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ABSTRACT

Spectrum sensing is an essential component in cognitive radios (CR). Machine learning (ML) algorithms are powerful techniques for designing a promising spectrum sensing model. In this work, the supervised ML algorithms, support vector machine (SVM), k-nearest neighbor (kNN), and decision tree (DT) are applied to detect the existence of primary users (PU) over the TV band. Moreover, the Principal Component Analysis (PCA) is incorporated to speed up the learning of the classifiers. Furthermore, the ensemble classification-based approach is employed to enhance the classifier predictivity and performance. Simulation results have shown that the highest performance is achieved by the ensemble classifier. Moreover, simulation results have shown that employing PCA reduces the duration of training while maintaining the performance.

1. Introduction

With the rising usage of dynamic mobile applications, it is becoming decisive for wireless devices to learn from the surrounding environment. Cognitive radio (CR) is described as a radio device able to learn and adapt to radio environment. Spectrum sensing is the key functional component of CR. In the last decades, spectrum surveys over many countries showed the possibility of improving the spectrum efficiency by utilizing the white space in TV band (TVWS). IEEE 802.22 wireless regional area network (WRAN) standard was developed to facilitate designing cognitive engines to opportunistically utilize the TVWS while protecting the primary users (PU) [1,2]. Therefore, several sensing techniques have been proposed based on energy detection (ED) [3], pilot detection (PD) [4], matched filtering techniques (MF) [5]. Furthermore, estimating the power spectrum density of detected signal has been utilized in [6]. On the other hand, combining or integrating two different detection techniques significantly improves the local detection of TVWS [7–9]. For instance, the authors in [9] proposed to combine ED and cyclosationary feature detection (CFD) to improve sensing the advanced television standard committee (ATSC) channel. However, severe radio conditions, i.e., hidden terminal problem, or noise uncertainty remarkably deteriorate the detection performance and sensing accuracy of such local spectrum approaches. In addition, some of spectrum sensing approach incur a high implementation complexity and require full or partial knowledge of the PU's signal features, e.g., MF and CFD techniques [10,11]. Therefore, cooperative spectrum sensing advocated as a means to improve sensing accuracy by tackling the inherent hidden terminal problems in wireless networks. The key element of CR is the willingness to program themselves or to learn autonomously. As a result, CR is anticipated to be intelligent by nature. Learning is a substantial component of any intelligent system, which justifies it being designated as a fundamental requirement of CRs [12,13]. Therefore, CR must be equipped with the capability of learning from its experience by interacting with its RF environment by attempting to make use of machine learning (ML) algorithms to coordinate the CR actions. In recent years, there has been a growing interest in adopting ML algorithms to CRs as a potential solution for enhancing the accuracy of spectrum sensing by employing spectrum measurements history, especially, in low signal to noise ratio (SNR) scenarios [14,15], since ML algorithms are considered as efficient ways of sensing the spectrum without prior knowledge of the radio frequency (RF) environment. In adition, ML

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techniques can be utilized to improve detection in different recent aspects and applications, such as cognitive radio vehicular networks (VANET) and internet of things (IoT) as described in [16–18]. Furthermore, ML can periodically be learned to adapt to the changing RF environment. However, incorporating ML techniques with conventional spectrum sensing approaches, such as energy detection and pilot detection techniques, results in a significant increase in processing time and implementation complexity, since developing such spectrum sensing models are mainly used for big data and large spectrum sensing datasets which are generated from spectrum measurement campaigns. This fact should be taken in a consideration when designing such spectrum sensing models. Therefore, adopting dimensionality reduction (DR) technique can significantly alleviate this dilemma. Principal component analysis (PCA) technique has been employed in [19–21] to enhance the efficiency of the cooperative spectrum sensing in cognitive radio network. On the other hand, the authors of [22] uses a different technique, they formulated spectrum sensing process as multi-class classification problem, adapting to unknown SNR variations, the results of the learning in one-off, regardless of the SNR variations. Moreover, a novel ML-based approach to approximate the distributions of the aggregated interference power in wireless networks was developed in [23]. The authors focused on spatial spectrum sensing in user centric networks where Poisson cluster process is used to model the primary users.

The main objective of this case study is to develop and investigate the design of spectrum sensing models (SSM) based on supervised ML techniques and DR technique to assess the spectrum occupancy over the TV bands. This work proposes and develops novel TV SSMs based supervised ML techniques supported by a DR technique to accelerate the training and testing of the classifiers of the employed ML techniques [24,25]. This work proposes to adopt PCA as a DR technique for its ability to minimize the dimensions of the gathered datasets, to limit the risk of overfitting, and to minimize the processing time of training and testing [26,27]. In other words, incorporating ML techniques leads to a significant increase of the computational burden and consumes extra time, therefore, PCA is adopted in the proposed model to reduce the computational burden and time. The proposed model is trained and tested using real data gathered over ten different locations across Windsor-Essex County as in [28–30]. The performances of the proposed models are evaluated and compared based on accuracy, F-measure, and Receiver Operating Characteristic (ROC).

The contributions of this work are summarized as:

- Developing a TV SSM based on different supervised ML algorithms to accurately assess the spectrum occupancy over the TV channels and determine the identity of the user whether it is a PU or a secondary user (SU). The proposed models adopt three supervised ML techniques; they are support vector machine (SVM) [31], decision tree (DT) [32], k-nearest neighbor (kNN) [33] and Ensemble classifier in work [34].
- Improving the proposed SSMs by adopting PCA as a DR technique. Furthermore, the detection performance of the proposed models are assessed and investigated by comparing the performances of the proposed models with each other, with and without PCA technique, to determine the best adopted supervised ML technique.

