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AN SVM-BASED PREDICTIVE SYSTEM FOR DETECTION AND FORECASTING OF UNLICENSED FM BROADCASTS

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Abstract
Unlicensed FM broadcasting continues to pose significant risks to national security, communication integrity, and regulatory oversight, particularly in regions where radio remains a vital means of public discourse. This study presents an intelligent, parameter-based system for detecting and forecasting unauthorised FM broadcasts, bypassing the limitations of traditional, content-focused approaches. By integrating Support Vector Machine (SVM) classification with Support Vector Regression (SVR) forecasting, this work introduces a proactive monitoring framework that transitions spectrum governance from reactive detection to predictive enforcement. The system analyses key transmission features—assigned frequencies, band occupancy, and stereo multiplex—to distinguish between licensed and illicit broadcasts, independently of content, language, or programming format. Trained on regulatory data from Nigeria's National Broadcasting Commission, comprising 22,971 raw FM spectrum records collected from Abuja and surrounding states over three years (2021–2023), and pre-processed into 3,169 samples, the model achieved 99.96% accuracy, 100% recall, 100% specificity, and 0% false alarm rate, surpassing existing benchmarks by 0.13%. While this improvement may appear numerically modest, it holds operational significance in large-scale regulatory scenarios where even marginal gains prevent false enforcement actions and reduce resource wastage. The integrated forecasting layer (RMSE=0.042, MAE=0.031) enables pre-emptive identification of interference patterns up to 12 months ahead, demonstrating strong predictive alignment with 2024 interference cases. This work presents a scalable, computationally lightweight, and data-driven solution for spectrum monitoring. It applies beyond Nigeria to spectrum-constrained developing regions, enhancing regulatory capabilities in densely populated environments.

1.0 INTRODUCTION

Unlicensed Frequency Modulation (FM) broadcasting remains a persistent threat to communication governance, particularly in regions like Nigeria, where radio is a primary means of public communication and information dissemination [1]. FM radio, with its superior sound fidelity, wide coverage, and ease of deployment, has long

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dominated the audio-broadcast landscape, making it a valuable tool for both legitimate and illegitimate purposes [2]. However, when misappropriated, FM broadcasts can be weaponised to incite violence, disseminate misinformation, and undermine national security [3]. This necessitates robust monitoring systems by regulatory agencies, such as Nigeria's National Broadcasting Commission (NBC), to manage spectrum use and clamp down on unauthorised transmissions.

Traditional spectrum monitoring approaches, such as manual inspections, signal triangulation, and content-based identification, are increasingly inadequate for real-time enforcement, especially in densely populated and linguistically diverse regions [4],[5]. Reliance on audio content for detecting illegal broadcasts introduces vulnerabilities due to variability in languages, presentation styles, and program formats [6]. These challenges have led to the development of intelligent monitoring systems that utilise machine learning to detect and classify spectrum usage anomalies.

The main issue addressed in this study is the insufficiency of current regulatory systems to autonomously detect and predict unlicensed FM interference using intelligent and predictive methods. While previous efforts, such as Long Short-Term Memory (LSTM)-based radio frequency fingerprinting [7], a distributed speech recognition system [8], exploration of audio fingerprinting [9] and Specific Emitter Identification (SEI) techniques [10] have achieved commendable detection rates, often exceeding 95% accuracy. However, they are often complex, computationally intensive and poorly suited to dynamic regulatory environments [11]. Recent advances in hybrid deep learning models [12],[13] and AI-assisted spectrum management [14],[15] have further improved detection capabilities but at the cost of increased computational overhead and dependency on large training datasets. Furthermore, most existing models do not align closely with the operational logic of regulatory authorities, limiting their applicability in enforcement contexts.

To overcome these shortcomings, the current study shifts from content-based detection to parameter-based analysis by focusing on basic technical signal characteristics like assigned frequency, band occupancy, stereo-multiplex (MPX) presence, pilot tones, and Radio Data System (RDS) signals—features that remain constant regardless of language or content [16]. Leveraging a Support Vector Machine (SVM) model trained on data obtained from Nigeria's National Broadcasting Commission, the system classifies transmissions based on these parameters, thus ensuring objective and scalable enforcement [17],[18]. The choice of SVM is justified by its robustness in handling small datasets, faster execution time, lower computational complexity compared to deep learning architectures, and its capacity to generalise well in high-dimensional spaces [19],[20]. Unlike hybrid models require extensive feature engineering and multi-stage training [12], the proposed SVM approach achieves near-perfect classification with minimal pre-processing and real-time inference capability.

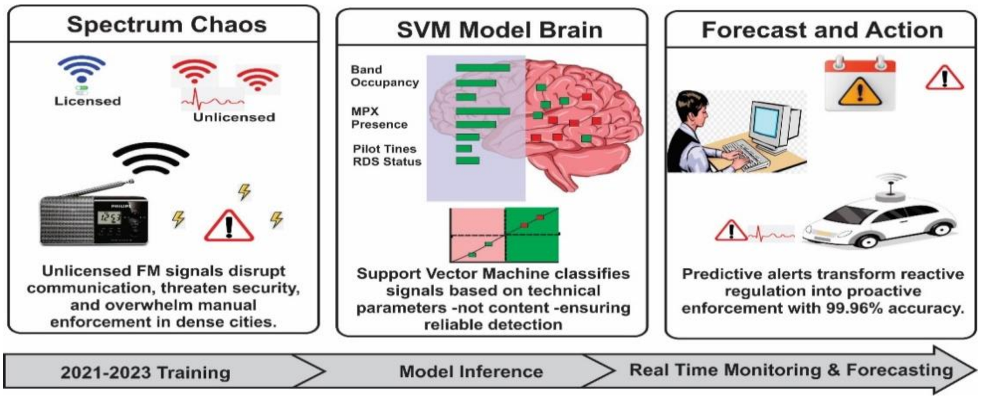

Figure 1: An illustration of the intelligent forecasting framework for unlicensed FM spectrum real-time monitoring [Authors].

