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Research Article

Enhanced Spectrum Sensing with Self-Organizing Maps and Deep Belief Networks: A Time-Efficient Approach

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ABSTRACT

In today's wireless communication era, Cognitive radio systems (CRS) report two pressing problems: the shortage or scarcity of usable frequencies and second is the efficient use of those frequencies by the legal (or "licensed") users. Spectrum sensing (or "Spectrum detection") is the key process in the CRS that allows these systems to be "cognitive." Demand of wireless communications is not narrowing and in fact, it is accelerating day by day, particularly in emerging economies. An increasing number of methods, both classical and modern, are being developed for the robust and timely spectrum sensing. Classic methods for spectrum sensing, like MLP, CNN, and LSTM, routinely encounter difficulties in a balancing between two main design targets as: accuracy and computational efficiency. The real-time nature of typical application scenarios makes this operational challenge particularly noticeable. In this paper's introduction and the review of related work we underline the same. Thus, a very strong approach should use to explore the new deep learning techniques which preferably have relatively low in required computational overhead at same time secure high detection accuracy. The application of Deep Belief Networks (DBNs) and Self-Organizing Maps (SOMs) for enhanced spectrum sensing in CRNs is the subject of our study. The critical task is to evaluate these two models for accuracy and speed in detecting spectrum availability. Insights into the trade-offs between detection performance and computational efficiency are especially vital concerning SOM and DBN models because they are fairly new as compared to traditional spectrum sensing methods. Challenging conditions for spectrum sensing were utilized to assess the performance of DBN and SOM models, and the results were compared to benchmarks established by traditional methods. The obtained results shows that SOM gets to an amazing accuracy of 95.77% with an execution time of only 0.02 seconds, makes it extremely suitable for real-time applications. Meanwhile, DBN achieves a supreme accuracy of 99.85%, but with a moderate execution time of 147.08 seconds, demonstrating its ability to extract features hierarchically and in a very deep way. Both models outperform traditional methods, and they strike a superior balance between accuracy and computational requirements with modern hardware. These gained results spotlight SOM and DBN based methods are next-generation CRN system competitors. SOM's architecture required low processing and power, and DBN's near-perfect detection capabilities. This meant that CRN systems using deep learning could handle the RF spectrum under even the worst conditions also. Their potential gains offered insights into several key trade-offs.

Keywords: Cognitive Radio Networks, Spectrum Sensing, Deep Belief Networks (DBN), Self-Organizing Maps (SOM), Time-Efficient Algorithms, Real-Time Processing, Wireless Communication, Dynamic Spectrum Access.

INTRODUCTION

A new technology called cognitive radio (CR) was created to encounter the increasing need for wireless communication services despite the limited availability of spectrum [1]. Conventional wireless networks use preset frequency bands that are allotted by regulatory bodies, which results in inefficient use of the spectrum and congestion

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in some frequency ranges [2]. Conversely, cognitive radio provides dynamic spectrum access by guaranteeing that devices do not interfere with licenced users while taking use of underutilised spectrum bands [3].

Cognitive radio networks rely heavily on efficient spectrum sensing because it allows devices to identify and take advantage of available spectrum possibilities without interfering negatively with core users. The identification of spectrum white spaces, or frequency regions where primary users are not actively transmitting and can be used by secondary users, is made possible in large part by spectrum sensing techniques. These methods include cyclostationary feature detection, which makes use of periodic properties in the received signals, and energy detection, which monitors the power level of received signals.

A CR must choose between two hypotheses based on its recorded observations for solving the detection/classification problem that is the core of the spectrum sensing challenge [4]. The scenario in which a PU is absent is represented by the null hypothesis, and the scenario in which a PU is present is represented by the alternate hypothesis. Stated differently, data collected beneath the null hypothesis is noise-only, but in such scenarios, data collected in the presence of PU includes both noise and the PU signal [5]. A CR's performance is frequently hampered by shadowing, fading, noise statistics, and receiver uncertainty. For a certain specified value of the chances of false alarms, the effectiveness of a Spectrum Detection algorithm is often gauged by the probability of detection [6].

Many detectors have been suggested to carry out Spectrum Sensing. Energy detector (ED) – which based on principle of energy of signal [7], Matched filter detector (MFD) -works with filters principle, Cyclostationary feature-based detector- works with stationarity of signal, geometric power detector- works with power principle [8], and differential entropy detector- works with differential entropy are a few examples of signal processing techniques that have been investigated For above each of technique which has some advantages and disadvantages. For instance, it is well known that the likelihood of finding ED declines with low signal-to-noise ratio (which is commonly called as SNR) and noise variance uncertainty. To employ MFD, the PU signal information must be available at CR, which is impractical. Despite outperforming ED, the cyclostationary detector has a high computational cost.

