# Automatic Modulation Classification in Cognitive-IoT Radios using Generalized Dynamic Bayesian Networks

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***Abstract*—This paper proposes a novel Automatic Modulation Classification (AMC) method for CR-IoT based on learning multiple Generalized Dynamic Bayesian Networks (GDBN) as representations of multiple signals under different modulation schemes. The CR-IoT performs multiple predictions on-line in parallel and evaluates multiple abnormality measurements based on a Modified Markov Jump Particle Filter (M-MJPF) to select the best model that better explains the received signal and recognize the modulation scheme accordingly. The simulated results based on a real dataset demonstrate that the proposed GDBN-based AMC method outperforms both Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN) in terms of classification accuracy.**

***Index Terms*—Cognitive Radio, Internet of Things, Automatic Modulation Classification, Bayesian Filtering.**

## I. Introduction

The rapid development of the Internet of Things (IoT) has attracted a multitude of research and industrial interests [1]. With the explosive growth in the number of connected IoT devices in a variety of applications, the scarcity of spectrum resources has become a serious problem [2]. In addition, most of the studies on IoT are focused on the communication, computing and connectivity aspects which are of great concern, however, IoT cannot fulfil its potentials and deal with growing challenges without comprehensive cognitive capabilities and empowering IoT with high-level intelligence [3]. It is envisioned that future IoT networks should be equipped with cognitive capabilities to think, learn and understand the demands of both the physical and social world [4]. Moreover, reliable communications realize the key to allow IoT devices to connect, interact and exchange information securely anytime, anywhere.

The integration of Cognitive Radio (CR) and IoT (known as CR-IoT) could alleviate the spectrum scarcity problem by enhancing the spectral efficiency and improving the network performance [5]. Furthermore, CR endows the IoT devices with cognitive facility to take smart decisions and perform intelligent operation by analyzing network conditions [6]. It can also provide intelligent services by processing different types of data generated by connected devices in a variety of applications such as smart manufacturing, smart homes and smart cities and handle intelligent tasks. CR is envisaged as a radio that employs the cognition cycle (observe-think-act) to achieve a high level of competence in radio-related domains [7]. It can autonomously observe and learn from the radio environment, infers the signals' dynamic behaviours to plan, decide and act accordingly. Awareness about the presence of licensed users to achieve optimum spectrum access is a precondition for CR, however, it is not enough to identify multiple licensed users' signals inside the spectrum. Therefore, Automatic Modulation Classification (AMC) is crucial in understanding the modulation scheme of the received (or sensed) radio signals and the type of communication has been used [8]. Also, since CR does not require control information about the transmitter a priori, it is essential for a CR receiver to detect the modulation mode of the received signal to be able in demodulating it correctly [9]. In addition, AMC is an indispensable task in CR towards achieving secure networks after being able to identify multiple malicious users (e.g., eavesdroppers and jammers) attacking the network due to the openness of the wireless medium and the dynamic nature of CR, as well as heterogeneity in IoT [6], [10].

In our previous investigations, we introduced the concept of Self-Awareness (SA) in CR to empower the radio with a brain for high-level intelligence [11], [12]. The SA module allows the radio to reach the capability of learning a representation of the radio environment encoded in a generative dynamic model and stored in the radio's brain. The generative model describes in a probabilistic manner how a given signal might have been generated by predicting new data samples and inferring the hidden states that caused the observed signal. This allows to evaluate the radio situation through different abnormality measurements at hierarchical levels and understand if the radio situation is normal or abnormal (e.g. detecting normal and jamming signals). If an abnormality is detected the radio can characterize it to discover the new rules and encode it incrementally in a new dynamic model. However, an important question that needs to be addressed here is *when* the radio must learn a new model based on the current radio situation? Abnormality detection is not enough to answer this question, while abnormality classification is an indispensable functionality towards this understanding. But why incremental learning is of fundamental importance in CR? Normally, CR does not know any prior knowledge about the surrounding radio environment, thus incremental learning is crucial to enable the radio with the capability to keep learning on-line in the field. Identifying the detected signals based on the knowledge acquired previously allows the radio to know when it is necessary to learn a new model. Hence, this work realizes the key to achieve incremental learning in CR.