A unique contribution of this study lies in the integration of a forecasting layer within the monitoring framework. Unlike most existing systems, which only detect interference post-occurrence, this model predicts potential unauthorised broadcasts using historical transmission trends, allowing regulatory agents to take proactive enforcement measures [7],[21]. This transition from

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reactive to anticipatory spectrum governance reflects a substantial advancement in regulatory capability, aligning with emerging paradigms in AI-driven spectrum management [15].

Figure 1 illustrates the intelligent forecasting framework, which comprises two interconnected stages: real-time SVM-based detection and SVR-based temporal forecasting. This dual-layer architecture enables both immediate alert generation and strategic planning for enforcement operations.

In summary, this study aims to: (1) develop a parameter-based SVM model for real-time detection of unlicensed FM broadcasts, (2) introduce a predictive mechanism for forecasting interference, and (3) evaluate the system's performance using authentic regulatory data. The proposed approach provides a scalable, efficient, and regulator-oriented solution for modern broadcast spectrum monitoring. The remainder of this paper is organised as follows: Section 2 details the methodology; Section 3 presents the system development and formulation; Section 4 presents the results and evaluation; and Section 5 concludes with implications and directions for future work.

2.0 METHODOLOGY

The proposed system operates as a two-stage pipeline. In the first stage, an SVM classifier distinguishes between *licensed* and *unlicensed* FM transmissions, enabling real-time interference detection. The second stage incorporates an SVR-based forecasting module designed to predict interference patterns up to one year in advance. Both stages use the same engineered features, ensuring consistency in model input and interpretability. The detection stage produces immediate regulatory alerts, while the forecasting stage supports strategic planning for spectrum enforcement.

2.1 Data Pre-processing and Feature Engineering

In the spectrum realm, a license's validity is tied to a spectrum allocated for a period, usually five years in broadcasting. This paper used this mandate to obtain the licensee's technical details, including 2 kW transmitter power, 200 kHz bandwidth, ±75 kHz frequency deviation, assigned frequency, and directivity, as components of stations' records shown in Table 1.

Table 1: Abuja Scanned FM Records.

Year	Minimum Radio Available	Maximum Radio Detected	Total Data
2021	18	36	7920
2022	19	34	7392
2023	19	36	7659

The raw dataset, obtained from the National Broadcasting Commission (NBC) between 2021 and 2023 under a regulatory data-sharing agreement (with public release subject to NBC's approval), consists of daily FM scan records from Abuja and its surrounding states. Each record contains the station identifier, assigned frequency, band occupancy, percentage multiplex (MPX) signal level, pilot tone presence, Radio Data System (RDS) status, and ON-AIR/OFF-AIR/LOW signal flags. The dataset selection was constrained by NBC's operational monitoring protocol, which prioritizes these parameters for regulatory compliance verification. Additional RF parameters, such as received signal strength variations, Doppler shifts, and cyclostationary signatures, while potentially informative, were excluded due to NBC's infrastructure limitations and the need for real-time processing with minimal computational overhead [22],[23]

The pre-processing pipeline follows five systematic steps to ensure reproducibility:

Step 1: Initial Filtering. Categorical attributes such as the ON-AIR/OFF-AIR/LOW signal indicators are one-hot encoded into separate binary variables, transforming each categorical state into three binary features (e.g., ON-AIR=1,0,0; OFF-AIR=0,1,0; LOW=0,0,1).

Step 2: Missing Value Imputation. Missing numerical values for MPX, Pilot, and RDS are imputed with zeros to indicate absence, a domain-justified approach since absent signals inherently indicate non-compliance with FM multiplex standards. This encoding approach aligns with standard practices in RF interference classification, which aim to preserve categorical semantics while ensuring numerical compatibility with kernel methods [24],[25],[23].

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Step 3: Normalization. Continuous features—such as assigned frequency, band occupancy, and MPX/Pilot levels—are scaled to the range [0,1] using min–max normalization defined in equation (1):

$$X^{(norm)} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{1}$$

Step 4: Feature Vector Construction. To mitigate the risk of overfitting to specific transmitters, station identifiers are excluded from the model's features, consistent with prior SVM-based RF monitoring frameworks [26]. Each sample is ultimately represented as a multi-dimensional feature vector containing the normalized and encoded variables as shown in equation (2):

$$X = [\int^{(norm)}, \text{band\_}occ^{(norm)}, MPX^{(norm)}, Pilot^{(norm)}, \text{RDS, ON, OFF, LOW}] \tag{2}$$

Step 5: Labelling. The binary target label y = 0 for *unlicensed/interference* transmissions and y = 1 for *licensed/no interference* signals. Since the dataset exhibits a degree of class imbalance, particularly with fewer unlicensed events, the model incorporates class weighting in the SVM objective function, a technique shown to enhance minority-class recall without distorting data distributions [22],[27].