Deep learning approach which is subset of Artificial Intelligence has become a potent method for cognitive radio network spectrum sensing in recent years. In feature extraction, pattern recognition, and classification tasks, deep learning models like Convolutional Neural Network (commonly known as CNNs), Recurrent Neural Network (RNNs), and Long Short-Term Memory (LSTM) network have confirmed to be remarkably effective. The large volume of data produced by cognitive radio systems can be efficiently selected to find complex patterns and relationships by using deep learning algorithms. This makes more accurate and reliable spectrum sensing result.

As compared to traditional spectrum detection methods, an addition of deep learning methods in spectrum sensing shows several benefits. These stand up mainly from the practice of deep learning models instead of conventional detection methods. From the raw spectrum data, deep learning algorithms automatically learn distinct features in an unsupervised manner. This approach removes the human aspect of feature engineering. This offers a clear advantage of deep learning methods over traditional methods, which require well-defined features to accomplish for effective detection.

In Wireless communication, spectrum insufficiency problem is being improved by Cognitive Radio Networks (CRNs). The use of CRNs allows for secondary users to make use of licensed spectrum frequencies which are be underutilized, while still ensuring that interference levels remain low enough to protect the primary users of those same bands. There are a number of core functionalities that CRNs perform. One of the most important is spectrum sensing or detection, where the main goal is to detect spectrum slots that are currently vacant/unused. There are traditional signal processing methods that have been in use for a long time like energy detection and cyclostationary feature detection. These methods are fairly well understood within the research community. These techniques have a number of limitations, and most of them based on the problem of operating in noisy environments. Deep learning algorithm-based approaches, including SOMs and DBNs, provide promising solutions to these challenges by offering robust data-driven methodologies.

LITERATURE REVIEW

Using the prime structure data of the modulated signals, the authors in paper has proposed a deep learning based signal detection and classification that provides cutting-edge detection performance without any previous understanding of a channel state evidence or ambient noise. It is important to note that the suggested strategy works noticeably better than other well-known cooperative sensing techniques. The authors of propose applying DRL method to CSS to resolve the challenges in cognitive radio network.

In [9], the spectrum detection problem is transformed into image processing related task as- an image recognition task, and the real world and noise are distinguished using machine learning approach. Signal's presence uses a training dataset of a few hundred samples. The CNN method's effectiveness is then compared to the throughput of further traditional energy detection methods as well as previously published outcomes of machine learning used for signal detection.

An attempt is made to assess the efficiency of cooperative based spectrum sensing (commonly known as CSS), which combines deep learning with data fusion techniques [10]. We study the performance of CSS based on convolutional neural networks in dynamic channel scenarios.

A hybrid approach of deep learning (DL)-based technique for spectrum detection was developed in [11] that effectively learns the statistical time series spectrum data which changes with respect to time. The cutting-edge testbed that obtains unprocessed spectrum data for a wide range of frequency patterns and signal’s SNR levels. Then corresponding evaluation is carried out and for this performance metrics like Pd & Pfa are examined and contrasted with other existing learning-based spectrum detection techniques. Studies reveal that even in low SNR situations, the proposed framework outperformed the alternative method in standings of better sensing accuracy as well as a better detection ratio.

This study in [12] provided a novel spectrum sensing technique for cognitive radio systems. The proposed approach uses the RNN- recurrent neural network, a popular deep learning technique, to determine the empty spectrum.

The recommended approach computes Cooperative spectrum sensing (CSS) is proposed in [13] using an ELM i.e. Extreme Learning Machine based method. ELMs stand feed forward neural networks where the hidden layer parameters are not optimized, only the output weights are. It was possible to replicate both a transient and persistent environment. These results suggest that ELM might be superior to traditional methods.

In [14], the authors test several signal-to-noise ratios in order to confirm that the recommended method performs better. The presence of a modulation format indicates the presence of an associated modulation format for the PU signal.

The results in [15] show that by reducing the sensing time (which is defined as time needed for spectrum sensing) and applying traditional fusion principles, the recommended technique is effective in decreasing the sensing cost. Additionally, the benefits of fusion centre (FC) are- lower energy consumption, better output, and enhanced detection capability with a low mistake probability by using improved sensing samples as the foundation for a global decision.

In [16, 17], the temporal series data of the signal are fed into an LSTM in order to extract the signal's temporal correlation characteristic.