In this paper, we propose an AMC framework based on learning Generalized Dynamic Bayesian Network (GDBN) models. Initially, the CR begins with null memory without any prior knowledge about the radio environment supposing that signals are evolving according to static rules and starts to build up the knowledge about the environment by exploiting the generalized errors (i.e. prediction errors) to discover the real dynamic rules of how the signals are behaving inside the radio spectrum. These errors can be clustered in an unsupervised manner to learn the corresponding GDBN model. After learning different GDBN models for multiple signals under different modulation schemes and by facing new radio experience the radio can use the acquired models in parallel to perform multiple predictions using a Modified Markov Jump Particle Filter (M-MJPF) and evaluate the best GDBN model that explains the current observation and recognize the modulation scheme consequently. The main contributions of this work are as follows: 1) we propose an efficient learning mechanism within the Growing Neural Gas (GNG) to capture the dynamic transitions of the radio signal modulated under certain modulation schemes; 2) we formulate the modulation classification problem in terms of an objective function that aims to minimize the surprise (i.e. abnormality); 3) extensive simulations verify that the proposed GDBN-based AMC performs with superior classification accuracy than Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN); 4) the GDBN models can achieve higher interpretability than Deep Learning-based models since they can explain the predictions explicitly at hierarchical levels and use the abnormality measurements and generalized errors as self-information to keep learning by understanding incrementally.

## II. Literature Review

AMC is widely used in both civil and military fields and finds applications in CR-IoT for an efficient spectrum management and secure communications. Deep learning-based methods for AMC are extensively investigated in the literature. In [13], a LSTM is used where the data-augmentation methods are studied to cope with small datasets by expanding the data and thus improving the robustness and classification accuracy. However, expanding the dataset might lead to several problems as increasing latency which is vital in some applications as IoT and vehicular communications. Authors in [14] proposed a gated recurrent residual network (GrrNet) consisting of a ResNet extractor module, fusion module and GRU-based classification module. However they used a supervised training by feeding the networks with the signal features along with the labels that indicate the modulation scheme of the input. This may require a big effort in labeling large amounts of training examples which can be expensive and time consuming. An interesting research has been conducted in [15] to study the visualization methods for deep learning-based AMC and thus understanding the modulation classification mechanism for better interpretability. However, such visualization techniques do not exploit the extracted radio features in an unsupervised way allowing the radio to encode the dynamic changes between different modulation schemes which by the way enhance the learning and perception processes of the radio.
Other studies treated the AMC as an image recognition problem by converting the radio signal into images as in [16], [17] and they obtained promising results. However, they require high computational processing to convert signals to images and they might lose important information and ignore crucial details by passing from time-frequency representation to image representation.

## III. System Model

We consider an IoT network as shown in Fig. 1, consisting of different clusters of IoT devices which are sending different information to the Base Station (BS). The BS collects data and processes them with its equipped cognitive capability aiming to classify between the received signals based on the modulation scheme used by IoT devices in each cluster. The

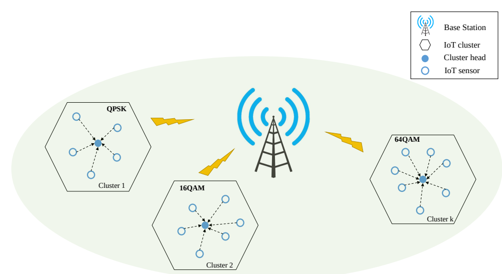


Fig. 1. Illustration of the system model

received signal under the *k-th* modulation scheme which is related to a specific IoT cluster is given by:

$$r_t = he^{j(2\pi ft+\theta)}s_t^{(k)} + v_t \tag{1}$$

where $h$ is the channel coefficient, $f$ the frequency offset and and $\theta$ is the phase offset. Moreover, $s_t^{(k)}$ is the complex symbol belonging to the *k-th* modulation scheme and $v_t$ is the Additive White Gaussian Noise (AWGN) which is drawn from a zero mean normal distribution with variance ($\sigma_v^2$).