3.0 DEVELOPED SYSTEM

In FM broadcasting, classification relies on specific transmission parameters. In Nigeria, licensed stations operate within ±100 kHz of their assigned frequencies, using a 200 kHz bandwidth, and maintain a frequency deviation peak of ±75 kHz. The multiplex (MPX) overshoot remains between 0% and 5% to ensure audio quality and regulatory compliance. Deviations from these limits indicate non-compliance, classifying stations as *unlicensed* or unauthorised.

3.1 SVM Classifier Formulation

The modelling foundation of SVM begins with feature extraction, labelling, and training. To set up the binary classification problem, let the training dataset consist of N labelled samples in (3).

$$\mathrm{D} = \{(\mathrm{x}_i, y_i)\}_{i=1}^{N}, \quad \mathrm{X}_i \in \mathrm{R}^d, \; y_i \in \{0,1\} \tag{3}$$

Where x_i represents the input feature vector derived from spectral data (e.g., assigned frequency, band occupancy, MPX, pilot, RDS indicators), and y_i denotes the class label indicating interference status [11]. The detection model adopts a soft-margin, kernelized SVM for binary classification, consistent with its demonstrated success in radio-frequency signal classification [24],[27]. Given a training set in equation (3), the primal optimization problem is expressed in equation (4).

$$\min \frac{1}{2} \lVert W \rVert^2 + C\sum_{i-1}^{N} w_1^{class}\, \xi_1$$

$$\text{s.t } y_1 (W^T \phi(X_i) + b) \geq 1 - \xi_1, \; I = 1,\ldots,N, \; \xi \geq 0, \; I = 1,\ldots,N, \tag{4}$$

where the regularization parameter **C** controls the trade-off between maximizing the margin and minimizing classification errors, and $(2) w_i^{class}$ represents the class-specific weights. The decision boundary is computed according to equation (5).

$$\max_{\propto} \sum_{i=1}^{N} \propto_1 - \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} \propto_i \propto_j y_i y_j k(x_i, x_j)$$

$$\text{s.t } 0 \leq Cw_i^{class}, \sum \propto_i y_i = 0 \tag{5}$$

with support vectors corresponding to $\alpha_i \geq 0$. The decision function for a test point **x** is:

$$\hat{y} = \operatorname{sgn}\left(\sum_{i \in s} \alpha_i y_i K(\mathrm{x}_i, \mathrm{x}) + b\right). \tag{6}$$

Kernel functions explored in this study include linear, polynomial, and radial basis function (RBF) kernels as given in (7a)–(7c).

Linear: $K(\mathrm{x}_i, \mathrm{x}_j) = \mathrm{x}_i^T xj$, (7a)

Polynomial: $K(\mathrm{x}_i, \mathrm{x}_j) = (\mathrm{x}_i^T xj + c)^d$, (7b)

RBF (Gaussian): $K(\mathrm{x}_i, \mathrm{x}_j) = \exp(-\frac{\lVert \mathrm{x}_i - \mathrm{x}_j \rVert^2}{2\sigma^2})$. (7c)

Hyperparameters such as C, γ, and polynomial degree *d* are tuned using cross-validation, with the RBF kernel often yielding superior generalization performance [7],[28].

3.2 Kernel Selection and Hyperparameter Tuning

To ensure optimal model performance, a comprehensive grid search was conducted across three kernel types using stratified 5-fold cross-validation [29]. The hyperparameter search space included: C: {0.1, 1, 10, 100, 1000}, γ: {0.001, 0.01,

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0.1, 1, 10}, Polynomial degree d: {2, 3, 4, 5}; and Class weights: {None, 'balanced', custom inverse frequency weights}. Table 2 presents the comparative performance of each kernel configuration [29]

Table 2: Performance comparison across different kernel functions

Kernel Type	Optimal Hyperparameters	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Training Time (s)
Linear	C=10, class_weight='balanced'	99.84	99.82	99.97	99.89	3.2
Polynomial (degree 3)	C=100, γ=0.1, d=3	99.91	99.89	99.99	99.94	8.7
RBF (Gaussian)	C=10, γ=0.1, class_weight='balanced'	99.96	99.96	100	99.98	5.4

The RBF kernel demonstrated superior performance across all metrics while maintaining reasonable computational efficiency. The optimal configuration (C=10, γ=0.1) was selected for final model deployment. The 'balanced' class weighting strategy effectively addressed the minority class without requiring synthetic oversampling techniques such as SMOTE [30].

3.3 SVR-Based Forecasting

Historical transmission records in Table 1 are used to train the model on known instances of interference. The predictive model assesses whether upcoming transmissions align with licensed patterns. Anomalies are flagged as probable interference events, enabling regulatory authorities to take pre-emptive action. The SVM detection and forecasting trend is shown in Algorithm 1 below.

