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Machine Learning Techniques in Spectrum Sensing

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ABSTRACT

The spectrum shortage brought on by the development of new technologies can be minimized through the use of cognitive radio (CR) technology. Cognitive networks struggle with the hidden primary user problem because the secondary user may classify the spectrum occupancy incorrectly. As a result, machine learning-based cooperative spectrum sensing (CSS) was used to solve this challenge. Gaussian Mixture Model (GMM) and Support Vector Machine (SVM) are two methods of machine learning approaches, where GMM is an unsupervised learning methodology and SVM is a supervised learning technique. The two phases of the aforementioned techniques—classification and training—determine the classes for channels that are available and unavailable. With a mixture of Gaussian density distributions, training features are determined using the Gaussian Mixture Model. A subset of training vectors for the SVM is used to create the decision surface. By increasing the space between the training and separation vectors, this is accomplished.

Keywords : Gaussian Mixture Model, cooperative spectrum sensing, cognitive radio, Support Vector Machine.

I. INTRODUCTION

At present times, the scarcity of spectrum increases rapidly due to not proper utilization of the spectrum resources. Most parts of the current spectrum resources is not utilized effectively this which leads to the unwanted denial of service events. To overcome this problem cognitive radio technology is used [1].

Cognitive radio (CR) allows wireless devices to sense the radio spectrum to decide whether a particular frequency band is occupied or not. The devices can use the licensed frequency bands when the primary is inactive [2]. Generally, cognitive networks struggle with the hidden primary user problem because the secondary user may classify the spectrum occupancy incorrectly [3]. As a result, cooperative spectrum sensing based on machine learning was used to solve this issue.

In the cooperative spectrum, the sensing data is exchanged between the CR devices and the fusion centre for the purpose of decision making. This technique can be used to increase the efficiency of spectrum usage and to reduce interference in the wireless network. It also helps in reducing PUs problems related to multipath fading and shadowing [4]-[6]. Cooperative Spectrum sensing uses two methods of machine learning approaches one is the Support vector machine (SVM) and the other is the

Gaussian mixture model (GMM). SVM is a supervised learning technique used for training [7]-[12] and GMM is an unsupervised learning technique used for classification [13]-[15].

II. LITERATURE REVIEW

Srinivas Samala et al., have discussed the machine learning based Adaptive Gaussian Mixture Model (AGMM) for pattern classification that is proposed in order to solve the problem of improper utilization of currently available spectrum resources. The performance of the suggested method is evaluated in terms of ROC (Receiver Operating Characteristics) curves, F1 score, recall, and accuracy [16]. A comparison is made between the suggested method and the existing K-mean clustering approach. As a result, based on all comparisons, the suggested method performs better than the existing method. Hurmat Ali Shah et al., proposed a reliable spectrum sensing scheme that uses the K-nearest neighbor machine learning algorithm for spectrum sensing. The proposed scheme learns from the environment by considering the correct status of the primary users (PU).

The sensing reports are stored in sensing classes, and the current sensing report is then classified. Based on the classification result, the primary user is declared present or absent [17]. The results of the proposed scheme have better performance in detection and spectral hole exploitation capability than the conventional OR rule. G. C. Sobabe et al., propose a cooperative spectrum sensing algorithm based on unsupervised learning. The proposed technique is designed to be absolutely blind and does not require any information about the communication system. It uses feature vectors that are more robust to noise and feeds them into the classifier. The unsupervised learning framework for spectrum sensing is based on K-means clustering algorithm and Gaussian mixture model (GMM) [18].

The simulation results show that the proposed algorithm outperforms other unsupervised learning algorithms based on energy vector. It's simple to obtain unlabeled training data, and the training process is entirely autonomous. The simulation demonstrates the proposed algorithm's higher performance. Mangesh V Deshmukh et al., have discussed energy detection in spectrum sensing for cognitive radio using BPSK and QPSK modulated signals in the presence of sampling period, sampling frequency with noise ratio. In this study, an energy detection technique is used to determine whether the primary user (PU) signal is present or absent in the channel. The simulation shows the performance of ROC (Receiver Operating Characteristics) curves for modulated signals (BPSK and QPSK) done on MATLAB with the probability of detection versus probability of false alarm using the Monte Carlo method. The hardware implementation is done on an FPGA for switching the vacant signal to the secondary user [19].

