Performance Validation of Spectrum Sensing Using Kernelized Support Vector Machine Transformation

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PERFORMANCE VALIDATION OF SPECTRUM SENSING USING KERNELIZED SUPPORT VECTOR MACHINE TRANSFORMATION

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Abstract-The constant development of interest experienced by wireless networks makes a spectrum accessibility challenge. Cognitive radio (CR) is a promising solution to overcome the challenges in spectrum utilization. The process of finding the spectrum holes (availability of spectrum) is called spectrum sensing (SS) which is a major task in cognitive radio network (CRN). Various creative methodologies are proposed in the literature to track the spectrum and identify the available holes. The use of Machine Learning strategies for spectrum sensing has attracted interest in the literature. Therefore, we have considered an ML technique, Support vector machine (SVM) method with Kernel transformation to achieve better results in spectrum sensing. The proposed conspire astoundingly further develops the spectrum detecting execution, but also essentially builds the open doors for dynamic access to the licensed spectrum for the unlicensed users.

Keywords- Classification, Machine Learning, SVM, Cognitive radio, Spectrum sensing

I. 1. Introduction

The interest for additional data transfer capacity and expansion in cellular traffic causes a serious spectrum shortage issue in the radio environment. Cognitive radio (CR) is a famous answer for conquering this by further developing the overall spectrum usage [1]. One key property of CRs is the capacity to gain from its environmental elements which are done by spectrum sensing (SS). It is observed from the literature [1], [2] that sometimes the spectrum will be free in the absence of primary users or licensed users.

This makes a way for unlicensed users, frequently called secondary users (SU) to get to the empty spectrum band artfully. Spectrum detecting in cognitive radios stays a test for superior execution and low-energy gadgets on the grounds that the energy-consuming undertakings frequently lessen the spectrum productivity of the SUs. This happens because of significant investment utilization on an alternate undertaking which is absent in communicated bits. Since SS-based channel status assessment is a sort of classification problem. In this manner, a few scientists took on the Machine Learning (ML) models as an inference tool [3], [4].

Imperative, Machine learning (ML) models can be utilized for pattern recognition, picture handling, edge registering, energy harvesting, and resource management [5]-[9], yet additionally be applied to classify correspondence signals [10], [11]. As of late, Machine learning (ML) based spectrum detecting innovation has given another arrangement in spectrum status for cognitive radio frameworks. In view of the huge number of spectrum perceptions caught by the Secondary user equipment (SUE) in the Cellular cognitive radio network (CCRN), this paper proposes a spectrum detecting plan in light of the primary user (PU) transmission mode arrangement. The researchers have taken on various ML empowered answers for tackling the difficulties of mind-boggling detecting models in agreeable spectrum detecting and finally proposed a technique in light of SVM kernel transformation which is a strong and adaptable class of supervised algorithms for both characterization and regression [12]. In our commitment, we will foster the instinct behind support vector machines and their utilization in classification issues.

II. 2. System Model

Specifically, a total Cooperative spectrum sensing (CSS) cycle can be depicted as follows. Initially, a secondary user (SU) who requires to communicate information, sends a solicitation to the fusion center (FC). The FC then advises all SUs in its inclusion to see the encompassing radio climate. At long last, the FC goes with a choice on the ongoing channel state as indicated by the energy signals got back from each SU and takes care of back this outcome to SU. The different spectrum sensing strategies are talked about in [13, 14]; Matched filter strategy [15], Energy detection methods [16, 17], and the cyclostationary detection procedure [18]. Energy detection (ED) stays the most involved technique for spectrum detection, because of its basic execution and does not need any data about the PU signal. Along these lines, in this work, we are keen on the ED strategy, in which the energy of the obtained signal is estimated and contrasted, and a threshold limit, which presents the noise present in the channel. On the off chance that the signal energy surpasses the limit, we decide the presence of the PU, in any case, it is missing [19].