## IV. Proposed Method for Automatic Modulation Classification.

### A. Radio Environment Representation

In our approach, we use a generalized state-space model to represent the radio environment. We assume, that the observed signal $\tilde{Z}_t^{(k)}$ which is modulated under the *k-th* modulation scheme, is a linear combination of one latent generalized state $\tilde{X}_t^{(k)}$ that represents the direct cause of the observation and a multivariate Gaussian noise $v_t$ and defined as follows:

$$\tilde{Z}_t^{(k)} = H\tilde{X}_t^{(k)} + v_t \tag{2}$$

where $H \in \mathbb{R}^{d\times d}$ is the matrix that maps hidden states to observations. The generalized observation $\tilde{Z}_t^{(k)} \in \mathbb{R}^d$ comprises the signal's states in terms of $I$ (in-phase) and $Q$ (quadrature) components and the corresponding first order temporal derivatives ($\dot{I}$, $\dot{Q}$), thus the space dimensionality $d$ is equal to $4$.

The evolution of the hidden generalized states $\tilde{X}_t^{(k)}$ can be approximated as a linear combination of the previous state $\tilde{X}_{t-1}^{(k)}$ which is guided by the deep hidden cause $\tilde{S}_t^{(k)}$ and formulated as follows:

$$\tilde{X}_t^{(k)} = A\tilde{X}_{t-1}^{(k)} + BU_{\tilde{S}_t^{(k)}} + w_t \tag{3}$$

where, $A \in \mathbb{R}^{d\times d}$ and $B \in \mathbb{R}^{d\times d}$ are the dynamic model and control model matrices. The generalized superstates ($\tilde{S}_t^{(k)}$) are discrete variables that explains the discrete regions of the signal. The evolution of these variables is expressed in the following form:

$$\tilde{S}_t^{(k)} = f(\tilde{S}_{t-1}^{(k)}) + w_t \tag{4}$$

where $f(.)$ is a non-linear function that describes the relationship between the previous superstate and the current superstate, realizing the dynamics of how the signal is transiting among the discrete regions and its evolution over time.

The BS equipped with cognitive capabilities aims to learn and encode the radio environment representation in a Generalized Dynamic Bayesian Network (GDBN) under each modulation scheme. Thus, after finishing the training process, it will be possessed with a set ($\mathcal{S}_{\mathcal{M}}$) of GDBN models, such that:

$$\mathcal{S}_{\mathcal{M}} = \{\mathcal{M}_1, \mathcal{M}_2, \dots, \mathcal{M}_K\} \tag{5}$$

where, model $\mathcal{M}_k$ is associated with the $k$-th modulation scheme and explains how the signal's dynamics evolve under this scheme.

### B. Learning Stage

We propose to learn a GDBN as a representation of the radio environment. GDBN can model dynamic processes describing the signal's temporal evolution at hierarchical levels. GDBN provides a graphical structure representing hidden and observed states in terms of random state variables encoding the conditional dependencies among them and specifying a compact parameterization of the model. It can be represented by two sets of parameters. The first includes the number of nodes in each time slice and the corresponding topology which depends on the state-space model in question, while the second set consists of the conditional probability distribution (CPDs) described by edges of the network. The proposed GDBN depicted in Fig. 2 consists of three levels. The discrete level stands for the discrete variables describing the discrete regions of the signal. The medium level stands for the continuous states encoded inside each discrete region and the bottom level stands for the observation.

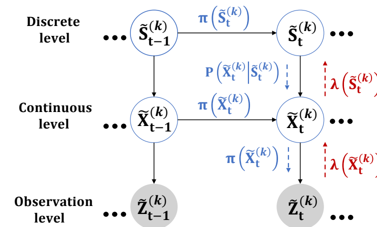


Fig. 2. Generalized Dynamic Bayesian Network.

