Efficient Spectrum Sensing using Robust Statistical Approach in Cognitive Radio Networks (CRNs)

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Abstract: Identification of spectrum holes in large frequency bands is quite important for primary users and Cognitive Radio Networks (CRNs) is a suitable approach for detection of spectrum holes and for efficient spectrum utilization. Moreover, one of the important feature of CRNs is spectrum sensing which detects presence or absence of primary user so that secondary user can switch to another frequency band in time. However, swift and accurate spectrum sensing is required due to change in frequency band occupation dynamically. Thus, a statistical model is presented to perform highly efficient spectrum sensing based on the probability density functions. The main focus of research is to enhance the sensing accuracy and spectrum detection results. Filtering mechanism is utilized to remove Gaussian noise present in received primary data samples. High Quality features are obtained based on the degree of randomness and classification is performed using Support Vector Machine (SVM) classifier. Simulation results are carried out in terms of detection probability and false alarm probability using two large datasets and compared with varied classifiers such as K- Nearest Neighbour (KNN) and Logistic Regression (LR).

Keywords: Spectrum Sensing, Sstatistical model, Support Vector Machine (SVM), Probability Density Function, Primary User (PU).

1 Introduction:

The demand of high data rate has massively enhanced in last few years. The mobile data requirements will enormously improve in next few years as well. Thus, internet service provider companies are facing critical challenge to fulfil mobile these high data expectations. As a result, the production of telecommunication devices and gadgets has amplified at a speedy rate in recent time. The high data rate demands can be met with 5-th generation cellular networks. Therefore, significant steps are needed to implement 5-G cellular services in real scenarios. Further, 5-G cellular networks are capable of handling large data rates with lightning speed and large coverage area [1]. However, high frequency band access is required to handle large data rates of 5-G cellular networks.

Recently, researchers have found out that mm-wave bandwidth spectrum can provide frequency from 30 GHz to 300 GHz. Thus, this large bandwidth spectrum can massively help 5-G cellular networks to meet enormous data requirement across the globe [2]. In comparison with available internet service providers, the capacity of mm-Wave systems is 200 times more and provides higher spectral efficiency. However, a survey conducted by U.S. Federal Communication Commission (FCC) has reported that the utilization of licensed spectrum is not at its full potential for varied frequency bands and geographical places [3]. The mm-wave frequency spectrum is a natural and limited resource. However, the congestion of wireless gadgets and devices has massively enhanced. Thus, Cognitive Radio Networks (CRNs) are the best solution for accessing spectrum.

Furthermore, spectrums are usually segregated into licensed and unlicensed frequency bands and all the channels come under licensed frequency bands can be accessible by licensed users. Further, the vacant channels of licensed bands are utilized by secondary users, if primary users are not accessing it. Thus, CRNs are a radio system, which can be easily configurable and learns from environment and effortlessly adjustable and can optimize network requirements and variable s. CRNs are highly reliable and can handle spectrum management efficiently. Therefore, the efficiency of spectrum utilization can be improved using Cognitive Radio Networks (CRNs). The main function of CRNs is spectrum access, spectrum sensing and spectrum handover. Spectrum sensing is the key function of CRNs to detect spectrum holes. This technique identifies occupied and vacant frequency bands in the large spectrum. Further, Primary Users (PUs) have license of a particular frequency band and from that licensed band, a certain portion of frequency bands is provided to Secondary Users (SUs). Further, interference between licensed primary users and unlicensed secondary users remains minimum by dynamic spectrum utilization using CRNs. Thus, cognitive radio networks have potential to handle spectrum utilization in an efficient manner and prove to be a crucial technology to enhance spectrum utilization efficiency of future wireless communication networks [4-5].

Spectrum sensing is also utilized to observe activation of primary users and when they require their spectrum back, handover process is performed. As a result, unlicensed secondary users need to vacate their occupied frequency band. Then, that frequency band is occupied by licensed primary user. CRNs has the potential to switch between varied portions of frequency bands [6]. Moreover, PUs and SUs co-exist in cognitive radio networks. Further, CRNs is used to perform varied tasks like spectrum access, spectrum sensing, spectrum observation and spectrum selection based on the observations made. The significance of Spectrum sensing (SS) in CRNs is massive due to detection of spectrum holes. However, continuous sensing and observation of licensed channels till CRNs find a channel, can cause shadowing effect and channel fading. As a result, spectrum efficiency becomes lower and computational complexity get enhanced. Thus, spectrum sensing in CRNs has become an essential research area for efficient spectrum utilization. Besides, several researchers have provided their efforts to improve spectrum utilization using CRNs using traditional signal processing techniques to analyse and sense spectrum. However, performance efficiency is affected by model uncertainties in the traditional signal processing methods [7]. Although, deep learning frameworks and machine learning techniques can efficiently identify vacant and occupied bands of spectrum by exploiting data samples. High-quality training is performed based on the captured data to examine and analyse environment conditions and generate better yield. Thus, these techniques have great potential to provide sophisticated solutions for the issues faced in CRNs.

Therefore, in this article, a statistical model is adopted to improve efficiency of spectrum sensing in Cognitive Radio Networks (CRNs). The proposed statistical model improves detection accuracy and reduces noise. The focus of this research work remains on spectrum sensing and spectrum analysis based on the detection probability and Gaussian errors are reduced using proposed statistical model which works on the principle of probability density function. The proposed statistical model shows robust behaviour towards noise and sensing accuracy based on probability density function. A high quality training is performed on varied performance metrics using proposed statistical model. Further, a detailed training on received samples is performed and efficient features are estimated using proposed statistical model. Here, the received signal analysis is carried out using proposed statistical model. The performance efficiency is evaluated in terms of detection probability, false alarm and Signal to Noise Ratio (SNR) using two real world datasets and compared against various classifiers such as support vector machine and k-nearest neighbour.

This paper is organized in following style which is discussed below. In Section 2, the literature survey related to spectrum sensing in Cognitive Radio Networks based on statistical model, their issues and solutions to eliminate these issues with the help of proposed statistical model. In Section 3, the methodology related to spectrum sensing in CRNs. Section 4 discusses about simulation results and their comparison with traditional spectrum sensing techniques and section 5 concludes the paper.