The rest of this work is organized as follows, Section 2 describes the adopted spectrum sensing database. Section 3 presents the system model and the proposed framework while Section 4 discusses the simulation results of the proposed models. Finally Section 5 provides the conclusions.

2. Description of the employed datasets

This work is considered as a complementary research work of our previous works [28–30] where a spectrum occupancy survey was performed to scan a UHF frequency band, i.e., 490 MHz to 740 MHz, which contains 32 ATSC channels, i.e., from channel number 19 to channel number 52, for a couple of days, to detect the existence of ATSC channels over a border city at different locations in the city. It is well-known that an ATSC channel has 6 MHz bandwidth with an ATSC pilot located at about 1.25 MHz from the lower frequency bound of the ATSC channel [35]. The work measured the occupancy of those ATSC channel using ED based on the sensing threshold determined in our previous works [28–30], i.e., the sensing threshold was determined according to WRAN, and detected ASTC pilots over the scanned frequency band. However, the impact of surrounding radio frequency condition, such as noise, shadowing, multipath fading, and interference caused by SUs, deteriorates the ATSC pilot detection and results in misdetecting the ATSC channels. However, it is noticed that the strength of ATSC pilot is existed in many cases but fainted due to interference and other RF environmental condition. Therefore, in this work, the ATSC pilot strength is classified into different classes accordingly, ML techniques are used to investigate their existence as described in the Section 3.

The adopted datasets cover the above-mentioned frequency band. The datasets were collected at ten different sites across Windsor-Essex County, Ontario, Canada, as illustrated in Fig. 1. The spectrum measurements were mainly collected to detect TV channels using a combination of ED and PD techniques.

As a case study in this work, spectrum measurements at Site 1, town of Amherstburg, were selected to investigate and assess the proposed TV spectrum sensing models, using simulations, for the following reasons; first, almost all sites in the spectrum measurement campaign reflect almost the same spectrum analysis. Moreover, describing all spectrum analysis for all sites will create redundancy. Second, the geographic location of the site 1 provides different received signal strengths, since it is a rural region and closed to the US borders.

3. System model and proposed framework

The spectrum power analysis of measured TV spectrum at Site 1 using waterfall technique showed various power spectrum behaviors of the collected spectrum measurements. This motivates us to categorize the measured power spectrum into five various ATSC channel classes according to their received signal strength. The proposed classes will be used for our proposed spectrum sensing model as ML classifiers to improve the detection performance. The five proposed ATSC channel classes are identifies as follows:

- Unoccupied channel (Class 0): it corresponds to a case where neither PU nor secondary user (SU), i.e., unlicensed user or CR, is found to exist in the channel. In this case, the channel is available to be used by CR. The channel in Fig. 2a represents this class.
- Strong ATSC (Class 1): it corresponds to the presence of a PU (i.e. a broadcast television station). The signal spectrum appears relatively uniform and flat across the bandwidth with a pilot tone located at the left edge of the channel as shown in Fig. 2b. The channel is considered unavailable for use and the CR must not transmit in this band in this condition.
- Weak ATSC (Class 2): this class corresponds to situations where an ATSC signal is found to be very faintly visible over the bandwidth. The channel in Fig. 2c exhibits a pilot tone with a weaker amplitude.

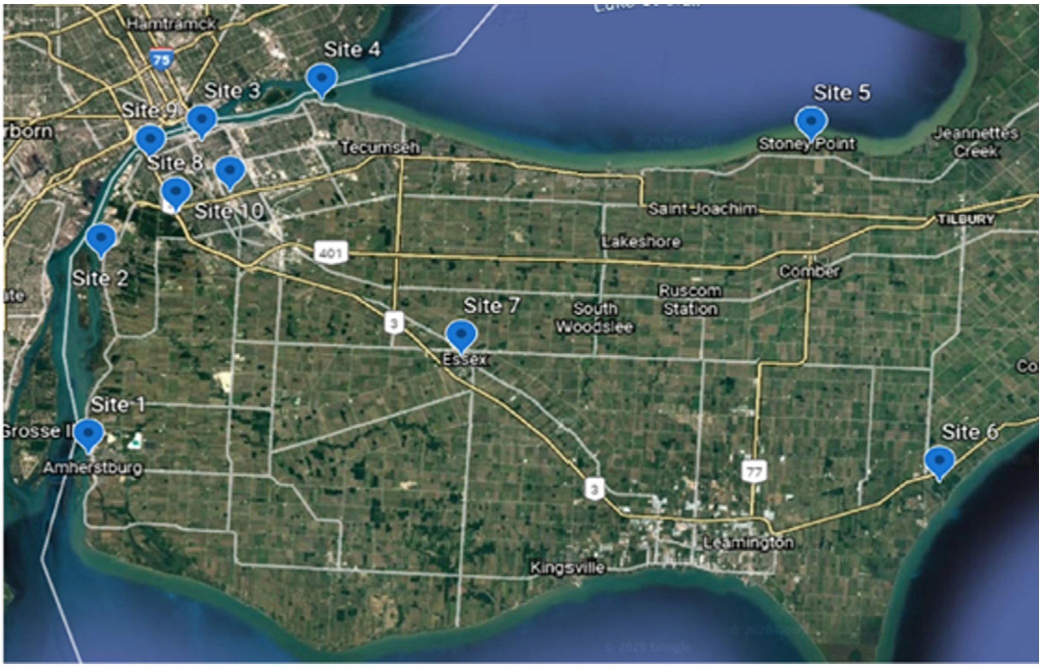


Fig. 1. Map of TV spectrum measurement sites across Windsor-Essex County, Ontario, Canada [30].