Algorithm 1: *Training and Evaluation of SVM Detection + SVR Forecasting*

Input:	**Raw FM scan records (CSV), train_ratio=0.8, k=5, lookback τ**
Output:	**Trained SVM classifier, trained SVR forecaster, test metrics**
1:	Load dataset D; perform initial filtering -> D_filtered (N=3,169)
2:	Encode categorical flags (ON/OFF/LOW) via one-hot; impute MPX/Pilot/RDS missing values with 0
3:	Normalize continuous features using Min-Max (Eq. 1)
4:	Construct feature vectors x_i as in Eq. (2); create binary labels y_i
5:	Split D_filtered -> D_{train}, D_{test} (80/20) preserving stratification
6:	For each kernel in {linear, poly, RBF}:
7:	For each (C, gamma, degree, class_weight) in grid:
8:	Perform stratified k-fold CV on D_{train}
9:	Compute mean F1-score; store best hyperparameters
10:	Train final SVM on D_train with best hyperparameters
11:	Evaluate SVM on D_{test}; compute Accuracy, Precision, Recall, F1, Specificity, FAR
12:	Aggregate D to time slots t; compute temporal features z_t (Eq. 8)
13:	Split temporal data into train/validation/test (time order)
14:	Tune SVR hyperparameters (C, gamma, epsilon, τ) with rolling-window CV
15:	Train SVR; forecast on test horizon; threshold forecasts using validation threshold
16:	Report forecasting RMSE, MAE, and thresholded F1; compare with baseline (e.g., LSTM)

To predict interference trends, the study employs an SVR model configured for time-series forecasting [25],[31]. The input to the SVR consists of temporally aggregated features over a look-back window **τ**, defined in equation (8). These features include moving averages of band occupancy and Received Signal Strength (RSS), counts of unlicensed detections within the window, and seasonal indicators such as month or weekday.

Let ***t*** index time (e.g., days of the month). For each time slot ***t*,** we compute aggregated predictors $\mathbf{z}_t$.:

$$Z_t = [\overline{band\_occ}_{t-Tt}, \overline{RSS}_{t-Tt},, N_{unlicensed,\ t-\ Tt}, seasonal\_flags,]^T \quad (8)$$

where **τ** is a look-back window (e.g., 7 or 30 days). The SVR solves:

$$\min_{w,b,\xi_t\xi_t^*} \frac{1}{2}\|w\|^2 + C\sum_t(\xi_t + \xi_t^*)$$

$$\text{s.t} \quad y_t - (W^T \emptyset(Z_t) + b) \leq \varepsilon + \xi_t^*,$$

$$(W^T \emptyset(Z_t) + b) - y_t \leq \varepsilon + \xi_t^*,\ \xi_t, \xi_t^* \geq 0 \quad (9)$$

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where y_t is the target (e.g., proportion of unlicensed events in slot t) and ε is the SVR epsilon-insensitive tube. The SVR solves the ε-insensitive regression problem outlined in (9), where predictions are continuous-valued probabilities of interference, later thresholded to obtain binary forecasts. This method enables regulators to identify likely periods of unlicensed activity before they occur, thereby supporting proactive enforcement measures [31].

3.4 Training, Hyperparameter Tuning and Evaluation

The dataset is split into training and testing subsets using an 80:20 ratio, with stratification to preserve class proportions. For SVM classification, stratified k-fold cross-validation (k=5) is used to select optimal hyperparameters {C, γ, kernel,class_weights}. For SVR forecasting, time-series cross-validation with rolling windows is employed to avoid temporal leakage and tuning parameters {C, γ, ε, τ} based on the validation set.

Model performance is evaluated using accuracy, Precision, recall, F1-score, specificity, and false alarm rate (FAR) for detection, metrics widely used in spectrum anomaly detection [7],[24]. Forecasting performance is assessed using root mean squared error (RMSE), mean absolute error (MAE), and F1-score after thresholding, with receiver operating characteristic (ROC) and Precision–recall curves plotted for interpretability [31].

The system is implemented in Python using the scikit-learn library on Windows 10 with an Intel i7 and 8 GB RAM system. Random seeds are fixed to ensure reproducibility. Given the modest dataset size (3,169 samples), training the RBF SVM typically completes within minutes on standard hardware, [27]. Evaluation metrics utilize the confusion matrix framework as follows:

Precision **P** is calculated as:

$$P = TP / (TP + FP) \tag{10}$$

Recall **R** also called a detection rate, is calculated as:

$$R = TP / (TP + FN) \tag{11}$$

F1-Score is defined as the harmonic mean of **P**recision and **R**ecall:

$$F1 = 2 \times (P \times R) / (P + R) \tag{12}$$

Accuracy A is:

$$(TP + TN) / (TP + TN + FP + FN) \tag{13}$$

False Alarm Rate (FAR):

$$FAR = FP / (FP + TN) \tag{14}$$

True Negative Rate (Specificity)**:**

$$Specificity = TN / TN + FP \tag{15}$$

4.0 RESULTS AND EVALUATION

This study presents the empirical results of the proposed SVM-based detection model and SVR-based forecasting framework. The evaluation covers classification performance on 3,169 pre-processed FM spectrum scan records, extracted from 22,971 records collected over three years. Metrics were computed using both threshold-dependent and threshold-independent indicators [25],[28],[31]