The issue of spectrum sensing activity can be numerically defined as follows:

$$\left.\begin{aligned} y_i &= w & ;h_0 \\ y_i &= \alpha * x_i + w & ;h_1 \end{aligned}\right\} \quad \text{where } 0 < \alpha \leq 1 \tag{1}$$

Where: y_i is the received signals, x_i is the signal to be detected, deterministic or random, but unknown, and w is the noise in the channel.

In Eq. (1), $y_i = w$ in the absence of primary user ($x(t) = 0$) for the hypothesis, h_0, whereas the hypothesis, h_1, represents the presence of PU. The energy of the received signal, y_i can be measured as follows,

$$E = \frac{1}{T}\sum_{n=1}^{N}[y_i]^2 \qquad \begin{cases} E > \tau & \mathrm{h}_1 \\ E < \tau & \mathrm{h}_0 \end{cases} \tag{2}$$

Whereas τ denotes the threshold value and the energy levels have more than the threshold is considered primary users (PU) and below the threshold are considered secondary users (SU).

The implementation of the energy detection technique is shown in Figure 1, the incoming high-frequency signal is captured by an RTL-SDR dongle and is converted into digital form and then the signal is passed through a bandpass filter with a center frequency of f_0 and bandwidth β and converted into frequency domain with the help of FFT with a transfer function of $H(f)$ (Eq. (3)) and measured energy (Eq. (4)) can be defined as follows as follows

$$H(f)=\begin{cases}\frac{2}{\sqrt{w_0}} & |f-f_0|\le\beta \\ 0 & |f-f_0|>\beta\end{cases} \tag{3}$$

$$E = \frac{1}{N}\sum_{k=1}^{N} |Y(f)|^2 \tag{4}$$

At long last, the estimated energy E is contrasted with a threshold λ (the noise energy) to choose if a signal is available (h_1) or not (h_0).

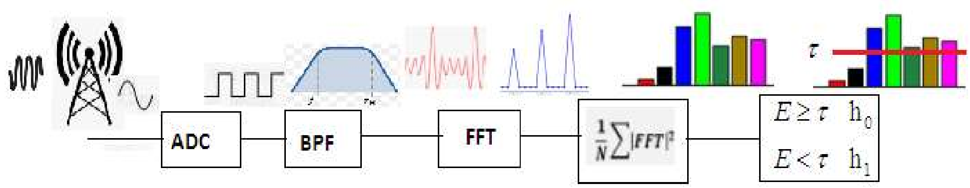

Fig. 1. Energy detection spectrum sensing

The inspiration driving the utilization of ML models in SS is the capacity to work even without a trace of information on the network boundaries. The essential target of a directed ML model is to the thought of a framework that can anticipate the mark or result of an obscure model with a specific level of confidence (in the event of a given arrangement of preparing inputs and the comparing name or results). Generally utilized and an effective ML strategy, Support vector machine (SVM) technique can be utilized to isolate two classes of information [20, 21] by finding an ideal hyperplane ' H_p'. This strategy is basically utilized for binary classification, however conceivable to arrange tests with various classes. What's more, tackling both linear and nonlinear grouping or regression problems can be utilized. In SVMs, each information example x_i, is addressed by a couple (x_k, y_k), where $\Re^n$ is the information instance. The training information T and its corresponding hyperplane H_p can be defined as follows:

$$T=\{(x_k, y_k)\in\Re^n, \quad k=1,....n\} \tag{5}$$

$$H_p : w_g . x_i + \tau \tag{6}$$

Where the vector 'w_g' is the weighing vector that defines the boundary of different classes of data, and 'τ' is a scalar threshold. The goal of the SVM arrangement is to anticipate the worth of y_k for new pieces of information x_k. There are two sorts of SVM arrangements: Linearly [22] and non-directly [23] distinguishable classification.

