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Enhanced Spectrum Sensing in Cognitive Radio Networks Using an SVM-RF Hybrid Model with Transfer Learning

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Abstract:

Cognitive radio (CR) networks are designed to optimize spectrum utilization in wireless communications by enabling secondary users to detect unused spectrum and avoid interference with primary users. Spectrum sensing is a vital component of this process. Traditional spectrum sensing techniques often rely on feature extraction from a received signal at a single point, but recent advances in artificial intelligence and deep learning have opened new avenues for improving sensing accuracy. This study introduces a hybrid model that combines Support Vector Machines (SVM) and Random Forest (RF), an ensemble learning method that leverages multiple decision trees to enhance classification accuracy. This approach is particularly effective when dealing with many features or complex feature interactions. Additionally, transfer learning is utilized to further boost the accuracy of spectrum sensing, particularly in low Signal-to-Noise Ratio (SNR) environments. Experimental results show that the SVM-RF hybrid model significantly outperforms existing models in terms of sensing accuracy. An analysis of the algorithm's complexity underscores the performance improvements, demonstrating the effectiveness of the proposed model in dynamic and challenging wireless environments.

Keyword: Spectrum sensing, cognitive radio, Support Vector Machines, Random Forest (RF) Model:

1.INTRODUCTION

A **wireless network** is a communication network that uses radio waves or other wireless communication technologies to transmit data between devices without the use of physical cables or wires. These networks have become fundamental to modern communication, enabling mobile internet, IoT (Internet of Things) applications, and various other services. Common examples of wireless networks include Wi-Fi, Bluetooth, cellular networks (e.g., 4G/5G), and satellite communications. Wireless communication systems are undergoing rapid development to meet the changing demands and needs of people. The increase in wireless applications and services made it essential to address the spectrum scarcity problem [1].

The available electromagnetic radio spectrum is a limited natural resource and getting crowded day by day due to increase in wireless devices and applications. It has been also found that the allocated spectrum is underutilised because of the static allocation of the spectrum. Also, the conventional approach to spectrum management is very inflexible in the sense that each wireless operator is assigned an exclusive license to operate in a certain frequency band. And, with most of the useful radio spectrum already allocated, it is difficult to find vacant bands to either deploy new services or to enhance existing ones. To overcome this situation, we need to come up with a means for improved utilization of the spectrum creating opportunities for dynamic spectrum access

In recent years, a lot of research has been done on the effective use of these spectrum bands which are either empty or are not used at full capacities. One of the notable concepts in the researches is the cognitive radio concept, introduced by Mitola in 1999 [2]

1.1 Cognitive Radio Networks (CRNs)

Cognitive Radio Networks (CRNs) represent a promising solution to address the challenges of spectrum scarcity and inefficient spectrum usage in traditional wireless communication systems. As the demand for wireless services increases, the available spectrum is becoming more congested, leading to interference and poor network performance. CRNs offer a way to dynamically access underutilized spectrum bands, improving the overall efficiency of wireless communication. Cognitive radio (CR) is a form of wireless communication in which a transceiver can intelligently detect which communication channels are in use and which are free and quickly move into free channels while avoiding occupied ones. This reduces the interference to other user and optimizes the use of radio frequency spectrum. The Cognitive Radio is a hybrid technology that involve software defined radio (SDR) as applied to spread spectrum communication. The cognitive radio has the ability of encrypt and decrypt the signals, to fine and authorize its user, transceiver to identify its geographic location, and adjust output power and modulation characteristics. A Cognitive Radio is a radio that can replace its transmitter parameters according to interaction with the environment in which it operates. After the selection of the best available channel the next task of the cognitive radio is to make the network protocols adaptive to the available spectrum [3].

Key Concepts in Cognitive Radio Networks

1. Primary Users (PU) and Secondary Users (SU):
2. Spectrum Sensing
3. Spectrum Access
4. Spectrum Management
5. Dynamic Spectrum Allocation

