Cognitive Engine Design for Spectrum Situational Awareness and Signals Intelligence

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***Abstract*—Cognitive radio technology is proposed as a means to achieve real-time spectrum situational awareness (SSA) and signals intelligence (SIGNIT) over a wide spectrum range by designing a cognitive engine that performs machine-learning based hierarchical RF signal identification. This allows the radio to classify and associate a signal using as fewer a number of features as possible. The classification algorithms can be based on any suitably chosen machine-learning algorithm such as artificial neural networks (ANNs) or deep learning. The proposed design allows the user to define, and modify, the SSA parameters during field operations. The specific example design proposed in this paper allows these definitions to be based on two levels of signal classification: a broad type of signals such as communications or radar and specific signals within each of these classes. It is shown that not only the proposed cognitive engine design allows realizing a large number of SSA definitions using permutations of the same two stage classifiers, but also the hierarchical approach may outperform dedicated classifiers with similar computational complexity. The design can easily be generalized to handle more than two levels of signal classification.**

***Index Terms*—Cognitive radios, machine learning, signal classification, signal identification, signal intelligence, spectrum situational awareness, wideband autonomous cognitive radios.**

I. Introduction

The proliferation of wireless telecommunications that provide seamless anywhere, anytime and anyhow connectivity has made spectrum awareness and agility essential radio capabilities, as more and more radios are expected to co-exist in heterogeneous spectrum environments (consisting of radios belonging to multiple distinct systems/networks). There is also an increasing demand for signals intelligence (SIGINT) that goes beyond traditional requirements that can be termed collectively as spectrum situational awareness (SSA). For example, the Advanced RF Mapping (RadioMap) project launched by the US Defense Advanced Research Projects Agency (DARPA) seeks real-time SSA in complex environments to provide a spectrum usage map to war-fighters enabling better planning and allocation of the spectrum [1], [2]. Indeed, successful communications in congested and contested spectrum environments requires the ability to infer the status of the RF spectrum in real-time and reconfigure the communications mode in response. A prime candidate to enable such spectrum-aware and agile communications is the cognitive radio technology [3]–[5].

In our earlier work [3], [6], [7], we proposed wideband autonomous cognitive radios (WACRs) that can self-configure the mode of operation in response to the given state of the overall system made of the radio, spectrum and the end-user. The unique feature of all cognitive radios is their ability to observe and infer the state of RF spectrum. In the case of WACRs, this includes not only detecting signals but the ability to fully characterize the spectrum of interest to the radio in real-time [3]. As a result, our previously proposed WACRs is an ideal technology to achieve advanced SIGINT and SSA. The key is the proper design of a cognitive engine to infer desired spectrum events/conditions, reconfigure in real-time both the RF and baseband hardware used for spectrum sensing, allow real-time modifications to parameters defining SSA and have the cognitive decision-making ability to provide situational awareness.

The literature on SSA is scattered over various aspects of the problem. A probabilistic reasoning model for SSA is introduced in [8]. For example, the SSA objective of [9] is to classify primary user (PU) behavioral patterns in a dynamic spectrum sharing (DSS) environment so that cognitive a secondary user (SU) can achieve achieve high throughput by efficiently avoiding PU interference. On the other hand, [8] introduces a probabilistic reasoning model for SSA by using Bayesian networks to represent the propagation environment and enables parameter estimation in uncertain environments such as path loss, transmitted power, and path distance. The authors in [10] address yet another aspect of SSA by proposing a 3D immersion based helical visualization for SIGINT analysis that can manage complex data.