2.1. Linearly separable classification

In this section, we present the general method of constructing the optimal hyperplane, which separates data belonging to two different linearly separable classes. Figure 2 gives a visual representation of the optimal hyperplane in the case of linearly separable data, which is satisfying in the following conditions:

$$\begin{cases} w_g * x_k + \tau \geq 1 & if \quad y_k = 1 \\ w_g * x_k + \tau \leq -1 & if \quad y_k = -1 \end{cases} \tag{7}$$

Which can also be represented as follows

$$y_k(w_g * x_k + \tau) \geq 1, \qquad k = 1, \ldots., n \tag{8}$$

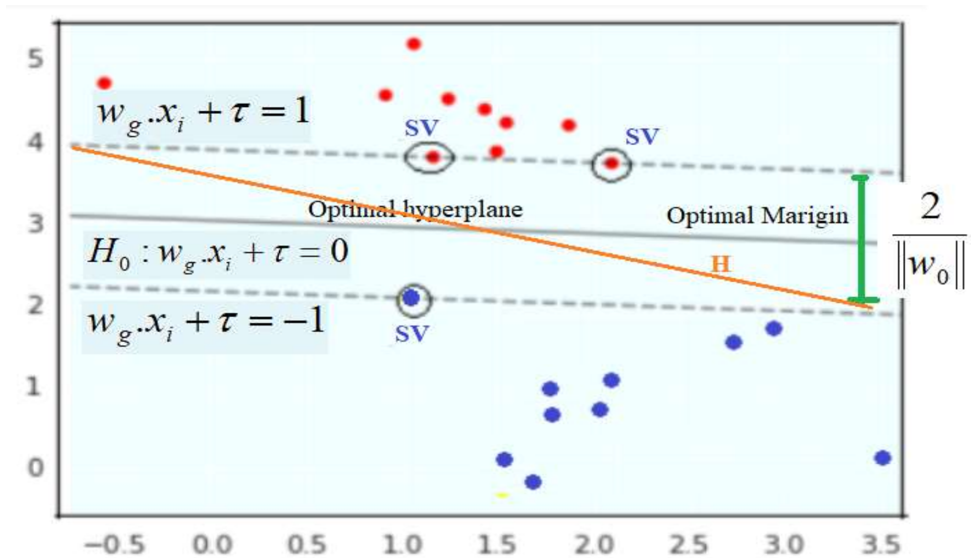

Figure 2. Usage of hyperplane in SVM method.

The ideal hyperplane H_0 maximizes the margin M, which addresses the smallest distance between the various information of the two classes and H_0. Augmenting the margin M is equivalent to boosting the amount of the distances between the two classes compared with H_0. The margin 'M' has the accompanying numerical articulation:

$$M = \min_{x_k|y_k=1} \frac{w_g.x_i + \tau}{\|w_g\|} - \max_{x_k|y_k=-1} \frac{w_g.x_i + \tau}{\|w_g\|} = \frac{1}{\|w_g\|} - \frac{-1}{\|w_g\|} = \frac{2}{\|w_g\|} \tag{9}$$

The ideal hyperplane can be gotten by expanding the condition (9). Which is identical to limiting (10):

$$\min_{w} \frac{\left\| w_g \right\|^2}{2} \tag{10}$$

Equation (10) can be tackled as a quadratic enhancement issue by the Lagrangian function:

$$L(w_g, \tau, \lambda) = \frac{\left\| w_g \right\|^2}{2} - \sum_{k=1}^{n} \lambda_k [y_k (w_g . x_k + \tau) - 1] \tag{11}$$

Where $\lambda_k = (\lambda_1, \ldots, \lambda_m) > 0$ is a Lagrangian multiplier factors. By deriving the equation (11) we obtain:

$$w_g = \sum_{k=1}^{n} \lambda_k y_k x_k \tag{12}$$

$$\sum_{k=1}^{n} \lambda_k y_k = 0 \tag{13}$$

Substituting (12) and (13) into Eq. (11), the optimal separating hyperplane can be obtained by solving the following dual representation of the optimization problem:

$$\min_{\lambda} \frac{1}{2} \sum_{i,j=1}^{n} y_i y_j (xixj) \lambda_i \lambda_j - \sum_{j=1}^{n} \lambda_j = 0 \tag{14}$$

$$\text{Subject to} \quad \sum_{i=1}^{n} \lambda_i y_k = 0$$

By tackling this double Lagrange work (14), λ is assessed. Therefore, w_g is assessed out from (12), and τ can be effectively determined from (15):

$$\tau = y_j - \sum_{i=1}^{n} \lambda_k y_k (x_i x_j) \tag{15}$$

Knowing that the classification function is defined by (16), where *sgn* is a Signum function.