Transfer learning approach which is one of the innovative theories in deep learning. In which a residual neural network (Res-Net) model has been applied for spectrum detection purpose [18].

The multilayer perceptron (MLP), which is one of the types of deep learning came under feed forward ANN category. In MLP, information bits are flows in a single direction only i.e. from the input layer to the output layer and passing through the hidden layers, and it is one of the most widely used ANNs. With the exception of the input layer, every layer is made up of neurons which are also called neural processing units, which add non-linearity to the model by calculating the weighted total of the associates between neurons and passing the result via an activation function [19].

The input signal values flow through the network's layers during the forward pass, usually as a multidimensional vector. Each layer's input neuron's value is multiplied by its associated weight before being added together. After that, a nonlinear activation function, like Sigmoid or ReLU, is applied to this total [20].

Every hidden layer in the FCN is the equal length as the input layer. To maintain this equal alignment, zero padding method is used in which appending of length (kernel size –1) is added to succeeding layers. Rather than using regular convolutions, the TCN uses causal convolutions [21] to stop future information leaks. An output signal obtained through hidden layer processing at time t is only convolved with items from time t and signal which is earlier in the previous layer of the causal convolution. Additionally, in order to facilitate an exponentially broad receptive field, the

TCN employs dilated convolutions [22-25]. Dilated convolutions, in contrast to regular convolutions, add a fixed step in between each pair of neighboring filter taps.

SOMs, introduced by Kohonen, are neural networks designed for unsupervised learning machine learning approach. They map high-dimensional data onto low-dimensional grids, preserving the topological structure of the input data [26]. Self-Organizing Maps shows better result in interpretation the spectrum occupancy and recognizing the spectrum usage in a dynamic or fast-changing environment. Their lightweight building facilitates real-time processing of the large amounts of data that must be handled for making quick decisions in a CRN. Recent work in spectrum detection has verified that self-organizing maps not only perform this essential task but also do so with a significant reduction in the amount of computation time while maintaining a respectable level of accuracy in a network of sensors.

Whereas Deep Belief Networks are generative models consist of layers of Restricted Boltzmann Machines (called as “RBMs”) stacked on top of another [27, 28]. They are superb at pulling out hierarchical features from the input data. Because of this makes them very good at spectrum classification like spectrum is used or unused. With this approach they can achieve classification accuracies higher than what is typically accomplished using MLP (Multilayer Perceptron) or CNN (Convolutional Neural Network) frameworks. Moreover, they get these results not only with better accuracy but also seem to achieve these results in less time than traditional approaches. All these observations are also seen from [29-36].

SPECTRUM SENSING

The spectrum sensing in cognitive radio is the identification and description of the spectrum bands surrounding the immediate environment and their occupancy status. This essential cognitive radio function allows it to find open frequency bands for opportunistic spectrum access while minimising interference with licensed incumbents and other primary users.

To detect RF signals, analysis of electromagnetic spectrum is required. For this signals and noise must be distinguished, and underutilized or underused frequency regions must be located. For this purpose, frequent methods are used, such as eigen value-based sensing, energy detection matched filtering detection, and cyclostationary feature detection. But what if we could use these methods not just to see if a signal is coming through, but also to see if the signal were coming through better than it usually does? Then, as now, the cognitive radio that can do this sort of thing is a very good radio indeed. Being a very good radio is no easy task.

Cognitive radios can optimize their transmission characteristics, frequency bands, and communication protocols to maximise spectral efficiency while minimising disturbance to incumbent users by continuously monitoring the spectrum environment and adjusting to changing conditions.

When the primary transmitter in a primary user network sends signals to the P.U., the secondary transmitter ensures that the primary user's communication with the primary transmitter is not harmed in any way. To find out if a P.U. receiver is inside its service area, the S.U. transmitter must conduct spectrum sensing. Spectrum sensing is a crucial prerequisite for the creation of cognitive radio spectrum sensing algorithms, which are required to be aware of and sensitively adjust to changes in their environment.

This is why CR networks cannot be realised without it. By identifying currently unoccupied spectrum sections, spectrum sensing allows CR users to adjust to the radio environment without interfering with the principal network.

Since main users get priority when it comes to using the bands, unlicensed users must always keep an eye on what the licenced users are doing to prevent interference and collisions [21]. The following equation shows hypothetical assumption of transmitter section-

$$X(t) = \begin{cases} n(t) & H0 \\ h\,(s(t)) + n(t) & H1 \end{cases} \tag{1}$$

here n(t) represents a zero-mean Additive White Gaussian noise (commonly name as AWGN), h is the channel's amplitude gain, s(t) is the primary user's broadcasted signal, whereas the term X(t) represents the signal that the CR user received. The null hypothesis, or H0, asserts that a certain spectrum band is devoid of any licenced user signals. A notion called H1 suggests that there may be a primary user signal.