In this paper we consider a problem that is of interest in many applications of SIGINT and SSA: the ability to discriminate and identify signals. In many wireless communications scenarios, there is a need to classify signals encountered in the RF environment. However, simple classification of signals may not be adequate for providing situational awareness. It is important that the radio can identify the origin of the signals and determine whether a particular signal is of *interest* to it at any given time. This requires the ability to not only classify signals, but also to identify and make real-time decisions based on this knowledge. What signals are of interest at any given time is determined by the parameters defining the SSA

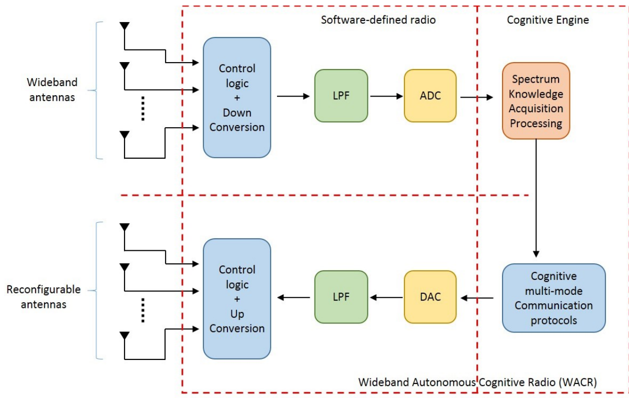

Figure 1. The basic architecture of a wide-band autonomous cognitive radio.

problem. It is desirable that these are modifiable in real-time.

We propose a cognitive engine design to provide SSA specifically addressing the above problem. The proposed cognitive engine design is based on a hierarchical architecture that uses machine-learning algorithms to classify signals followed by decision-making algorithms to provide situational awareness. It is a scalable architecture that lends itself to handle complex signal environments spanning a wide spectrum range. Although this paper does not delve in to details of how to achieve real-time spectrum awareness over a wide spectrum range, in the next section we will briefly outline how the proposed cognitive engine design can support such wideband operation [3].

The rest of the paper is organized as follows: In Section II we give a concise introduction to WACRs. Next, in Section III we detail the proposed cognitive engine design to achieve SSA through machine learning based hierarchical RF signal identification. In Section IV we briefly discuss a hierarchical signal classification framework to serve as the classification engine in the proposed RF signal identification system. Section V provides examples to highlight the value and flexibility of the proposed CE design in achieving RF SSA. In Section VI we will conclude the paper by discussing main challenges that needs to be addressed in future research to fully develop the proposed cognitive engine.

II. Wideband Autonomous Cognitive Radio System Model

Figure 1 shows the concept of WACRs, as envisioned in [3], [6]. It is made of a reconfigurable RF front-end, a software-defined radio baseband module and a cognitive engine. The cognitive engine acts as the brain of the WACR by managing the overall cognitive and intelligent operation of the radio.

The cognitive processing of the radio, performed within the cognitive engine, is divided in to two parts, as shown in Fig. 1: spectrum knowledge acquisition and cognitive communications protocols. Spectrum knowledge acquisition deals with gaining knowledge and comprehension about the states of the RF environment, network, radio and the user [3]. This knowledge allows the radio to make decisions on how best to achieve its communications and SSA objectives. The cognitive communications protocols take this knowledge as an input to decide and act in order to achieve user communications objectives. This module is responsible for issuing instructions to both the SDR and the RF front-end on how to reconfigure their modes of operations and parameters in response to the interpreted states of the RF environment, radio network, WACR itself and user. Both communications and sensing RF front-ends shown in Fig. 1 can, in general, be controlled this way to achieve real-time reconfigurability.

III. Proposed Cognitive Engine for SSA through Machine-learning based Hierarchical RF Signal Identification

Following [3], let us assume that spectrum of interest to the WACR is segmented in to a set of N_b sub-bands. Spectrum sensing to detect signal activities is a staple in cognitive radio applications [5]. Broader interpretations of cognitive radio technology have also considered classifying those detected signals. The SSA and SIGINT problems, however, require even more cognitive processing. For concreteness, let us assume a general class of SSA problems in which decisions are to be made to determine whether a detected signal is what the radio will consider to be of interest. This can be thought of as simply a two-class classifier: important vs. unimportant. However, what signals are deemed important can vary depending on the context: In one situation, radar signals may considered to be the signals of interest while in another situation it may be communications signals. In yet another situation, it may be that specifically pulsed radars are of interest. For instance, we may desire to determine whether an adversary is attempting to detect our presence and we may have advance knowledge that the type of radar the adversary may be using is a pulsed radar. Things may get even more complicated if any modulated continuous-wave signals are to be considered important since this can include some communications as well as some radar and/or GPS signals. This last situation highlights the inadequacy of simply designing a set of dedicated RF signal classifiers for each one of these possibilities, if we are to support SSA: At best, it is inefficient to design a cognitive engine that has been trained to classify for all possible combinations of signal classes.

