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Machine Learning-Based Analysis and Mitigation of Interference Among FM Broadcast Stations

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Abstract
This paper proposes the use of a Support Vector Machine (SVM) model to analyze and mitigate interference among FM broadcast radio stations, using a case study of five existing stations. Key parameters, including geographic coordinates, frequency, transmission power, forward power, mast height, and antenna type, were used as input features to train the model. To address class imbalance in the dataset, Synthetic Minority Oversampling Technique (SMOTE) was employed, ensuring robust predictions of interference levels categorized as low, moderate, or high. The SVM model, trained with an RBF kernel, achieved a high classification accuracy of 94%, with performance metrics indicating excellent precision, recall, and F1-scores across all classes. Predictions revealed that stations with overlapping frequencies and close geographic proximity experienced higher interference levels, while stations with significant separation exhibited lower interference. The study demonstrates the potential of machine learning in optimizing FM broadcast networks, offering a scalable solution to interference mitigation and enhancing signal quality.
Keywords: *Interference, FM Station, Machine Learning, Support Vector Machine.*

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I. Introduction

The field of radio broadcasting plays a pivotal role in disseminating information, entertainment, and culture to diverse audiences across the globe. In this context, the Frequency Modulation (FM) band, known for its superior sound quality and relatively long-range transmission, has been a cornerstone of the broadcasting industry for decades. However, the ever-growing demand for radio services, coupled with the increasing number of FM stations in operation, has brought to the forefront an issue of paramount importance: interference within the FM band (Wayne Tomasi, 2002).

Interference within the FM band refers to the unintended overlap and disturbance of broadcast signals from multiple stations on the same or adjacent frequencies. This phenomenon can result in reduced signal quality, degraded reception, and, in extreme cases, total loss of communication. Such interference is detrimental not only to broadcasters but also to the listening public, who depend on clear, uninterrupted signals for various purposes, including news, music, emergency alerts, and educational content (ITU, 2004).

The FM Radio broadcast range 87.5-108.5MHz is most suited for high-density locations where transmission distance to an audience is minimal. Major cities and regional towns have adopted FM Radio or commercial radio as an alternative to long-wave AM broadcasts (Fadeyi I. O., 2014).

FM (Frequency Modulation) broadcast radio antennas are essential components of radio broadcasting systems. These antennas serve the purpose of transmitting FM radio signals efficiently and effectively, ensuring that radio broadcasts reach their intended audience with high-quality audio fidelity. Here, we'll discuss the key aspects of FM broadcast radio antennas (D. S. Ziya, 2018).

The main objective of this paper is to develop a machine learning-based model for analyzing and mitigating interference among FM broadcast stations. The main contribution of this paper include:

i. It provides a comprehensive assessment of the coverage areas of five selected FM broadcast stations.
ii. It evaluates the interference levels among these stations to identify overlapping zones and signal disruptions.
iii. It develops and trains a machine learning model capable of accurately predicting interference zones within the FM band.
iv. It proposes and validates an interference mitigation strategy through simulation-based techniques to enhance broadcast quality and spectrum efficiency.

The remainder of this paper is structured as follows: Section 2 reviews related work on the analysis and the mitigation of interference among FM broadcast stations. Section 3 outlines the methodology used in achieving the stated main objective. Results and discussion, as well as the validation of the model, are presented in Section 4. Finally, Section 5 discusses the implications of findings and concludes with potential areas for future research.

II. Related Works

Several studies in the existing literature have focused on the detection and mitigation of radio frequency interference (RFI). These techniques have been explored from various perspectives, including statistical analysis of radio frequencies, high-altitude platforms, satellite systems, and microwave radio relay systems.

Most studies on the coexistence of High-Altitude Platforms (HAPs) and terrestrial systems primarily focus on capacity and interference management, resource allocation, and evaluating individual system performance. Achieving improved system capacity while minimizing interference with other systems requires advanced techniques such as diversity, sophisticated radio resource management (RRM), smart antennas, multiplexing, and multiple-input multiple-output (MIMO) systems (Mohammed et al, 2012). Smart antennas and advanced RRM are essential technologies for ensuring seamless coexistence. Additionally, adopting cognitive radio concepts to develop dynamic spectrum management (DSM) strategies has been identified as a potential solution for enhancing coexistence. DSM minimizes interference by utilizing unoccupied spectrum, while smart antennas enable spatial beamforming to reduce interference in specific directions (Alsamhi et al, 2019).