$$class(x) = \operatorname{sgn}(w_g . x_k + \tau) \tag{16}$$

Finally, we can classify an unknown data x_i by utilizing the following function:

$$class(x) = \operatorname{sgn}\left[\sum_{k=1}^{n} \tau_k y_k (x_k x) + \lambda\right] \tag{17}$$

In this context, we have proposed an SVM indicator outline for signal characterization (spectrum detecting) (Fig. 2). where the energy computation block is supplanted by an SVM block. The SVM bit decision is basic to characterizing adaptability and arrangement power. The most utilized bits are: straight, polynomial degree '*p*', and Gaussian.

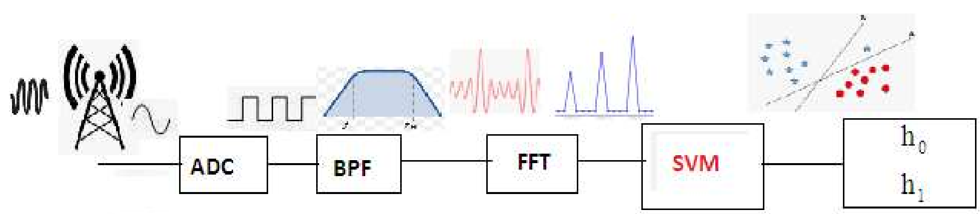

Fig. 2. SVM detection

III. 3. Results and Discussion

In Bayesian characterization, generative models are utilized to decide labels for new focuses probabilistically. Though in discriminative grouping: rather than demonstrating each class, we basically track down a line or bend (in two aspects) or complex (in numerous aspects) that partitions the classes from one another. To act as an illustration of this, consider the straightforward instance of the classification task among primary (Blue dots) and secondary users (Red dots), in which the two classes of points are all around isolated as displayed in Fig. 3(a). A linear discriminative classifier would endeavor to define a straight boundary isolating the two arrangements of information, and accordingly make a model for classification. For two-layered information like that displayed here, this is an errand we could do the hard way. However, quickly we see an issue: there is more than one potential isolating line that can entirely separate the two classes as displayed in Fig. 3(b). These are three altogether different separators which, in any case, completely segregate between these examples. Contingent upon which you pick, another piece of information (e.g., the one set apart by the "X" in this plot) will be allocated an alternate name! Clearly our basic instinct of "defining a boundary between classes" isn't sufficient, and we want to think a bit further.

