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A Support Vector Machine with Elastic Net Regularization and Radial Basis Function based Spectrum Sensing for Cognitive Radio Networks

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***Abstract*—In recent years, communication technologies are growing significantly and Cognitive Radio (CR) networks is an expert system to adjust the radio spectrum. However, wireless communication diverse scenarios and distinguishing spectrum occupancy poses a significant challenge in Spectrum Sensing (SS). As it requires high-performance and flexible solutions to accommodate varied characteristics and ensure seamless connectivity. Hence, a Machine Learning (ML) based algorithm namely Support Vector Machine along with Elastic Net Regularization and Radial Basis Function (SVM-ENR-RBF) is proposed to detect and classify spectrum signals. Initially, the spectrum signals are collected from RadioML2016.10b dataset which are preprocessed by Min-Max scaler to normalize In-phase (I) and Quadrature Components (QC) of modulated signals. Finally, SVM classifier provides a regularization technique namely ENR and a kernel function RBF to make easier to analyze as well as classify the spectrum occupancy. The combination of SVM-ENR-RBF improves the detection accuracy, robustness and generalization capabilities. From the results, SVM-ENR-RBF method offers high results of probability of detection, prediction accuracy, and computation time results as 99.8%, 99.2%, and 1.6sec respectively when compared with existing Reinforced Learning-Extreme Learning Machine.**

***Keywords*—cognitive radio networks, elastic net regularization, machine learning, radial basis function, spectrum sensing, support vector machine.**

I. Introduction

In general, Cognitive Radio Networks (CRNs) utilize ML algorithms to detect Idle Frequency Bands (IFB) and optimize SS. It helps in enabling dynamic spectrum access and mainly divided into two types of users namely Primary Users (Pus) as well as Secondary Users (SUs). The Cognitive Radio (CR) operates under an overlay scheme, where users perform a listen-before-talk (LBT) procedure to sense the channel for interference-free usage before transmission, only transmitting when the channel is detected as idle [1]. However, they do not have limited spectrum usage rights. Here, SUs are also known as unauthorized users and utilize the spectrum together with PUs [2]. The rising of wireless communication containing developments in infrastructure, and emerging technologies crucially effects SS in CRNs. Here, SS is the process of detecting spectrum holes or IFB, enabling energetic spectrum access, and improved wireless network capacity [3]. The enabling effective reprocess refining wireless communication and rapidly increasing spectrum scarcity. Also, wireless device propagation and rising data rate demands increase spectrum scarcity, requiring innovative spectrum controlling results immediately [4].

The CR devices transmit their precisely estimated energy levels to the fusion center, enabling informed decision-making through data fusion and optimized spectrum sensing. The CR encounters a significant obstacle in the form of the Hidden Terminal Problem (HTP), which is exacerbated by shadowing and fading effects. These phenomena lead to false alarms and misdetection issues, resulting in interference to Pus. Here, augmenting SS in CR is dynamic for revealing effective spectrum utilization, and improve network capacity [5]. Similarly, a Dynamic Spectrum Access (DSA) systems control innovative devices to utilize provisional spectrum holes, easing scarcity and enhancing efficiency by reusing underutilized FB [6]. Furthermore, a Covariance Matrix-aware Convolutional Neural Networks (CM-CNN) influences general CM training samples to optimize constraints, creating a cultured SS mapping function and LSTM-ANN (Long Short-Term Memory-Artificial Neural Network) records multi-slot correlations, showing complex consecutive dependencies and patterns in dynamic spectrum access [7]. Additionally, K-means clustering and SVM algorithms utilize low-dimensional probability vectors as feature vectors, allowing effective spectrum categorizing and grouping [8].

- The spectrum signals are taken from input data and then preprocessed by using Min-Max scaler to normalize the In-phase (I) and Quadrature Components (QC) of modulated signals, where this transformation conserves the signal's distribution and relationships.
- The normalized data is processed with Elastic Net Regularization (ENR), as it robust feature selection, reduces overfitting, and remove irrelevant features.
- Finally, RBF transforms the processed non-linear data into a higher-dimensional space by creating it linearly

discrete and enables non-linear separation of spectrum states and achieved best results in detection probability, prediction accuracy, and computation time.

The construction of this paper is given as follows: section 2 describes about existing models along with their advantages and limitations, section 3 summaries the proposed methodology, section 4 demonstrates the experimental results, section 5 delivers a discussion of the results, section 6 concludes the paper.