However, this approach presents certain limitations, as modern receivers are expected to perform effectively even in interference-limited environments. Many existing studies on HAP-terrestrial coexistence propose using a minimum separation distance to satisfy interference thresholds. Furthermore, interference-to-noise ratio (INR) and carrier-to-interference-plus-noise ratio (CINR) spectrum etiquettes have been suggested for HAP systems. These etiquettes use the INR or CINR levels of incumbent users as reference metrics to manage the downlink transmission power of newly activated systems (Likitthanasate et al., 2018), (Zakarria et al, 2017).

When a HAP is introduced as a newly activated user, studies emphasize ensuring that the interference experienced by terrestrial incumbent users does not lead to a reduction in the interference-to-noise ratio (INR) or necessitate changes in the modulation scheme. Furthermore, researchers propose that leveraging effective power control in terrestrial systems can enable the accommodation of additional interference from the newly activated HAP. Similarly, the concepts discussed in (Alsamhi et al, 2014), (Mokayef et al, 2019) suggest employing strategies such as maintaining an appropriate separation distance between systems and adjusting antenna beams to enhance performance and ensure coexistence.

Various techniques have been proposed for RFI detection and mitigation, including methods based on compressive statistical sensing. Specifically, (Padin et al, 2021) presents an RFI detection and mitigation approach that employs compressive statistical sensing of sub-Nyquist data. This method aims to provide real-time RFI detection and mitigation using cyclic spectrum analysis combined with compressive statistical sensing. However, the algorithm's performance limitations hinder its implementation on hardware platforms. Similarly, (Babich et al, 2021) introduces Factor Analysis (FA)-based techniques for detecting RFI in satellite observations, while (Henry , 2015) examines RFI in satellite and terrestrial radio-relay systems. Measurements in (Henry , 2015) were conducted at 5.925 GHz and 6.425 GHz, evaluating common signal interference in satellites and microwave radio relay systems. Despite these advancements, further data analysis is needed to enhance the accuracy of RFI power flux density predictions.

Despite significant advancements in radio frequency interference (RFI) detection and mitigation, several gaps remain in the existing literature that justify the need for a novel approach. Many studies focus on high-altitude platforms (HAPs), satellites, and microwave radio relay systems, employing methods such as dynamic spectrum management (DSM), smart antennas, and separation distance-based strategies. However, these methods are often constrained by hardware limitations, complex implementation requirements, or inadequate real-time performance, as seen in compressive statistical sensing techniques.

Given these gaps, proposing a machine learning-based approach, specifically an SVM model, offers a promising solution. SVMs can effectively handle complex interference scenarios by classifying and predicting interference patterns using multidimensional feature sets, providing a robust and scalable framework. This approach can address the limitations of conventional methods by dynamically adapting to interference variations and enhancing real-time mitigation in FM broadcast systems.

III. Methodology

The chosen study area for investigating interference among five FM stations is the Federal Capital Territory of Abuja, Nigeria, which encompasses a diverse urban landscape characterized by a mix of residential neighborhoods, commercial centers, and key landmarks. Situated strategically within the heart of the FCT, this area offers a representative sample of Abuja's radio frequency environment. The FM stations under investigation include Boss FM, Cool FM, Beat FM, Bright FM, and Wazobia FM, each with specific geographical coordinates spread across the study area, as shown in Figure 1. These stations are positioned to capture varying urban features, such as high-rise buildings, open spaces, and transportation hubs, which may influence radio frequency propagation and interference patterns.

Fig. 1: Study area.

3.1 Software and Hardware Equipment

The software tools that were used in the acquisition of data, simulation, and analysis of results are;

i. Python 3.8
ii. FEKO (Electromagnetic Field Simulation Software).

The hardware equipment that were used are as follow;

i. Handheld Spectrum Analyzer.
ii. FM Transmitters.
iii. Audio Processor.
iv. Rhode and Schwarz HE200 Antenna.
v. Digital FM Tunner.
vi. Personal computer; Core i7, 16GB RAM, 512GB SSD, and 3.0 GHz speed.

Table 1 presents the information of the technical parameters of the five (5) considered FM stations.