2 Related Work:

The high data rate demands across all over the globe has cause a certain panic for cellular service providers. Implementation of high speed future cellular networks in real-time is a massive challenge. Thus, mm-Wave system is a best possible solution for achieving high data rates due to their bandwidth spectrum. However, due to path attenuation and channel interference, direct access of mm-wave system is a critical process. Thus, Cognitive Radio Networks (CRNs) are adopted to handle these spectrum problem and to improve spectrum utilization efficiency by sensing occupied and vacant channels efficiently. Several researchers have presented their ideas and overviews about issues in CRNs. Varied architectures and supervised learning methods are presented which discusses about spectrum sensing in CRNs. Some of the related works are discussed in the following paragraph. A robust spectrum sensing technique is adopted to analyze basic functionalities of cognitive radio network in [8]. The Cognitive Radio enabled Internet of Things (IoT) system is presented to design a spectrum sensing technique. The CL enabled IoT method improves network efficiency by minimizing noise components. A detailed comparative analysis is presented in terms of detection performance and computation complexity. A Cooperative Spectrum Sensing [9] technique is adopted to enhance sensing accuracy based on the Reinforcement Learning. Here, centralized training features are computed to detect spectrum and improve training efficiency. A deep deterministic policy gradient reduces synchronization and communication overhead. Simulation results are obtained in terms of sensing accuracy. A Hybrid Matched Filter [10] is adopted to sense spectrum based on Monte Carlo simulations. The simulation results are obtained in MATLAB and results are computed in terms of probability of false alarm, the signal-to-noise ratio (*SNR*) against total number of samples. A study on Energy Detection mechanism is conducted to achieve probability of false alarm. A Spectrum Sensing technique is introduced in CRNs to improve spectrum utilization efficiency under varied noise environments [11]. Additionally, a non-linear combining scheme is adopted to evaluate performance of CRNs in terms of probability density function. The spectrum detection accuracy is enhanced than the conventional spectrum methods. In [12], a Kernel Least Mean Square Algorithm is presented to sense spectrum in Cognitive Radio Networks (CRNs). A novel cyclostationary method is adopted to generate weights. The proposed spectrum sensing method is used to measure detection probability and compared against varied spectrum sensing methods. A soft decision algorithm is introduced in [13] to improve spectrum utilization efficiency in CRNs based on machine learning algorithms. Power Spectral Density is classified using Cooperative Spectrum Sensing to estimate statistical characteristics. The soft decision algorithm is compared against SVM linear algorithm. In [14], a Prediction-Driven spectrum sensing algorithm is introduced to reduce energy consumption of cognitive radio networks. A parallel fusion model is presented to perform sensing operations based on local cooperative estimation model. Simulation results improve spectral efficiency of Prediction-Driven spectrum sensing algorithm. In [15], a Cognitive Sensor Network is presented to analyse global probability of detection based on spectrum sensing. Experimental results are evaluated in terms of detection probability and false alarm probability. Statistical analysis is performed to enhance network lifetime based on cumulative density function.

However, still a significant improvement is required in terms of spectrum detection accuracy and detection probability. Further, challenges like interference, low classification accuracy and higher computational complexity have reduced efficiency of spectrum detection. Therefore, proposed statistical model is adopted to improve efficiency of spectrum sensing in Cognitive Radio Networks (CRNs). A comprehensive mathematical modelling of the proposed statistical model is presented in the next section.

3 Modelling for Spectrum Sensing using Proposed Statistical Model:

This section discusses about the mathematical representation of proposed statistical model to perform spectrum sensing in Cognitive Radio Networks (CRNs). The main focus area of this work is to improve efficiency enhancement of spectrum detection. Further, identification of accurate spectrum bands is essential to distinguish between occupied and vacant bands. Besides, observation for activation of primary users is essential to handover spectrum from secondary users. The proposed statistical model performs high quality training on large datasets and eliminates noise and improves detection accuracy efficiently. Figure 1 demonstrates working procedure of Cognitive Radio Networks (CRNs) in which spectrum analysis, channel detection, resource handling and spectrum handling are the key works. Here, channel detection block consists of spectrum sensing and spectrum prediction sub-blocks. Further, spectrum estimation and spectrum sensing is performed to evaluate vacant and occupied

frequency bands using proposed statistical model. A comprehensive mathematical modelling of proposed spectrum sensing model is presented in following paragraph.

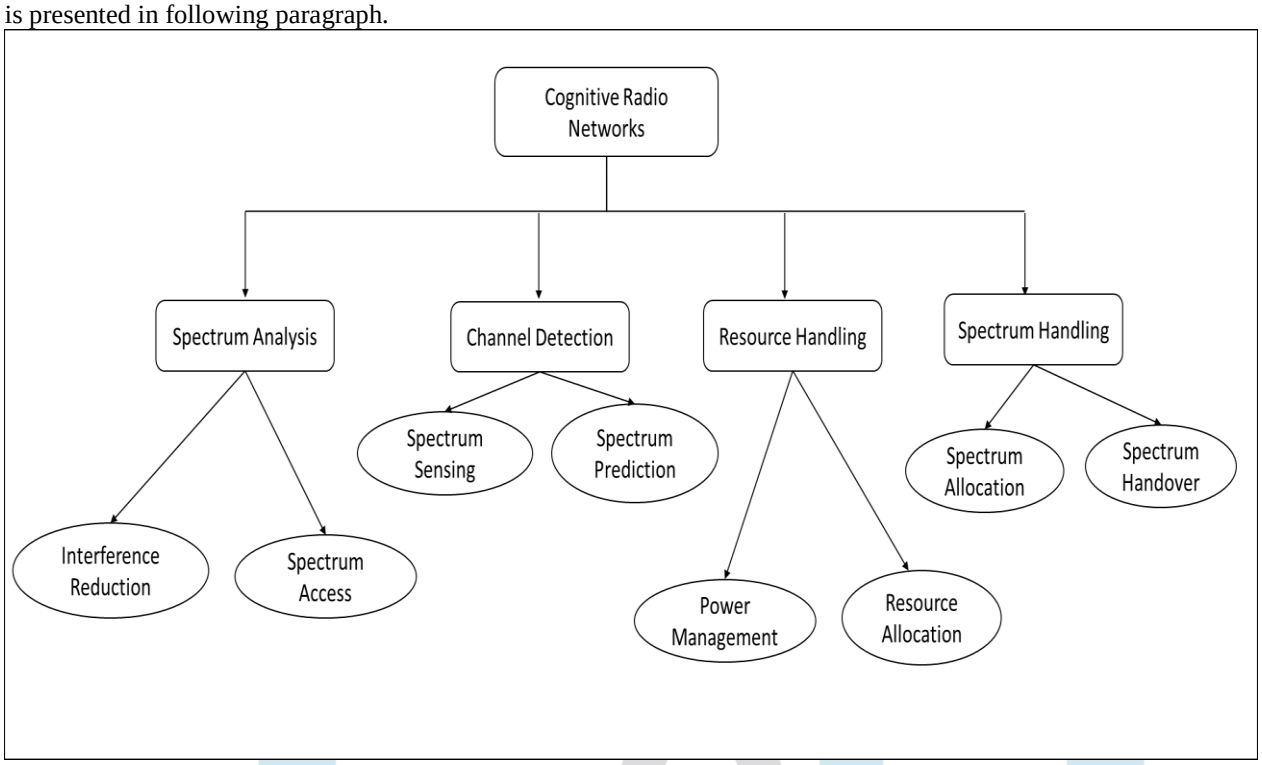


Figure 1 Working Model of Cognitive Radio Networks (CRNs)

3.1 Review of Energy detection based Spectrum Sensing Model:

Cognitive Radio Networks (CRNs) consists of different users such as Primary Users (PUs) and Secondary Users (SUs). Spectrum Sensing is key part of CRN and spectrum sensing provide information related to the spectrum availability and different environment scenarios. However, a key challenge in CRNs is identification of primary user's presence in a licensed spectrum so that second users can vacant their frequency bands immediately and switch to another frequency band to avoid any kind of interference towards primary users. This is main concept of spectrums sensing and spectrum sensing is an essential step for spectrum utilization to their full potential. Further, Spectrum sensing is majorly evaluated using energy detection model and details of energy detection model is given in the following paragraph.Energy detection based spectrum sensing model is massively utilized due to their low complexity design. Prior knowledge regarding primary samples is not required in this model which is a major advantage of this model. In this energy model, the detection of spectrum take place using pre-defined threshold value. Threshold value is computed based on the noise levels. Then, obtained energy is compared against pre-defined threshold value and based on the output, the presence of primary user is decided. Here, two type of decisions are taken in which first decision provide information related to absence of primary user and second decision gives information regarding presence of primary user. First decision is denoted by L_o and second decision is expressed by L_1. Based on channel conditions and environmental scenarios, threshold value is selected and an essential decision is taken that whether to keep fixed threshold or variable threshold. Here, signal presence is estimated based on the comparison of pre-defined threshold against received energy. The pre-defined threshold is evaluated based on the noise statistics. Thus, detection of primary signal's availability using spectrum sensing is given by following equation,

$$L_0 : C(d) = B(d) : Primary\ User\ Absent$$
$$L_1 : C(d) = B(d) + F(d) : Primary\ User\ Present \quad (1)$$