II. Literature Review

Diego Fernando Carrera et al [9] demonstrated a Multilayer Extreme Learning Machine (M-ELM) to takeaway Multiple-input Multiple-output (MIMO) organisms for MilliMeter-wave (mmWave) organizations. The suggested M-ELM method augmented hidden layer neuron count to maximize system demonstration and minimize receiver problem in CR method. The M-ELM method crucially decreased processing time while conserving accuracy corresponding to ELM receivers, improving real-time CRNs performance. However, ideal performance required careful configuration of hidden layer neurons, striking a balance between model complexity and simplification.

Shanshan Wang et al [10] introduced an Online Sequential ELM (OS-ELM) for active intervention behavior in cognitive radar. The suggested OS-ELM method utilizes models namely such as OS-ELM Angle Prediction (OS-ELM-AP), Frequency Prediction (OS-ELM-FP) to calculate frequency and angle in cognitive radar, by permitting capable and accurate active interference calculation. The OS-ELM method demonstrated superior prediction accuracy with lower computational complexity, confirmed through simulations and measured interference data analysis. However, the OS-ELM method's efficiency was delayed by high computational complexities, regulating its suitability for dynamic interference prediction applications in real-time CRNs.

N. Sureka and K. Gunaseelan [11] developed Reinforced Learning (RL) and ELM (RL-ELM) to detect emulation attacks in dynamic CR-based wireless communication networks. By integrating RL with ELM led to rapid learning capabilities, RL-ELM effectively identifies and diminishes emulation attacks. The suggested RL-ELM efficiently traced and identified Primary User Emulation Attack (PUEA) patterns with minimal processing time and optimal accuracy. Here, RL-ELM algorithms, with reduced complexity, enhanced detection rates and suitability for dynamic CR environments by enabling real-time SS and efficient resource allocation. However, its dependence on ML algorithms controlled scalability and robustness along with introducing exposure to data quality, noise, and adversarial attacks.

S. Sindhuja et al [12] established a Global Channel State Information (GSCI)-Fuzzy ELM (GSCI-FELM) to diagnose local spectrum dumps and assign optimal channel to the Secondary User-Internet of Things (SU-IoT) devices effectively. The suggested GSCI-FELM identified the spectrum holes at SU-IoT, resolving PU identification by changing it into Idle Channel State (IDC) recognition and classification. The GSCI-FELM technique significantly minimized energy consumption in CR-IoT networks, achieved in reduction, and enhanced sustainability. However, it has limited improvement in accuracy and potential for further optimization in time-consuming and interference signal identification existed.

M. Varun and C. Annadurai [13] presented the two tier Learned Distributed Networking (LDN) framework for sensing the spectrum of cellular networks. The suggested LDN framework has two phases: first feature extractor phase where distinguished feature vectors were collected and next phase, Optimized ELM (O-ELM) used for evaluation. The LDN framework exceeded innovative O-ELM by achieving superior performance, it was enhanced accuracy, and reduced computational complexity for effective healthcare spectrum detecting in CRNs. However, the ELM's scalability was slowed down by its dependence on a limited dataset and simplistic features led to restricting its adaptability to complex and real-world CR environments.

III. Methodology

The proposed SVM-ENR-RBF methodology is done in four steps including first step, it begins with collecting spectrum signals from the RadioML2016.10b dataset, a complete repository of wireless communication signals. Then, in second step, the collected data given for preprocessing, where Min-Max scaling normalizes the In-phase (I) and Quadrature Components (QC) of modulated signals by enhancing data stability. Next, the normalized data is fed into an SVM classifier, authorized by ENR and RBF kernel. Then, this combination enables the SVM spectrum sensor to distinguish between occupied and unoccupied spectrum states, boasting excellent performance with high accuracy and detection probability. By using ENR's balanced regularization and RBF's non-linear separation capabilities, the proposed method enhances SS, making it a game-changer for effective spectrum consumption in CRNs. The block diagram in Fig. 1. displays the outline of proposed system.