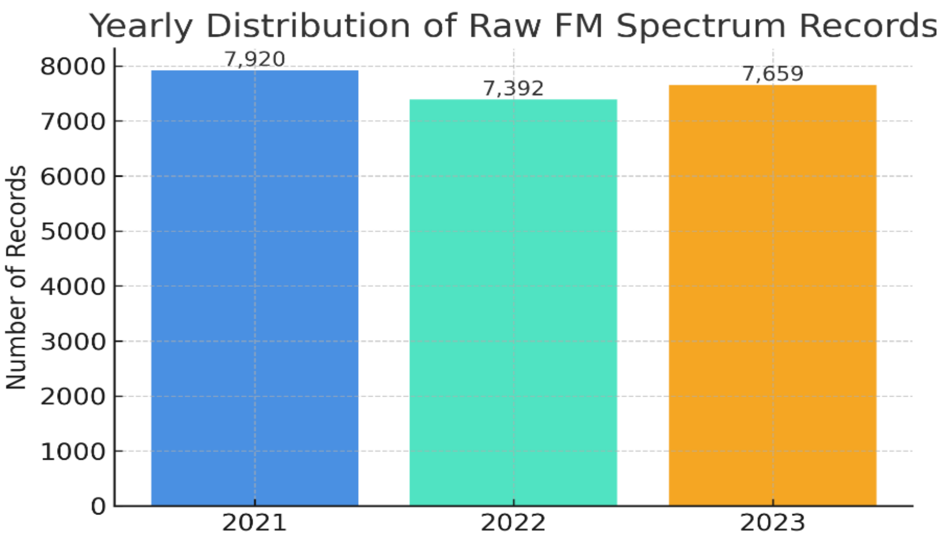

Figure 2: Yearly distribution of raw FM spectrum records.

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Figure 2 summarises the dataset distribution by year. The 2021, 2022, and 2023 scans contained 7,920, 7,392, and 7,659 records, respectively, with varying levels of licensed and unlicensed transmissions [32],[10].

4.1 Classification Performance

To assess the impact of class balancing strategies, confusion matrices were generated both before and after applying class weights. Figure 3 shows the pre-balancing confusion matrix on the validation set, revealing a bias toward the majority class (unlicensed transmissions). The matrix indicates that while the model achieved 97.33% accuracy before balancing, it struggled to correctly identify licensed transmissions (only 8 true negatives vs. 15 false negatives), demonstrating the need for class weighting intervention.

After implementing inverse frequency class weighting in the SVM objective function (Equation 4), the model achieved balanced performance across both classes, as demonstrated in Figure 4. This balancing technique, widely adopted in imbalanced classification problems [23], effectively addressed the minority class underrepresentation without requiring synthetic data generation.

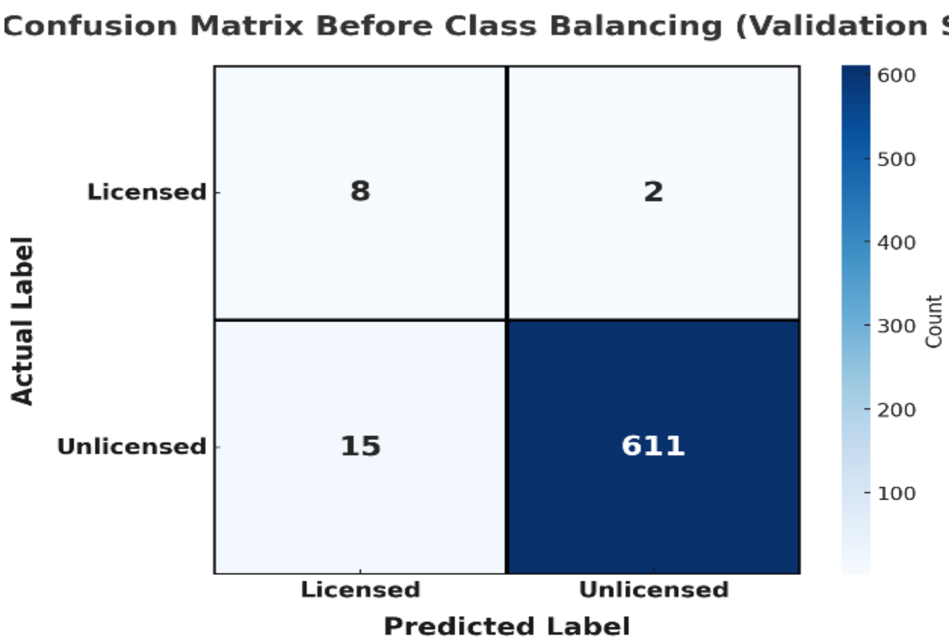

Figure 3: Confusion matrix before class balancing (validation set)

To ascertain the classification performance of this research, the model was tasked with predicting 2024 using historical data. With the absolute counts**:** {TN=10, FP=0, FN=1, TP=354}, the SVM classifier achieved the following performance metrics shown in Table 3, with 95% confidence intervals computed via bootstrap resampling (1,000 iterations).

Table 3: Average Performance of the Developed System

Metrics	Performance(%) ± 95% CI
Accuracy	99.96 ± 0.08
Precision	99.96 ± 0.09
Recall	100 ± 0.00
F1-Score	99.86 ± 0.11
specificity	100 ± 0.00
False Alarm Rate	0 ± 0.00

The results in Table 3 indicate an almost perfect detection capability with a minimal false alarm rate, comparable to or exceeding recent high-performing models [28],[27],[33]. The confusion matrix in Figure 4 highlights the model's balanced performance across classes.