In general, there are four categories into which spectrum sensing techniques can be divided: First parameter is Detection of the primary transmitter, secondly it is considered as detection of the cooperative transmitter, third parameter is detection of the primary receiver, and finally management of interference temperature. The principal transmitter detection method, which is frequently used to identify the primary user, is the main topic of this study. Once more, three methods are employed to find the main transmitter signals. These include the following: feature detection, matching filter detection, and energy detection .

The adoption of SOM and DBN for spectrum sensing in CRNs represents a significant advancement over traditional methods. By leveraging their unique strengths real-time processing in SOM and hierarchical feature extraction in DBN this study underscores their potential to transform spectrum sensing. These findings provide a strong foundation for developing intelligent CRNs capable of meeting the demands of next-generation wireless networks.

I. Dataset

Passive scanning is one easy way to gather information for Cognitive Radio smart spectrum sensing. To perform this, Cognitive Radio devices must be placed in different areas and given permission to passively scan the spectrum without actively sending out signals. The gadgets have the ability to gather data on things like neighbouring radio systems' modulation methods, signal intensity, and frequency occupancy. In order to determine accessible spectrum bands, identify interference, and maximize spectrum use for Cognitive Radio networks, this data can then be combined and examined. We have collected the data as per the specified principle above.

Dataset Description is provided in experimental setup part.

II. Proposed Spectrum Sensing Mechanism

The method of predicting a channel's future state using data that has already been collected is known as spectrum prediction. Below equation (2) is based on the spectrum model of the channel that Ref. [23] suggested.

$$Tt = Pi + Si + Ti \tag{2}$$

here the entire transmission time of Secondary User-SU (Tt) is composed of first parameter prediction time (Pi), then calculated sensing time (Si), and transmission time (Ti). K channels are included in the wireless spectrum under consideration in this work. One network (PU) has a licence for the K channels, while numerous unlicensed networks (SU) keep an eye on them in case of opportunistic use. The SU observes and learns each of these channels independently.

We take up, the spectrum data as X at frequency band over a specific time slot is which is denoted as Xf,t which is shown in below Equation (3).

$$Xf,t = \rho f,t + \omega f,t \tag{3}$$

here the term ρf,t represents the obtained signal power value and ωf,t signifies the noise power value. Figure 1 And then measured signal data strength are compared with a threshold value denoted by symbol λ which is used to calculate the channel's occupancy as either 1 (this status indicate channel is occupied) or 0 (this state indicate channel is idle/non-occupied) is the toggle or binary output yi and is denoted as in following Equation (4).

$$yi = \begin{cases} 1 & (\text{if } xf,t \geq \lambda) \\ 0 & (\text{if } xf,t < \lambda) \end{cases} \tag{4}$$