Where, $F(d)$ is expressed as the transmitted signal of primary user and received samples by secondary user are given by $C(d)$ and Gaussian noise is denoted by $B(d)$ with zero mean. In this energy detection model, the received signal is filtered to eliminate noise using band pass filter. Then, the obtained filtered output is fed to analog to digital convertor block. Then, the resultant output is squared first and then squared output is integrated in a fixed time-period. Then, the resultant output is utilized to form a test signal. Thus, formulated test signal is given by following equation,

$$E = \sum_{d=0}^{D} |C_d|^2 \quad (2)$$

Where, the number of samples utilized for spectrum detection based on spectrum sensing model as $d = 0,1,2,3, \ldots . D$ and in a statistical distribution E considering D number of samples, the test distribution is modelled according to the Gaussian distribution. Then, this hypothesis is simplified as follows,

$$\begin{cases} L_0 : E \sim Norm\left(D\rho_d^2 + D2\rho_f^4\right) \\ L_1 : E \sim Norm\left(\rho_d^2 + \rho_f^2\right), 2N\left(\rho_d^2 + \rho_f^2\right)^2 \end{cases} \quad (3)$$

Where, signal variance and noise variance is denoted by ρ_f^2 and ρ_d^2 , respectively. Then, the received test signal E is compared against prefixed threshold Ψ to check availability of primary signal. Thus, performance of energy detection model is assessed based on comparison results of test signal and threshold value. Thus, spectrum sensing is evaluated based on the crucial parameters such as probability of detection S_g, false detection probability S_h and missed detection probability S_i which is expressed in following equations,

$$S_g = S\left(E > \frac{\Psi}{L_1}\right) = k_R(r)\left(\frac{\Psi - D\left(\rho_d^2 + \rho_f^2\right)}{\sqrt{2D\left(\rho_d^2 + \rho_f^2\right)^2}}\right) \quad (4)$$

$$S_h = S\left(E > \frac{\Psi}{L_0}\right) = k_R(r)\left(\frac{\Psi - D(\rho_d^2)}{\sqrt{2D}\rho_d^4}\right) \quad (5)$$

$$S_i = 1 - k_R(r)\left(\frac{\Psi - D\left(\rho_d^2 + \rho_f^2\right)}{\sqrt{2D\left(\rho_d^2 + \rho_f^2\right)^2}}\right) \quad (6)$$

Where, $k_R(r)$ is expressed as a Gaussian distribution Model and in this way, presence of primary user is detected in the spectrum using energy based spectrum sensing model. Thus, energy detection based spectrum sensing model is massively utilized due to their simplicity. However, the main limitation of this energy based spectrum sensing model is performance becomes inferior at lower Signal to Noise (SNR) values. Similarly, matched filter detection based spectrum sensing has their own issues such as required prior information regarding samples of primary user and also need a strong synchronization between primary and secondary users. Thus, to overcome this issues, the proposed statistical model based spectrum sensing is utilized to detect presence of primary users based on the integration of essential modifications in energy detection model. Thus, proposed statistical model in the following section.

3.2 Spectrum Sensing Estimation using proposed statistical model:

A cognitive radio networks (CRNs) is considered with Q number of observations. This observations are generated from a transmitter of Primary User (PU). The PU transmitter works in a specific frequency band. Consider that the received data samples are equally distributed and remain independent in nature based on null hypothesis. The proposed statistical model based spectrum sensing model follows a Gaussian Distribution Model (GDM). Here, GDM contains shape and scale variables where shape variable is denoted by β and scale variable is denoted as δ. Further, shape variable ranges from $\beta \in (0,2]$ and scale variable remains always positive. Then, the probability of density function is denoted as $k_R(r)$ and represented by the following equation,

$$k_R(r) = \left(2\delta\aleph\left(\frac{1}{\beta}\right)\right)^{-1} \exp\left(-\frac{|R|^\beta}{\delta}\right), \ R \in \mathbb{T} \quad (7)$$

Moreover, statistics related to the received data samples are considered as unknown based on alternate hypothesis and mainly depends on the samples of primary users (PUs) and wireless network scenarios. Then, the main contribution of this research work is to construct quality features so that efficient classification of received data samples is performed based on the proposed statistical model. Further, threshold value is evaluated based on the probability density functions. Moreover, this concept is utilized to eliminate uncertainties present in the GDM and it evaluates probability of density based on the determined threshold. Thus, degree of randomness value $m(Y)$ of a parameter Y with a probability density function $k_Y(y)$ in the interval $(-\infty, \infty)$is evaluated by following equation,

$$m(Y) = -\int_{\infty}^{\infty} k_Y(y)\log\left(k_Y(y)\right).dy \quad (8)$$

Where, the probability density function of Y is given by $k_Y(\cdot)$ and the statistics regarding degree of randomness and energy variables remains relatively higher when receiver data samples remains unknown based on alternate hypothesis than in

comparison with independent and equal distribution based null hypothesis. Thus, the degree of randomness for continuous distribution is estimated by following equation,

$$m(R) = (\beta)^{-1} - \log\left(\frac{\beta}{2\delta\aleph(1/\beta)}\right) \quad (9)$$

Where, likelihood estimates of variable δ present in equation (6) is estimated with respect to variable β by following equation as,

$$\hat{\delta} = \left[\frac{\beta}{Q}\sum_{j=1}^{Q}\left|R_j - \hat{R}\right|^{\beta}\right]^{1/\beta} \quad (10)$$

Then, obtained features constructed from receiver data samples are represented by their maximum likelihood approximations using following equation,

$$\widehat{m}(R) = (\beta)^{-1} - \log\left[\beta.\left(2\aleph\frac{1}{\beta}\right)^{-1}\right] + (\beta)^{-1}\log\left[\beta.(Q)^{-1}\sum_{j=1}^{Q}\left|R_j - \hat{R}\right|^{\beta}\right] \quad (11)$$

Where, variable $\beta \in (0,2]$ is utilized to control Gaussian Distributed Noise and R_j is represented as the $j-th$ received data sample and average of received data samples is denoted as $\hat{R}$ and j is defined as the $j = 1,2,3 \ldots\ldots\ldots\ldots, Q$. Then, mean received data samples are represented by following equation,

$$\hat{R} = (Q)^{-1}\sum_{j=1}^{Q} R_j \quad (12)$$

Where, noise variance of Gaussian distribution is given by ρ_d^2 and then the scale variable is defined by following equation,

$$\delta = \left(\frac{\rho_d^2\aleph(\beta)^{-1}}{\aleph\left(\frac{3}{\beta}\right)}\right)^{1/2} \quad (13)$$