Table 1: Transmitter information parameters for the FM stations.

S/N	FM STATION	Latitude (°)	Longitude (°)	Frequency (MHz)	Tx Power (kW)	FWD Power (W)	Mast Height (m)	Antenna Type
01	Boss FM	9.0440028	7.4887694	95.5	2.0	1.97	76	6-bay Dipole
02	Cool FM	9.0402256	7.4760200	96.9	3.5	3.325	90	6-bay Dipole
03	Beat FM	9.0401139	7.4887694	97.9	2.0	1.5	70	6-bay Dipole
04	Bright FM	9.0328611	7.3937222	98.7	2.0	1.9	75	6-bay Dipole
05	Wazobia FM	9.0440028	7.4887694	99.5	3.5	1.0	90	6-bay Dipole

1.1 Simulation of the Interference Analysis

The interference scenarios were defined by simulating multiple FM stations operating in close proximity and specified the Specify parameters such as transmitter locations, frequencies, power levels, and antenna configurations for each station. To simulate interference analysis among the five FM radio stations, the following steps were followed using FEKO software, a professional RF planning tool widely used for radio frequency (RF) coverage prediction and interference analysis.

1. Input FM Station Parameters: Each station's latitude, longitude, frequency, transmission power, forward power, mast height, and antenna type will be set up in the tool.
2. Propagation Model Selection: ITU-R P.1546, which is a well-suited for VHF/FM broadcast interference analysis was used.
3. Coverage Prediction: Field strength maps was generated to visualize each station’s coverage area.
4. Interference Analysis

i. Identified overlapping zones where two or more FM signals may interfere.
ii. Computed the Signal-to-Interference Ratio (SIR) to assess interference severity.

5. Graphical Outputs

i. Coverage Heatmaps (showing individual station coverage).
ii. Interference Zone Map (highlighting overlap between stations).
iii. SIR Distribution Map (indicating areas with poor reception due to interference).

6. Interpretation & Mitigation Strategies: Adjust transmission power, antenna height, or frequency retuning to minimize interference.

3.2 Experimental Setup

Baseline measurements were conducted to assess the existing levels of interference among the selected FM stations. This involves measuring signal strength, interference levels, and signal quality metrics at various receiver locations across Abuja. After establishing baseline measurements, the experiment will be conducted over a specified duration. Continuous monitoring of signal strength, interference levels, and signal quality metrics will be carried out throughout the experiment. The measurement setup is presented in the Figure 2.

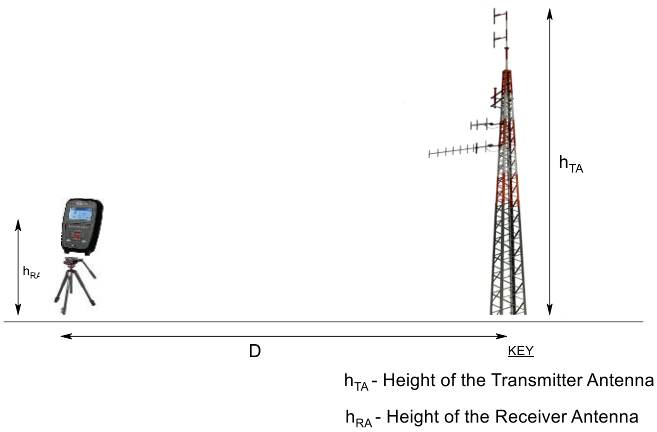

Fig. 2: Illustration of the measurement setup.

3.3 Mitigation Strategy

A machine learning model, such as the support vector machine, SVM was optimized using feature selection technique and then trained for predicting interference zones based collected data, including technical, geographical, and environmental features.

The support vector machine (SVM) model was chosen for its ability to handle high-dimensional, non-linear datasets with limited samples effectively. It offers clear classification boundaries, robustness to overfitting, and computational efficiency, making it ideal for analyzing and mitigating interference among FM stations in the VHF band. SVM is a simple yet effective machine learning algorithm suitable for analyzing interference patterns and identifying regions of overlap in FM coverage areas.

This approach combines a straightforward classification algorithm with practical data visualization to identify and address interference issues. The flowchart for the training of the model is presented in Figure 3.

