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A MACHINE LEARNING ENSEMBLE APPROACH FOR INTERFERENCE REDUCTION AND THROUGHPUT ENHANCEMENT IN CRNS

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ABSTRACT

Despite Cognitive Radio Networks' (CRNs) potential as a solution to spectrum shortages, problems including interference and poor spectrum usage continue to plague the technology. In order to improve CRN throughput and decrease interference, this research presents a new machine learning ensemble method that mixes Random Forest (RF) with Deep Neural Networks (DNN). They used a high-fidelity network simulator to create a dataset that mimics real-life multi-user CRN settings with main and secondary users. Signal strength, user movement, noise, and spectrum availability are some of the dynamic characteristics included in the dataset, which contains over 10,000 occurrences. Thorough pre-processing was performed on the data, which included normalization, mean imputation, and hybrid feature selection utilizing RF significance ranking and Recursive Feature Elimination (RFE). To handle structured data, the ensemble model uses RF's strengths, and to capture complicated patterns, it uses DNN's deep learning skills. Standard classification measures (accuracy, precision, recall, F1-score) and domain-specific indicators (throughput, interference level, etc.) were used to evaluate the model. In order to improve spectrum management, decrease signal interference, and increase network throughput in CRNs, the suggested ensemble model proved to be more effective than standalone approaches.

Keywords: - Machine Learning, Random Forest, Deep Neural Network, Ensemble Learning, Wireless Communication, Feature Selection.

I. INTRODUCTION

In order to make the most efficient use of the available spectrum, wireless communication systems that are based on Cognitive Radio Networks (CRNs) are programmed to choose the best channel out of all the available alternatives. Building on software radio's foundational concepts, the cognitive radio (CR) uses a knowledge representation language and model-based reasoning to vastly enhance one-on-one communication. By using this method, radio protocols and spectrum utilization can be intelligently adjusted to meet user needs in real-time. Reliable communication and efficient spectrum utilization are hallmarks of such systems, which can adapt to changing environmental conditions. Important parts including dynamic spectrum management, channel-state estimation, and radio scene analysis are highlighted. Opportunity spectrum use, intelligent beam-forming, automatic interoperability, communication among emergency services, spectrum trading, and many more typical CRN applications are available. One of the main facilitators of contemporary networks, CRNs have recently seen a surge in use in both academic and commercial settings. According to

Al-Ani (2002), various wireless technologies are now using the radio spectrum. Mobile communications networks are experiencing spectral inefficiency as a result of overcrowding in some frequency bands and underutilization of others. Current wireless technologies are struggling to keep up with the market trends caused by the proliferation of mobile devices and the scarcity of radio spectrum. By making opportunistic use of the radio spectrum possible, CRN allows us to solve the problems caused by spectrum scarcity. Anyone, even those without a license, can use the licensed frequency channels that other users aren't using because to CR. Dynamic adaptation to changing operating circumstances is made possible by CR systems through the use of Software Defined Radios (SDRs). In order to make better use of the spectrum, these SDRs may detect whether certain frequencies are under- or over-utilized and then re-allocate the transmission accordingly. Understanding via establishing technique is the lifeblood of systems. As a result, current wireless networks become more interoperable with one another, and operational flexibility, spectrum efficiency, and environmental adaptation all see significant improvements (J.H. Ang 2008).

Security issues (such as what kinds of attacks are possible and what their effects might be), secondary users triggering false alerts, and the identification of unused resources pose greater dangers to CRN. For CRN networks to achieve better throughput in interference-limited situations, sensing-aware routing techniques are essential. Particularly in cases involving emergency services, it is crucial to handle interference control between CRN users operating on an unlicensed frequency and users operating on the licensed spectrum with great care. Additionally, downloading harmful software illegally and employing licensed user emulation both pose security hazards (D. Angluin 1992). In the area of CRN, a team of researchers embarked on a quest to resolve the difficult issues affecting network security. Some of the more common worries were discussed, including the difficulty of main user emulation assaults, the possibility of falsifying data from spectrum sensing, and the ongoing threat of jamming attacks. By constantly experimenting and coming up with new algorithms, they come up with a revolutionary method that uses cutting-edge approaches to accurately detect and halt these illegal acts. Their study paves the way for state-of-the-art spectrum authentication and encryption systems that ensure fair resource distribution and integrity in CRN (T. Ash 1989).