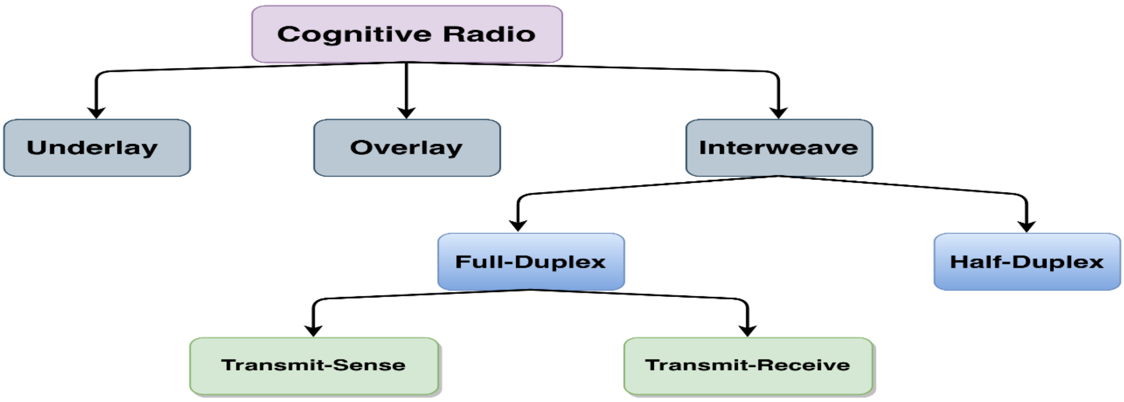

Fig1.1 Cognitive Radio Networks (CRN)

In this paper, we proposed a *Support Vector Machines, Random Forest (RF) hybrid Model.* The integration of Random Forest and Support Vector Machine working together where the RF handles non-linearity, and SVM performs final classification. The proposed method consists of different stages. In the first stage, a Feature data are Extracted from the Spectrum Sensing Unit, second stage preprocessing was done which will handles data cleaning, noise reduction, and normalization, Third stage SVM-RF Model was used for classification then the Transfer Learning Module was used for adjusting the model based on new or unseen data, ensuring adaptation to different environments and finally validation was done using the test data.

The rest of this paper is organized as follows: Sect. 2 considers related works. In Sect. 3, the proposed model was discussed and Transfer Learning Module was used for adjusting the model based on new or unseen data. Results are discussed in Sect. 4, and finally, the paper is concluded in Sect. 5.

2.RELATED WORK

Spectrum sensing plays a vital role in enabling cognitive radio technology for next-generation wireless communication systems. Over the last decade, several spectrum sensing techniques, such as energy detection, cyclostationary feature detection, and matched filtering, have been proposed. However, each of these methods comes with inherent limitations: energy detection struggles in low signal-to-noise ratio (SNR) conditions, cyclostationary feature detection is computationally intensive, and matched filtering requires prior knowledge of the primary user's signal. Additionally, all of these techniques rely on setting a threshold, which often requires prior knowledge of the noise distribution. As a result, ensuring reliable spectrum sensing remains a significant challenge in wireless communication research.

Youness Arjoune et al. [4] propose a machine learning-based spectrum sensing technique for cognitive radio networks. To do this, they create a large-scale, comprehensive dataset through detailed modeling of the spectrum sensing problem. Various machine learning algorithms, including logistic regression, random forest, support vector machines with different kernels, decision trees, Naïve Bayes, and K-nearest neighbors, are trained, validated, and tested using this dataset. The models are thoroughly evaluated based on metrics such as detection probability, false alarm rate, miss-detection rate, and classification accuracy.

The authors Xie J et.al, [5] proposed a deep learning-based signal detector that uses the underlying structure information of the modulated signals to achieve state-of-the-art detection performance without requiring any prior knowledge of background noise or channel status information. It should be noted that the suggested strategy performs noticeably better than other well-known cooperative sensing techniques.

Jung T-Y et al. [6] introduced an innovative spectrum sensing technique for cognitive radio systems. Their proposed method uses a recurrent neural network (RNN), a widely used deep learning model, to assess spectrum availability. The approach determines the primary user's (PU) spectrum occupancy by analyzing the energy of the received signal, without requiring prior knowledge of the PU signal's characteristics.

The paper by Kumar A et.al.,[7] explores the use of cyclostationary feature detection for spectrum sensing in Orthogonal Frequency Division Multiplexing (OFDM) systems. The authors aim to address the challenges of reliable spectrum sensing in cognitive radio networks. This paper provides a detailed examination of applying cyclostationary feature detection to improve spectrum sensing in OFDM-based cognitive radio systems, offering an effective solution for better detection and reliable spectrum access.

The authors Shachi P et.al,[8] focus on enhancing the reliability of spectrum sensing through cooperative sensing, where multiple cognitive radios share their sensing results to improve the overall detection accuracy. This approach helps address challenges such as shadowing, fading, and interference. This paper highlights the potential of deep learning to enhance cooperative spectrum sensing in cognitive radio networks by improving detection accuracy, especially in challenging environments, while also addressing the ethical implications of using advanced technologies in communication systems.