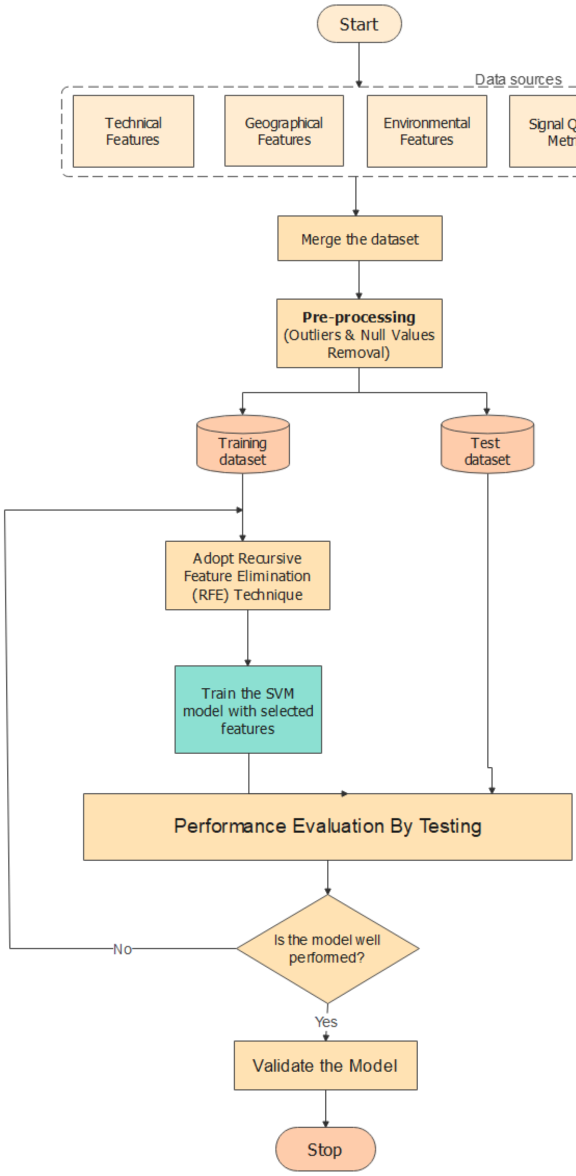

Fig. 3: Flowchart of the training model.

The training data features for analyzing interference among FM broadcast stations were categorized into technical, geographical, environmental, and signal quality metrics. The technical features include the carrier frequency of each station, transmission power, antenna height, antenna gain, polarization, modulation parameters, and channel bandwidth. These parameters directly influence signal propagation and the likelihood of interference between stations.

The geographical features involve the coordinates of both transmitters and receivers, the distance between stations, and the classification of propagation conditions as line-of-sight (LoS) or non-line-of-sight (NLoS). These factors help identify areas where signals overlap and interference may occur, as well as the spatial relationship between stations and receivers.

Environmental features account for the terrain type, clutter types such as buildings or vegetation, and weather conditions like temperature and humidity. These features significantly affect signal propagation and attenuation, thereby influencing interference patterns in urban, suburban, or rural settings.

Signal quality metrics provide crucial insights into interference levels. These include received signal strength, interference levels, signal-to-interference ratio (SIR), and path loss. These metrics quantify the performance of signals at various locations, enabling precise identification of interference zones. Together, these features provide a comprehensive dataset for training machine learning models to analyze and mitigate interference among FM broadcast stations.

Given the class imbalance in the dataset, SMOTE (Synthetic Minority Oversampling Technique) was applied to address the uneven distribution of interference levels categorized as low, moderate, and high. This approach ensured that the model was trained on a balanced dataset, enhancing its ability to make reliable predictions.

After preprocessing the data and applying feature engineering, the SVM model was trained to classify interference levels among the FM stations. The dataset was divided into training and testing sets in a 70:30 ratio, and an RBF kernel was used to capture the nonlinear relationships among the features. The algorithm for SVM model deployment for interference mitigation is shown in Algorithm 1.