- Strong interference (Class 3): this class corresponds to the presence of SUs whose amplitudes are sufficiently large over the channel bandwidth as exhibited in Fig. 2d.
- Weak interference (Class 4): it corresponds to the presence of SUs whose amplitudes are small over the channel bandwidth as illustrated in Fig. 2e.

The five proposed ATSC channel classes can be summarized as in Table 1.

Fig. 2 shows the spectrum power measured, in dB full scale (dBFS), at Site 1 for five different ATSC channels. Note that the ATSC channels illustrated in the figure were selected to present the five proposed ATSC channel classes.

3.1. Model description

The ATSC channels of the licensed users, in the frequency band from 490 to 740 MHz, are considered as PUs. The scanned spectrum might consist of M channels occupied by PUs, or by SUs, i.e., interference.

The channel m is available only for the CR network to exploit when there is no PU or unknown signals in the active state in that channel. If A denotes channel availability:

$$A = \begin{cases} +1 & \text{if} \quad C_m = 0, \quad \forall m \\ -1 & \text{otherwise} \end{cases} \tag{1}$$

where C_m denotes the class of channel m.

3.2. Proposed framework of spectrum sensing model

The main goal of the proposed ML models is to correctly assess the availability of channels. Since the suggested algorithms are supervised learning. The FFT samples for each channel will be used with their labels to train the classifiers.

The ML model will be able to detect the presence of PU by observing the pilot signal. In Fig. 3, the framework of the proposed ML models is demonstrated. The dotted blocks show that the PCA technique is employed as a DR technique before the classification.

Let Y represents the set of measured samples for training dataset after normalization, i.e., the input:

$$Y = \begin{pmatrix} y_{11} & \cdots & y_{1N} \\ \vdots & \ddots & \vdots \\ y_{T1} & \cdots & y_{TN} \end{pmatrix}, \tag{2}$$

where N and T represent the number of FFT samples for each channel and the scanning duration for the channels, respectively. Let C represents the class of the channels, i.e. the output, corresponding to Y:

$$C = \begin{pmatrix} c_1 \\ \vdots \\ c_T \end{pmatrix} \tag{3}$$

Let Z is the output of the PCA that represent the transformation of Y into a lower dimension:

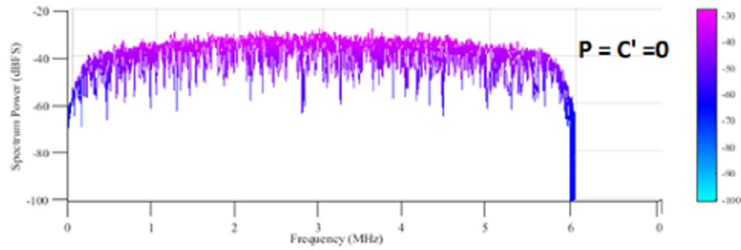
$$Z = \begin{pmatrix} z_{11} & \cdots & z_{1n} \\ \vdots & \ddots & \vdots \\ z_{T1} & \cdots & z_{Tn} \end{pmatrix}, \tag{4}$$

where $n < N$.

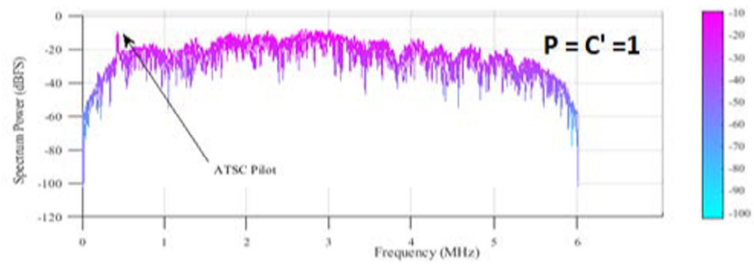
In Fig. 3, the proposed framework for SSM based on ML models is demonstrated, comprising of the data preprocessing, DR technique, classification training, and testing. The dotted blocks illustrate using PCA as a DR technique before the classification.

Once the classifier has been effectively trained, the samples in the testing data are ready for evaluation of the performance of the classifiers. Let Y' and Z' denote the FFT samples for testing and their new representations after applying the DR technique, respectively. If C' denotes the corresponding detected channel classes, i.e., as indicated in Table 1 and Fig. 2, for the testing samples and P is the predicted class by the classifier, then we can write:

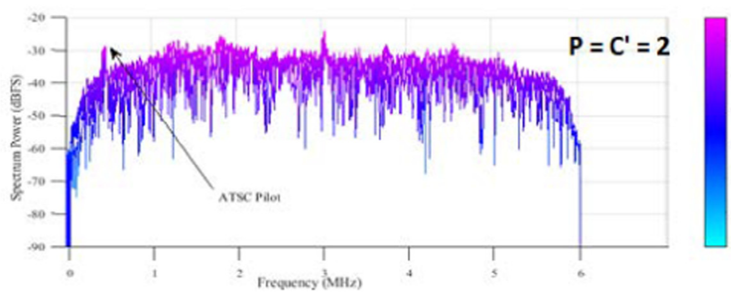
$$P = \begin{cases} C' & detection \\ otherwise & mis-detection \end{cases} \tag{5}$$