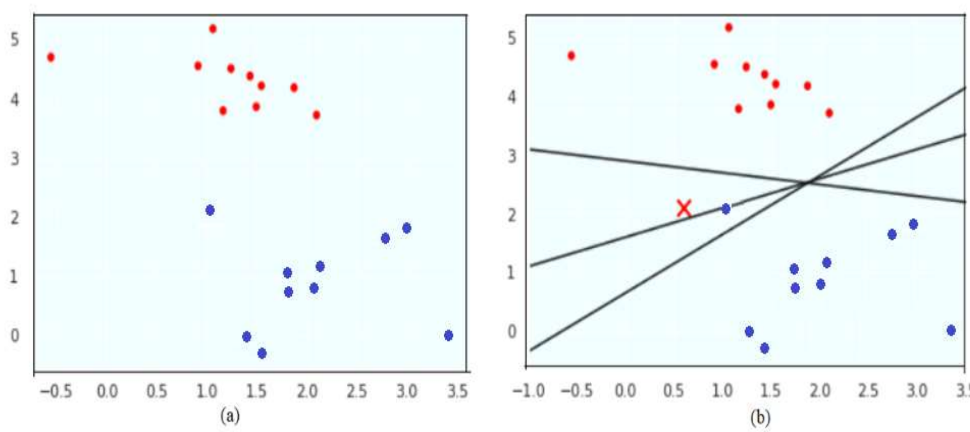

Fig. 3. Classification of Primary and Secondary users using a linear separator

Support vector machines offer one method for enhancing this. The instinct is this: instead of just drawing a zero-width line between the classes, we can define around every boundary an edge of some width, up to the closest point as displayed in Figure 4(a). In support vector machines, the line that boosts this margin is the one we will pick as the ideal model. Support vector machines are an illustration of such a greatest margin assessor.

A partitioning line that increases the margin between the two arrangements of points is utilized in Figure 4(b). It is seen that a couple of the training points simply contact the margin: they are shown by the dark circles. These points are the significant components of this fit, and are known as the support vectors, and give the algorithm its name. A key to this classifier's prosperity is that for the fit, just the place of the support vectors matter; any points further from the margin which is on the right side don't change the fit! Actually, this is on the grounds that these points don't add to the misfortune of work used to fit the model, so their situation and number don't make any difference in as much as they don't cross the margin. We can see this, for instance, in the event that we plot the model gained from the initial 20 places and initial 40 marks of this dataset as displayed in Figure 5: In Figure 5(a), we see the model and the support vectors for 20 training points. In Figure 5(b), we have multiplied the number of training points, yet the model has not changed: the three support vectors from the left board are as yet the support vectors from the right board. This harshness toward the specific way of behaving at far-off points is one of the qualities of the SVM model.

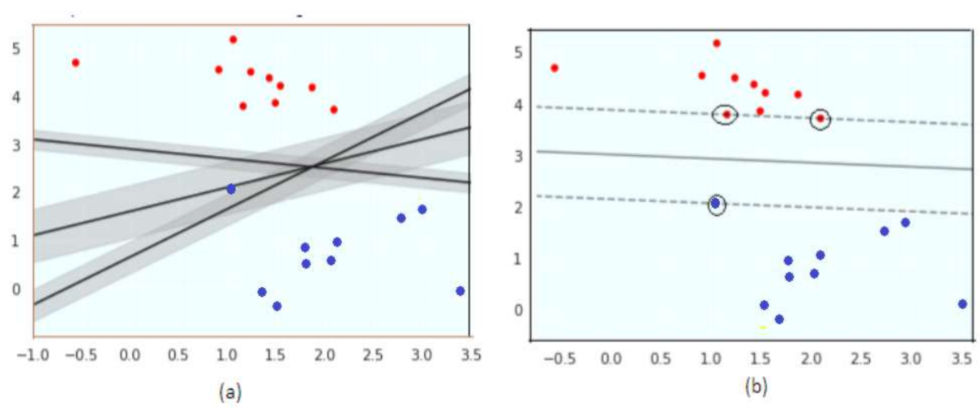

Fig. 4.(a) Classification using Linear separator (b) Classification using the principle of Support vector machine.

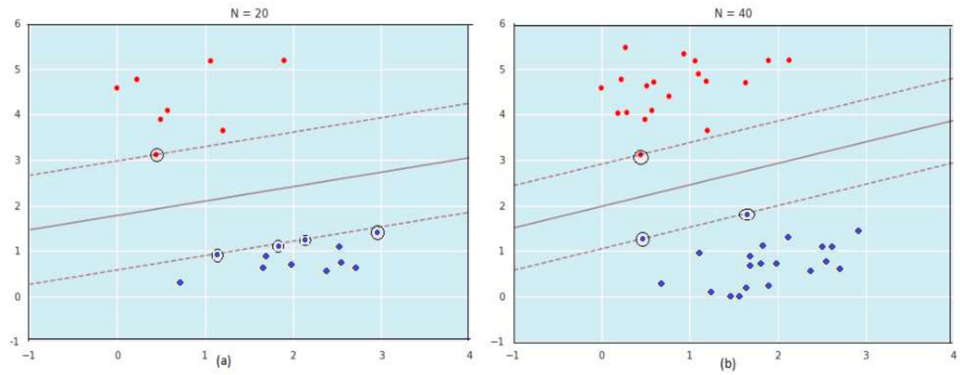

Fig. 5. (a) SVM model with training points of 20 (b) training points of 40.