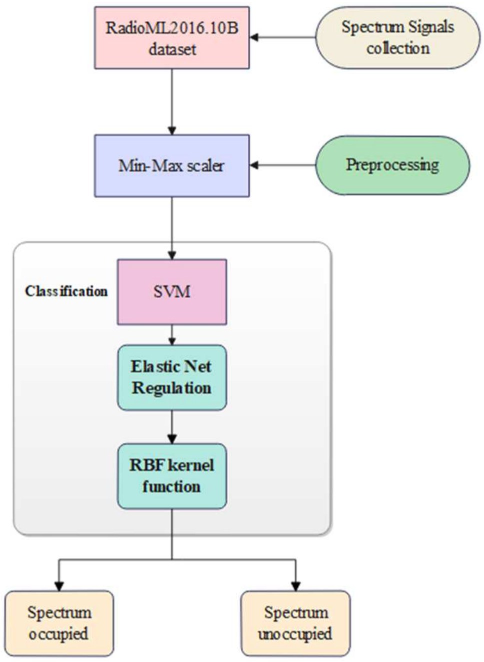

Fig. 1. Block digram of proposed model

A. Dataset

This SVM-ENR-RBF method utilizes the publicly available RadioML2016.10B dataset [14], generate by O'Shea and Corgan. This dataset consists of 10 modulated signal types namely 8 digital namely BPSK, QPSK,8PSK, QAM16, QAM64, CPFSK, GFSK, and PAM4. Also, 2 analog signals such as AM-SSB and AM-DSB modulations along with Signal-to-Noise Ratio (SNR) values, where it has range from -20 dB to +13 dB in 2 dB increments. This dataset is divided into two samples namely positive and negative, where positive samples includes 8 digital modulated signals and negative samples includes additive noise following the zero-mean Circularly Symmetric Complex Gaussian (CSCG)distribution. The dataset has 2×1024 time samples per signal, with I and QCs separated. The data is subdivided into training (70%), validation (15%), and testing sets (15%) to estimate the performance of the ML-based SS approach.

B. Preprocessing

For the proposed SVM-ENR-RBF method, preprocessing step applies new filtering and constrained techniques to improve the signals and SNR. It helps to remove transient peaks, eliminating anomalies and normalizing the data for effective analysis. Also, preprocessing ensures high-quality input data by improving SS and categorization tasks in CRNs [15]. For preprocessing the spectrum signals, Min-Max scaler is used to normalize the I and QCs of modulated signals. This scaler is taken from scikit learn library and the signals are denoted as composite valued time-series data, with 1024 samples per signal. Then, the scaler subtracts the minimum value and then divides the normalizing data by ranging 0 and 1 for each signal. This transformation conserves the signal's distribution and relationships by confirming the model learns from relevant designs rather than scale differences [16]. Here, preprocessed spectrum data is given as input into classification process to determine occupied or unoccupied status of spectrum with high accuracy.

C. SVM Classification

For classification process of proposed SVM-ENR-RBF method, the SVM [17] takes normalized signals as input and creates a linear hyperplane as a decision boundary by dividing two classes while augmenting the border or distance between the boundary lines. By exploiting this border, SVM improves the classification and efficiency in differentiating between classes by finding the best hyperplane which is able to reduce the risk of misclassification and improves overall classification accuracy. Here, SVM provides some regularization techniques namely Lasso Regression (LR), Ridge Regression (RR), ENR, and Dropout regularization (DR) [18] to decrease the feature quantity, scale and dropout features during the training period. Here, SVM classifier utilizes ENR and RBF, where ENR balances L1 and L2 penalties for thinly distributed and robust feature selection. While, the RBF kernel enables non-linear separation of spectrum states. Also, a two-class SVM model is modified by using the one-versus-rest method to overcome two-class classification problems. The optimum classification boundary is defined by the Equation (1) given below:

$$wx + b = 0 \tag{1}$$

Where, w is defined as weight vector acquired during training, x is an input vector, and b is the constant bias. Support vectors are identified as data points that satisfy Equation (2) below:

$$y(wx + b) = 1 \tag{2}$$

Where, $y\epsilon\{+1, -1\}$ represents the class label, w is weight vector, and b is bias. To classify the test observations, the decision function Equation (3) is employed.

$$f(x) = sign(wx + b) \tag{3}$$

Here, SVM kernel functions are used to convert input features into a higher-dimensional space by enabling linear categorization with a hyperplane, where patterns are non-linearly separable. This process is called as kernel trick, where it allows SVM classifiers to map non-linear relationships into linearly separable spaces efficiently leads to accurate classification. Also, SVMs provides three kernel functions namely linear, polynomial, and RBF. Here, the main objective is to increase the optimum hyperplane, as SVM ensures a strong classification and refinement between spectrum occupancy classes. However, the proposed SVM method influences the strengths of ENR and the RBF kernel function to classify spectrum occupancy.