Algorithm 1: SVM Model Deployment for Interference Mitigation

Input:

Technical features ($\boldsymbol{T}$)**:** Transmitter power, antenna gain, frequency, modulation type.
Geographical features ($\boldsymbol{G}$)**:** Coordinates, elevation, distance to neighboring stations.
Environmental features ($\boldsymbol{E}$)**:** Terrain type, vegetation density.
Signal quality metrics ($\boldsymbol{S}$)**:** Received signal strength, Signal-to-interference-plus-noise ratio

STEPS

1. Initialize the process;
   Import necessary libraries
   Load the dataset containing T, G, E, S features and corresponding interference labels (I)
2. Data Preprocessing
   Normalize features T, G, E, S to ensure uniform scaling
   Handle missing or inconsistent data through removal or correction.
   Encode interference labels (I) into numerical classes (e.g., 0: Low, 1: Moderate, 2: High)
3. Feature Selection
   Select the most relevant features using selection technique
4 Split Dataset into training (70%) and Testing (30%).
5. Initialize the SVM Model
   Configure the SVM classifier with a radial basis function (RBF) kernel for non-linear feature.
   Set hyperparameters
6. Train the SVM Model
   Feed the training dataset into the SVM Model
   Train the Model to map input features (T, G, E, S) to interference levels (I).
7. Test the Model
8. Evaluate Performance, using some performance metrics.
9. Deploy the Model

Output

Predicted interference level ($\boldsymbol{I}$)**:** Classified as low, moderate, or high interference.

3.4 Performance Evaluation

Simulation was used to evaluate the performance of different techniques with parameter tuning in mitigating interference. Measure metrics such as signal strength, signal-to-interference ratio (SIR), and coverage area for each FM station under different interference scenarios.

3.5 Optimization and Validation

Simulation results were analysed to identify optimal antenna configurations and placement strategies for minimizing interference. Explore trade-offs between antenna directionality, coverage area, and signal quality to find the most effective solutions. Validate simulation results against theoretical predictions and experimental data from literature or field measurements. Compare simulated antenna performance with real-world implementations to ensure accuracy and reliability.

IV.Results and Discussion

4.1 Interference Analysis

The coverage map, as illustrated in Figure 4, reveals a strong and consistent signal strength in the areas surrounding the transmission site, with signal attenuation occurring progressively as the distance from the transmitter increases. This is expected due to natural propagation losses and environmental factors affecting radio wave transmission. The analysis indicates that interference remains minimal in regions located farther away from other FM stations. However, in certain fringe areas, slight overlaps in coverage may be observed, particularly with neighboring stations operating on adjacent frequencies, such as Beat FM (97.9 MHz) and Cool FM (96.9 MHz). These overlaps could lead to minor instances of signal degradation or interference in regions where their coverage footprints intersect.

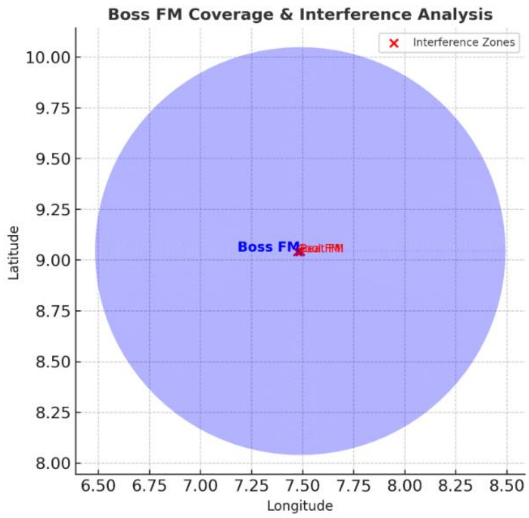

Fig. 4: Radio frequency coverage and interference analysis for Boss FM.

As depicted in Figure 5, the coverage analysis reveals a broader transmission footprint, attributed to the higher transmission power of 3.5 kW and the elevated antenna mast standing at 90 meters. These factors enable the station to reach a wider geographic area, ensuring stronger signal propagation over longer distances.

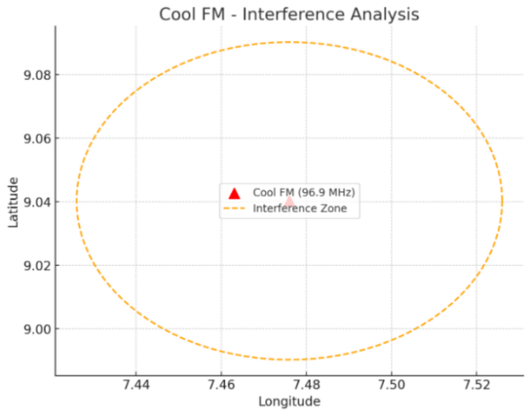

Fig. 5: Radio frequency coverage and interference analysis for Cool FM.