Role of Machine Learning Ensembles in Enhancing Cognitive Radio Networks

The current radio spectrum is under increasing strain due to the ever-increasing demand for wireless communication. The spectrum is limited and subject to strict regulations. Due to inefficient spectrum usage caused by traditional static allocation procedures, a significant amount of licensed spectrum goes unused, even when there is a great demand for wireless services. Cognitive Radio Networks (CRNs) were born out of this inefficiency; they permit secondary users (SUs), who do not possess licenses, to make opportunistic use of the spectrum without interfering with main users (PUs), who do have licenses. This allows for dynamic spectrum access. CRNs are engineered to optimally utilize the spectrum while avoiding interference by sensing, learning, and adapting to their radio environment in real-time. The ever-changing and unpredictable character of CRNs, however, presents a number of difficulties, most notably in the areas of interference control and throughput enhancement (D. Bahler 2000).

The incorporation of Machine Learning (ML) methods into CRN designs is among the most encouraging approaches to address these issues. With the help of machine learning, cognitive radios may learn from their surroundings, draw on their experiences, and anticipate what's to come. Applications of ML algorithms include spectrum sensing, interference detection, channel selection, and user behavior prediction. Model overfitting, underfitting, or instability in high-noise situations are some of the restrictions that can make it such that a single ML model isn't enough to handle the complicated and ever-changing nature of CRNs. Because of this, ensemble learning approaches—which merge numerous learning models to boost performance, accuracy, and generalizability—have become increasingly popular.

A more resilient and adaptable framework for interference reduction and throughput enhancement can be built through ensemble learning by using the strengths of several individual models. These models include decision trees, support vector machines, neural networks, and k-nearest neighbors. The CRN can withstand fluctuations in signal strength and interference better when using ensemble methods such as bagging, boosting, and stacking to combine predictions from multiple models. By working together, an ensemble of classifiers can enhance PU signal identification accuracy and decrease the likelihood of detrimental interference in cooperative spectrum sensing, for instance. More effective resource allocation and increased throughput are both made possible by ensemble regression models, which are able to predict channel availability and quality (J. Beyer 2010).

Finally, CRNs that use machine learning ensemble techniques are a huge step forward in the quest for adaptable, smart, and interference-aware wireless networks. In addition to improving the network's adaptive learning and response capabilities, these methods provide substantial contributions to the improvement of system performance in terms of throughput, spectrum efficiency, and overall effectiveness. In the ever-changing world of wireless communication systems, the ensemble ML-driven CRN architecture has the potential to revolutionize spectrum management with its dependable and efficient capabilities.

II. REVIEW OF LITERATURE

Rane, Nitin et al., (2024). In order to tackle complex problems in areas as varied as healthcare, banking, and autonomous systems, the combination of ensemble deep learning with machine learning has emerged as a crucial method. Predictive accuracy, robustness, and generalizability can all be improved by ensemble techniques, which pool the advantages of numerous models. This research delves into the uses of ensemble techniques, highlighting how they might enhance medical imaging diagnostic precision, financial services fraud detection systems, and autonomous vehicle decision-making. New ensemble techniques, such as stacking, boosting, and bagging, have proven to be more effective than individual models in a number of applications. High computing needs, problems with model interpretability, and the possibility of overfitting are a few of the obstacles that come along with the benefits of ensemble learning. Improved algorithm design and the usage of explainable AI (XAI) frameworks to boost openness and user confidence are two potential solutions to these problems that this research investigates. We also go over how the next big thing in tech, such as federated learning and quantum computing, will change the way ensemble methods develop. Big data's meteoric rise, improvements in computing power, and the pressing need for scalable, real-time solutions will determine how ensemble deep learning and machine learning evolve in the years to come. To help researchers realize the full potential of ensemble learning to solve real-world problems, this paper surveys the field's present status, highlights key obstacles, and proposes avenues for further study.