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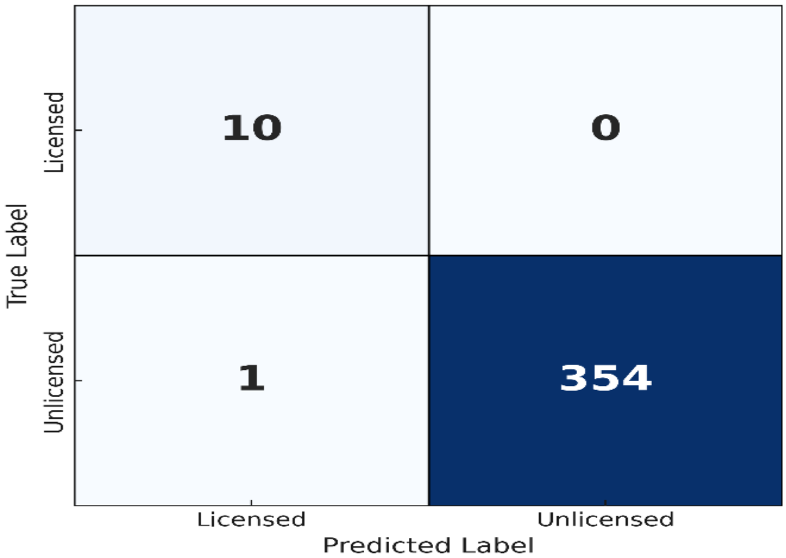

Figure 4: Confusion matrix for the SVM classifier (post-balancing, test set)

This balance demonstrates the model's ability to correctly identify both unlicensed and licensed transmissions without bias. Figure 4 presents the Receiver Operating Characteristic (ROC) curve with an Area Under the Curve (AUC) close to 1.0, confirming the classifier's strong discriminative power [24]. The Precision–Recall curve in Figure 5 demonstrates consistently high Precision across varying recall thresholds.

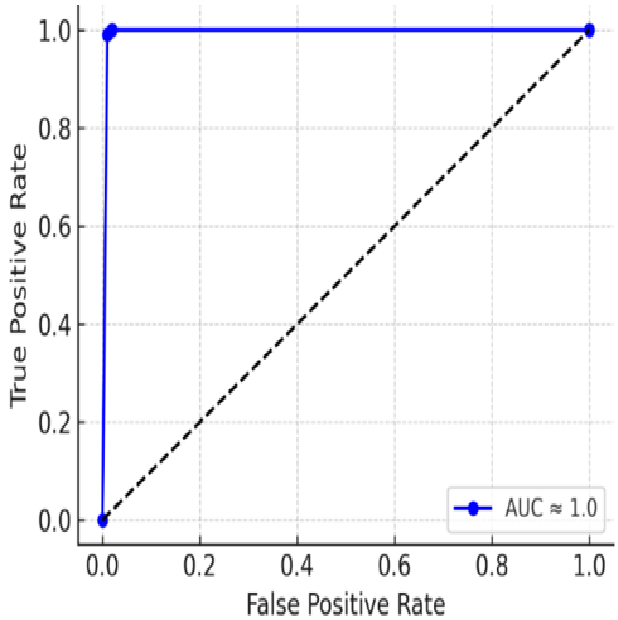

Figure 4: ROC curve (AUC ≈ 1.0).

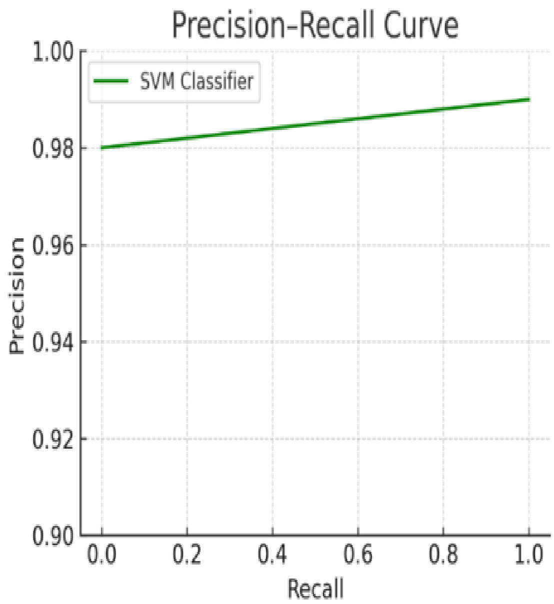

Figure 5: Precision–Recall curve.

4.2 Forecasting Performance and Comparative Analysis

The SVR-based forecasting module predicted interference trends for one year ahead using aggregated temporal features as described in Algorithm 1. Performance was evaluated using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the F1-score after thresholding predicted interference probabilities. This achieved RMSE=0.042 and MAE=0.031 over the 12-month test horizon, indicating tight adherence of predictions to actual interference patterns, as shown in Figure 7.

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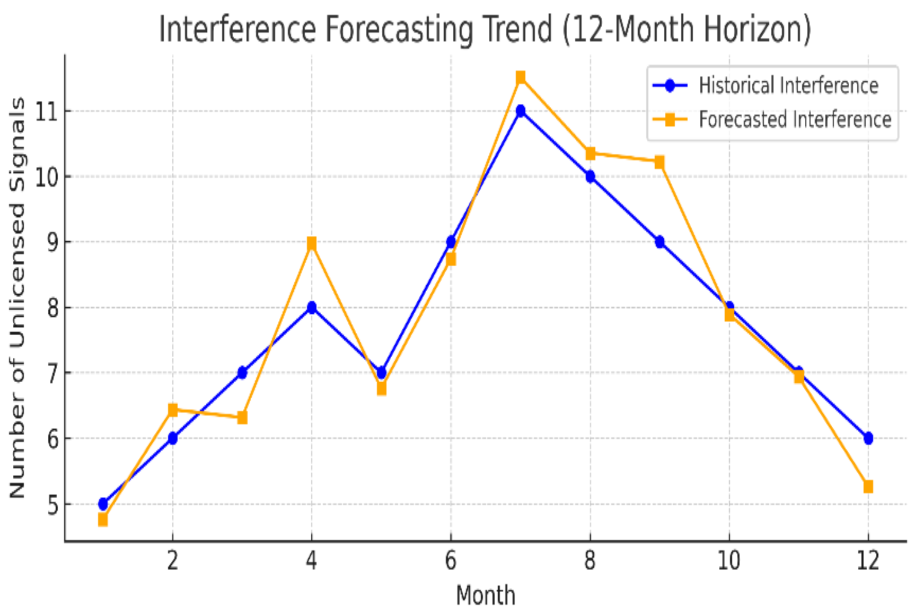