Where, Gaussian distribution is performed by keeping variable β as $\beta = 2$. Based on the hypothesis of Gaussian distribution model, obtained features obtained provide efficient performance by keeping variable β as 2. Then, hypothesis of Gaussian distribution model is analyzed based on a degree of randomness and so that given data samples belongs to $k_Y(\cdot)$ or not is identified,

$$\widehat{m}(R) > \varphi \quad (14)$$

Where, φ is defined as the selected threshold identifier which is selected appropriately based on the decision statistics and noise level of the received signal for detection of primary users and $\widehat{m}(R)$ provide information related to degree of randomness considering continuous distribution. By placing $\beta = 2$ in equation (3), we get the following equation,

$$\widehat{m}(R) = \frac{1}{2} - log\left[\frac{1}{\aleph\left(\frac{1}{2}\right)}\right] + \frac{1}{2}log\left[\frac{2}{Q}\sum_{j=1}^{Q}\left|R_j - \hat{R}\right|^2\right] > \varphi \quad (15)$$

Then, equation (7) is further simplified by following equation,

$$\widehat{m}(R) = \frac{1}{Q}\sum_{j=1}^{Q}\left|R_j\right|^2 > \varphi \quad (16)$$

Consider that $\mathbb{A}R = 0$ and provide statistical information related to spectrum sensing decision. Thus, performance is evaluated based on the obtained decision matrix from obtained features using proposed statistical model. Then, the probability of false alarm is given by following equation with respect to shape variable β and scale variable δ,

$$S\{\hat{\delta}^{\beta} > R\} = 1 - \frac{\Omega\left(\frac{Q}{\beta}, \frac{rQ}{\beta\delta^{\beta}}\right)}{\aleph\left(\frac{Q}{\beta}\right)} \quad (17)$$

Then, equation (10) is further simplified in following equations as,

$$S_k = S\{\hat{m}(R) > \varphi | R\} \quad (18)$$

$$S_k = S\left\{(\beta)^{-1} - \log\left[\frac{\beta}{2\aleph(1/\beta)}\right] + \frac{1}{\beta}\log(\hat{\delta}^{\beta}) > \varphi\right\} \quad (19)$$

$$S_k = S\left\{\hat{\delta}^{\beta} > \exp\left[\beta_{\varphi} + \beta\log\left(\frac{\beta}{2\aleph(1/\beta)}\right) - 1\right]\right\} \quad (20)$$

Therefore, using false detection probability and probability of detection parameters, the efficiency of proposed statistical model is evaluated.

4 Result and Discussion:

This section discusses about the performance analysis of proposed statistical model based spectrum sensing model to efficiently utilize spectrum and detect presence of primary users. The proposed statistical model is used to evaluate threshold value and perform comparison between degree of randomness and evaluated threshold value. Performance is massively enhanced using proposed statistical model by adopting highly efficient training on large datasets. A modelling review on traditional energy detection model is presented to detect occupied and vacant frequency bands and some modifications are integrated to improve spectrum detection accuracy based on degree of randomness. The proposed SM model enhance performance of spectrum sensing in cognitive radio networks. Performance of proposed statistical model is analyzed in terms of probability of detection, Signal to Noise Ratio and Probability of false alarm against traditional energy detection model.

Threshold statistics are computed using proposed statistical model and based on degree of randomness, the spectrum detection accuracy is enhanced and Gaussian distribution model is utilized to evaluate primary signal's presence or primary signal's absence. Here, two classes are evaluated to classify received data samples in which class with zero value shows absence of primary user and class with one value shows presence of primary user. Class evaluated using proposed statistical model consists of error variables and accurately estimated variables. Classification classes are evaluated based on the critical threshold to perform spectrum detection. The proposed statistical model based spectrum sensing model is mainly function into three steps. Here, first step is pre-processing based on filtering mechanism to eliminate noise and structured data is prepared for efficient training. Second step is data processing and computation of feature weights from the received data. Third step is classification based on evaluate feature weights to distinguish between primary user presence and primary user absence in terms of probability of detection and false detection probability. Key steps are summarized in the following paragraph to detect primary user's availability.

1. For each data sample, probability of detection is determined for varied SNR values and classes are constructed.
2. For both classes (primary user presence class and primary user absence class) critical threshold is determined based on the probability density functions.
3. Adaptive filters are utilized to pre-process received data and gather data in a structured way after noise elimination.
4. Feature weights are computed using proposed statistical model based spectrum sensing.
5. Mean feature weights are evaluated and based on this feature weights, data is classified in form of detection probability.
6. Performance metrics are computed in terms of false probability and probability of detection.

4.1 Dataset Details:

Performance is analyzed for proposed statistical model based spectrum sensing model using cognitive radio (CR) dataset captured at a primary user (PU) frequency as 2.48 GHz [16]. A primary transmitter is utilized with a transmission rate of 500 kbps and data is captured using a differential phase shift modulator with 1 MHz transmission bandwidth. A discrete Fourier transform is utilized with 1024 frequency bins. A Gaussian distribution model is employed with variance and multiple parameters. Finally, real world data is gathered from the installed CR nodes. Another dataset is utilized to assess performance of proposed statistical model based spectrum sensing model. This dataset is gathered from a laboratory present in Thailand [17]. The data of cognitive radio system is gathered using an unidirectional antenna. This antenna is linked with RF Explorer spectrum analyser. Central frequency of primary user is 650 MHz and the range of operating frequency to capture data is 510 to 790 MHz and data is captured from three unlike places and data is captured from indoor and outdoor scenarios. Data is gathered at higher values of signal-to-noise ratio (SNR).

4.2 Varied Classification Methods:

This section provide details of varied classifications methods such as logistic regression (LR), support vector machine (SVM), K-nearest neighbour (KNN) and random forest (RF).

i. K-nearest neighbour (KNN):

K-nearest neighbour is a supervised classification model and based on Euclidean distance, classification is performed in this KNN model. This model utilizes testing and training data of nearest neighbours to evaluate classification accuracy. For a given data sample, distance is evaluated between specific points and training points. Classification is performed by assigning labels in an underlying set and provides good performance based on the training classes.

ii. Logistic Regression (LR):

Logistic Regression (LR) technique utilizes multiple variables to examine large data present in the dataset and this variables remain independent in nature. This technique classifies input data samples by cost function minimization to fit into linear regression model. Further, the cost function is minimized using gradient coefficients. Feature weights are used to estimate class of test data samples.

iii. Support Vector Machine (SVM):

Support vector machines (SVM) is a supervised learning model used for classification of test data samples in binary form [18]. For a given dimensional vector data in fixed set, classification is performed on testing data samples. Thus, classification accuracy is obtained based on hyperplane of two separate classes. Higher-order features are generated to improve classification accuracy based on efficient SVM training model using varied kernels such as quadratic kernel or linear kernel etc.

4.3 Comparative Analysis:

This section discusses about the comparison analysis of proposed statistical model based spectrum sensing model against classical energy detection based spectrum sensing model in terms of false detection probability and probability of detection. Classification is performed based on the obtained features and compared against varied supervised learning based classifier models such as LR, SVM and KNN. Features are generated from two different Cognitive Radio datasets and classification is performed on those obtained features. It is analysed from performance results that classification accuracy is quite higher in case of Support vector machines (SVM) classifier than other varied classifiers.

Table 1 demonstrates performance comparison in terms of Probability of Detection values considering varied values of β using proposed statistical model based spectrum sensing model. The proposed SM utilizes SVM classifier to evaluate classification accuracy of proposed statistical model against classical supervised learning based KNN and LR classifiers. Probability of Detection values are determined by taking mean of nine different values obtained from training of KNN, LR and SVM models taking SNR from -20 dB to 0 dB with an interval of -2 dB and this values are obtained by using data samples of CR Dataset-1. SVM classifier based on proposed proposed statistical model outperforms both traditional KNN and LR classifiers. It is examined that SVM model performs slightly better in terms of PD values for different δ values and it is also observed that increase in β value, can decrease PD results. Thus, PD results is inversely proportional to β values.