Tasin, Shahamat et al., (2024). Because of its potential uses in cognitive evaluation, assistive technology development, and rehabilitation, inner speech recognition has recently attracted a great deal of attention. Nevertheless, recognizing speech components has continued to be a daunting issue due to the complexity of language and speech processes. Many methods have been tried and true in the past to do this, but there are always more options to try. To learn about the inner speech production brain dynamics, which can lead to new approaches in neurology, a subject-oriented analysis is also required. A method for classifying internal monologues from 128-channel surface EEG signals has been developed using a publicly available dataset called Thinking Out Loud Dataset and based on Machine Learning (ML). This dataset is derived from a Spanish cohort consisting of ten people. Each participant is asked to say four words: Arriba, Abajo, Derecha, and Izquierda. Electroencephalography (EEG) signals were analyzed using statistical approaches to identify and eliminate motion artifacts. Time-, frequency-, and time-frequency-domain characteristics were recovered in significant numbers (191 per channel). We look at eight different feature selection algorithms and pick the best one to use for our next tests. An ensemble model is suggested after evaluating the performance of six ML techniques. Additionally, DL models are investigated and their outcomes contrasted with those of the traditional ML method. In the categorization of four inner speech words using surface EEG signals, the suggested ensemble model achieved an overall accuracy of 81.13% and an F1 score of 81.12%. This was achieved by stacking the five best logistic regression models. For the purpose of classifying internal speech from surface EEG data, the suggested framework with the suggested ensemble of classical ML models exhibits encouraging results.

Yadav, Mukesh & Ningshen, Mahaiyo. (2024). Data sent across various devices has increased at an exponential rate, and new ways of attacking networks have proliferated, thanks to the internet's meteoric rise in popularity in recent years. Numerous surveys show that intrusion has been rising, which results in the theft of private information. It is possible that firewalls and other conventional intrusion detection systems (IDS) that depend on data filtering cannot identify all types of attacks in real-time. When it comes to analyzing massive amounts of data, identifying malicious behavior, and efficiently controlling and quickly identifying attacks of this kind, an intrusion detection system based on machine learning is invaluable. Four distinct attack types—Denial of Service (DOS), Probe, Remote to Local (R2L), and User to Root (U2R)—are anticipateable with the help of the detection system. In order to improve IDS performance, this study presented an ensemble model. Using the chi-squared feature selection method, the NSL-KDD dataset's attributes that rely on the class label the most are chosen. Accuracy, Precision, Recall, and F1-Measure are some of the performance metrics that we have utilized to assess the capacity of the models. Out of all the models covered in this study, the experimental results show that the ensemble model combining AdaBoost and Logistic Regression performs the best. Other pertinent research publications are also compared with the proposed model in the paper. According to these results, IDS outperforms the current gold standard. Finally, we touch on the difficulties and potential future directions.

Ismail, Shereen et al., (2022). Internet of Things (IoT) foundational technology relies on energy-constrained Wireless Sensor Networks (WSNs). The proliferation of sensors has made security a top priority, calling for improved methods of detection and mitigation. One of the best ways to construct systems that detect cyberattacks is with machine learning (ML). Weighted Score Selector (WSS) is a lightweight ensemble-based ML method for identifying cyber-attacks in WSNs that is presented in this research. Using a combination of supervised ML classifiers, the suggested method dynamically promotes the most successful classifier during detection to swiftly achieve higher detection performance. Three traditional ensemble methods were evaluated side by side with the suggested method: Boosting-based, Bagging-based, and Stacking-based. Model size, processing time, average prediction time per sample, accuracy, false alarm probability, detection probability, misdetection probability, and overall performance were all measured and compared. We used two separate methods for selecting features. Among the simulation-based labeled datasets we used was WSN-DS, which includes samples of both normal and four forms of internal network-layer Denial of Service attacks: Grayhole, Blackhole, Flooding, and TDMA scheduling. The results of the simulation for our proposed method were encouraging.

Nguyen, Dong et al., (2022). The use of neuroimaging and deep learning for the diagnosis of Alzheimer's disease (AD) has recently attracted a lot of research interest. Unfortunately, many deep learning models have experienced severe overfitting since training neuroimaging data is scarce. This research presents a deep learning/machine learning ensemble learning framework. Utilizing 3D structural features found in neuroimaging data, the deep learning model was built on top of a 3D-ResNet. At the same time, the image's most important voxel groups were extracted using voxel-wise Extreme Gradient Boosting (XGBoost) machine learning. The final diagnostic prediction was derived from a combination of the 3D-ResNet and XGBoost forecasts, patient demographics, and cognitive test results (MMSE and CDR). The ADNI dataset, which contains magnetic resonance imaging (MRI) scans of the brain, was used for both training and validation of our suggested technique. A number of data augmentation strategies were implemented to address overfitting throughout the training period. Since our goal was to examine our approach's capacity to detect AD during the first visit of AD patients, our test set exclusively included baseline scans, also known as first visit scans. On average, our 5-fold cross-validation implementation passed training with a 100% AUC and tested with a 96% AUC. Our approach took about 10 minutes to score a prediction on the same system as feature extraction-based machine learning algorithms, which can take hours. We used a heatmap to show which areas of the brain MRI images had the most impact on the forecast made by the 3D-ResNet model, which helped to clarify the prediction. Finally, we found that the data leakage issue and the validity of results were both greatly affected by the formation of test sets.