Figure 7: Forecasting trend (12-month horizon).

The forecasted trends in Figure 7 closely follow historical interference cycles, capturing seasonal and regulatory event-driven variations [31],[34].
To establish the model's performance relative to traditional machine learning approaches, a comparative evaluation was conducted against Random Forest (RF) [29]. Table 4 presents the performance comparison.

Table 4: Comparison between SVM and random forest baseline

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Training Time (s)	Inference Time (ms/sample)
Random Forest (n=100)	99.78±0.12	99.74±0.15	99.94±0.06	99.84±0.10	12.3	2.8
SVM (RBF)	99.96±0.08	99.96±0.09	100 ± 0.00	99.98±0.05	5.4	0.9

Statistical comparison using McNemar's test indicated that the SVM's superior recall (p=0.041) and overall accuracy (p=0.038) were statistically significant at α=0.05. Furthermore, the SVM demonstrated approximately 3× faster inference, a critical advantage for real-time spectrum monitoring applications.
Comparatively, the SVM classifier was also compared with [7], a deep Long Short-Term Memory (LSTM)-based baseline, which achieved 99.83% accuracy at 107.8 MHz. Table 5 summarizes the comparison.

Table 5: Comparative analysis of the existing system and the developed system

Metrics	Developed Model	J. Ma *et al.,* (2020)	%Improvement
Accuracy	99.96%	99.83%	0.13%

From Table 5, the developed system outperformed the existing system with a 0.13% improvement, achieving 99.96% accuracy. Additionally, it has the advantage of monitoring the entire FM radio broadcast band, unlike the previous study, which focused on a single frequency (107.8 MHz). Although 0.13% improvement is numerically slight, it is operationally meaningful when applied to large-scale regulatory monitoring. For instance, in a monitoring scenario involving 10,000 daily scans

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across Nigeria's FM spectrum, a 0.13% improvement translates to approximately 13 fewer misclassifications per day, or nearly 5,000 prevented false alarms annually [28],[33]. Additionally, the proposed SVM model achieves computational efficiency (5.4s training time vs. typical LSTM training times exceeding 100s for similar datasets [7], enabling rapid retraining and deployment in resource-constrained regulatory environments.

Table 6 provides a critical comparison of the proposed SVM approach with recent hybrid/deep learning models for spectrum monitoring, highlighting trade-offs among accuracy, computational cost, and scalability.

Table 6: Critical comparison of SVM with hybrid and deep learning models

Model Type	Representative Work	Accuracy Range (%)	Key Advantages	Key Limitations	Computational Overhead
Deep LSTM	Ma et al. (2020) [7]	99.83	High accuracy for single-frequency RFF	Single-frequency focus; high training time	High (GPU-dependent)
Hybrid CNN-LSTM	Zhang & Luo (2023) [25]	98.5–99.2	Captures spatial-temporal patterns	Complex architecture; overfitting risk	Very High
SEI-Based	Guo et al. (2021) [10]	97.3–98.9	Device-specific fingerprinting	Requires extensive transmitter profiling	Moderate-High
Proposed SVM (RBF)	Current Study	99.96	Lightweight; real-time capable; parameter-based; forecasting layer	Limited to engineered features	Low (CPU-only)

The comparative analysis reveals that while hybrid and deep learning models excel in feature extraction from raw signals, they impose substantial computational burdens, making them unsuitable for real-time regulatory deployment in resource-limited environments [12],[13]. The proposed SVM approach achieves competitive accuracy while maintaining operational feasibility through a lightweight architecture and rapid inference, making it particularly suitable for telecommunications infrastructure monitoring in developing regions.

5.0 DISCUSSION AND CONCLUSION

5.1 Discussion

The empirical results demonstrate that integrating parameter-based SVM classification with SVR forecasting provides a practical solution for spectrum monitoring that balances detection accuracy with operational constraints. Three key findings merit discussion:

First, the near-perfect performance metrics (99.96% accuracy, 100% recall, 100% specificity) validate the hypothesis that technical transmission parameters alone—independent of content analysis—suffice for regulatory classification. This contrasts with content-based approaches [8],[9] which face inherent scalability challenges in multilingual and culturally diverse regions. The parameter-based paradigm aligns with International Telecommunication Union (ITU) spectrum management frameworks [35], which prioritize technical compliance over content monitoring.