Figure 2 shows graphical representation for performance of proposed statistical model based spectrum sensing using SVM classifier with varying β values considering dataset 1. The graph is plotted between probability of detection against varied β values while keeping SNR as -5 dB, -10 dB, and -15 dB and it is analysed from graphical results that performance is quite higher for lower β values and the increase in β values, reduces detection probability. Here, detection probability is measured for varying β values which ranges from 0.5 to 2 with an interval of 0.5 and the performance is measured considering CR dataset

Table 1 Comparison of Probability of Detection values for different values of δ using CR Dataset-1

Classification Algorithms	β		
	0.5	1	2
KNN	0.9925	0.8775	0.8124
LR	0.9930	0.8831	0.8148
SVM	**0.9966**	**0.9693**	**0.8722**

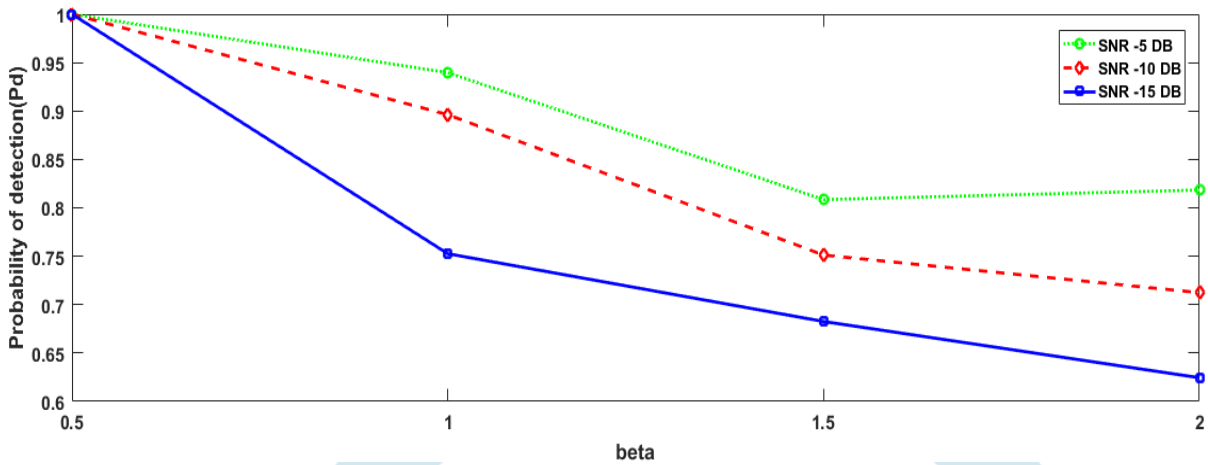


Figure 2 Performance of proposed statistical model based spectrum sensing using SVM classifier with varying β values considering CR dataset-1

Figure 3 shows graphical representation for performance of proposed statistical model based spectrum sensing using SVM classifier with varying SNR values ranges from -25 dB to -10 dB with an interval of -5 dB considering CR dataset 1. The graph is plotted between probability of detection against varied SNR values while keeping fixed $\beta = 1$ and it is analysed from graphical results that performance is quite higher in case of SVM in comparison with KNN and LR classifiers. The performance of detection probability shows better results for lower SNR values.

Similarly, Figure 4 shows graphical representation for performance of proposed statistical model based spectrum sensing using SVM classifier with varying SNR values ranges from -20 dB to 0 dB with an interval of -2 dB considering CR dataset 1. The graph is plotted between probabilities of detection against varied SNR values while keeping fixed $\beta = 2$. It is evident from performance results that the performance of SVM is higher than its counterparts in terms of detection probability.

Similarly, Figure 5 plots a graph of SVM classifier with varying SNR values ranges from -20 dB to 0 dB with an interval of -2 dB considering CR dataset 1. The graph is plotted between probabilities of detection against varied SNR values while keeping fixed $\beta = 0.5$. The graph is plotted against traditional classifiers KNN and LR. It is evident from performance results that the performance of SVM is higher than its counterparts in terms of detection probability. The detection probability shows best results when β value is fixed at $\beta = 0.5$.

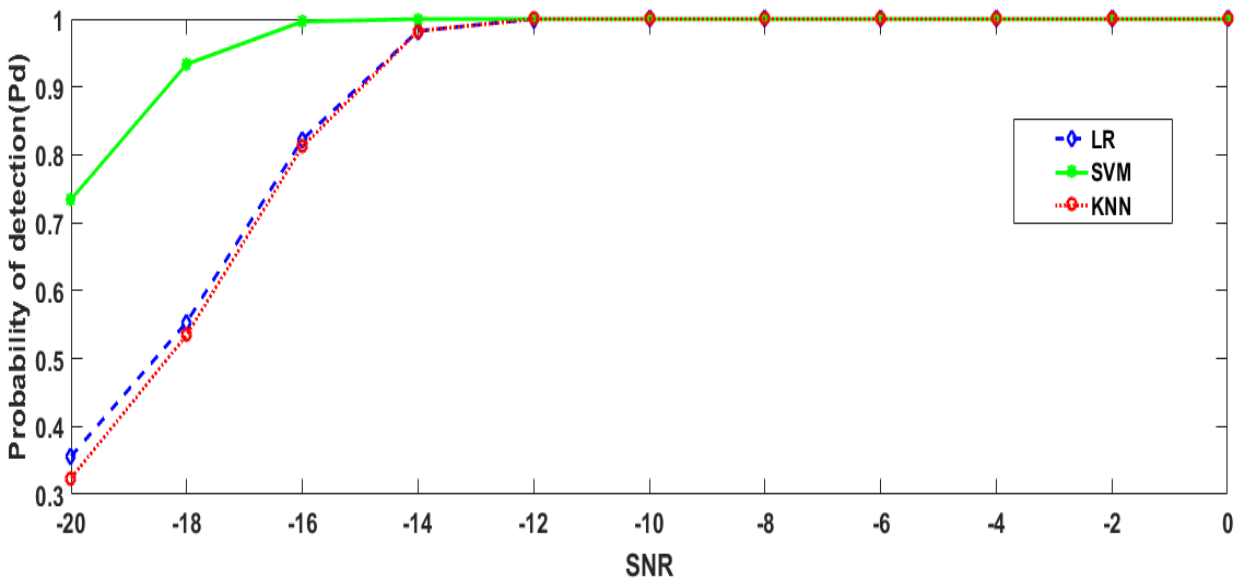


Figure 3 Performance of proposed statistical model based spectrum sensing using SVM classifier is compared against different classifiers with varying SNR values considering CR dataset-1 at $\beta = 1$