Initially, the cognitive BS starts perceiving the radio environment using an initial GDBN (i.e., a null force filter with static assumption about the environmental states) by interpreting the received generalized observations $\tilde{Z}_t^{(k)}$ that comprises the variable and its generalized coordinates of motion coming from the receivers. In fact, since the signals inside the radio spectrum are following a certain dynamic behavior the BS will detect abnormalities all the time and calculate the generalized errors ($\tilde{\varepsilon}_t^{(k)}$) which are the differences between predictions and observations and it is expressed as:

$$\tilde{\varepsilon}_t^{(k)} = H^{-1}\tilde{Z}_t^{(k)} - \tilde{X}_t^{(k)} \tag{6}$$

The generalized errors that capture the real dynamics of the signal are used as input to an unsupervised clustering technique, the Growing Neural Gas (GNG). GNG encodes the generalized errors into discrete regions described by a set of neurons or superstates $\mathbf{S}^{(k)}$, such that:

$$\mathbf{S}^{(k)} = \{S_1^{(k)}, S_2^{(k)}, \dots, S_M^{(k)}\} \tag{7}$$

where $M$ is the total number of neurons. After obtaining the neurons we analyzed how the signal is transiting between them to learn the transition matrix $\Pi^{(k)}$ by estimating the transition probabilities: $\pi_{ij}^{(k)} = P(S_t^{(k)} = i | S_{t-1}^{(k)} = j)$ over a period of time (i.e. the training time), where $i, j \in \mathbf{S}^{(k)}$. Thus, the generalized superstates ($\tilde{\mathbf{S}}^{(k)}$) can be expressed in terms of current discrete variable $S_t^{(k)}$ and the event $E(.)$ of passing to that variable conditioned to be in $S_{t-1}^{(k)}$ in the previous time instant and it is given by:

$$\tilde{S}_t^{(k)} = [S_t^{(k)} \ \dot{S}_t^{(k)}] = [S_t^{(k)} \ E(S_t^{(k)} | S_{t-1}^{(k)})] \tag{8}$$

Each discrete variable $\tilde{S}_m^{(k)}$ ($\tilde{S}_m^{(k)} \in \mathbf{S}^{(k)}$) is associated with specific statistical properties as covariance matrix $\Sigma_{\tilde{S}_m^{(k)}}$ and *generalized mean value* $\tilde{\mu}_{\tilde{S}_m^{(k)}} = [\mu_{\tilde{S}_m^{(k)}}, \dot{\mu}_{\tilde{S}_m^{(k)}}]$ that consists of the mean value $\mu_{\tilde{S}_m^{(k)}}$ describing the average of all the data samples encoded in this superstate in terms of $I$ and $Q$ as well as the average of the corresponding derivatives (i.e. $\dot{\mu}_{\tilde{S}_m^{(k)}}$).

In this work we propose to learn additional statistical properties for each $\tilde{S}_m^{(k)}$, namely, a set $\boldsymbol{\tilde{\mu}}_{\boldsymbol{\tilde{S}_m^{(k)}}}$ of *transition generalized mean values* defined as:

$$\boldsymbol{\tilde{\mu}}_{\boldsymbol{\tilde{S}_m^{(k)}}} = \left[\tilde{\mu}_{\tilde{S}_m^{(k)}|\tilde{S}_1^{(k)}}, \tilde{\mu}_{\tilde{S}_m^{(k)}|\tilde{S}_2^{(k)}}, \dots, \tilde{\mu}_{\tilde{S}_m^{(k)}|\tilde{S}_M^{(k)}}\right] \tag{9}$$

where the *transition control vectors* ($\boldsymbol{U}_{\tilde{\boldsymbol{S}}_m^{(k)}}$) are encoded such that:

$$\boldsymbol{U}_{\tilde{\boldsymbol{S}}_m^{(k)}} = \left[ U_{\tilde{S}_m^{(k)} | \tilde{S}_1^{(k)}}, U_{\tilde{S}_m^{(k)} | \tilde{S}_2^{(k)}}, \ldots, U_{\tilde{S}_m^{(k)} | \tilde{S}_M^{(k)}} \right] \quad (10)$$