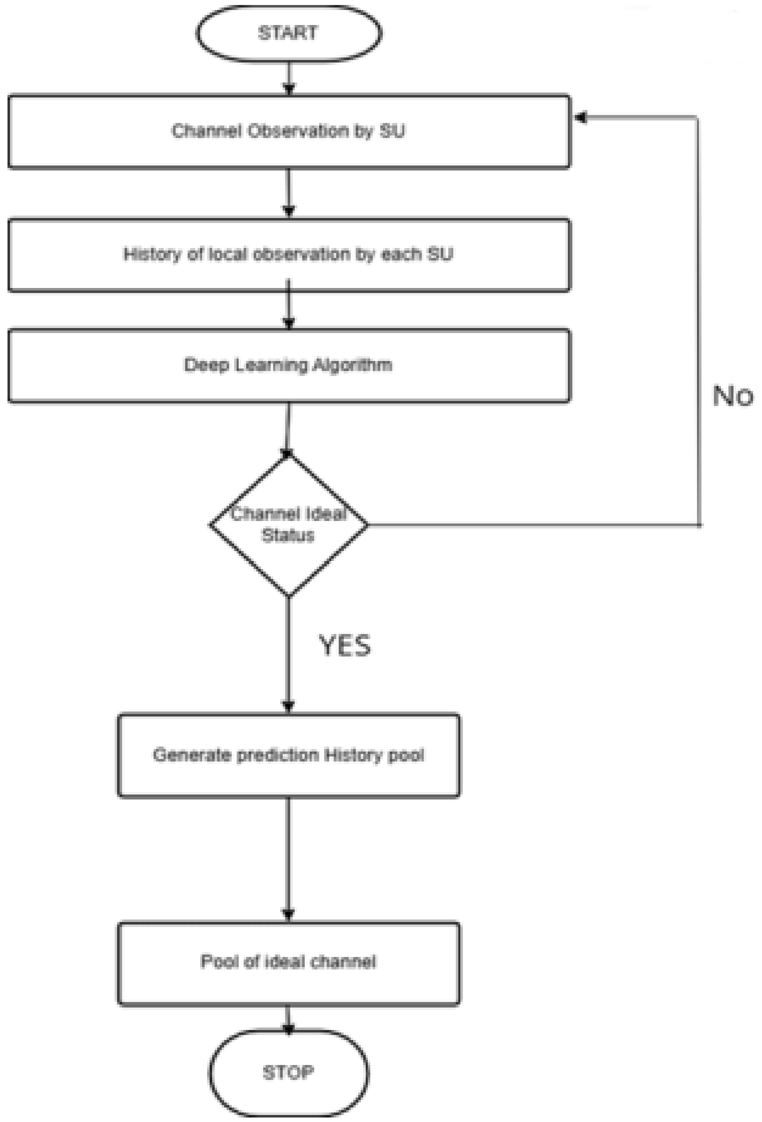

Fig. 1. Proposed Spectrum Prediction Model

III. Proposed Deep Neural Network Architectures

We outline the DNN architectures that were taken into consideration for SS in this section.

A. Self-Organizing Map (SOM)

An unsupervised deep learning neural network-based framework is primarily employed for clustering and visualization tasks with high-dimensional data. To accomplish this Self-Organizing Map (SOM) is used. The SOM itself includes a grid-like arrangement of neurons residing in a lower-dimensional space (usually two-dimensional). These neurons work together to learn and capture the essential structure of the input data.

i. Input Layer: The input layer of a Self-Organizing Map consists of neurons that represent features of the data. Each input vector, representing a data- point in a high-dimension space, is fed into the SOM. The neurons present in the input layer receive the values of these features, and the purpose is to map these high-dimensional vectors into a lower-dimensional representation through a process of competitive learning.

ii. Neuron Grid (SOM Map): The majority of the computation in a SOM occurs in the grid of neurons, which typically forms a 2D or 3D lattice. The neurons in the grid represent different regions of the input space, and during training, each neuron updates its weights to better match the input vectors. The neurons in the grid compete to represent the input data, with the most similar neuron (the "winner") updating its weights and those of its neighboring neurons. The number of neurons in the grid and the dimensions of the grid depend on the complexity and structure of the input data.

iii. OutputRepresentation:
The output of the SOM is a 2D or 3D map where similar data points are represented closer to each other on the grid, effectively grouping similar patterns. The network can disclose innate structures and clusters within the data. The output neurons are not classifying but rather mapping topologically—that is, organizing in a way that reflects the similarities between the data points entering the different output neurons. Neuron weights are updated according to an unsupervised algorithm that nudges them toward the winning neuron based on a neighbourhood function. Through this competitive process, the SOM organizes the data in a way that reflects the underlying distribution of the data. Once trained, the SOM can be used to visualize clusters and relations within the data—often a step preceding further analysis or classification.

