Ricci, "Spectrum sensing by higher-order SVM-based detection," in *2019 27th European Signal Processing Conference (EUSIPCO)*, Sep. 2019, pp. 1–5.

[36] O. P. Awe, A. Deligiannis, and S. Lambotharan, "Spatio-Temporal Spectrum Sensing in Cognitive Radio Networks Using Beamformer-Aided SVM Algorithms," *IEEE Access*, vol. 6, pp. 25 377–25 388, 2018.

[37] S. U. Jan, V. H. Vu, and I. S. Koo, "Performance Analysis of Support Vector Machine-Based Classifier for Spectrum Sensing in Cognitive Radio Networks," in *2018 International Conference on Cyber-Enabled Distributed Computing and Knowledge Discovery (CyberC)*, Oct 2018, pp. 385–3854.

[38] Y. Qi, Y. Wang, and C. Lai, "An Improved SVM-Based Spatial Spectrum Sensing Scheme via Beamspace at Low SNRs," *IEEE Access*, vol. 7, pp. 184 759–184 768, 2019.

[39] O. P. Awe and S. Lambotharan, "Cooperative spectrum sensing in cognitive radio networks using multi-class support vector machine algorithms," in *2015 9th International Conference on Signal Processing and Communication Systems (ICSPCS)*, 2015, pp. 1–7.

[40] M. Bkassiny, Y. Li, and S. K. Jayaweera, "A Survey on Machine-Learning Techniques in Cognitive Radios," *IEEE Communications Surveys Tutorials*, vol. 15, no. 3, pp. 1136–1159, 2013.

[41] J. Perez, I. Santamaria, and J. Via, “Adaptive EM-Based Algorithm for Cooperative Spectrum Sensing in Mobile Environments,” in *2018 IEEE Statistical Signal Processing Workshop (SSP)*, June 2018, pp. 732–736.

[42] J. Xie, J. Fang, C. Liu, and L. Yang, “Unsupervised Deep Spectrum Sensing: A Variational Auto-Encoder Based Approach,” *IEEE Transactions on Vehicular Technology*, vol. 69, no. 5, pp. 5307–5319, 2020.

[43] G. C. Sobabe, Y. Song, X. Bai, and B. Guo, “A cooperative spectrum sensing algorithm based on unsupervised learning,” in *2017 10th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics (CISP-BMEI)*, Oct 2017, pp. 1–6.

[44] A. P. Shrestha and S. Yoo, “Optimal Resource Allocation Using Support Vector Machine for Wireless Power Transfer in Cognitive Radio Networks,” *IEEE Transactions on Vehicular Technology*, vol. 67, no. 9, pp. 8525–8535, Sep. 2018.

[45] A. P. Dempster, N. M. Laird, and D. B. Rubin, “Maximum Likelihood from Incomplete Data via the EM Algorithm,” *Journal of the Royal Statistical Society. Series B (Methodological)*, vol. 39, no. 1, pp. 1–38, 1977. [Online]. Available: http://www.jstor.org/stable/2984875

[46] Chih-Wei Hsu and Chih-Jen Lin, “A comparison of methods for multiclass support vector machines,” *IEEE Transactions on Neural Networks*, vol. 13, no. 2, pp. 415–425, 2002.

[47] C. Cortes and V. Vapnik, “Support-vector networks,” *Machine Learning*, vol. 20, no. 3, pp. 273–297, Sep. 1995. [Online]. Available: https://doi.org/10.1007/bf00994018

[48] S. Chen, B. Shen, X. Wang, and H. Wu, “SVM and Decision Stumps Based Hybrid AdaBoost Classification Algorithm for Cognitive Radios,” in *2019 21st International Conference on Advanced Communication Technology (ICACT)*, Feb 2019, pp. 492–497.

[49] J. Shawe-Taylor and N. Cristianini, *Kernel Methods for Pattern Analysis*. USA: Cambridge University Press, 2004.

[50] K. G. M. Thilina, E. Hossain, and D. I. Kim, "DCCC-MAC: A Dynamic Common-Control-Channel-Based MAC Protocol for Cellular Cognitive Radio Networks," *IEEE Transactions on Vehicular Technology*, vol. 65, no. 5, pp. 3597–3613, May 2016.

[51] K. P. Bennett and A. Demiriz, "Semi-supervised support vector machines," in *Advances in Neural Information processing systems*, 1999, pp. 368–374.