Our proposed solution to the SSA problem, as shown in Fig. 2, is to decouple the signal classification from signal identification and, in general, from SSA decision-making. Several basic classification engines are provided, organized in a hierarchial architecture, whose outputs can be combined in various ways to achieve complex decision-making logic functions. In addition, the outputs of these basic classifiers can be either soft or hard outputs. In the following, we also propose a simple approach to compute the soft outputs.

The basic classification engines can be selected based on the application context. For example, in Fig. 2 we have shown a cognitive engine architecture for SSA made of two levels of basic classification engines: Stage I and Stage II classifiers. According to the assumed decision-making logic, the Stage I

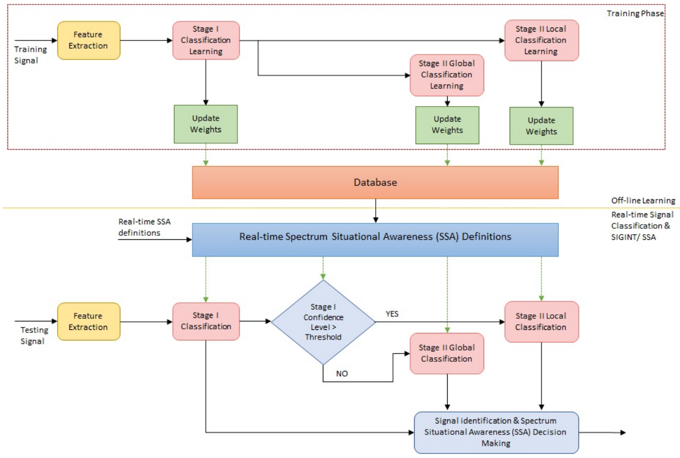

Figure 2. Proposed hierarchical RF signal classification and identification system for spectrum situational awareness.

classification is used to make the signal identification decisions if current SSA decisions can indeed be based on this level of classification output. If not, the WACR will proceed to Stage II classification. However, rather than just a hard classification label, Stage I of our proposed hierarchical classifier will produce a soft output that will indicate the confidence level (CL) associated with this decision. As an example, this confidence level can be a measure related to posterior probability.

The proposed hierarchical architecture in Fig. 2 can indeed be used to provide a more efficient and effective solution to the above example SSA problem of determining whether a detected signal is of interest according to the current SSA objectives that may be modified in real-time. We design the Stage I classifier in Fig. 2 to separate signals in to broader types whereas the Stage II classifiers are to determine exact signal origin through detailed classification within each of the broader classes assumed in Stage I. Specifically, we use the first level of classification (stage I classification) to determine whether a particular signal is a radar or a communications signal. The Stage II classification determines exactly which type of communications (e.g. LTE/A, WiFi or a satellite communications signal) or radar (e.g. pulsed, continuous-wave, moving-target indicator, pulse-Doppler) signal it is.

Of course, the objective of the proposed system is not merely to classify signals: Decisions are also to be made on whether a particular signal, or signals, is of interest. As already pointed out, the criteria for determining what is of interest will depend on the application scenario. The proposed design allows the radio to define this based on the context: operating spectrum band, user needs/inputs and application scenario. Once the signals of interest are defined, the radio will use its database and learned-knowledge to select and configure the classification engines as well as the final decision-logic functions as described below.