Where SVM turns out to be very strong is the point at which it is joined with kernels, in which our information is projected into higher-layered space characterized by polynomials and Gaussian basis functions, and subsequently had the option to fit for nonlinear associations with a linear classifier. In SVM models, we can utilize a variant of a similar thought. To rouse the requirement of kernels, how about we take a gander at our information that isn't directly distinguishable as displayed in Figure 6(a). Obviously, no direct segregation can at any point isolate this information. However, we can draw an illustration from the basis function regressions in Linear Regression, and contemplate how we could extend the information into a higher aspect with the end goal that a linear separator would be adequate. For instance, one straightforward projection we could utilize is to register an outspread premise work focused on the center bunch. We can envision this additional information aspect utilizing a three-layered plot, We can utilize the sliders to turn the plot as displayed in Figure 6(b). We can see that with this extra aspect, the information turns out to be inconsequentially straightly divisible, by drawing an isolating plane at, say, r=0.7.

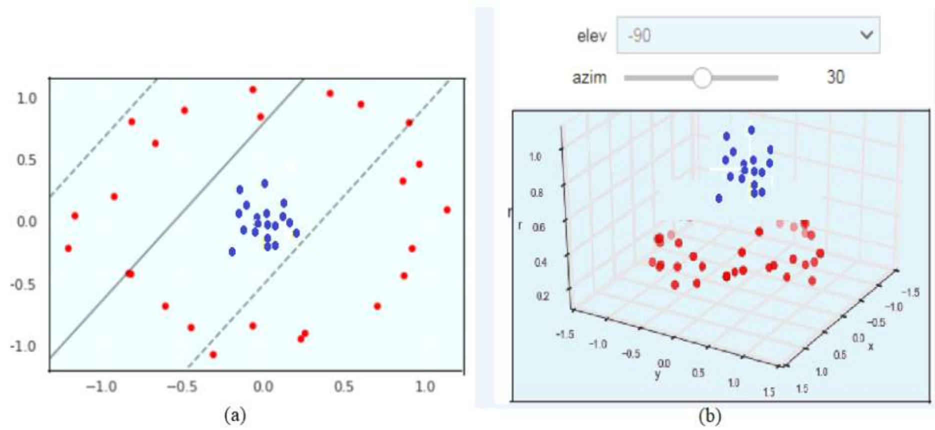

Fig. 6. (a) The dataset that can not be separated by Linear regression (b) Three-dimensional view of data separation

Here we needed to select and cautiously tune our projection: on the off chance that we had not focused our outspread basis work in the right area, we could never have seen such spotless, straightly divisible outcomes as displayed in Figure 7(a). As a general rule, the need to settle on such a decision is an issue: we might want to some way or another naturally observe the best basis functions to utilize.

One procedure to this end is to process a premise work focused on each point in the dataset and let the SVM algorithm filter through the outcomes. This kind of basis function change is known as a kernel transformation, as it depends on a likeness relationship (or kernel) between each sets of points. An expected issue with this technique — projecting N points into N aspects — is that it could turn out to be computationally escalated as N develops large. Notwithstanding, in light of a perfect little methodology known as the kernel trick, a fit on bit changed information should be possible certainly — that is, while never constructing the full N-layered representation of the kernel projection! This kernel trick is incorporated into the SVM and is one reason the technique is so strong. We can apply kernelized SVM essentially by changing our linear kernel to a RBF (radial basis function) kernel, utilizing the bit model hyperparameter. Utilizing this kernelized support vector machine, we become familiar with a reasonable nonlinear choice limit. This kernel transformation procedure is utilized frequently in machine learning to transform quick direct techniques into quick nonlinear strategies, particularly for models in which the bit stunt can be utilized. Our conversation so far has based on extremely clean datasets, in which an ideal choice limit exists. However, imagine a scenario where your information has some measure of cross-over. For instance, the information is displayed in Figure 7(b).