and a set $\boldsymbol{\Sigma}_{\tilde{\boldsymbol{S}}_m^{(k)}}$ of *transition covariance matrices* defined as:

$$\boldsymbol{\Sigma}_{\tilde{\boldsymbol{S}}_m^{(k)}} = \left[ \Sigma_{\tilde{S}_m^{(k)} | \tilde{S}_1^{(k)}}, \Sigma_{\tilde{S}_m^{(k)} | \tilde{S}_2^{(k)}}, \ldots, \Sigma_{\tilde{S}_m^{(k)} | \tilde{S}_M^{(k)}} \right] \quad (11)$$

This additional information allow to understand not only the dynamic random changes at the discrete level (through the transition probabilities encoded in the transition matrix) but also to discover the force of those changes and the rules by which the signal is shifting among them which by the way describe the dynamic flow of the signal at the continuous level. This realizes the key towards predicting efficiently the dynamic changes of different modulation modes.

### C. Testing Stage

GDBN can decompose data with complex and non-linear dynamics into segments that are explainable by simpler dynamical units. The Modified Markov Jump Particle Filter (M-MJPF) (which is an evolved version of the MJPF introduced in [18]) is a specific class of switching dynamic systems employed on the learned GDBN model to discover the dynamical units and explain their switching behaviour and their dependency on both observations and discrete/continuous hidden states during the real-time process. The M-MJPF uses a combination of Particle Filter (PF) to predict the generalized superstates at the discrete level and a bank of Kalman Filters (KFs) at the continuous level to predict the generalized states. The M-MJPF within the Bayesian Filtering framework provides two probabilistic inference modes, namely the predictive or causal inference (top-down) and the diagnostic inference (bottom-up). The predictive inference is based on passing predictive messages in a top-down manner where predictions are performed based on the acquired knowledge in previous experience. The diagnostic inference is based on propagating likelihood messages after receiving the real measurement in a backward manner from bottom to up where the likelihood messages evaluate how much the observation matches the predictions at hierarchical levels to update the belief in hidden variables accordingly. PF relies on a proposal density encoded in the learned transition matrix to sample a set of particles realizing the predicted superstates at the discrete level. Initially,

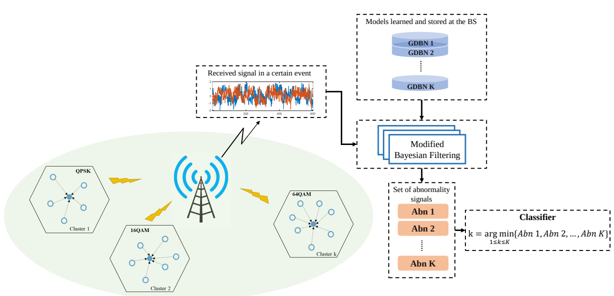


Fig. 3. GDBN-Based Modulation Classification Framework.

PF propagates $N$ equally weighted particles associated with a specific superstate, such that:

$$< \tilde{S}_t^{(k)n}, W_t^{(k)n} > \sim < \pi(\tilde{S}_t^{(k)}), 1/N >, \; n \in N \quad (12)$$