As shown in Fig. 2, the confidence-level associated with the first stage decisions, along with the decision-making logic, will trigger which type of classification is to be performed during Stage II: A global classification or local classification. For example, suppose that the signals of interest for current SSA are the continuous radar signals. If the Stage I classification is provided with a confidence-level exceeding a certain threshold, then the Stage II classification can be a local classification: i.e. if Stage I determined with high confidence that the signal is a radar signal, then the Stage II will only attempt to classify the signal in to one of many possible radar signal types (e.g. pulsed, continuous-wave, moving-target indicator, pulse-Doppler). It will not re-consider the signal as a possible communications signal in Stage II classification process. On the other hand, when confidence-level associated with Stage I decisions are relatively low, Stage II classification can be a global classification that will attempt to classify the signal among a large set of possible classes representing signals of various different types such as communications and radar. Essentially, global classification may ignore Stage I outputs.

On the other hand, if the signals of interest according to the current SSA objective are radar signals, then the goal of the classification is to be able to classify in to two classes: radar or communications. In this case, if Stage I confidence level of signal being a radar is above a certain threshold, then the stage I output can directly be the final output. If it is below the threshold, then Stage II global classification will be invoked and if the signal is classified in to any of the radar types then the final output will be to declare a radar signal.

The proposed cognitive engine operates in two possible modes: training and real-time. As shown in Fig. 2, during the training mode, cognitive engine is provided with sets of data with associated labels so that basic classification engines can learn to classify as described above. It is important to note that, by only training a set of local classifiers and a single global classifier, the proposed design drastically reduces the need for training a large number of different classifiers. Even in the relatively simpler example of SSA decisions based on two levels of classification, the number of all combinatorial possibilities lead to an exponential number of classifiers which is clearly not desirable. The proposed design, on the other hand, allows any of these exponential number of combinations to be computed in real-time using the decision-making module that is based on the individual classifier outputs.

The final SSA output is provided by the SSA decision-making module shown on Fig. 2. Decision-making algorithms can be implemented to derive the required SSA based on the Stage I and II classifier outputs. As a simple example, suppose that the final classifier outputs are hard outputs and the SSA definition of an important signal is any modulated continuous-wave signal. In this case, a decision logic module will infer this based on either the local or global classifier output in Stage II. In general, however, it is possible to use soft outputs from the classifiers to obtain posterior densities that may support more refined SSA definitions.

In Section V below, we will specifically focus on two SSA decision-making objectives (Of course, the decision-making logic module considered in this paper can be replaced with a suitable design to handle more complex SIGINT and SSA

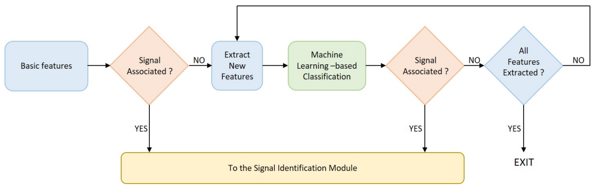

Figure 3. Multi-stage hierarchical signal classification.

definitions):

1) SSA decision problem #1: The signals of interest are the radar signals, so that the goal of the classification is to be able to classify in to two classes: radar or communications.
2) SSA decision problem #2: The signals of interest are the pulsed radar signals.

IV. Machine-learning based hierarchical RF signal classification

Signal classification within each stage of the proposed cognitive engine can itself be composed of several stages as originally proposed in [3]. The basic idea in multi-stage classification, as shown in Fig. 3, is to classify signals with a minimum number of features. For example, consider the local classification module of Stage II. This involves classification of a signal in to a specific class within the type of signals it was classified during the Stage I. Suppose that Stage I classification result was that the signal is a communications signal. Then, the goal of local classification module of Stage II is to identify which type of a communications signal it is.

As shown in Fig. 3, our multi-stage hierarchical signal classification framework will first attempt to associate the signal with a particular communications signal class using a simple set of features (as determined by the context). If this cannot be achieved with a required level of confidence, the WACR will try signal classification by including additional set of features. This process will continue until either the signal is associated with a particular communications signal class with the required minimum level of confidence or all available features are exhausted, in which case an identification failure can be reported to the signal identification module. Due to space, in this paper we do not delve in to details of how to handle such situations but refer the interested reader to [3] for a more comprehensive discussion.