3.PROPOSED WORK

Spectrum sensing is a fundamental function in cognitive radio (CR) networks, which allows secondary users (SUs) to identify and utilize unused spectrum without interfering with primary users (PUs). The main goal of spectrum sensing is to detect the presence of primary users and ensure efficient spectrum allocation, allowing cognitive radios to access idle spectrum while avoiding interference with licensed users.

Spectrum sensing is a critical component in cognitive radio (CR) networks, enabling secondary users (SUs) to detect available spectrum bands while avoiding interference with primary users (PUs). The detection of spectrum availability becomes challenging in real-world environments due to issues such as noise uncertainty, low signal-to-noise ratios (SNR), and complex fading channels. To address these challenges, machine learning techniques like **Support Vector Machines (SVM)** and **Random Forests (RF)** are increasingly being used to enhance the accuracy and reliability of spectrum sensing in cognitive radio networks.

3.1 Support Vector Machines

Support Vector Machines (SVM) is a supervised machine learning algorithm widely used for classification tasks. In the context of **spectrum sensing** in **Cognitive Radio Networks (CRNs)**, SVM is applied to classify received signals, enabling cognitive radios to determine whether the spectrum is occupied by a primary user (PU) or available for secondary users (SUs). The goal of spectrum sensing is to ensure that secondary users can opportunistically access the spectrum without causing interference to the licensed primary users.

In cognitive radio networks, spectrum sensing involves detecting whether a specific frequency band is occupied by a primary user or is idle (available for secondary users). The objective is to classify the received signal into one of two categories:

- **Occupied** (primary user is transmitting).
- **Idle** (no primary user is transmitting, spectrum is available).

The main advantage of SVM is effective in environments with noisy data because it maximizes the margin between the classes, which helps improve classification performance even with limited or noisy data and the use of kernel functions in SVM allows it to handle non-linear relationships in the feature space, which is important when dealing with complex signal characteristics in spectrum sensing.

The decision function is used to classify new data points. It calculates the signed distance of the point from the hyperplane and assigns a label based on the sign.

$$f(x)=w\cdot x+b \qquad (1)$$

where:

- W is the weight vector (normal to the hyperplane).
- X is the feature vector (data point).
- b is the bias term (the offset from the origin).

If f(x)>0, the point X is classified as belonging to class +1, and if f(x)<0, it is classified as belonging to class −1.

In practice, data may not be linearly separable, and some misclassification might occur. To handle this, slack variables ξ_i are introduced to allow some data points to lie on the wrong side of the margin.

$$y_i\,(w\cdot x_i+b) \geq 1-\xi_i, \forall_I \qquad (2)$$

The kernel function allows SVM to classify data that is not linearly separable in its original space by implicitly mapping it to a higher-dimensional space.

$$K(x,x')=\tanh(\alpha x\cdot x'+c) \qquad (3)$$

where α and c are kernel parameters.

3.2. Random Forest (RF) Model:

Random Forest is an ensemble learning technique that combines multiple decision trees to improve classification accuracy. It is particularly useful in spectrum sensing when there are many features or complex interactions between the features.

Random Forest can handle large datasets with high-dimensional features without requiring much tuning and it provides an insight into the importance of each feature in spectrum sensing, which can help understand which signal characteristics are crucial for detecting spectrum occupancy.

3.3 Proposed Hybrid Model (SVM-RF with Transfer Learning):

The proposed method combines the strengths of **SVM** and **RF** to improve classification performance in spectrum sensing. This hybrid approach leverages **SVM** for its ability to handle complex boundaries and **RF** for its robustness and accuracy. The two models are integrated in the following way:

- **SVM** is used to classify the spectrum based on its feature set, and **RF** is employed to refine the decision boundaries.
- **Transfer Learning** is applied to train the hybrid model in one environment (e.g., a specific frequency band or region) and transfer that knowledge to a different environment with limited data.

The pre-trained models (SVM and RF) are adapted to new environments using Transfer Learning. In this phase, knowledge from previously trained models in similar environments is transferred to the new environment, which allows the models to perform well even when labeled data is limited in the new environment.