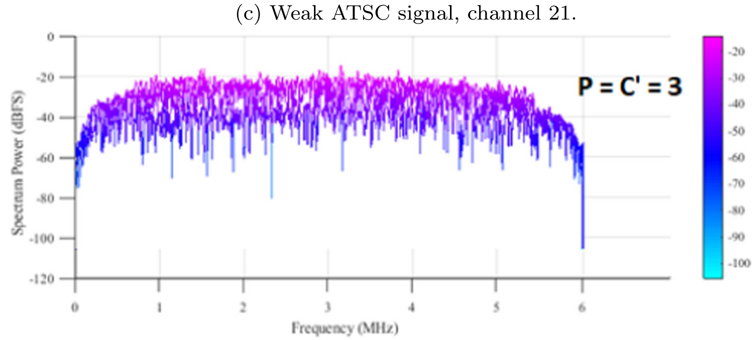
(a) Unoccupied, channel 51



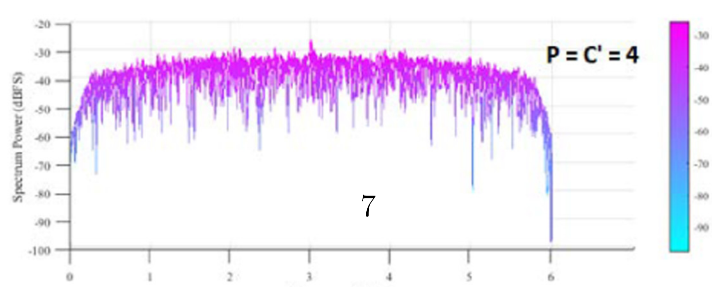
(b) Strong ATSC signal, channel 41.



(c) Weak ATSC signal, channel 21.



(d) Strong interference signal, channel 44.



(e) Weak interference signal, channel 35.

Fig. 2. Spectrum power in (dBFS) for some TV channels at site 1.

For instance, if the testing samples are for a channel that is occupiedby an active PU and the model classifies the channels as occupied, it is misdetected.

For a comprehensive comparison between used ML approach in this case study, an Ensemble classifier will be employed. The Ensemble classification is defined as a process of effectively gener-

Table 1
ATSC channels classes.

ATSC channels classes	Class (C)
Unoccupied (PUs and SUs are inactive)	0
ATSC Present, strong (PU active)	1
ATSC Present, weak (PU active)	2
Strong interference (SU active)	3
Weak interference (SU active)	4

ating and combining multiple classifiers to solve a specific ML problem as illustrated in Fig. 4 [34]. The proposed Ensemble classifier consists of several decision tree classifiers and an algorithm to combine them. Bootstrap Aggregation (Bagging) is adopted as an algorithm to combine these weak classifiers. It generally trains multiple independent classifiers, each trained by sampling with replacement percentage of instances from the training data. The diversity in the Ensemble is ensured by the variations in replicas on which each classifier is trained and therefore it enhance the classifier predictivity and performance [31].

3.3. Performance metrics

To evaluate the proposed SSMs, the following performance metrics will be used: *accuracy, precision, recall, F-measure*, and ROC. The performance metrics are defined as

- *Accuracy* is defined as the measure of all the correctly identified samples. It is mostly used when all the classes are equally important and it is calculated as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{6}$$

where *TP* (True Positive) is the outcome where the model correctly predicts samples belong to the designated class, e.g., class 2, *TN* (True Negative) is an outcome where the model correctly predicts samples do not belong to that particular class, e.g., class 2, and *FP* (False Positive) is an outcome where the model incorrectly predicts samples of other classes as samples of class 2, while *FN* (False Negative) is an outcome where the model incorrectly predicts samples of the designated class, e.g., class 2 as they belong to other classes.

- *Recall* is defined as the percentage of actual positives that are correctly identified. It is also called the true positive rate (*TPR*), the sensitivity, or the probability of detection and is calculated as:

$$Recall = TPR = \frac{TP}{TP + FN} \tag{7}$$

- *Precision* is defined as the number of true positives divided by the number of true positives plus the number of false positives. It shows the ability of a classification model to return only actual samples belong to the class.

$$Precision = \frac{TP}{TP + FP} \tag{8}$$

- *False-positive rate* (*FPR*) is the proportion of negative samples incorrectly identified as positive samples in the testing data. It is also called the probability of false alarm.

$$FPR = \frac{FP}{FP + TN} \tag{9}$$

- *F-measure* (Also called *F1 score*) is the harmonic mean of precision and recall and gives a better measure of the incorrectly classified cases than the accuracy metric. It is calculated as:

$$F - measure = \frac{2TP}{2TP + FP + FN} \tag{10}$$

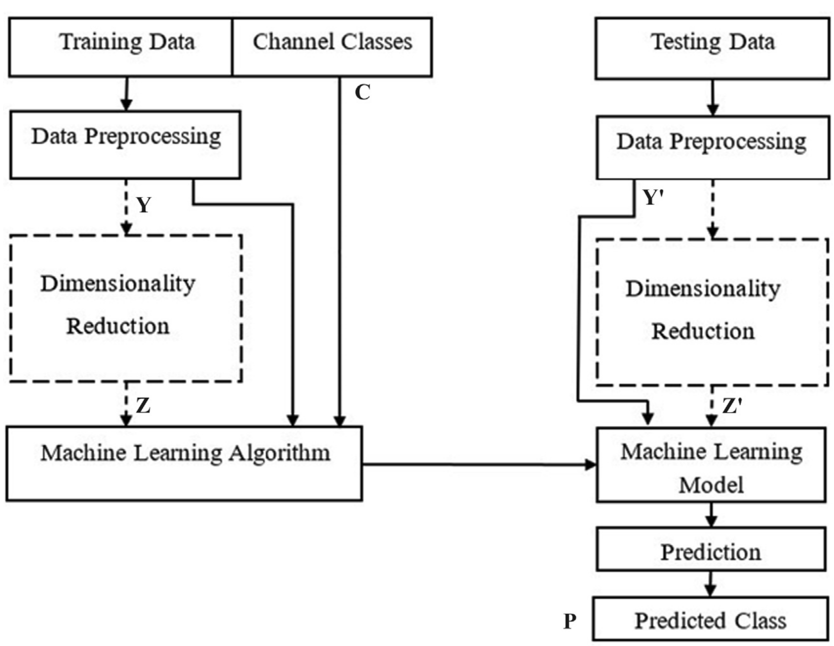


Fig. 3. ML-based spectrum sensing framework.

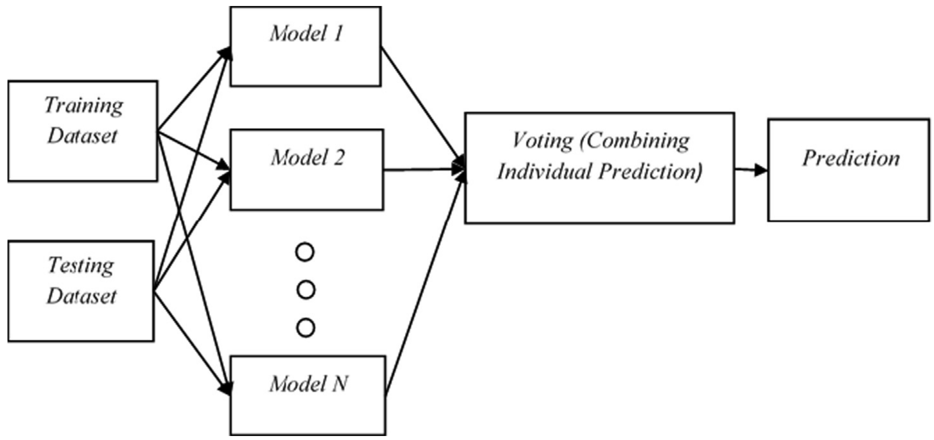


Fig. 4. Ensemble classifier structure.

- ROC curve is a graphical tool that illustrates the behavior of TPR with respect to the FRP which reflects the performance of a classification model at different classification thresholds.

Moreover, it is noted that K–fold cross-validation is employed in performance evaluation, since it usually leads to a less biased or less optimistic estimation of the model than other techniques. In the proposed SSM, the dataset is randomly divided into K groups or folds, then the model is trained using $(K-1)$ folds and the models are tested using the remaining Kth fold. The process is repeated until every K-fold serves as the test set. The value of K is set to 5.

This work proposes two algorithms for spectrum sensing based on ML models as depicted in Fig. 3. Algorithm 3.3 presents an SSM based ML techniques, while Algorithm 3.3 presents a modified SSM that adopts the PCA technique as a DR technique. The algorithms are described as follows:

Algorithm. Spectrum sensing model based on ML classification techniques

1: Define Y as the normalized values of the FFT samples collected by the sensing unit and C as the classes labeled for the scanned channels.

2: Determine the classifier and initialize the parameters.
3: Train the classifier model using Y and C in step 1.
4: Cross validate and test the trained model using Y.
5: Predict the class of the testing data C using the trained model.

Algorithm. Modified spectrum sensing model based on ML classification adopting DR technique

1: Define Y as the normalized values of the FFT samples collected by the sensing unit and C as the classes labeled for the scanned channels.

2: Compute Z as in (4) by finding the principal components of Y as in (2) using PCA.
3: Select a suitable value n for the number of principal components for PCA where $n < N$.
4: Determine the classifier and initialize the parameters.
5: Train the classifier model using Y and C in step 1.
6: Cross validate and test the trained model using Y.
7: Predict the class of the testing data C using the trained model.

4. Simulation results and discussions

The simulation results of the proposed spectrum sensing-based ML models using the four classifiers are evaluated employing different performance metrics. The performance metrics are accuracy, F-measure, and ROC curve will be employed to evaluate the performance of the four classifiers using 5 K-fold cross-validations. Moreover, the impact of employing the PCA technique on the detection performance of the proposed model is discussed in this section.

Table 2 shows that the accuracy and F-measure are slightly dropped from 0.93 and 0.83 to 0.92 and 0.8, respectively, as a result of losing information in the dataset after implementing the PCA technique. Moreover, it can be perceived from Table 3 that the accuracy and F-measure have increased from 0.88 and 0.72 to 0.92 and 0.8, respectively; this is because of the fact that the kNN classifier operates better with a small number of features, i.e., lower dimension, than a large number of features, i.e., higher dimension.

Table 4 shows that the averages of the accuracy and F-measure are approximately the same for the DT classifier with and without using the PCA technique. Therefore, using the PCA technique is retaining the classification performance while reducing the number of features in the datasets. Similarly, Table 5 shows also that the accuracy and F-measure have slightly decreased from 0.94 and 0.86 to 0.92 and 0.83, respectively, as a result of losing information in the dataset after applying the PCA technique.

Table 2
SVM classifier performance with and without PCA, at site 1.