It is worth noting that in our scenario there is no need to use a big number of particles since the discrete level consists of a finite number of discrete regions and thus it is sufficient to use few particles to represent the posterior accurately with low complexity (unlike the continuous space which may need a huge number of particles to represent the posterior correctly). After that, a KF is employed for each particle $(.^n)$ to predict $\tilde{X}_t^{(k)}$. The prediction at this level (continuous level) is guided by the prediction performed at the higher level as pointed out in (3) and can be expressed in terms of the conditional probability $P(\tilde{X}_t^{(k)} | \tilde{X}_{t-1}^{(k)}, \tilde{S}_t^{(k)})$. In (3), the control vector ($U_{\tilde{S}_t^{(k)}}$) which realize the dynamic flow of the signal starting from the previous state, depends on the transition control vector defined in (10) which by the way depends on the predicted event at the discrete level to choose the proper vector. The posterior probability associated with the predicted generalized state is given by: $\pi(\tilde{X}_t^{(k)}) = P(\tilde{X}_t^{(k)}, \tilde{S}_t^{(k)} | \tilde{Z}_{t-1}^{(k)})$, where $P(\tilde{X}_t^{(k)}, \tilde{S}_t^{(k)} | \tilde{Z}_{t-1}^{(k)}) = \int P(\tilde{X}_t^{(k)} | \tilde{X}_{t-1}^{(k)}, \tilde{S}_t^{(k)}) \lambda(\tilde{X}_{t-1}^{(k)}) d\tilde{X}_{t-1}^{(k)}$ and $\lambda(\tilde{X}_{t-1}^{(k)}) = P(\tilde{Z}_{t-1}^{(k)} | \tilde{X}_{t-1}^{(k)})$. Accordingly, a message backward propagated from the bottom-level to the higher levels once a new evidence $\tilde{Z}_t^{(k)}$ is received can be exploited to adjust the expectations in hidden variables and estimate the posterior probability $P(\tilde{X}_t^{(k)}, \tilde{S}_t^{(k)} | \tilde{Z}_t^{(k)})$ which is defined as: $P(\tilde{X}_t^{(k)}, \tilde{S}_t^{(k)} | \tilde{Z}_t^{(k)}) = \pi(\tilde{X}_t^{(k)}) \lambda(\tilde{X}_t^{(k)})$. Consequently, the likelihood message $\lambda(\tilde{S}_t^{(k)})$ is propagated towards the top-level to update the belief in the hidden discrete variable by updating the weights according to: $W_t^{(k)n} = W_t^{(k)n} \lambda(\tilde{S}_t^{(k)})$. The message $\lambda(\tilde{S}_t^{(k)})$ is a discrete probability distribution represented by: $\lambda(\tilde{S}_t^{(k)}) = \lambda(\tilde{X}_t^{(k)}) P(\tilde{X}_t^{(k)} | \tilde{S}_t^{(k)})$, where $P(\tilde{X}_t^{(k)} | \tilde{S}_t^{(k)}) \sim \mathcal{N}(\mu_{\tilde{S}_m^{(k)}}, \Sigma_{\tilde{S}_m^{(k)}})$ denotes a Gaussian distribution with mean $\mu_{\tilde{S}_m^{(k)}}$ and covariance $\Sigma_{\tilde{S}_m^{(k)}}$. While, $\lambda(\tilde{X}_t^{(k)}) = P(\tilde{Z}_t^{(k)} | \tilde{X}_t^{(k)})$ denotes a Gaussian distribution with mean $\mu_{\tilde{Z}_t^{(k)}}$ and covariance $R$ such that $\lambda(\tilde{X}_t^{(k)}) \sim \mathcal{N}(\mu_{\tilde{Z}_t^{(k)}}, R)$ (refer to [12] for the detailed calculation of $\lambda(\tilde{S}_t^{(k)})$). After updating the weights, PF uses the Sequential Importance Resampling (SIR) and discriminate among all the available particles to select the one associated with the maximum weight.

We have seen that predictive and diagnostic reasoning can be used to estimate a joint posterior at different hierarchical levels. An additional process can be done here to evaluate the differences between two messages arriving at a given node and estimate the surprise (i.e. the abnormality) using a proper probabilistic distance (e.g. Bhattacharyya distance, Kullback–Leibler divergence, etc.). In this paper, we use the abnormality indicator (*Abn*) based on the Bhattacharyya distance between the two messages, that represent multivariate Gaussian probability distributions, $\pi(\tilde{X}_t^{(k)})$ and $P(\tilde{X}_t^{(k)} | \tilde{S}_t^{(k)})$. This allows to evaluate if the predictions at the continuous level matches the predictions at the discrete level and thus explains if the signal's dynamics at both the discrete and continuous level evolve according to the rules learned before in a way that it can explain the received signal.

$$Abn = -\ln\left(\mathcal{BC}\big(\pi(\tilde{X}_t^{(k)}), P(\tilde{X}_t^{(k)}|\tilde{S}_t^{(k)})\big)\right) \tag{13}$$

where, $\mathcal{BC} = \int \sqrt{\pi(\tilde{X}_t^{(k)})P(\tilde{X}_t^{(k)}|\tilde{S}_t^{(k)})}d\tilde{X}_t^{(k)}$, is the Bhattacharyya Coefficient.