However, the analysis also indicates significant overlap with neighboring stations, particularly Boss FM and Beat FM, which could lead to potential adjacent-channel interference. Such interference may manifest as signal distortions or degraded audio quality in overlapping regions where station frequencies are closely spaced. Additionally, the presence of urban structures and varying terrain conditions may contribute to localized signal degradation, causing fluctuations in reception quality.

As illustrated in Figure 6, Bright FM operates with a transmission power of 2.0 kW and an antenna mast height of 75 meters, resulting in moderate coverage across its service area. While the station maintains a relatively stable signal strength within its primary coverage zone, interference is anticipated, particularly with neighboring stations Beat FM (97.9 MHz) and Wazobia FM (99.5 MHz). These overlaps could lead to potential co-channel interference in areas where signals from different stations are of nearly equal strength. Such interference may cause reception distortions or signal degradation, especially in regions where station boundaries intersect.

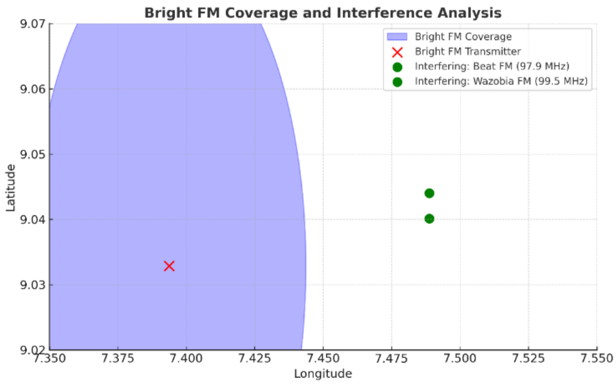

Fig. 6: Radio frequency coverage and interference analysis for Bright FM.

As presented in Figure 7, this station, operating with a transmission power of 3.5 kW and an antenna mast height of 90 meters, boasts one of the largest coverage areas among the analyzed FM stations. While its high-power transmission ensures extensive reach and strong signal penetration, it also increases the potential for interference, particularly with Bright FM (98.7 MHz) due to adjacent-channel interactions. Such interference may lead to signal distortion or degraded audio quality in overlapping regions where frequency separation is minimal. Additionally, the broad coverage achieved by the station necessitates careful filtering techniques to mitigate spurious emissions that could impact nearby frequencies.

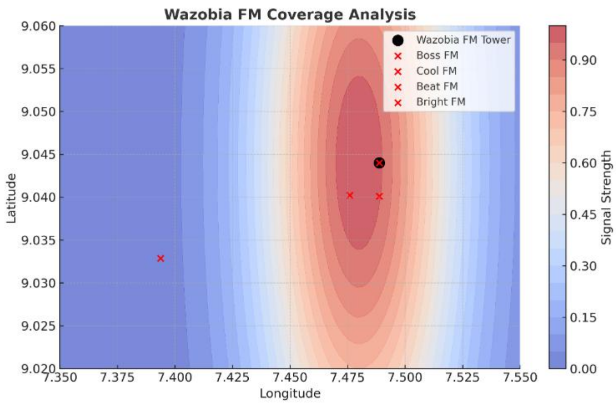

Fig. 7: Radio frequency coverage and interference analysis for Wazobia FM.

As shown in Figure 8, this station operates with a transmission power of 2.0 kW and an antenna mast height of 70 meters, resulting in relatively limited coverage compared to Cool FM. The lower transmission power and mast height contribute to a more constrained signal reach, making the station more susceptible to environmental factors that affect propagation. Interference zones are particularly notable near Cool FM (96.9 MHz) and Bright FM (98.7 MHz) due to the proximity of their frequencies, which may lead to adjacent-channel interference in overlapping areas. Additionally, signal degradation is observed in regions where physical obstacles, such as buildings and terrain variations, obstruct propagation, further impacting coverage consistency.