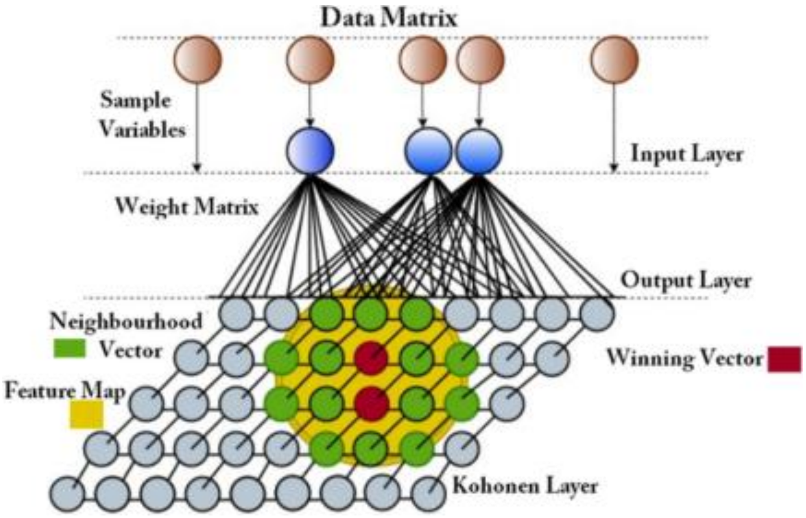

Fig. 2. Kohonen Self Organizing Map: An overview

Self-Organizing Map (SOM) network architecture consists of 2 layers: first one is an input layer and second layer is the output layer. Both layers contain the feature map whereas the SOM has no hidden layers, which is a configuration typical of most neural networks. In the working principle of SOM, weight values are passed to the output layer without applying an activation function in the neurons. The direction path begins from the input layer and ends to the output layer which makes the SOM feed-forward direction. Neurons in the network are assigned weights based on the input space, and the 2D grid of nodes in the output layer is fully connected to the neurons in the input layer. Figure 2 illustrates the SOM architecture and provides an overview of Kohonen's work.

SOM make use of competitive learning for weight adjustment. The nano-architecture has three main stages as Competition stage, Cooperation stage, and lastly Adaptation stage.

In the first stage, all neurons in the Kohonen layer compete to be the "best matching unit" (which is also called as BMU), based on the calculated distance from the input vector. The neuron with the smallest distance is the winner. After this, the second stage starts—Cooperation, in which nearby neurons (those that are neighbors to the winning neuron) help out the winner to give a better response for similar input vectors in future presentations.

B. *Deep Belief Network (DBN)*

DBN i.e. Deep belief network is a generative model that employs numerous layers of stochastic, latent variables to model the probability distribution of input data. It is a sort of deep neural network made up of several layers of restricted Boltzmann machines (RBMs), where each layer learns a sort of hierarchical representation of the input data. DBNs can be trained in an efficient, layer-by-layer, unsupervised manner.

i. **Input Layer**:

A DBN model has an input layer that includes neurons which representing the features of the input data. Each neuron corresponds to one specific element of the input vector. Then the data is fed into the network layer by layer. The model architecture learns complex, hierarchical patterns and dependencies in the data through multiple layers of representation. The first layer captures low-level information and simple features whereas the deeper layers capture the more complex, high-level patterns in the data.

ii. **Hidden Layers:**

Composed of several hidden layers, the DBN learns more and more abstract representations of the input data. The layers in the DBN are typically RBMs, which are type of generative model. As you read, the neurons in the hidden layers of the DBN, which are RBMs, are learning a weighted sum of their inputs followed by a probabilistic activation. This activation function is learned in parallel by all the neurons in a layer during pre-training. The kind of activation function learned by an RBM gives it a certain "contrastive" quality, which is an essential ingredient in the backbone of "deep learning" models.

iii. **Output Layer:**

The final output produced after all the hidden layers is passed through occurs at the output layer of a DBN. For classification tasks, the output layer typically consists of neurons corresponding to the number of classes, and the activations of these neurons are used to determine the predicted class. For regression tasks, the output neurons represent the predicted continuous values. The output layer, unlike the previous layers, is trained using supervised learning. In this case, the weights are tuned such a way that to minimize the error value among the predicted output and the actual target values. The DBN is trained in two phases. Each layer is pre-trained in an unsupervised manner and then all layers are fine-tuned together using gradient-based methods. After these phases, the DBN can perform various tasks, including classification and regression, using the unsupervised hierarchical feature representation it has formed. Figure 3 The DBN can arrange high-dimensional input data into a manageable structure and then output predictions at the layer farthest from the input.

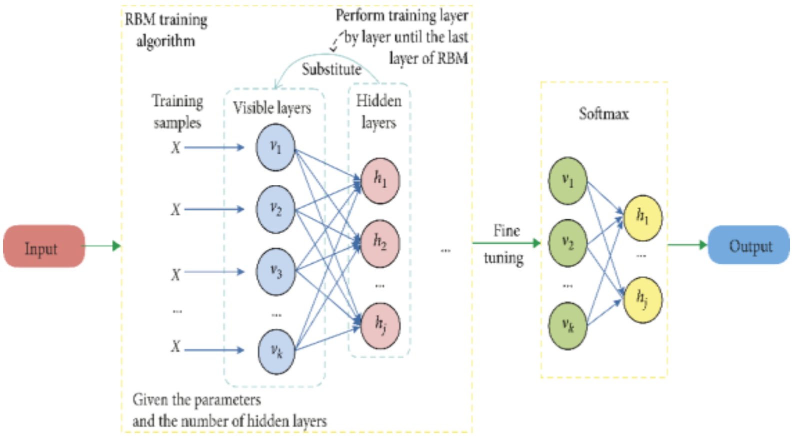

Fig. 3 DBN Architecture

IV. Experimental Setup

A. Dataset Description

Table 1. Dataset description

Parameter	Description
Spectrum	GSM 900
Band	890 MHz–915 MHz (GSM uplink)
Channels	1 - 124 RF channels
Signal Power (for each channel)	(-40 dBm) to (-120 dBm)
Noise Power (for each channel)	(-15 dB) to 15 dB
Total channel setup	N =51
Total samples	13465