There is a large body of literature on the problem of signal classification. As we have discussed in our previous work [3], the success of classification will critically depend on the extracted features. In the case of RF signals, there are numerous useful signal features that can be used as the features. Some of the common examples that have been investigated in literature include bandwidth, cyclo-stationary features and higher-order statistics [3], [11]–[15]. While specific choices will depend on the particular application context, it is conceivable that future systems may also include features related to location, direction-of-arrival(DOA) information as well as RF fingerprints associated with signal sources and origins.

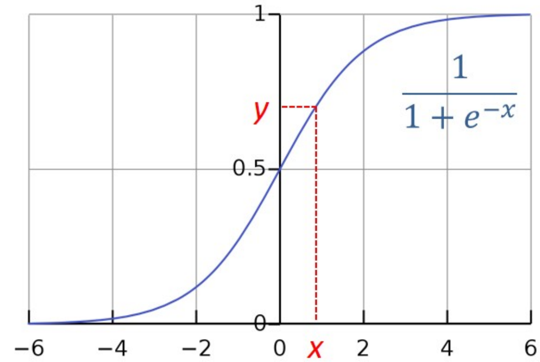

Figure 4. Confidence level computation.

Each stage of the proposed architecture may consist of several classifiers, as can be seen from Fig. 3. Hence, the proposed cognitive engine does not have to be based on a single particular machine learning paradigm or an algorithm. Indeed, it is logical to expect that different machine learning algorithms may provide the best fit for different classification problems. Although both Stage I and Stage II classifications are to be performed using artificial neural network (ANN) structures in the specific example of the cognitive engine design in this paper, some of these may be replaced by other classification algorithms such as support vector machines (SVM). Given the promising performance observed in other similar problems, deep learning techniques are also worth exploring for RF signal classification modules in both Stages I and II.

V. Simulation Results

Let us consider an RF environment with 4 possible signals: continuous radar, pulsed radar, WiFi and LTE signals. The continuous radar signal uses frequency modulation with sweep bandwidth = 0.5 MHz. The pulsed radar signal, on the other hand, uses biphase pulsed wave with the following parameters: chip width = 1 μsec, number of chips = 50 $chips/pulse$ and pulse repetition frequency (PRF) = 0.4 $Kcycles$.

The Stage I classifier is to identify whether the signal is a radar or a communications signal based on the cyclic profile. It is well-known that the cyclic profile of a signal exhibits multiple cyclic frequencies that may be related to features such as duty cycle, coding rate and modulation scheme which can discriminate between radar and communications signals [16]. Stage II is made of two types of classifiers: global and local. Local classifiers depend on the Stage I classification results whereas the global classifier ignores these. Stage II local classification provides the choice of two possible classifiers. One of them classifies a signal identified as a radar in stage I between continuous and pulsed radar classes. The input feature for this classifier is the duty cycle of a signal. The other local classifier classifies a signal identified as a communications signal in the Stage I in to either WiFi or LTE classes. Signal bandwidth is used as the feature input for this classifier. Stage

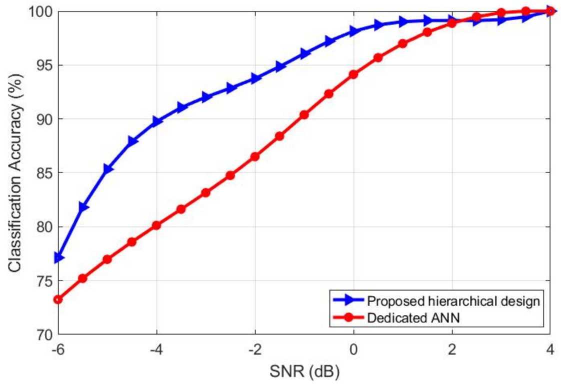

Figure 5. SSA decision problem #1: The overall classification accuracy between two classes.