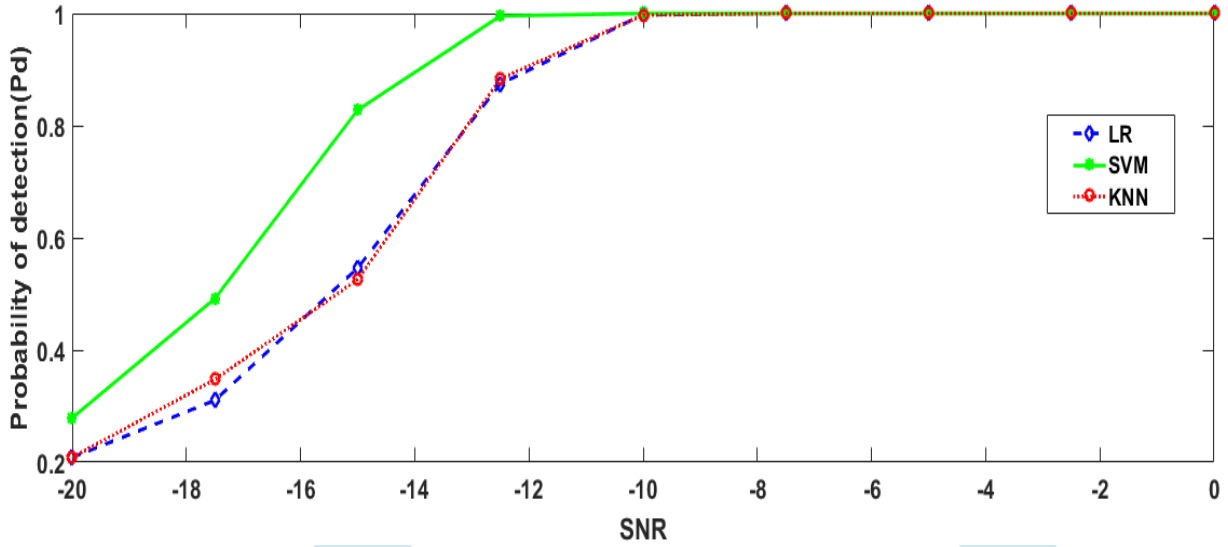


Figure 4 Performance of proposed statistical model based spectrum sensing using SVM classifier is compared against different classifiers with varying SNR values considering CR dataset-1 at $\beta = 2$

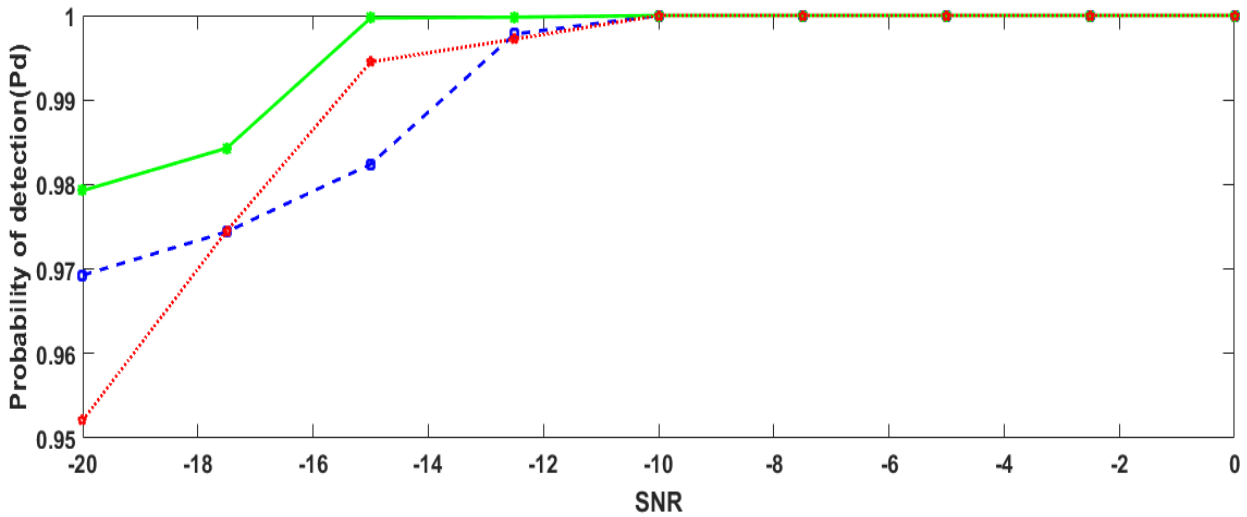


Figure 5 Performance of proposed statistical model based spectrum sensing using SVM classifier is compared against different classifiers with varying SNR values considering CR dataset-1 at $\beta = 0.5$

Figure 6 plots a graph of proposed statistical model against traditional energy detection model in terms of probability of false alarm against probability of detection considering CR dataset 2. It is evident from performance results that the performance of proposed statistical model is significantly higher in comparison with energy detection model for spectrum sensing.

Figure 7 shows a graphical representation of probability of false alarm against probability of detection using SVM classifier based on proposed statistical model against KNN classifier considering CR dataset 2. It is evident from performance results that the performance of SVM classifier is significantly higher in comparison KNN classifier.

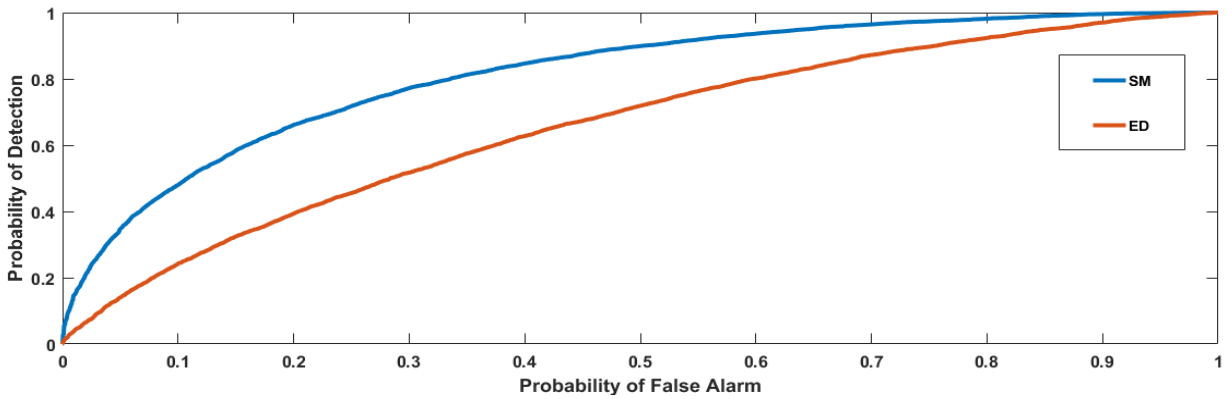


Figure 6 Comparison of Proposed Statistical Model in terms of probability of false alarm against probability of detection