### *D. Classifier*

In order to recognize the correct modulation scheme of the received signal (i.e. current observation), the BS will perform multiple predictions in parallel using the learned and stored models during the training process. Thus, at each time instant $t$, we have multiple predictions related to multiple GDBN models, where each model $\mathcal{M}_k$ explains the signals dynamics modulated under the *k-th* modulation scheme. The BS can evaluate which of these predictions explain the current radio situation by using the abnormality measurement defined in (13). A set of abnormalities $\mathcal{S}_{Abn}$ is available at each time instant $t$, such that:

$$\mathcal{S}_{Abn}(t) = \{Abn_1, Abn_2, \dots, Abn_K\} \tag{14}$$

The classifier at the BS is supposed to recognize correctly the modulation scheme of the received signal from a set ($\mathcal{S}_k$) of candidate modulations denoted by integer values, such that: $\mathcal{S}_{mod} = \{1, \dots, K\}$. Then, the modulation classification can be made by comparing between all the abnormality values and selecting the index of the minimum abnormality in the set $\mathcal{S}_{Abn}(t)$ to recognize the modulation scheme, which is given by:

$$\hat{k}(t) = \min\ \{\mathcal{S}_{Abn}\}, \text{where } \hat{k}(t) \in \mathcal{S}_{mod} \tag{15}$$

The probability of correct classification $P_{cc}$ can be used as performance metric to evaluate the AMC task, calculated as:

$$P_{cc} = \frac{1}{T}\sum_{t=1}^{T} P(\hat{k}(t) = k(t)|k(t)) \tag{16}$$

where, $T$ is the total testing time and $P(\hat{k}(t) = k(t)|k(t))$ is the probability that the modulation scheme is correctly predicted as $k(t)$ at time $(t)$.

## V. Experimental Results

### *A. Real DataSet*

We employed a real dataset named RadioML (version 2018[1]) [19] to assess the performance of the proposed GDBN-based AMC after running extensive simulations. The candidate set of the modulation schemes picked from the dataset is $\mathcal{S}_{mod}$={OOK, QPSK, 32-PSK, 16-QAM, 32-QAM, 64-QAM, 256-QAM}. The dataset was built using GNU radio block that includes different effects as center frequency offset, sample rate offset, selective fading and AWGN to simulate real-world radio conditions. The dataset consists of about 2 million examples (which we call events) under different SNR values. The SNR ranges from -20dB to +30dB with a step size of 2dB. In our study, each event is divided into two subsets 50% for training and 50% for testing and the classification task is performed at each event to classify between single complex symbols. The challenge of this approach is the ability to perform accurate classification without requiring many symbols which improve the latency and make it possible to recognize the modulation scheme in real time manner just by processing one symbol which is crucial in the IoT networks.

[1]Data set available on https://www.deepsig.ai/datasets

### *B. Results and discussion*

During the training process, the CR-IoT learns a GDBN model for each modulation scheme. After this process, the radio possesses $K$ GDBN models stored in its brain where each model encodes the dynamic behaviour of the corresponding modulation. During the testing process, the radio performs multiple predictions in parallel and calculate the abnormality indicator as defined in (13) where the classifier pick the minimum abnormality signal (among the $K$ abnormality signals) as defined in (15) to recognize the modulation scheme.