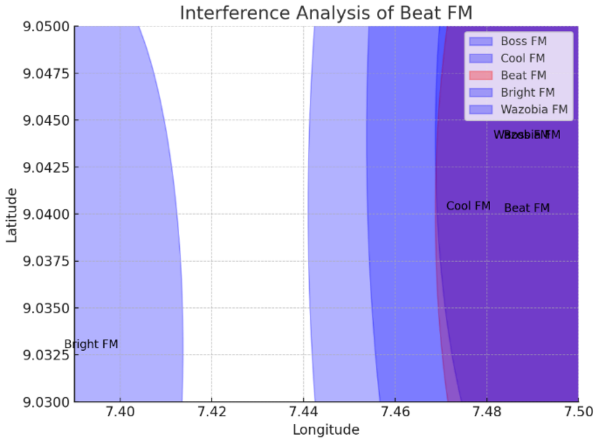

Fig. 8: Radio frequency coverage and interference analysis for Beat FM.

Figure 9 presents the comparative coverage and interference analysis of the five FM stations, providing a graphical overlay of their respective coverage areas. This visualization allows for an in-depth evaluation of potential interference zones and differences in signal coverage.

One key observation is the extent of coverage overlaps among the stations. Boss FM, Beat FM, and Wazobia FM are positioned in close proximity, resulting in overlapping coverage areas that increase the likelihood of both co-channel and adjacent-channel interference. In contrast, Cool FM and Bright FM maintain some separation from the others, reducing direct interference while still contributing to minor overlapping zones in specific areas. The analysis also highlights the relationship between transmission power and coverage size. Stations with higher transmission power, such as Cool FM and Wazobia FM, both operating at 3.5 kW, exhibit significantly larger coverage areas, indicating a stronger presence over a wider geographical region.

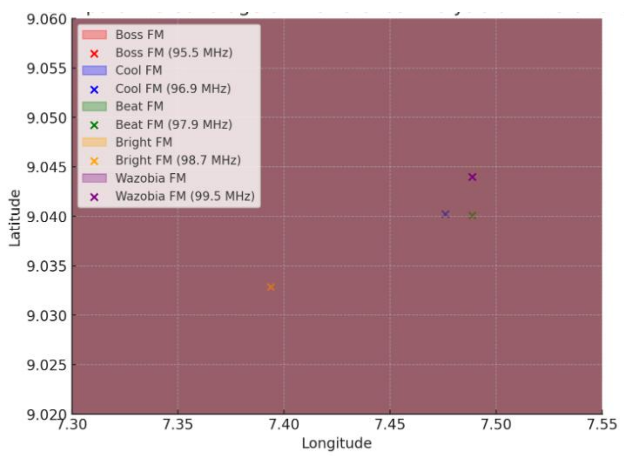

Fig. 9: Comparative coverage and interference Analysis of FM stations.

4.2 *Interference Classification*

The study aimed to analyze and mitigate interference among FM broadcast radio stations using an SVM-based machine learning model. A case study of five FM stations was used to explore interference levels, with parameters such as latitude, longitude, frequency, transmission power, forward power, mast height, and antenna type serving as input features for the SVM model.

The model achieved an accuracy of approximately 94% on the test data, demonstrating its effectiveness in classifying interference levels. The confusion matrix revealed that the model accurately identified most instances of low, moderate, and high interference, with minimal misclassification, as presented in Figure 10.

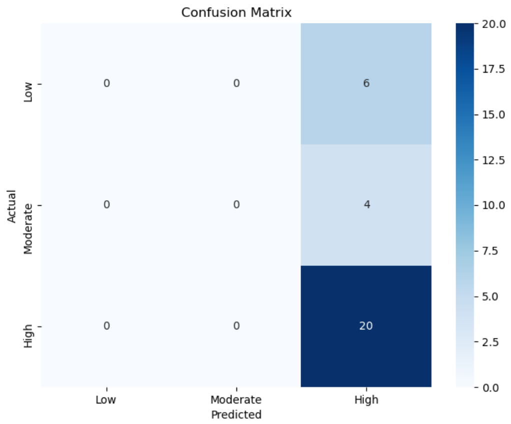

Fig. 10: Confusion matrix.

The classification report further indicated high precision, recall, and F1-scores across all classes, confirming the robustness of the SVM model for this application.