The band used for experimentation is the GSM 900. In which encompasses the frequencies from 890 MHz to 915 MHz used for GSM uplink purpose. We set up our experiment with 124 RF channels out of which we actually used 51 channels. Table 1 Which are used with controlled signal power from -40 dBm to -120 dBm. Noise power was controlled between -15 dB and 15 dB. This experimental setup allowed us to collect an adequate number of 13,465 samples over the course of the evaluation. Performing this setup in an acoustic chamber provides an opportunity to rigorously assess the performance of spectrum sensing models.

B. Hyperparameters of Models

Table 2. Hyperparameters of the Models

Hyperparameter	Deep Belief Network (DBN)	Self-Organizing Map (SOM)
Number of Layers	2 RBM layers + 1 Neural Network	2D grid (10x10 nodes)
Hidden Units	64 (1st RBM), 32 (2nd RBM)	Not applicable (nodes in grid)
Epochs (Pre-training)	10 (for each RBM)	100
Epochs (Fine-tuning)	50	Not applicable
Batch Size	32	Not applicable
Activation Function	ReLU (hidden layers), Softmax (output layer)	Not applicable
Learning Rate	Adaptive (Adam optimizer for NN fine-tuning)	0.5
Weight Initialization	Random (RBM: scaled by 1 / sqrt(n_visible + n_hidden))	Random initialization
Neighborhood Function	Not applicable	Gaussian
Sigma	Not applicable	1
Optimization Method	Contrastive Divergence (RBM pre-training), Backpropagation (NN)	Competitive learning
Validation Split	20%	Not applicable
Input Dimensionality	Depends on dataset (e.g., X_train_scaled.shape[1])	Same as input feature length (X_train_scaled)

The DBN model has two RBM layers with 64 and 32 hidden units respectively. Which is followed by a neural network for fine-tuning purpose. Table 2 For this model, ReLU was used as the activation function for hidden layers and Softmax - used as activation function for the output layer. The RBMs were pre-trained for 10 epochs each. The neural network was fine-tuned for 50 epochs having a batch size of 32 and a validation split of 0.2. The optimizer used for fine-tuning was Adam. The weights of the RBM were initialized randomly according to the input dimensions.

The Self-Organizing Map (SOM) model is a 2D grid of 10x10 nodes with a Gaussian neighborhood function. For this model, we kept a learning rate of 0.5 and a sigma value of 1.0 was used for neighborhood size. The SOM was trained using competitive learning over 100 iterations with random weight initialization based on the input features

C. Evaluation Metrics for Spectrum Sensing

For SOM and DBN models, the evaluation metrics accuracy, precision, recall, F1 score and time were considered for evaluating the performance of spectrum sensing in cognitive radio.

Accuracy: Computes the percentage of cases that are correctly classified out of all the samples.

Precision: Shows how relevant the positive predictions are by assessing the model's capacity to detect true positives.

Recall: Shows how well the model identified every genuine positive occurrence in the sample.

F1 Score: Shows the harmonic mean of precision and recall, providing a balanced metric even with imbalanced datasets.

Time: In order to evaluate computational efficiency- a crucial component for real-time applications- the amount of time it took for each model to finish training and assessment was noted as a distinct metric

V. Performance analysis

A. Accuracy, Precision, Recall and F1 Score

The obtained results prove that the Deep Belief Network (DBN) achieved a F1 score, accuracy, precision, recall of 99.85%, highlighting its exceptional performance in classification tasks. The Self-Organizing Map (SOM), while slightly less accurate, still achieved strong results with a F1 score, accuracy, precision, recall of 95.77%, showcasing its effectiveness in clustering and pattern recognition. These metrics confirm the reliability and robustness of both algorithms in their respective tasks, with the DBN excelling in classification and the SOM offering efficient clustering with a shorter training time.

In Table 3, we present the evaluation metrics for both algorithms, providing a clear comparison of their effectiveness in handling the given data.