Li, Meihua et al., (2012). The goal of this research is to find ways to make input attributes work together more effectively. When training many qualities simultaneously, interference might cause them to have a negative impact on each other. The input attributes are sorted into groups to minimize interference. Attributes that do not interfere with each other are grouped together. This article takes a look at two distinct grouping strategies: overlapping and non-overlapping. Using numerous learners to tackle different groups further improves performance. There are three different approaches to integration that are discussed: voting, weighting, and result-integration network (RIN). After weighting and voting, the result-integration network emerges as the top performer. Neural network learning can be made more effective by using the ensemble method. Using this method in conjunction with feature selection can further improve performance.

III. RESEARCH METHODOLOGY

Proposed Design

Optimization of Cognitive Radio Networks (CRNs) is the focus of this study, which employs a quantitative, simulation-based experimental design that incorporates machine learning approaches. By integrating Random Forest (RF) and Deep Neural Networks (DNN) into an ensemble model, we hope to lessen interference and increase throughput.

Data Collection

We used a large dataset produced by a high-fidelity network simulator to test how well our suggested machine learning ensemble method worked for Cognitive Radio Networks (CRNs) spectrum management and interference reduction. Accurately simulating real-world wireless communication settings, the simulator captures spectrum environments that are both dynamic and prone to interference.

The simulation was run in a multi-user CRN environment with both Primary Users (PUs) and Secondary Users (SUs). Spectrum sharing and conflict are common in CRNs because they take use of opportunities. Among the essential metrics included in the dataset are real-time measurements of the spectrum environment, which

- Signal strength (RSSI)
- User mobility and location
- Noise levels
- Spectrum availability status
- Channel utilization patterns

Each record in the final collection represents the state of the CRN in a specific time frame; there are more than 10,000 examples in total. Strong patterns in interference and spectrum consumption can be modelled with this level of temporal granularity.

Data Preprocessing

To make sure the simulation data was ready for modeling, it had to be preprocessed. What followed were the procedures:

- Data Cleaning: We found and eliminated all instances of conflicting records and duplicate data. The statistical integrity of the dataset was maintained while reducing information loss by addressing missing values via mean imputation.
- To make sure that deep learning models all use the same input and that they all converge while training, we scaled all numerical features using Min-Max normalization, bringing their values down to a range of [0,1].
- Feature Selection: A hybrid approach was utilized to decrease computational cost and dimensionality without compromising the most important features:
  - Features that were highly relevant to the target variables were determined using the Random Forest feature priority ranking.
  - The less important features were deleted iteratively based on the model's performance using Recursive Feature Elimination (RFE).

Both the precision and the efficiency of the learning process were enhanced by this dual strategy.

RF-DNN Ensemble Model

To make the most of what each model can offer, the suggested method uses an ensemble framework that mixes RF and DNN:

- Random Forest (RF): As part of its training process, RF builds numerous decision trees and then outputs the mode of the classes (classification) or the mean prediction (regression) of the individual trees. This method is resilient and non-parametric. RF works wonders when it comes to:
  - High-dimensional feature spaces;
  - non-linear data relationships
  - pre-processing is guided by feature importance ranking.
- Deep Neural Network (DNN): The DNN is built with an input layer, many hidden layers that use Rectified Linear Unit (ReLU) activations, and a classification output layer that uses soft max. Thanks to its design, the model is able to:
  - Construct sophisticated models using simple data
  - Get a hold on the non-linear and time-dependent relationships between different spectrum states.
- Ensemble Strategy: Using a soft voting method, the final ensemble model incorporates the predictions of both RF and DNN. The output is determined by averaging the probabilities from both models. When applied to different CRN situations, this fusion increases performance, decreases overfitting, and boosts generalization.