Mustefa Badri Usman et al., presented energy detection with the entropy method for spectrum sensing. The main purpose of this study is to focus on the implementation of spectrum sensing techniques in cognitive radio (CR). The ED non cooperative spectrum sensing (SS) approach is used for implementation purposes. In order to improve SS performance for CRs, entropy is additionally added to the energy detection approaches. This method provides better sensing performance in low SNR (signal-to-noise ratio) circumstances than conventional energy detection. The simulation shows that the proposed method has a significant improvement in the performance of about 18.58% when compared to conventional energy detection (CED) [20].

CLASSIFICATION OF SPECTRUM SENSING

Spectrum sensing is the process of detecting the presence of signals in a particular frequency band of the electromagnetic spectrum. It is an essential component of cognitive radio networks, which allow secondary users to opportunistically access a spectrum that is not in use by primary users [21].

Spectrum sensing can be divided into two main categories:

- Non-Cooperative Spectrum Sensing
- Cooperative Spectrum Sensing

Non-cooperative spectrum sensing:

It involves the detection of spectrum usage without relying on any external assistance from other users. Examples of this include energy detection, cyclostationary, feature detection, and matched filter detection.

Cooperative Spectrum Sensing:

It involves the detection of spectrum usage with the assistance of other users. Examples of this include collaborative detection and decode-and-forward relaying.

Cooperative spectrum sensing based on machine learning is a technique used in cognitive radio networks that allows user nodes equipped with radios to share sensory information with each other. The nodes use machine learning algorithms to detect the presence of a primary user in the spectrum and take appropriate actions. This technique gives better performance than traditional spectrum sensing techniques, since it makes use of the collective knowledge of all the user nodes in the network [22].

The advantages of cooperative spectrum sensing based on machine learning include improved detection accuracy, improved spectrum utilization, and improved transmission reliability. The improved detection accuracy is achieved due to the processing of the sensory data by all the nodes in the network.

Furthermore, the improved spectrum utilization is achieved due to the increased number of nodes that can detect the presence of a primary user in the spectrum, allowing more efficient use of the spectrum. Additionally, the improved transmission reliability is achieved due to the collaborative nature of the technique.

Components of Spectrum Sensing

Secondary Users (SU) and Primary Users (PU) both have cognitive radio capabilities and access to licenced spectrum bands, whereas Secondary Users (SU) and Primary Users (PU) do not. SU has the ability to identify unused band space. SU asks PU permission to exploit this untapped spectrum for wireless connectivity. Priority is given to PUs over SUs. Secondary Users make use of the spectrum to prevent interference with PUs [23]. Figure illustrates the spectrum sensing components, including the dimension space, hardware issues, spectrum sensing methodologies, and the idea of cooperative sensing.

III. MACHINE LEARNING ALGORITHMS

Utilising sample data or prior knowledge, machine learning involves programming computers to optimise a performance criterion. We have a model, as shown in Fig. 1, that is defined up to a certain point, and learning is the application of a computer programme to optimise the model's parameters using training data or prior knowledge. The model may be descriptive to learn from the data or predictive to make future predictions. The phrase "Machine Learning" was first used in 1959 by Arthur Samuel, an early American pioneer in the fields of artificial intelligence and computer gaming. Samuel was working for IBM at the time. Machine learning, according to him, is "the field of study that gives computers the ability to learn without being explicitly programmed”. The types of Machine learning techniques are listed below.