	Without PCA		With PCA	
5 K folds	*Accuracy*	*F-measure*	*Accuracy*	*F-measure*
fold 1	0.9333	0.8333	0.9215	0.8038
fold 2	0.9354	0.8385	0.9267	0.8167
fold 3	0.9297	0.8244	0.9205	0.8013
fold 4	0.9262	0.8154	0.9118	0.7795
fold 5	0.9308	0.8269	0.9108	0.7769

Table 3
kNN classifier performance with and without PCA, at site 1.

	Without PCA		With PCA	
5 K folds	*Accuracy*	*F-measure*	*Accuracy*	*F-measure*
fold 1	0.8887	0.7218	0.9262	0.8154
fold 2	0.8892	0.7231	0.9164	0.7910
fold 3	0.8846	0.7115	0.9241	0.8103
fold 4	0.8826	0.7064	0.9103	0.7756
fold 5	0.8846	0.7115	0.9195	0.7987

Table 4
DT classifier performance with and without PCA, at site 1.

	Without PCA		With PCA	
5 *K* folds	*Accuracy*	*F-measure*	*Accuracy*	*F-measure*
fold 1	0.9144	0.7859	0.9128	0.7821
fold 2	0.9272	0.8179	0.8990	0.7474
fold 3	0.9164	0.7910	0.8990	0.7474
fold 4	0.9108	0.7769	0.9103	0.7756
fold 5	0.9149	0.7872	0.9010	0.7526

Table 5
Ensemble classifier performance with and without PCA, at site 1.

	Without PCA		With PCA	
5 *K* folds	*Accuracy*	*F-measure*	*Accuracy*	*F-measure*
fold 1	0.9446	0.8615	0.9282	0.8205
fold 2	0.9436	0.8590	0.9328	0.8321
fold 3	0.9374	0.8436	0.9256	0.8141
fold 4	0.9441	0.8603	0.9241	0.8103
fold 5	0.9533	0.8833	0.9354	0.8385

In order to develop the ROC curves for the different classifiers, Algorithm 3.3 is executed for several attempts using different parameters and the best results for specific parameters are shown in Fig. 5. The figure exhibits the ROC curves of the four classifiers without employing the PCA technique. By inspection, the Ensemble classifier has the highest true positive rate (TPR), i. e., probability of detection, for a given false alarm rate (FPR). For this reason, the Ensemble classifier outperforms the other classifiers since it combines multiple classifiers, while SVM classifier comes in the second rank by finding the hyper-plane that maximizes the margin between the classes.

Likewise, Algorithm 3.3 is executed to generate ROC curves for different classifiers when adopting the PCA technique as a DR technique; the curves are illustrated in Figs. 6 and 7. Fig. 6 displays ROC

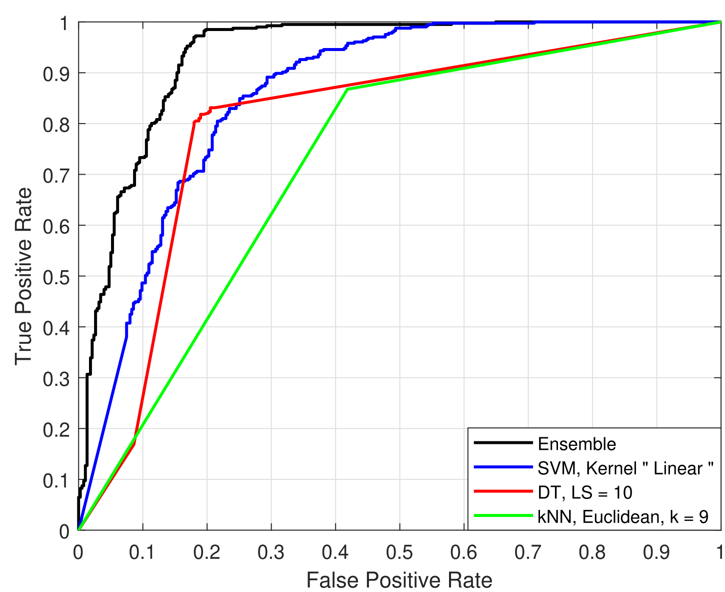


Fig. 5. Comparison of ROC curves for all employed classifiers without the PCA technique, at site 1.

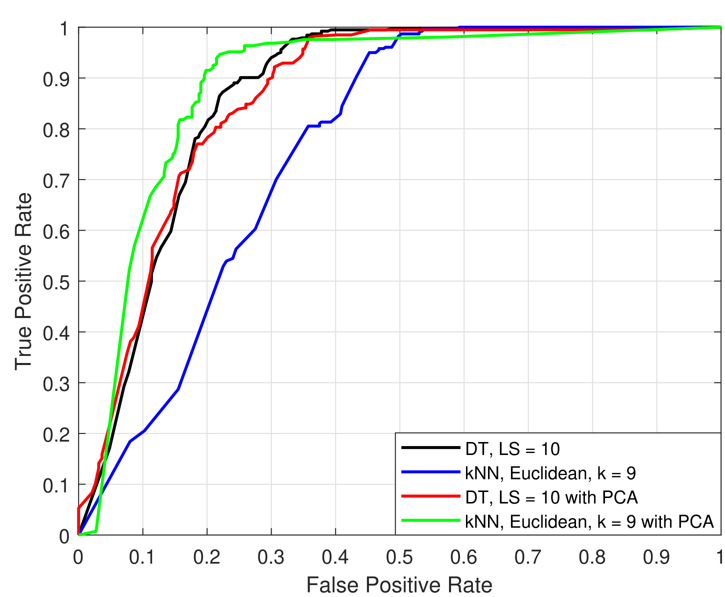


Fig. 6. Comparison of ROC curves obtained by kNN and DT classifiers with and without using the PCA technique, at site 1.