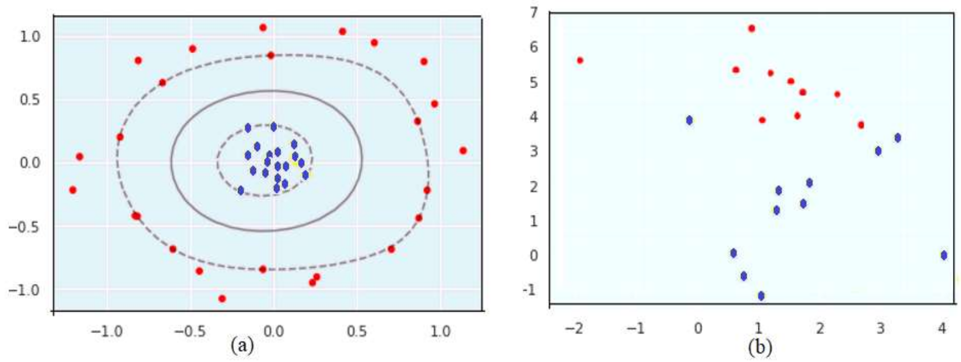

Figure 7(a)Expected projection (b)Crossover information

To deal with this case, the SVM execution has somewhat of a fudge factor that "softens" the edge: that is, it permits a portion of the points to creep into the margin assuming that permits a superior fit. The hardness of the margin is constrained by a tuning boundary, most frequently known as C. For extremely huge C, the margin is hard, and focuses can't lie in it. For more modest C, the margin is softer and can develop to incorporate a few places. The plot displayed in Figure 8 gives a visual image of what a changing C boundary means for the last fit, through the conditioning of the margin. The ideal worth of the C boundary will rely upon provided dataset and ought to be tuned utilizing cross-validation or a comparable system.

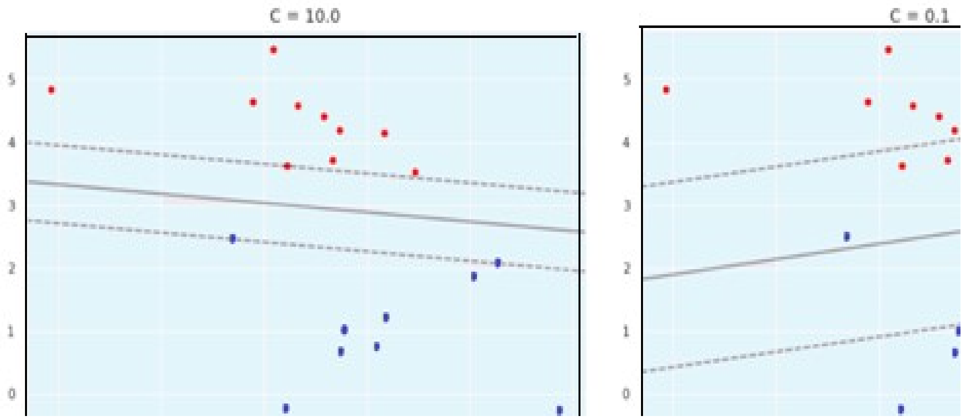

Figure 8. SVM execution for a fudge factor of (a) 10 (b) 0.1

4. Conclusion

In this paper, the necessity of integrating machine learning with the cognitive radio concepts, especially spectrum sensing is demonstrated. Support vector machine (SVM) method with Kernel transformation is considered to classify the primary users and secondary users from the energy detection spectrum sensing. The relevant mathematics is presented for Energy detection spectrum sensing as well as Linearly separable classification. Obtained results shown that the classification with SVM Kernel transformation has shown improved results.

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Data Availability:

No datasets are used in this paper.