- supervised learning.
- unsupervised learning
- semi-supervised learning
- reinforcement learning

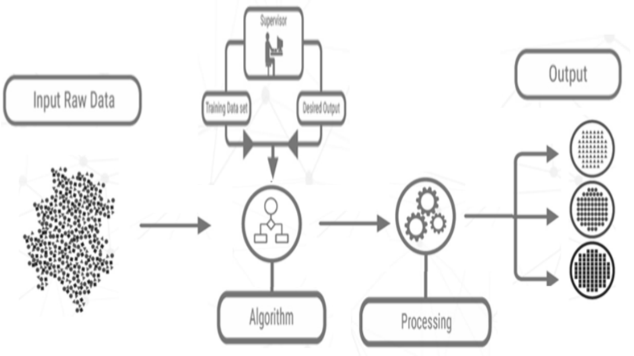

Fig.1 Machine Learning Model

Supervised Learning: This type of machine learning algorithm that uses a known dataset (labeled data) to make predictions. It uses data from past observations to learn from and make decisions about future data points.

Unsupervised Learning: This type of learning uses machine learning algorithms to analyse and cluster unlabeled datasets. These algorithms discover hidden patterns or data groupings without the assistance of a human.

In this paper, we use both supervised and unsupervised learning methods. Under unsupervised learning, we use the Gaussian Mixture Model and in supervised learning, we use the Support Vector Machine.

Support Vector Machine:

Support Vector Machines (SVM) are a type of supervised machine learning algorithm used for both classification and regression [24, 25]. They are used to identify patterns in data and to classify data points as belonging to one of two or more classes. SVM can be of two types: Linear SVM and Non-linear SVM.

Linear SVM.

Linear SVM is used for linearly separable data, which refers to data that can be divided into two classes using a single straight line. Linear SVM is used to classify such data, and the classifier used is known as the linear SVM classifier.

Non-linear SVM.

Non-linear SVM is used for non-linearly separable data, which refers to data that cannot be divided into two classes by a straight line.

In spectrum sensing, SVM can be used to detect the presence of a signal in a given frequency band. The basic idea behind SVM is to find the optimal hyperplane that separates the data points into two classes. In the case of spectrum sensing, the data points are the power levels at different frequencies. The hyperplane is found by solving the optimization problem of minimising the misclassification error. An optimal hyperplane is one that best separates the "signal" class from the "noise" class.

To train an SVM for spectrum sensing, the input data is first divided into two sets: a training set and a test set. The training set is used to adjust the parameters of the SVM and create the optimal hyperplane. The test set is used to evaluate the accuracy of the model.

Once the SVM is trained, it can be used to classify a new data point as either signal or noise. This is done by computing the distance between the new data point and the hyperplane. If the distance is greater than a certain threshold, the data point is classified as noise. Otherwise, it is classified as a signal. SVM is a powerful tool for spectrum sensing. They can be trained quickly and used to accurately classify signals in a given band.

The main advantage of SVM in spectrum sensing is that it provides high accuracy and efficiency by using a combination of machine learning techniques. It can also be used to detect and classify signals with a high degree of accuracy, even in the presence of noise or interference. SVM is less computationally complex than some other machine learning algorithms, making it suitable for implementation in low-power and low-complexity devices.

Gaussian Mixture Model

The Gaussian Mixture Model (GMM) algorithm is a clustering algorithm used to classify data points into distinct clusters. It works by assigning each data point to a cluster based on its probability of belonging to that cluster. The GMM algorithm uses a probability-based approach to make assignments, which means that it takes into account the probabilities of the data points belonging to each cluster. It then uses these probabilities to assign the data points to the most likely cluster. The GMM algorithm works by first creating a mixture of Gaussian distributions, each representing a different cluster. It then assigns data points to the cluster that has the highest likelihood of containing that data point. The GMM algorithm is useful for finding patterns and clusters in datasets with complex distributions.

In spectrum sensing, GMM is used to detect the presence of a signal in a specific frequency band. It works by detecting the presence of a signal by looking at the distribution of the signal in the frequency band. The GMM algorithm uses a set of Gaussian distributions to model the distribution of the signal in the frequency band. It then uses a set of weights to determine which of the Gaussian distributions best fits the observed data. The GMM algorithm then makes a decision about the presence of the signal based on the weights assigned to the Gaussian distributions. The GMM algorithm is used in spectrum sensing to detect the presence of a signal in a frequency band and also to estimate the power of the signal.