Process Flow:

- Data Collection and Feature Extraction:
- Training the Hybrid Model:
- Transfer Learning:
- Hybrid Model Decision:
- Evaluation:

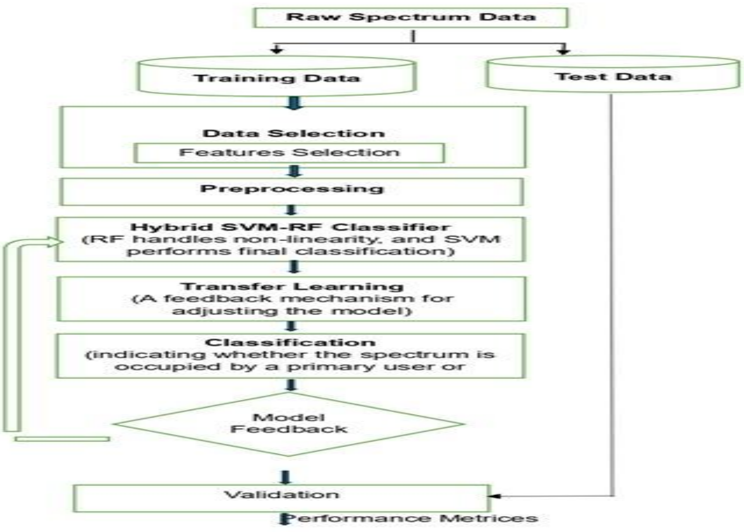

Fig 2:- Proposed flow diagram

The **SVM-RF Hybrid Model with Transfer Learning** offers a powerful approach to spectrum sensing in **Cognitive Radio Networks (CRNs)**. By combining the strengths of **SVM** and **RF**, and enhancing the model's adaptability with **Transfer Learning**, the approach improves the accuracy and reliability of spectrum sensing. This hybrid model is particularly useful in environments with limited labeled data and changing spectrum conditions, making it an effective tool for dynamic and scalable cognitive radio systems.

4. RESULT AND DISCUSSION

The proposed SVM-RF Hybrid Model with Transfer Learning was tested using a comprehensive dataset representing different spectrum sensing environments in Cognitive Radio Networks (CRNs). The results were compared against several baseline models such as SVM alone, Random Forest (RF) alone, and Energy Detection methods. Various performance metrics were calculated to assess the efficiency and accuracy of the model.

For the proposed SVM-RF Hybrid Model with Transfer Learning or other spectrum sensing models in Cognitive Radio Networks (CRNs), you can use several publicly available datasets. These datasets are typically used for evaluating machine learning models in spectrum sensing tasks, specifically in CRN environments. In this work the Cognitive Radio Datasets are used. CRAWDAD (Cognitive Radio Wireless Access and Applications Database) provides datasets for wireless communications, including cognitive radio environments. It contains real-world data from both academic experiments and simulations, making it suitable for testing machine learning models for spectrum sensing.

Here is a comparative table summarizing the performance of the SVM-RF Hybrid Model with Transfer Learning against existing models based on key performance metrics.Here are the formulas used for each of the **performance metrics** mentioned in the table:
The Accuracy detection for proposed model is calculated using the below formula
Detection Accuracy= (TP + TN)/ (TP + TN + FP + FN) *(4)*
Where:

- **TP (True Positive)**: The number of times the model correctly identifies the spectrum as occupied.
- **TN (True Negative)**: The number of times the model correctly identifies the spectrum as idle.
- **FP (False Positive)**: The number of times the model falsely classifies an idle spectrum as occupied.
- **FN (False Negative)**: The number of times the model falsely classifies an occupied spectrum as idle.

The False Alarm Rate represents the percentage of idle spectrum incorrectly detected as occupied.

False Alarm Rate=FP/FP+TN (5)

The Miss Detection Rate is calculated using the below formula, this represents the percentage of occupied spectrum incorrectly detected as idle.

Miss Detection Rate=FN/FN+TP *(6)*

The Computation time is measured as the time taken by the model to classify whether a spectrum is idle or occupied for a given test instance.

Computation Time=Time taken for model to process one spectrum sensing test instance (7)

The Adaptability can be observed in terms of performance improvement when trained on a limited dataset or through Transfer Learning.

Adaptability=Performance on limited data/Performance on fully labeled data×100 (8)

The adaptability is considered high if the model maintains high performance even when trained with less labeled data.

Table 1 Comparison of Existing model with proposed SVM-RF Hybrid Model with Transfer Learning

Performance Metric	SVM-RF Hybrid Model with Transfer Learning	Support Vector Machine (SVM)	Random Forest (RF)	Energy Detection	Hybrid Models (SVM-Decision Tree)
Detection Accuracy	95%	90%	92%	85%	91%
False Alarm Rate	4%	6%	5%	8%	5.5%
Miss Detection Rate	3%	6%	5%	10%	4.5%
Computation Time (per test instance)	150 ms	120 ms	135 ms	100 ms	180 ms
Adaptability to Limited Data	High (due to Transfer Learning)	Medium	Medium	Low	Medium