II global classifier attempts to directly identify the exact signal origin based on a feature vector input made of bandwidth, duty cycle and cyclic profile.

In this paper, both Stage I and Stage II classifiers are designed to be ANN classifiers based on back-propagation. For simplicity and fairness in comparisons, all ANNs were constrained to have a single hidden layer. Stage I ANN classifier had 4 neurons in its hidden layer whereas Stage II global classifiers's hidden layer had 8 neurons. Both local classifiers in Stage II had hidden layers with 2 neurons.

In order to train the ANNs, multiple signals are generated with a signal-to-noise-ratio (SNR) of 6 dB and their corresponding features are extracted for each classification stage. Once the training phase is completed, the learned weights of the ANNs are recorded in the database to use in real-time signal classification, as shown in Fig. 2.

1) SSA decision problem #1: Identify whether a given signal is a radar or a communications signals: Let class 01 represents radar signals and class 02 represents communications signals. If we were to use a dedicated signal classifier for this problem, we may use the complete feature vector of (cyclic profile, duty cycle, bandwidth) as an input to a two-class ANN classifier. On the other hand, if we were to use the proposed hierarchical design, it will proceed as follows: First, Stage I classifier will classify signals in to either class 01 (radar) or 02 (comm). If the CL of the output is above the required threshold, this output will be taken as the final output. If not, the Stage II global classifier will classify in to one of 4 possible classes. The decision logic module will map these outputs in to either class 01 or 02.

We propose a confidence level (CL) definition based on the soft output of the sigmoid function of the output neuron:

$$CL = \frac{|y - 0.5|}{0.5}, \quad \text{with} \quad y = \tfrac{1}{1+exp(-x)}, \tag{1}$$

where x and y are the input and the output of the sigmoid function, respectively, as shown in Fig. 4.

Figure 5 shows the overall classification accuracy (CA) of a dedicated ANN and the proposed cognitive engine for classifying between the two classes. Note that, for the proposed technique, we have assumed a Stage I CL threshold of 85%. The superiority of the proposed cognitive engine over a dedicated two-class ANN can clearly be seen from Fig. 5. The performance improvement is especially visible in low SNR region. For example, at SNR= -2 dB, the overall CA of the proposed technique and the dedicated ANN are 93.75% and 86.5%, respectively. At SNR= -4 dB, the proposed technique has CA of about 90%, while the dedicated ANN achieves only a CA of 80.2%.

It is interesting to note that the classification accuracy of the Stage I classifier seems to be, *on average*, closely related to the confidence level, as can be seen from Table I. Note that the average confidence level (ACL) in Table I is computed by averaging the output confidence levels over the whole test set. Moreover, Table I indicates that as the SNR decreases, the CL also decreases.

In this SSA decision problem, the proposed cognitive engine provides two advantages. One, of course, is the superior overall CA performance seen in Fig. fig:ssadp01. The second aspect is the reduced complexity both in terms of not having to have a dedicated ANN for this particular classification problem as well as the ability to get away using only the relatively simpler Stage I classifier at least in majority of test cases. Table II shows the percentage of Stage I classified signals with $CL >$ 85%. Indeed, we may see that even when SNR is really low, majority of signals will only need to be processed by the Stage I classifier.

2) SSA decision problem #2: Identify whether a given signal is a pulsed radar signal: In this problem, the proposed hierarchical design is used to identify one signal of interest. The signal of interest, the pulsed radar, is represented by class 1, while class 2 represents the remaining 3 types of signals (continuous radar, WiFi and LTE). As before, a dedicated two-class ANN classifier can be used with the complete feature vector of (cyclic profile, duty cycle, bandwidth). In this case, the proposed hierarchical design will proceed as follows: the signals first pass through Stage I classification in which they will be classified into radar or communications signals with a certain CL. If the CL of a classified signal is above 85% it is passed to a Stage II local classifier. Otherwise it is passed to the Stage II global classifier. In local classification, the radar signals are classified into 2 classes: class 1 (pulsed radar) and class 2 (continuous radar). On the other hand, if the signal was a communications signal from Stage I, the local classifier classify it directly as class 2. As before, the Stage II global classifier classifies the signal into one of 4 possible classes. In this case, the decision logic module will map a pulsed radar signal into class 1, while the other 3 types of signals will be mapped to class 2.