1) Elastic Net Regularization: In this SVM-ENR-RBF method, ENR combines the benefits of L1 (LR) and L2 (RR) regularization techniques which are provided by SVM classifier. By combining these two consequent terms into loss function, ENR reduces overfitting, improve generalization and selects relevant features efficiently. Here, L1 term $(\lambda_1 \|w\| 1)$ groups irrelevant weights to zero stimulating sparse models and removing irrelevant features. Similarly, the L2 term $(\lambda_2 \|w\| 1)$ decreases the size of large weights by soothing the model and avoiding unnecessary weighting [20]. The loss function is given in Equation (4):

$$L(w, b) = {}^{1}/{}_{2}\,\|w\|^2 + C1 \sum|wj| + c2 \sum wj^2 \tag{4}$$

Where, $L(w, b)$ is loss function, $C1$ and $c2$ are regularization parameters and $\|w\|^2 = w.w$ control the two regularization strengths. The objective function to minimize for ENR is Equation (5):

$$minimize \sum_{i=1}^{m}(y_i - w.x_i - b)^2 + \propto \rho \sum_{j=1}^{n} + \frac{\propto(1-\rho)}{2} |w^2 j| \tag{5}$$

Where, y_i is the actual output, coefficients $w = w_1, w_2, \dots \dots w_n$ to minimize the residual data.

2) RBF kernel function: Then, RBF kernel is also named as the Gaussian kernel or squared exponential kernel and it is a common kernel function utilized in SVMs, Neural Networks (NNs) and other ML algorithms. Here, RBF transforms non-linear data into a higher-dimensional space by creating it linearly discrete. It also maps input data to a new feature space by using Equation (6):

$$K(E, y) = exp(-\gamma\|E - y\|^2) \tag{6}$$

Where, E is vector of energy statistic, y is the output vector, and γ is a constant.

In this SVM-ENR-RBF method, RBF kernel acquires complex relationships between SS features, by differentiating occupied and idle spectrum efficiently. This method improves robustness beside noise and intervention, improves reliability in energetic environments. Also, it enhances detection accuracy, classification effectiveness, improves spectrum utilization in CRNs, and flexible SS for next-generation wireless communication systems [21].

IV. Experimental results

This study aims to classify spectrum signals either spectrum occupied or unoccupied with SVM-ENR-RBF model which is implemented by a python package called Scikit learn. The experimental setup utilized Windows 10, intel core i5 CPU, 8 GB of memory and a 3.20 GHz processing speed. For evaluating, the results various metrics are used, such as prediction accuracy, probability of detection, and computation time are considered and described as Equation (7) to (9).

Where, TN and TP signifies true negative and positive, FN, FP refers false negative and false positive.

$$Prediction\ accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{7}$$

$$Probability\ of\ detection = \frac{Total\ no\ of\ Primary\ Users\ (PU)}{Total\ no\ of\ User\ (PU+Noise\ signals)} \tag{8}$$

$$Computation\ time = c1 * (n^2 * d + n^3) \tag{9}$$

A. Performance analysis

The proposed SVM-ENR-RBF model is analyzed on RadioML.2016.10b dataset. The performance evaluation is achieved by providing a regularization and a kernel function namely ENR and RBF respectively. For performance analysis, the proposed SVM model is compared with Random Forest-SS (RF-SS), K-Nearest Neighbor (KNN), and Artificial Neural Networks-SS (ANN-SS). The evaluation of SVM classification model is explained below in Table 1.

Table 1 describes comparison of proposed method with existing models, the results showcased that the SVM model's dominance in probability of detection 99.8%, prediction accuracy 99.2%, and computation time 1.6 sec as shown in Table 1.