The GMM (Gaussian Mixture Model) has several advantages in spectrum sensing. Firstly, it can provide efficient discrimination between signal and noise. The GMM can be effectively used for identifying the presence of signal in the spectrum by considering the signal-noise mixture as a mixture of Gaussian distributions. This allows for the estimation of the parameters of the signal and noise components using a maximum likelihood approach. Secondly, GMM can detect and identify different types of signals in the spectrum. Unlike other techniques such as matched filter detection, GMM can detect and identify different types of signals in the spectrum based on their characteristics. Thirdly, GMM is relatively easy to implement and can provide accurate results. Finally, the GMM can be used to estimate the parameters of the signal and noise components in the spectrum, which can be used to improve the signal detection and classification performance.

The steps involved in GMM for spectrum sensing are given below:

1. Data Collection: The first step in the GMM algorithm for machine learning based cooperative spectrum sensing in cognitive radio is to collect the data from the primary user and the secondary user. This data is used to train the model and build a statistical model of the signal.
2. Feature Extraction: In this step, the data collected in the previous step is used to extract the features from the signal. These features are used to represent the signal and to capture the characteristics of the signal.
3. Model Training: After extracting the features from the signal, the next step is to train the model. This is done by using the features extracted in the previous step to build a statistical model of the signal.
4. Model Testing: After the model is trained, it is tested on the data collected from the primary user and the secondary user. This is done to evaluate the performance of the model and to ensure that it is able to accurately identify the signals from the primary user and the secondary user.
5. Deployment: After the model is tested, it is deployed in the cognitive radio system. This is used to enable the cooperative spectrum sensing between the primary user and the secondary user.

IV. RESULT AND DISCUSSION

The performance evaluation of the classifier at different sampling values is also done using MATLAB. By using training samples, the performance of the classifier based on accuracy, recall, and F1-Score in percentage is evaluated. The mathematical calculation for these parameters are listed below:

Accuracy:

It is calculated by dividing the number of correct predictions by the total number of predictions made.

$$\text{Accuracy} = \frac{\text{(True Positive + True Negative)}}{\text{Total Predictions}} \quad \text{.........(1)}$$

Recall:

Recall in machine learning is a metric used to measure the ability of a model to correctly identify all relevant instances in a given dataset. It is calculated as the number of true positives divided by the sum of the number of true positives and the number of false negatives,

$$\text{Recall} = \frac{\text{(True Positives)}}{\text{(True Positives + False Negatives)}} \quad \text{.........(2)}$$

F1-Score:

F1 score is a metric used to measure the accuracy of a model. It is calculated by taking the harmonic mean of precision and recall. It is defined as:

$$\text{F1 Score} = \frac{2 * \text{(Precision * Recall)}}{\text{(Precision + Recall)}} \quad \text{.........(3)}$$

The average training duration for classifiers and the performance of the classifier are represented in Table 1. Then, the average classification delay for classifiers is represented in Table 2.

Table 1: Average Training Durations For Classifiers (5x5 SUs) in Seconds

Classification Methods	Number of training samples			Accuracy in %	Recall in %	F1-Score in %
	100	300	500			
GMM	0.0309	0.1773	0.35527	99.38	99.84	98.77
SVM-Linear	0.01114	0.01792	0.0268	97.92	99.72	95.97

Table 2: Average Classification Delay for Classifiers (5x5 SUs) in Seconds

Classification Methods	Number of Training Samples		
	100	300	500
GMM	3.8 x 10^{-5}	3.8 x 10^{-5}	3.8 x 10^{-5}
SVM-Linear	1.92 x 10^{-5}	3.87 x 10^{-5}	4.86 x 10^{-5}

V. CONCLUSION

Thus, in this paper, the machine learning techniques are compared between the Gaussian Mixture Model (GMM) and Non-Linear Support Vector Machine (SVM). It is found that the GMM technique gives better results compared to SVM technique. The results are compared based on three parameters which are Accuracy, Recall and F1-Score. The GMM for 5X5 secondary users was 99.38, 99.84 and 98.77% respectively. The time delay was also found to be much reduced in GMM. The results are also based on the different sample sizes.

In future the techniques may be done with Deep Neural Network and with AI methods with larger data sets for better accuracy and reduced delay.

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