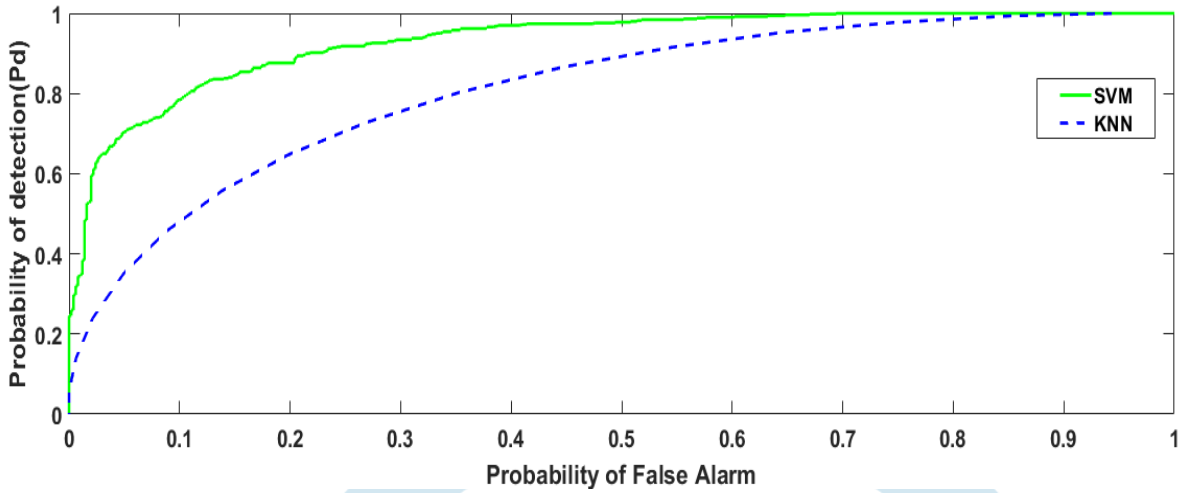
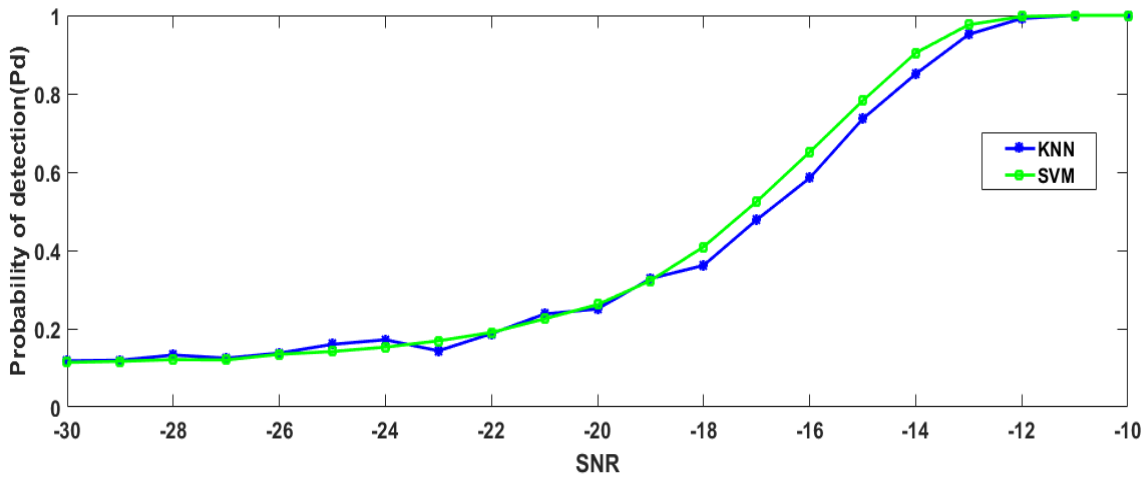


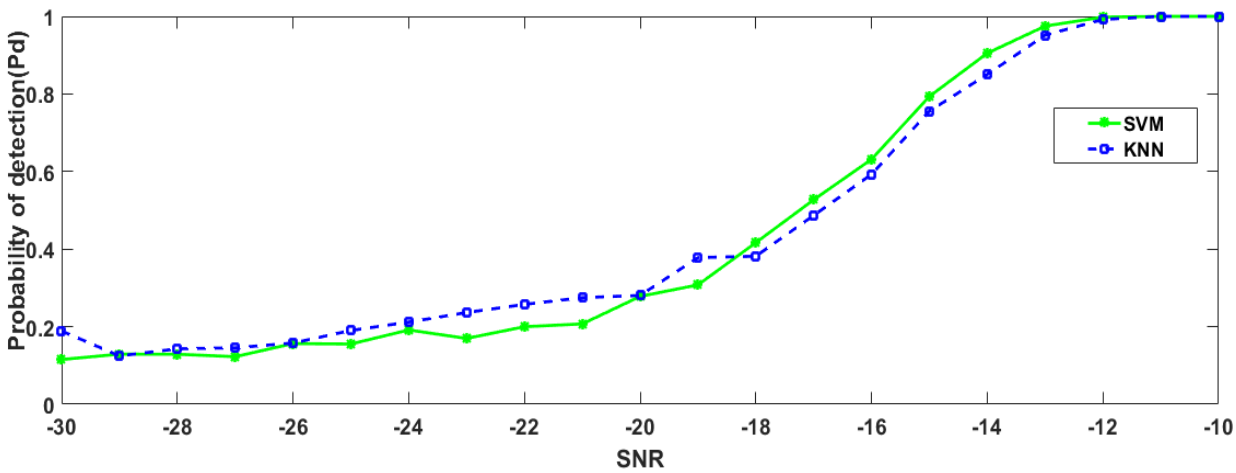
Figure 7 Performance Analysis of proposed Statistical Model based spectrum sensing model considering CR dataset-2

Table 2 demonstrates performance analysis in terms of Probability of Detection values considering varied SNR values using CR Dataset-2 and Probability of Detection values are determined using proposed Statistical Model taking SNR from -30 dB to -10 dB with an interval of -2 dB and this values are obtained by using data samples of CR Dataset-2. Figure 8 (A), Figure 8 (B) and Figure 8 (C) shows plot of detection probability for different SNR values considering β values as 1.5, 1 and 0.5, respectively. Finally, Figure 8 (D) shows a plot between detection probabilities against different β values while SNR is fixed at -30 dB, -20 dB, and -10 dB and proposed Statistical Model outperforms traditional spectrum sensing methods.

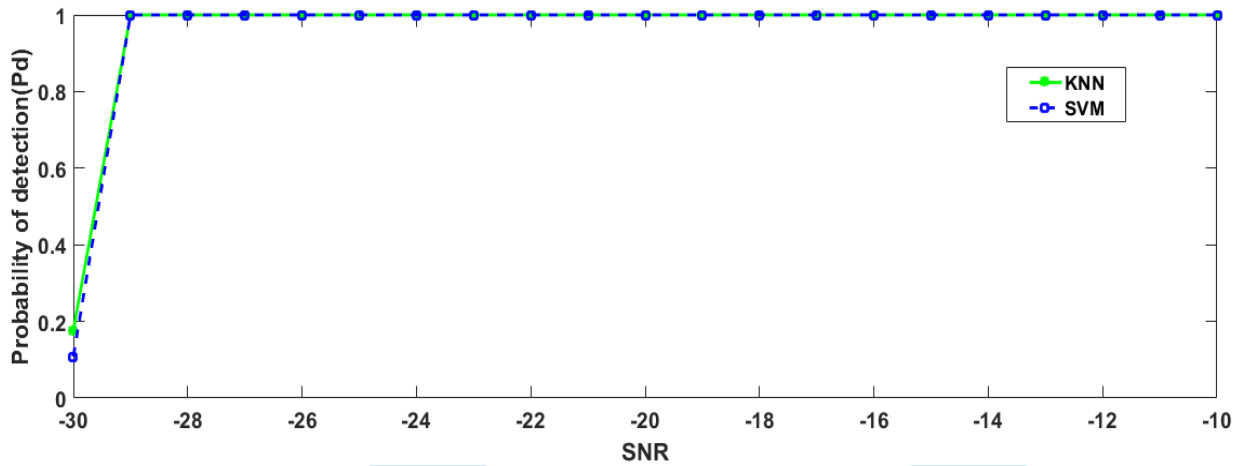
Table 2 Performance Analysis of proposed Statistical Model based spectrum sensing considering CR dataset-2