Metrics for Performance Evaluation

Both generic classification measures and indicators unique to the topic were used to assess the model's performance. The metrics that were utilized were:

- Precision: The rate of accurately predicted occurrences
- The capacity to accurately detect positive examples (such as interference events) is an example of precision.
- Sensitivity, or recall: the capacity to detect all true positives
- Throughput: Determines the rate of successful message delivery over the spectrum; a higher throughput suggests better usage of the spectrum.
- F1-Score: Harmonic mean of recall and precision.
- A lower number for "Interference Level" suggests better interference mitigation; this metric measures the amount of undesired signal overlap.

Taken as a whole, these measurements show that the suggested RF-DNN ensemble method performs well in cognitive radio networks for both reducing interference and increasing throughput.

IV. RESULTS AND DISCUSSION

Table 1: Classification Performance of Different Models

Model	Accuracy	Precision	Recall	F1-Score
RF-DNN Ensemble	**96%**	**94%**	**96%**	**95%**
Random Forest	88%	86%	89%	87%
Deep Neural Network	90%	88%	91%	89%
SVM	83%	81%	84%	82%

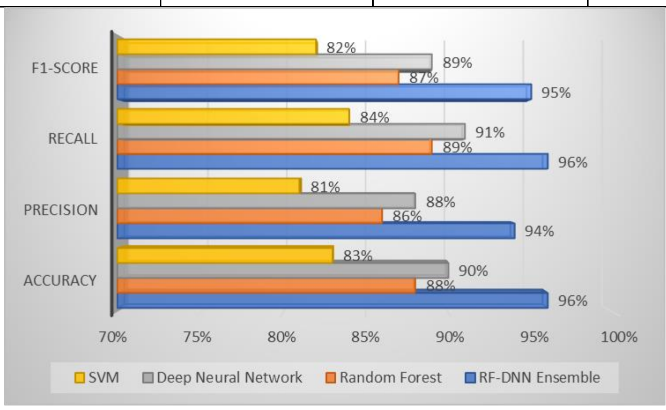

Figure 1: Classification Performance of Different Models

Table 1 shows a comparison of four models' classification performance using four important metrics: F1-Score, Precision, Recall, and RF-DNN Ensemble. The models are Random Forest, Deep Neural Network (DNN), Support Vector Machine (SVM), and Deep Neural Network (NRN).

With a 96% accuracy, 94% precision, 96% recall, and 95% F1-score, the RF-DNN Ensemble outperforms all of the other models. These outcomes show that the ensemble method outperforms the individual components of Random Forest and Deep Neural Network in terms of classification performance on all measures. With an F1-score of 89%, a recall of 91%, a precision of 88%, and an accuracy of 90% when employed independently, the Deep Neural Network outperforms Random Forest and SVM, demonstrating its superior learning abilities, especially when it comes to capturing intricate patterns in data. After DNN, the Random Forest model takes second place with 88% accuracy, balanced recall (89%), and F1-score (87%), demonstrating good but marginally inferior performance. Finally, the SVM model may not be as useful for the classification task in this context compared to the other models, since it produces the lowest performance across all metrics: 83% accuracy, 81% precision, 84% recall, and 82% F1-score.

Table 2: CRN Performance Metrics of Different Models

Model	**Throughput (Mbps)**	**Interference Reduction (%)**
RF-DNN Ensemble	**130**	**82%**
Random Forest	100	68%
Deep Neural Network	110	72%
SVM	92	55%