Table 3. Evaluation parameter values for Algorithms

Algorithm	Deep Belief Network (DBN)	Self-Organizing Map (SOM)
Accuracy	0.9985	0.9577
Precision	0.9985	0.9578
Recall	0.9985	0.9577
F1 Score	0.9985	0.9577

B. Detection Probability vs SNR

Additionally, we analyzed the Detection Probability vs. SNR graph, shown in Figure 4, to understand the performance of the algorithms under varying Signal-to-Noise Ratios (SNR). This graph provides insights into how well the models perform in challenging noise conditions, showcasing their adaptability and robustness. The advantages of this analysis include improved understanding of model performance in real-world scenarios and the ability to optimize algorithms for deployment in dynamic environments.

Together, the tabular metrics and graphical analysis underline the potential of these deep learning models for accurate and efficient spectrum sensing in cognitive radio systems.

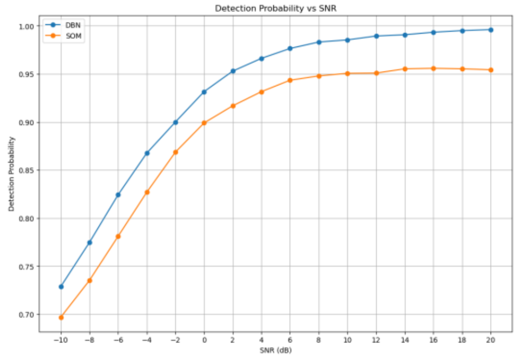

Fig 4. Detection Probability vs SNR

From the above graph we got the idea - The DBN proves to be a more robust and accurate model for detection tasks across varying SNR levels, particularly in low-SNR scenarios where noise significantly impacts detection accuracy. Table 4 While the SOM demonstrates reasonable performance, its limitations in higher detection probabilities at high SNR make it less suitable for applications requiring precision.

C. Execution Time

The time taken for the training and evaluation of each algorithm is summarized in Figure 5. The Self-Organizing Map (SOM) was the fastest, taking only 0.02 seconds, owing to its simpler architecture and competitive learning mechanism. In contrast, the Deep Belief Network (DBN) required 147.80 seconds due to the additional complexity of pre-training multiple Restricted Boltzmann Machine (RBM) layers and fine-tuning a neural network.

This evaluation highlights the trade-off between model complexity and computation time. Table 5 While the SOM offers rapid training and evaluation, it may not achieve the same level of accuracy as the DBN, which performs significantly better in terms of detection metrics but at the cost of increased computational time. These time measurements emphasize the need to balance computational efficiency with performance, depending on the specific requirements of the task.

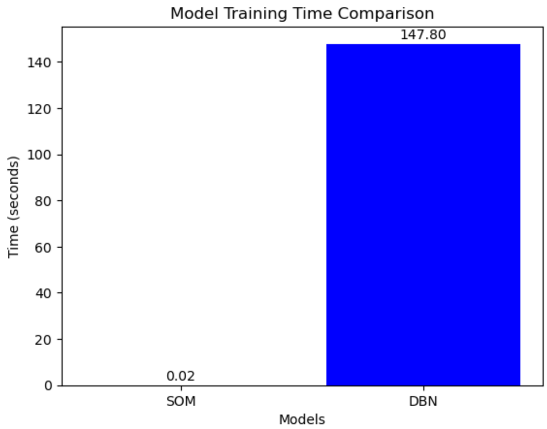

Fig 5. Execution Time Analysis

CONCLUSION

From the evaluation of the two algorithms—DBN and SOM—it is evident that both models performed effectively in their respective tasks. The DBN achieved exceptional performance with accuracy, precision, recall, and F1 score values exceeding 99%, as shown in Table 3. This highlights its reliability and robustness for classification tasks. Meanwhile, the SOM demonstrated solid clustering capabilities with accuracy and other evaluation metrics around 95.77%.

The time analysis, summarized in Figure 5, emphasizes the computational efficiency differences between the two algorithms. The SOM was significantly faster, requiring only 0.02 seconds for training and evaluation due to its simpler architecture. In contrast, the DBN, being more complex with its pre-training and fine-tuning steps, required 147.80 seconds.

For applications where computational time is critical and simplicity is prioritized, SOM is an ideal choice due to its rapid execution. However, for tasks requiring high precision and reliability in classification, the DBN is the better option despite its longer computational time.

Additionally, the Detection Probability vs. SNR graph, shown in Figure 4, provides valuable insights into the robustness of the models under varying SNR conditions. The DBN consistently outperformed the SOM across all SNR levels, demonstrating superior detection reliability, particularly in low-SNR environments.

Overall, the choice between DBN and SOM depends on the specific requirements of the application, balancing the trade-offs between accuracy, computational efficiency, and strength under challenging conditions.

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