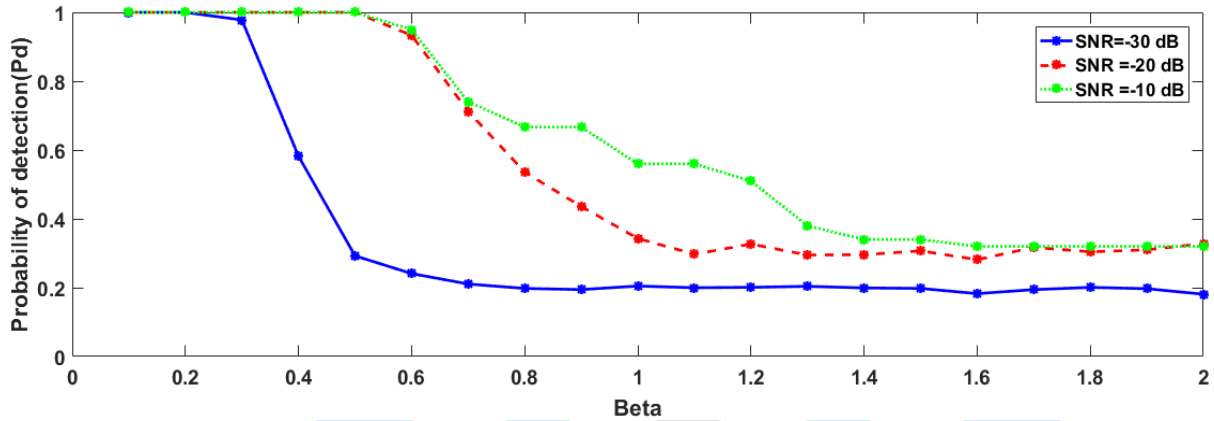
(Figure -8A)



(Figure – 8B)



(Figure -8C)



(Figure -8D)

5 Conclusion:

The significance of spectrum sensing is quite high in detection of primary user presence and to efficiency utilize spectrum and perform switching from one band to another for secondary user to avoid interference between frequency bands of primary and secondary users. Thus, in this article, a statistical model is adopted based on probability density to perform spectrum sensing and enhance efficiency of spectrum utilization in Cognitive Radio Networks (CRNs). Gaussian noise is eliminated while pre-processing from received primary signals. A detailed mathematical modelling for the review of tradition energy detection model and proposed statistical model is presented to detect presence or absence of primary users based on degree of randomness and compared to threshold values. High quality features are extracted based on degree of randomness and sensing parameters for efficient classification of data samples. Performance is analyzed using two large datasets in terms of detection probability and false alarm probability. Experimental results are obtained based on the large training preformed on selected datasets. Performance of proposed statistical model is compared against traditional energy detection model for spectrum sensing in terms of detection probability as well as comparison is performed against different classifiers like KNN and LR in terms of detection probability against varied SNR and β values. Thus, the proposed statistical model outperforms classical spectrum sensing methods.

References:

[1] S. Shorgin, K. Samouylov, I. Gudkova, O. Galinina and S. Andreev, “On the benefits of 5G wireless technology for future mobile cloud computing,” 2014 International Science and Technology Conference (Modern Networking Technologies) (MoNeTeC), Moscow, 2014, pp. 1-4, doi: 10.1109/MoNeTeC.2014.6995601.

[2] T. S. Rappaport, J. N. Murdock, and F. Gutierrez, “State of the art in 60-GHz integrated circuits and systems for wireless communications,” Proc. IEEE, vol. 99, no. 8, pp. 1390–1436, Aug. 2011

[3] N. Kaabouch and W.-C. Hu, “Handbook of Research on Software-Defined and Cognitive Radio Technologies for Dynamic Spectrum Management,” IGI Glob. J., 2014.

[4] A. Ali and W. Hamouda, ``Advances on spectrum sensing for cognitive radio networks: Theory and applications," *IEEE*

Commun. Surveys Tuts., vol. 19, no. 2, pp. 1277_1304, 2nd Quart., 2016.

[5] [7] A. N. Akhtar, F. Arif, and A. M. Siddique, ``Spectrum decision framework to support cognitive radio based IoT in 5G," in *Cognitive Radio in 4G/5G Wireless Communication Systems*. London, U.K.: IntecOpen, 2018, p. 73.

[6] A. M. Wyglinski, M. Nekovee, and T. Hou, Cognitive radio communications and networks: principles and practice. Academic Press, 2009.

[7] Ridhima and A. Singh Buttar, "Fundamental operations of cognitive radio: A survey," in Proc. IEEE International Conference on Electrical, Computer and Communication Technologies (ICECCT), Feb. 2019, pp. 1–5.

[8] Z. Idrees, M. Usman, H. E. Gelani and L. Zheng, "Fast and Robust Spectrum Sensing for Cognitive Radio Enabled IoT," in IEEE Access, vol. 9, pp. 165996-166007, 2021, doi: 10.1109/ACCESS.2021.3133336.

[9] A. Gao, C. Du, S. X. Ng and W. Liang, "A Cooperative Spectrum Sensing With Multi-Agent Reinforcement Learning Approach in Cognitive Radio Networks," in IEEE Communications Letters, vol. 25, no. 8, pp. 2604-2608, Aug. 2021, doi: 10.1109/LCOMM.2021.3078442.

[10] A. Brito, P. Sebastião and F. J. Velez, "Hybrid Matched Filter Detection Spectrum Sensing," in IEEE Access, vol. 9, pp. 165504-165516, 2021, doi: 10.1109/ACCESS.2021.3134796.

[11] S. Lee, S. R. Park, Y. H. Kim and I. Song, "Spectrum sensing for cognitive radio network with multiple receive antennas under impulsive noise environments," in Journal of Communications and Networks, vol. 23, no. 3, pp. 171-179, June 2021, doi: 10.23919/JCN.2021.000016.

[12] M. Nouri, H. Behroozi, N. K. Mallat and S. A. Aghdam, "A Wideband 5G Cyclostationary Spectrum Sensing Method by Kernel Least Mean Square Algorithm for Cognitive Radio Networks," in IEEE Transactions on Circuits and Systems II: Express Briefs, vol. 68, no. 7, pp. 2700-2704, July 2021, doi: 10.1109/TCSII.2021.3051087.

[13] M. Golvaei and M. Fakharzadeh, "A Fast Soft Decision Algorithm for Cooperative Spectrum Sensing," in IEEE Transactions on Circuits and Systems II: Express Briefs, vol. 68, no. 1, pp. 241-245, Jan. 2021, doi: 10.1109/TCSII.2020.3010587.

[14] P. Chauhan, S. K. Deka, B. C. Chatterjee and N. Sarma, "Cooperative Spectrum Prediction-Driven Sensing for Energy Constrained Cognitive Radio Networks," in IEEE Access, vol. 9, pp. 26107-26118, 2021, doi: 10.1109/ACCESS.2021.3057292.

[15] A. Bagheri and A. Ebrahimzadeh, "Statistical Analysis of Lifetime in Wireless Cognitive Sensor Network for Multi-Channel Cooperative Spectrum Sensing," in IEEE Sensors Journal, vol. 21, no. 2, pp. 2412-2421, 15 Jan.15, 2021, doi: 10.1109/JSEN.2020.3021459.

[16] S. Gurugopinath and R. Muralishankar, "Geometric power detector for spectrum sensing under symmetric alpha stable noise," *Electron. Lett.*, vol. 54, pp. 1284–1286, Nov. 2018.

[17] B. M. Pati. Raw spectrum data. [Online]. Available: https://github.com/ bipungithub/spectrum_data

[18] M. A. Hearst, S. T. Dumais, E. Osuna, J. Platt, and B. Scholkopf, "Support vector machines," *IEEE Trans. Intell. Transp. Syst.*, vol. 13, no. 4, pp. 18–28, Jul. 1998.

[19] T. N. Ho, "The random subspace method for constructing decision forests," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 20, no. 8, pp. 832–844, Aug. 1998.