TABLE I. PERFORMANCE ANALYSIS FOR CLASSIFICATION MODELS

Performance of existing models	Probability of detection(%)	Prediction Accuracy(%)	Computation time (sec)
RF-SS	98.3	98.7	8.3
KNN	97.8	98.4	5.0
ANN-SS	97.62	98.51	3.4
Proposed SVM model	99.8	99.2	1.6

B. Comparative analysis

The suggested SVM-ENR-RBF model is associated with Reinforced Learning (RL) and Extreme Learning Machine (RL-ELM) [11], Global Channel State Information (GSCI)-Fuzzy ELM (GSCI-FELM) [12], and Learned Distributed Networking (LDN) framework [13] with probability of detection, prediction accuracy and computation time which are given below in Table 2.

TABLE II. COMPARATIVE ANALYSIS OF PROPOSED MODEL

Comparative models	Probability of detection(%)	Prediction Accuracy(%)	Computation time (sec)
RL-ELM [11]	98.9	N/A	10.0
GSCI-FELM [12]	92.5	98.2	7.2
LDN framework [13]	99.0	99.0	N/A
Proposed SVM	99.8	99.2	1.6

From Table 2, the proposed SVM-ENR-RBF model offered high results of probability of detection, prediction accuracy, and computation time results with 99.8%, 99.2%, and 1.6 sec respectively by comparing with existing models namely RL-ELM [11], GSCI-FELM [12], and LDN framework [13]. The probability of detection of RL-ELM [11] is 98.9% along with its computation time 0.6 sec. Similarly, probability of detection, prediction accuracy, computation time of GSCI-FELM [12] is 92.5%, 98.2%, and 7.2 sec respectively. Moreover, at last compared with the LDN framework [13], where its probability of prediction is 99.0%, and prediction accuracy is 99.0%. Here, Table 2 showcasing the proposed model's effectiveness in detection and prediction tasks. It helps to improve detection accuracy, robustness to noise and enhanced simplification abilities.

V. Discussion

For efficient SS in CRN frameworks, an SVM-ENR-RBF model is proposed by manipulating the interaction of ENR and RBF kernel. The ENR balances L1 (LR) and L2 (RR) penalties efficiently by ensuring the robust feature selection though reducing overfitting. Moreover, the RBF kernel allows non-linear separation of spectrum occupancy either occupied or unoccupied by improving sensing accuracy. In augmenting the deal between regularization techniques and kernel parameters, the proposed SVM-ENR-RBF spectrum sensor achieved higher performance, by reaching 99.8% of detection probability, 99.2% of prediction accuracy, and a computation time of just 1.6 seconds only. This outperforms existing models, namely RL-ELM [11] (probability of detection is 98.9% along with its computation time 0.6 sec), GSCI-FELM [12] (probability of detection, prediction accuracy, computation time is 92.5%, 98.2%, and 7.2 sec respectively), and LDN framework [13] (probability of prediction is 99.0%, and prediction accuracy is 99.0%). It is showing that the proposed SVM-ENR-RBF model's excellent performance and effectiveness in detection and calculation tasks by improving detection accuracy, enhancing robustness to noise and intervention. This SVM-ENR-RBF model improved the generalization abilities diagonally in various situations, earlier processing time and decreased computational complexity. Also, it has a greater performance in low SNR atmospheres, and authenticating its prospective for real-world CR and wireless communication applications.

VI. Conclusion

In this, an ML based SVM-ENR-RBF model is proposed to accurately analyze and classify spectrum signals. This process begins with the collection of spectrum signals from the RadiML2016.10b dataset. Then, the spectrum signals are preprocessed by using Min-Max scaler to normalize the I and QCs of modulated signals. Next, the normalized data is given as input to SVM classifier. Here, SVM classifier provide ENR and RBF kernel, where ENR technique balances L1 and L2 penalties by ensuring robust feature selection and decreasing overfitting. Although, RBF kernel permits non-linear separation of spectrum either it is occupied or unoccupied states by improving the detection accuracy. By integrating SVM with ENR and RBF kernel, it has achieved an outstanding performance in probability of detection, prediction accuracy, and computation time with 99.8%, 99.2%, and a lightning-fast 1.6 seconds. This combination leads to improve in detection accuracy, toughness to noise and generalization abilities by creating it a perfect result for SS applications. It is trained on preprocessed SS data and achieved high accuracy in detection probability, differentiating spectrum occupancy with enhanced robustness to noise and interference, so augmenting spectrum utilization in CRNs. In future, an ML based spectrum sensing model will be developed to maximize the sensing capabilities of each CR user and improve overall sensing efficiency of the entire CRNs.

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