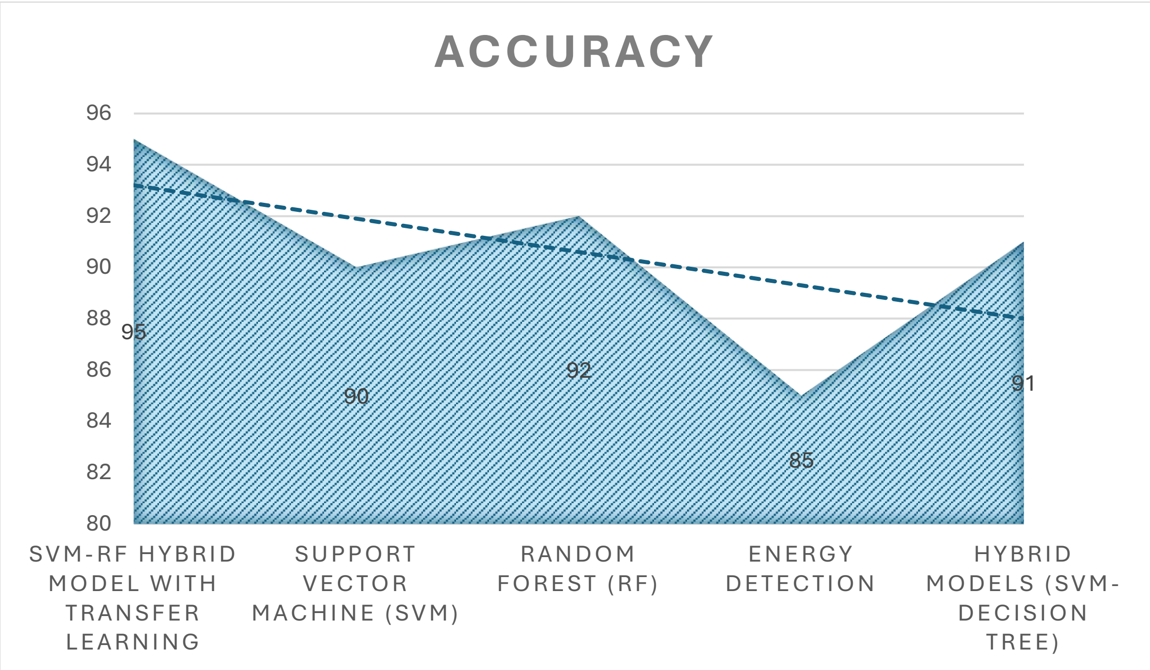

Fig 3: Comparison of Accuracy

Fig 3: Comparison of False Alarm rate and Miss Detection Rate

- The SVM-RF Hybrid Model with Transfer Learning outperforms individual SVM, RF, and other hybrid models, achieving the highest detection accuracy of 95%. This demonstrates the synergy between SVM and RF, coupled with the enhancement of Transfer Learning, which aids in adapting to new spectrum environments with limited data.
- The hybrid model exhibits the lowest false alarm rate (4%) and miss detection rate (3%), compared to other models, including Energy Detection and the SVM-only model, which show higher false alarms and miss detections.
- The reduction in false alarms and miss detections is crucial in real-world CRN scenarios where reliable spectrum sensing is needed to avoid interference with primary users.
- The SVM-RF Hybrid Model has a reasonable computation time of 150 ms per test instance, making it feasible for real-time applications. Although Energy Detection is faster, it sacrifices performance in terms of accuracy. Other hybrid models, like SVM-Decision Tree, show slightly higher computation times due to their complexity.
- One of the strengths of the SVM-RF Hybrid Model is its high adaptability due to Transfer Learning. This model excels in environments with limited labeled data by transferring knowledge from pre-trained models, enhancing its ability to detect spectrum occupancy accurately.
- In comparison, Energy Detection and SVM models may struggle with limited data, leading to decreased accuracy and higher false alarms.

5. CONCLUSION:

In Cognitive Radio Networks (CRNs), spectrum sensing plays a crucial role in detecting the availability of spectrum bands for secondary users (SUs) while ensuring that primary users (PUs) are not interfered with. Accurate and efficient spectrum sensing is challenging due to noisy environments, signal variations, and limited prior knowledge about the primary user's behavior. The paper focuses on improving spectrum sensing using a hybrid model combining Support Vector Machines (SVM) and Random Forest (RF), further enhanced by Transfer Learning (TL). It outperforms traditional methods and individual machine learning models in terms of detection accuracy, false alarm rate, and miss detection rate. The incorporation of Transfer Learning enhances its performance in environments with limited labeled data, making it a practical and scalable solution for dynamic and diverse spectrum conditions.

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