In Fig. 4, we showed the classification accuracy of the proposed GDBN for each modulations scheme in $\mathcal{S}_{mod}$. We can observe that GDBN achieves high classification accuracy for most of the modulation schemes especially at SNR>5dB. The low accuracy at low SNRs (<0dB) for the majority of the modulation schemes in $\mathcal{S}_{mod}$ can be explained by the fact that at low SNR the data samples of each modulation are concentrated around the origin (in the complex IQ plane) and thus the dynamics become very fast which make it difficult to discover and capture these dynamic rules that are encoded in the GDBN model in an efficient way. In addition, we compared the performance of the proposed GDBN with the CNN and the LSTM. We followed the same approach used to learn the GDBN (thus by using the same state vector which is used as input to the GNG to learn the GDBN) for both CNN and LSTM for a fair comparison. Moreover, for CNN we used the same configuration (i.e. same number of layers) employed in [19] but with different input, here we used a state vector consisting of $IQ$ components and the corresponding derivatives. While the LSTM used here has 3 layers, one LSTM layer, one fully connected layer and finally a dense softmax layer that maps the classified features to one of the available modulations schemes in $\mathcal{S}_{mod}$. Again, Fig. 4 shows the performance comparison between the proposed GDBN, LSTM and CNN. It can be seen that the GDBN outperforms the other techniques in the majority of the available modulation schemes. This can be understood better by plotting the overall comparison performance, i.e., the average probability of correct classifications among all the $P_{cc}$ related to each modulation. The overall comparison is depicted in Fig. 5 and it shows that the proposed GDBN beats both LSTM and CNN especially at SNR>5dB. This means that the proposed approach succeeded to learn the dynamic proprieties (at hierarchical levels) of the signal under a certain modulation scheme, which allows to predict the future behaviour of the signal based on the rules encoded in that model. In addition, LSTM and CNN performs the supervised learning by using the input vector along with the labels of each modulation scheme during the learning process while in the case of GDBN we followed an unsupervised approach to learn the model. Also, we have seen that GDBN allows to learn the relationships among the random variables (at hidden layers) in the network explicitly and evaluate the situation using abnormality measurements which can be used as self-information by the radio itself to extract new features and learn emergent rules representing new radio situations incrementally. This is difficult in the case of LSTM and CNN where the dependencies between the hidden variables at multiple layers are viewed as a black-box and thus results can not be explained. This limitation impact the capability of learning by understanding which is crucial in CR to learn continually while observing the environment.

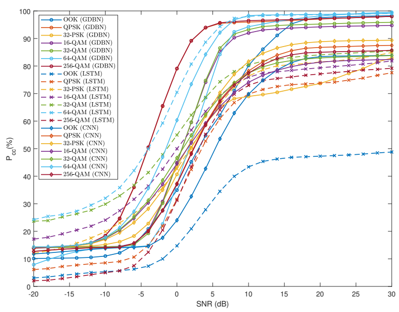


Fig. 4. The performance comparison between GDBN, LSTM and CNN.

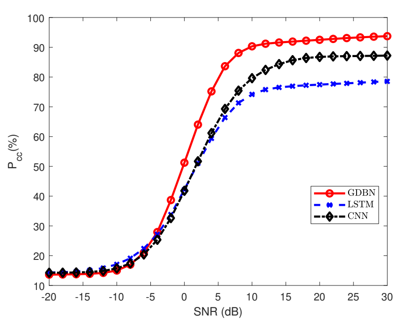


Fig. 5. The overall performance comparison among GDBN, LSTM and CNN.

## VI. Conclusion and Future Work

We proposed a method for AMC in CR-IoT network based on learning a set of GDBN models representing multiple signals inside the radio spectrum under different modulation schemes. The method performs multiple predictions using the M-MJPF during a new radio experience and selects the best model that explains the current situation to recognize the modulation scheme of the received signal. Simulation results using a real dataset showed that the proposed method outperforms both LSTM and CNN as well as providing interpretable results where multiple abnormality measurements and generalized errors can be used as self-information to keep learning incrementally. Our future objectives include optimizing the proposed approach to achieve high classification accuracy at low SNR and studying the interaction among multiple models stored in the radio's brain to understand the causality among them to drive the incremental learning process.

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