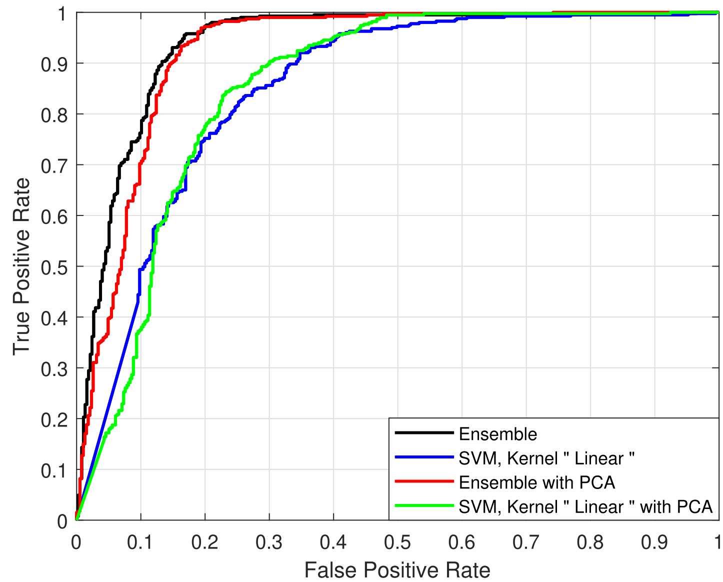


Fig. 7. Comparison of ROC curves obtained by Ensemble and SVM classifiers with and without using the PCA technique, at site 1.

curves of kNN and DT classifiers with and without using the PCA technique. It can be observed for a given FPR, the TPR of the kNN classifier with the PCA technique is higher than kNN without the PCA technique. Consequently, the performance is enhanced after implementing the PCA technique, since the kNN classifier works efficiently on datasets of lower features. Furthermore, applying the PCA technique maintains the performance of the DT classifier by extracting features relevant to the classification problem. On other hand, the ROC curves of Ensemble classifier and SVM classifiers with and without using the PCA technique are depicted in Fig. 7. The classification performance based on ROC curves after utilizing the PCA technique is insignificantly declined as for Ensemble and SVM classifiers this comes a result of information loss during reducing the dimension.

5. Conclusions

Supervised ML algorithms based on the SVM, kNN, DT, and Ensemble classifiers are examined to detect the presence of PU and unknown users over the TV bands. The simulation results of the four classifiers have been presented and demonstrated in terms of accuracy, F-measure, and ROC. The results have shown that the Ensemble classifier exceeds the other classifiers based on performance metrics followed by the SVM classifier. Nevertheless, the performance comes at the expense of greater computational complexity.

Moreover, the SVM classifier attempts to find the hyper-plane that maximizes the margin between the classes which results in increasing the training duration compared with the kNN and the DT classifiers. Furthermore, the results have shown that employing a DR technique, such as the PCA technique, before the classifier significantly speeds up the training process across the four classifiers by extracting the most essential features and removing the redundancy in the employed datasets. However, the PCA execution should be examined to make sure that non- redundant information are maintained. As a future work, developing a new spectrum sensing model-based ML to classify and identify the broadcasting station identity, i.e., to determine the identity of broadcaster, i.e., PU, can significantly improve the spectrum utilization. In other words, the identification will add a potential advantage to the spectrum sensing model to determine the best spectrum sharing technique can be employed, i.e., interweave, underlay or overlay, or to switch from sharing technique to another. Moreover, multiresolution technique-based ML technique can be employed to incredibly improve detecting and identifying a specific PU among multiple PUs transmitting simultaneously.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

[1] Stevenson CR, Chouinard G, Lei Z, Hu W, Shellhammer SJ, Caldwell W. Ieee 802.22: The first cognitive radio wireless regional area network standard. IEEE Commun Mag 2009;47(1):130–8.
[2] He A, Gaeddert J, Bae KK, Newman TR, Reed JH, Morales L, et al. Development of a case-based reasoning cognitive engine for ieee 802.22 wran applications. ACM SIGMOBILE Mob Comput Commun Rev 2009;13(2):37–48.
[3] Molina-Tenorio Y, Prieto-Guerrero A, Aguilar-Gonzalez R. Real-time implementation of multiband spectrum sensing using sdr technology. Sensors 2021;21(10):3506.
[4] Shellhammer SJ. The theoretical performance of atsc spectrum sensing. In: 2011 IEEE International Symposium on Dynamic Spectrum Access Networks (DySPAN). IEEE; 2011. p. 521–30.
[5] Cong Y, Xing L, Bi J. Spectrum sensing algorithm based on atsc dtv signal structure. Int J Smart Sens Intell Syst 2013;6(5).
[6] Molina-Tenorio Y, Prieto-Guerrero A, Aguilar-Gonzalez R, Ruiz-Boqué S. Machine learning techniques applied to multiband spectrum sensing in cognitive radios. Sensors 2019;19(21):4715.