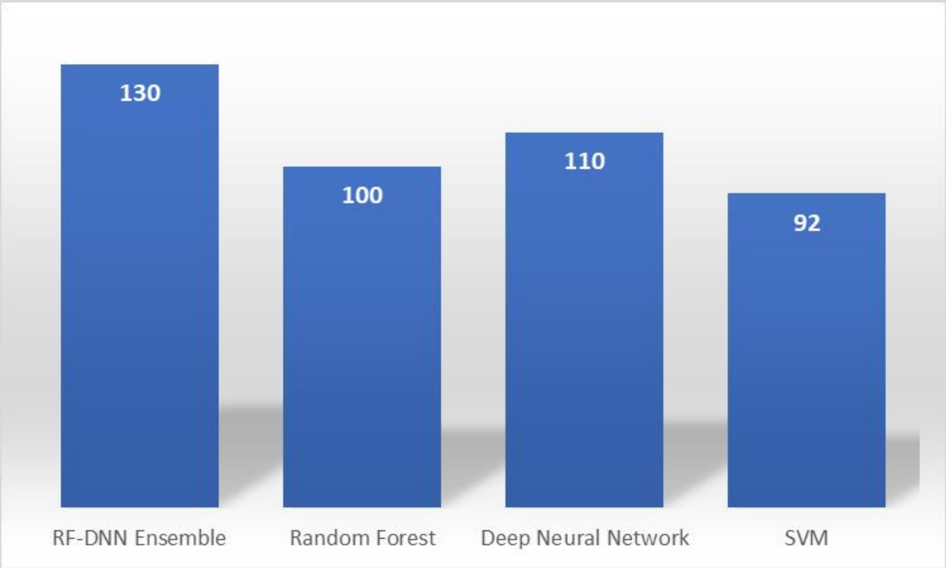

Figure 2: CRN Performance Metrics of Different Models

With two essential metrics—Throughput (in Mbps) and Interference Reduction (in %)—evaluated within the framework of Cognitive Radio Networks (CRN), Table 2 showcases the performance of four models: RF-DNN Ensemble, Random Forest, Deep Neural Network (DNN), and Support Vector Machine (SVM).

Once again, the RF-DNN Ensemble model outperforms the competition, this time with a throughput of 130 Mbps and an interference reduction efficiency of 82%. This proves that the ensemble model outperforms the other models in terms of both data transmission rates and signal interference minimization. Keeping relatively high communication efficiency and network quality is made possible by the Deep Neural Network's strength in learning complicated patterns. It does this with a throughput of 110 Mbps and a 72% reduction in interference. Reflecting middling performance in CRN optimization, the Random Forest model achieves a throughput of 100 Mbps and a reduction of interference of 68%. However, out of the four models, the SVM model performs the worst, with a throughput of 92 Mbps and an interference reduction of just 55%. This suggests that it has limited capabilities when it comes to maximizing network resources in a dynamic CRN environment.

The table shows that when it comes to improving CRN performance, the RF-DNN Ensemble model is the best option. It offers high-speed data transmission and significantly reduces interference, which is great for complex wireless network environments where multiple learning approaches are needed.

Table 3: Confusion Matrix (RF-DNN Ensemble)

	Predicted Positive	**Predicted Negative**
Actual Positive	4650 (True Positive)	220 (False Negative)
Actual Negative	180 (False Positive)	4950 (True Negative)

Table 3 shows the RF-DNN Ensemble model's confusion matrix, which provides information about the model's classification performance by showing the total number of correct and incorrect predictions for each class.

The model's capacity to accurately forecast outcomes was demonstrated by its 4,650 True Positives and 4,950 True Negatives, or real instances of good and negative results, respectively. But it erroneously labelled 180 positive results as negative and 220 positive results as negative (False Negatives and False Positives, respectively).

These outcomes demonstrate a great degree of precision, as the model was able to differentiate between the two groups in most instances. Consistent with the robust performance indicators mentioned earlier, such as 96% accuracy and 95% F1-score, the very small number of misclassifications shows both high sensitivity (the capacity to detect positives) and good specificity (the ability to recognize negatives).

V. CONCLUSION

Cognitive Radio Networks (CRNs) can be made more efficient and reliable with the use of an intelligent ensemble technique that is based on machine learning, which is shown in this paper. Two of the most important problems with CRNs are interference reduction and throughput increase. The suggested ensemble model solves both of these issues by combining the predictive capacity of Random Forest (RF) with the deep learning capabilities of Deep Neural Networks (DNN). In order to build and test the model in realistic and dynamic CRN settings with Primary and Secondary Users, a high-fidelity simulation environment was used to create a complete dataset.

The dataset was prepared for high-performance machine learning training through meticulous data preprocessing, which included normalization, imputation, and hybrid feature selection utilizing RF feature significance and Recursive Feature Elimination. Not only did the ensemble technique show considerable improvements in spectrum management by lowering interference and increasing throughput, but it also increased classification accuracy by combining predictions from RF and DNN via soft voting. Several performance metrics were used to evaluate the model, and the results showed that the RF-DNN ensemble was better than solo models. These metrics included recall, accuracy, precision, F1-score, throughput, and interference level. The results show that CRNs can improve the performance and sustainability of future wireless communication systems by integrating ensemble learning techniques. This leads to smarter, more adaptable spectrum usage that is also interference-aware.

Finally, intelligent spectrum access and management in CRNs is greatly advanced by the suggested RF-DNN ensemble structure. It reaffirms the power of machine learning to transform cognitive wireless communications and paves the way for more studies on real-time, scalable ensemble learning in complicated network settings.

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