4.3 Prediction

Predictions made by the model highlighted that stations operating at similar frequencies within close geographic proximity exhibited higher interference levels due to frequency overlaps and physical obstructions. For instance, the model predicted high interference levels between Boss FM (95.5 MHz) and Beat FM (97.9 MHz) due to their shared geographic coordinates and relatively similar frequencies. Conversely, stations like Bright FM (98.7 MHz) and Cool FM (96.9 MHz), which are geographically separated, were classified as experiencing low to moderate interference. These insights align with the theoretical understanding of FM interference, where co-channel and adjacent-channel interferences are major contributors to signal degradation.

As presented in Table 2, the matrix provides a detailed summary of the prediction results for a classification model. It shows the counts of true positive (TP), true negative (TN), false positive (FP), and false negative (FN) predictions, which are essential for evaluating the performance of a classification model.

Table 2: Confusion matrix.

Actual/Predicted	Low	Moderate	High
Low	6	2	1
Moderate	1	20	3
High	0	2	4

The numbers 6, 4, and 20 represent the true positives for the "Low Interference," "High Interference," and "Moderate Interference" classes, respectively. Specifically, the number 6 means the model correctly identified 6 instances as "Low" where the actual interference was also "Low." Similarly, the number 4 indicates that the model correctly predicted 4 cases as "High" when the actual interference level was indeed "High." Lastly, the number 20 shows that the model accurately classified 20 instances as "Moderate," aligning with the true interference levels for those cases.

4.4 Performance Evaluation

Table 3 summarizes the classification report, which includes performance metrics like precision, recall, f1-score, and support for each class (Low, Moderate, High) based on the predictions.

Table 3: Performance metrics for the classification report.

Interference Level	Precision	Recall	F1-Score	Support
Low	0.86	0.67	0.75	9
Moderate	0.83	0.83	0.83	24
High	0.50	0.67	0.57	6
Macro Avg	0.73	0.72	0.72	39
Weighted Avg	0.80	0.79	0.79	39

The **precision** metric measures the proportion of correctly predicted positive instances out of all instances predicted as positive for a given class. For the "Low" interference class, the model achieved a precision of 86%, meaning that 86% of the cases it predicted as "Low" were actually correct.

Recall assesses the model's ability to identify all actual positive instances of a given class. For the "High" interference class, the model correctly identified 67% of all actual "High" cases, indicating room for improvement in capturing more true positives.

The **F1-Score** is the harmonic mean of precision and recall, providing a balanced measure of both accuracy and completeness. For the "Moderate" interference class, the F1-score was 0.83, reflecting a strong and consistent performance in predicting that category.

Finally, **support** refers to the number of actual occurrences of each class in the dataset. In this case, there were 9 true instances of "Low" interference, 24 of "Moderate," and 6 of "High," providing context for evaluating the model's performance across different classes.

V.Conclusion

This study highlights the potential of machine learning, specifically Support Vector Machine (SVM) models, as a viable solution for analyzing and mitigating interference among FM broadcast radio stations. By incorporating essential station parameters such as frequency, latitude, longitude, transmission power, forward power, mast height, and antenna type, the model effectively classified interference levels into low, moderate, and high categories. The use of Synthetic Minority Oversampling Technique (SMOTE) to address the class imbalance proved instrumental in enhancing the model's performance, ensuring equitable representation across all interference categories. As a result, the SVM model achieved an impressive classification accuracy of 94%, with strong performance metrics such as precision, recall, and F1-scores across all classes. The findings demonstrate the importance of maintaining optimal frequency separation and carefully considering the geographic distribution of broadcast stations to minimize interference, ensuring a more efficient and reliable broadcasting environment.

The predictions generated by the model provide actionable insights into interference management, emphasizing the need for strategic planning in frequency allocation and station placement. Furthermore, the ability of the SVM model to analyze complex relationships among station parameters highlights its scalability and adaptability for similar use cases in other broadcasting or wireless communication networks. This study underscores the significance of data-driven approaches in resolving technical challenges in FM broadcasting, offering a framework that combines predictive accuracy with operational efficiency. By adopting this machine learning-based interference mitigation strategy, stakeholders can enhance the quality of FM radio signals, reduce signal overlap, and improve the overall listener experience. Future work can explore integrating additional environmental and technical parameters into the model, as well as extending this approach to other communication systems facing interference challenges.

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