[7] Corral-De-Witt D, Ahmed S, Rojo-Álvarez JL, Tepe K. Rapid estimation of tvws: A probabilistic approach based on sensed signal parameters. Telecom, vol. 1, no. 3. Multidisciplinary Digital Publishing Institute; 2020. p. 161–80.
[8] Communications on Applied Electronics (CAE) – ISSN : 2394-4714 Foundation of Computer Science FCS, New York, USA Volume 2 – No.3, June 2015, pp 23–28.
[9] Lim S-M, Jung H-Y, Kim S-W, Jeong B-J. The novel atsc signal detection and data fusion algorithms for cr system in tv white space. J Kor Inst Commun Inform Sci 2011;36(8A):723–9.
[10] Awin F, Abdel-Raheem E, Tepe K. Blind spectrum sensing approaches for interweaved cognitive radio system: A tutorial and short course. IEEE Commun Surv Tutorials 2018;21(1):238–59.
[11] Awin FA, Alginahi YM, Abdel-Raheem E, Tepe K. Technical issues on cognitive radio-based internet of things systems: A survey. IEEE Access 2019;7:97887–908.
[12] Clancy C, Hecker J, Stuntebeck E, O'Shea T. Applications of machine learning to cognitive radio networks. IEEE Wirel Commun 2007;14(4):47–52.
[13] Bkassiny M, Li Y, Jayaweera SK. A survey on machine-learning techniques in cognitive radios. IEEE Commun Surv Tutorials 2012;15(3):1136–59.
[14] Li Z, Wu W, Liu X, Qi P. Improved cooperative spectrum sensing model based on machine learning for cognitive radio networks. IET Commun 2018;12 (19):2485–92.
[15] Thilina KM, Choi KW, Saquib N, Hossain E. Machine learning techniques for cooperative spectrum sensing in cognitive radio networks. IEEE J Sel Areas Commun 2013;31(11):2209–21.
[16] Hossain MA, Md Noor R, Yau K-LA, Azzuhri SR, Z'aba MR, Ahmedy I, et al. Machine learning-based cooperative spectrum sensing in dynamic segmentation enabled cognitive radio vehicular network. Energies 2021;14 (4):1169.
[17] Ahmed R, Chen Y, Hassan B, Du L. Cr-iotnet: Machine learning based joint spectrum sensing and allocation for cognitive radio enabled iot cellular networks. Ad Hoc Netw 2021;112:102390.
[18] Shah HA, Koo I. Reliable machine learning based spectrum sensing in cognitive radio networks. Wireless Commun Mob Comput 2018;2018.
[19] Elrharras A, Saadane R, Wahbi M, Hamdoun A. Signal detection and automatic modulation classification based spectrum sensing using pca-ann with real word signals. Appl Math Sci 2014;8(160):7959–77.
[20] Sindhubargavi R, Sindhu MY, Saravanan R. Spectrum sensing using energy detection technique for cognitive radio networks using pca technique. Indian J Sci Technol 2014;7(4S):40–5.
[21] Nasser A, Mansour A, Yao K-C, Abdallah H, Chaitou M, Charara H. Spectrum sensing enhancement using principal component analysis. In: 2016 IEEE International Symposium on Signal Processing and Information Technology (ISSPIT). IEEE; 2016. p. 263–7.
[22] Tian J, Cheng P, Chen Z, Li M, Hu H, Li Y, et al. A machine learning-enabled spectrum sensing method for ofdm systems. IEEE Trans Veh Technol 2019;68 (11):11374–8.
[23] Shang B, Liu L. Machine learning meets point process: Spatial spectrum sensing in user-centric networks. IEEE Wirel Commun Lett 2019;9(1):34–7.
[24] Salo F, Nassif AB, Essex A. Dimensionality reduction with ig-pca and ensemble classifier for network intrusion detection. Comput Netw 2019;148:164–75.
[25] Reddy GT, Reddy MPK, Lakshmanna K, Kaluri R, Rajput DS, Srivastava G, et al. Analysis of dimensionality reduction techniques on big data. IEEE Access 2020;8:54776–88.
[26] Hou S, Qiu R, Browning JP, Wicks M. Spectrum sensing in cognitive radio with robust principal component analysis. In: 2012 International Waveform Diversity & Design Conference (WDD). IEEE; 2012. p. 308–12.
[27] Han Y, Lee H, Lee J. Spectrum sensing using robust principal component analysis for cognitive radio. In: 2013 IEEE 78th Vehicular Technology Conference (VTC Fall). IEEE; 2013. p. 1–5.
[28] Corral-De-Witt D, Younan A, Fatima A, Matamoros J, Awin FA, Tepe K, et al. Sensing tv spectrum using software defined radio hardware. In: 2017 IEEE 30th Canadian Conference on Electrical and Computer Engineering (CCECE). IEEE; 2017. p. 1–4.
[29] Awin F, Younan A, Corral-De-Witt D, Tepe K, Abdel-Raheem E. Real-time multi-channel tvws sensing prototype using software defined radio. In: 2018 IEEE International Symposium on Signal Processing and Information Technology (ISSPIT). IEEE; 2018. p. 212–7.
[30] Corral-De-Witt D, Ahmed S, Awin F, Rojo-Álvarez JL, Tepe K. An accurate probabilistic model for tvws identification. Appl Sci 2019;9(20):4232.
[31] Breiman L. Random forests. Mach Learn 2001;45(1):5–32.
[32] Patel HH, Prajapati P. Study and analysis of decision tree based classification algorithms. Int J Comput Sci Eng 2018;6(10):74–8.
[33] Jhajj HK, Garg R, Saluja N. Aspects of machine learning in cognitive radio networks. In: Progress in Advanced Computing and Intelligent Engineering. Springer; 2018. p. 553–9.
[34] Polikar R. Ensemble based systems in decision making. IEEE Circ Syst Mag 2006;6(3):21–45.
[35] Fay L, Michael L, Gómez-Barquero D, Ammar N, Caldwell MW. An overview of the atsc 3.0 physical layer specification. IEEE Trans Broadcast 2016;62 (1):159–71.

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