Figure 6 shows the overall CA of a dedicated two-class classifier ANN and the proposed hierarchical signal identification approach. For SNR values above 0 dB, both approaches show excellent performance with CA ranging from 98% to 100%. However, for SNR ranging from -6 dB and -2 dB, the proposed hierarchal design outperforms the dedicated

Table I
CLASSIFICATION ACCURACY (CA) AND AVERAGE CONFIDENCE LEVEL (ACL) OF STAGE I.

SNR	**8 dB**		**6 dB**		**4 dB**		**2 dB**		**0 dB**		**-2 dB**		**-4 dB**		**-6 dB**	
	ACL	CA	ACL	CA	ACL	CA	ACL	CA	ACL	CA	ACL	CA	ACL	CA	ACL	CA
Class 01	99.59%	100%	99.57%	100%	99.3%	100%	93.93%	97.25%	86.08%	89.5%	85.02%	83.75%	83.82%	77.5%	84.22%	77.75%
Class 02	99.38%	100%	99.37%	100%	99.34%	100%	99.23%	100%	98.1%	97.75%	94.81%	97.5%	83.76%	86%	76.41%	73.75%
Total	99.48%	100%	99.47%	100%	99.32%	100%	96.58%	98.63%	92.09%	94.62%	89.91%	90.63%	83.79%	81.75%	80.32%	75.75%

Table II
THE PERCENTAGE OF SIGNALS THAT PASSES SATGE I CLASSIFICATION WITH $CL > 85\%$

SNR	**8 dB**	**6 dB**	**4 dB**	**2 dB**	**0 dB**	**-2 dB**	**-4 dB**	**-6 dB**
All signals	100%	100%	99.88%	94.5%	87%	82.25%	69.75%	63.63%

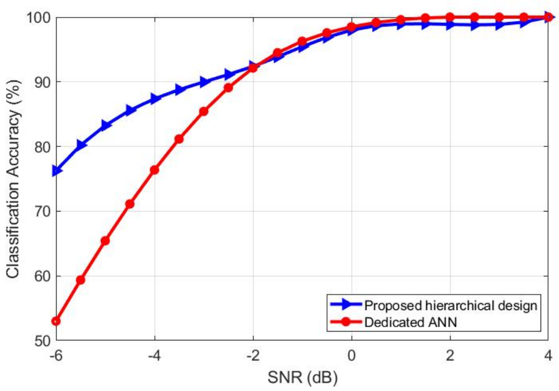

Figure 6. SSA decision problem #2: The overall classification accuracy for identifying one signal of interest.

ANN classifier. For example, at SNR$= -4$ dB, the proposed technique achieves a CA of 87.4% CA, while the dedicated ANN has a CA of 76.3%.

VI. CONCLUSION

In this paper, we have proposed a cognitive engine design for machine-learning based hierarchical RF signal identification. The objective of this design is to provide real-time SIGINT and SSA over a wide spectrum range of interest. The proposed cognitive engine design allows the user to define and/or modify the parameters of situational awareness in real-time. The specific design we outlined in this paper allows these definitions to be based on two levels of signal classification: a broad types of signals such as communications, radar or GPS and specific signals within each of these classes. It is a relatively straightforward step to generalize the proposed design to handle more than two levels of signal classification. Drawing from our previous work, we also showed a hierarchical signal classification framework that can be used within each stage of our signal identification approach. This allows the radio to classify and associate a signal using a minimum number of features.

Further research is needed to develop feature extraction modules and evaluate the performance of individual classification stages with candidate machine learning algorithms. A particularly important approach is to explore the suitability of various deep learning structures that have shown promising performance in other similar problem contexts.

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