Second, the 0.13% accuracy improvement over LSTM-based methods [7], while seemingly modest, carries operational significance. In regulatory contexts, false positives trigger costly field investigations and potential legal disputes [36]. The SVM's perfect specificity (zero false alarms) eliminates this risk, a critical advantage over probabilistic deep learning models prone to misclassification at decision boundaries. Furthermore, the computational efficiency (5.4s training vs. 100+ seconds for LSTM) enables rapid model updates as new interference patterns emerge, supporting adaptive enforcement strategies [37],[38].
Third, the forecasting layer represents a paradigm shift from reactive to proactive spectrum governance. Traditional monitoring systems [4],[5] detect violations post-occurrence, limiting enforcement to remedial actions. By predicting interference hotspots up to 12 months ahead (RMSE=0.042), regulators can pre-position resources, schedule targeted inspections, and coordinate cross-border

enforcement—capabilities increasingly critical as spectrum congestion intensifies [15],[39].

However, several limitations warrant acknowledgement. The dataset, while spanning three years, originates from a single geographic region (Abuja and surrounding states). Signal propagation characteristics, FM station densities, and interference dynamics vary across countries, potentially affecting model generalizability. Additionally, the reliance on NBC-monitored parameters (assigned frequency, band occupancy, MPX, pilot, RDS) excludes potentially informative features such as cyclostationary signatures [40] and higher-order spectral statistics [41], which could improve detection in adversarial scenarios where transmitters deliberately mimic licensed parameter profiles.

5.2 Broader Implications and Future Work

While this study focuses on Nigerian spectrum regulation, the proposed framework has broader applicability across sub-Saharan Africa and other developing regions. Cross-border FM interference remains a persistent issue where national broadcasting footprints overlap [42]. The parameter-based SVM approach, requiring minimal infrastructure, can be deployed in multi-country monitoring networks coordinated through regional bodies such as the African Telecommunications Union (ATU). Unlike deep learning models that require GPU clusters, the SVM framework operates on standard computing hardware (Intel i7, 8GB RAM), making it accessible to regulatory agencies with limited IT budgets and aligning with UN Sustainable Development Goal 9 [43]. The ITU Radio Regulations emphasize technical parameter compliance for spectrum allocation [35], and the proposed system's parameter-based logic directly maps to ITU standards. While demonstrated for FM broadcasting (87.5–108 MHz), the methodology extends to other congested bands such as VHF/UHF television, maritime communications, and aeronautical radio navigation [2],[21].

Future work will address these limitations through specific strategic initiatives: expanding the dataset to multi-regional collaboration involving spectrum regulators from Kenya, Ghana, South Africa, and Tanzania to enable robust generalization and cross-border interference tracking; integrating cyclostationary feature extraction [40] and higher-order spectral analysis [41] to improve detection where adversarial transmitters attempt parameter mimicry; exploring hybrid architectures combining SVM with CNN-based feature extractors [12] to capture nuanced interference patterns while retaining lightweight classifier efficiency; implementing adaptive forecasting mechanisms incorporating online learning algorithms [44] to enable dynamic recalibration to recent interference trends; deploying cloud-connected IoT-based architectures to facilitate large-scale, continuous enforcement across distributed monitoring stations; and pursuing collaboration with ITU and regional telecommunications organizations to standardize parameter-based monitoring protocols, enhancing interoperability across national regulatory frameworks [35].

5.3 Conclusion

This study developed and validated an SVM-based predictive model for monitoring unlicensed FM broadcast spectrum, integrating an SVR forecasting component for proactive interference management. Using 22,971 raw FM spectrum records from 2021–2023 and a 3,169-record pre-processed dataset, the model achieved 99.96% accuracy ± 0.08% (95% CI), 99.96% Precision ± 0.09%, and 100% recall ± 0.00% in classifying unlicensed transmissions in the 2024 prediction scenario. These results demonstrate that lightweight machine learning classifiers can attain near-perfect performance while maintaining low computational overhead—an essential criterion for real-time spectrum regulation [45],[46].

From an operational perspective, the perfect specificity and zero false alarm rate are critical achievements. In regulatory contexts, misclassifying licensed transmissions as unlicensed not only wastes enforcement resources but may also trigger legal disputes [36]. The model's ability to completely avoid such misclassifications while maintaining high recall ensures that enforcement actions are both accurate and defensible. Furthermore, the SVR-based Forecasting captured seasonal interference patterns (RMSE=0.042, MAE=0.031), enabling agencies to shift from reactive to predictive enforcement strategies, a paradigm increasingly promoted in modern spectrum management frameworks [37],[38],[15].

In conclusion, the proposed SVM-based predictive model offers a practical, accurate, and computationally efficient solution for detecting and forecasting unlicensed FM broadcasts. Its strong empirical performance, scalability potential, low computational overhead, and alignment with international regulatory standards position it as a valuable tool for enhancing the operational

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capabilities of spectrum regulatory bodies in Nigeria and beyond. With continued refinement and broader deployment, particularly through regional collaborations and integration with global spectrum management frameworks, such models can play a pivotal role in safeguarding the integrity of broadcast spectrum amid evolving interference and security challenges.

REFERENCES

[1] Melkote, S. R., and Singhal, A., "Handbook of communication and development," *Edward Elgar Publishing*, Cheltenham, UK, 2021.

[2] Apaza, R. D., Knoblock, E. J. and Li, H., "A New Spectrum Management Concept for Future NAS Communications," in *Proc 39th AIAA/IEEE Digital Avionics Systems Conference (DASC),* San Antonia, TX, USA, pp 1-8, 2020.

[3] Khan, M. and Pembecioglu, N., "Destructive role of radio in society: Case study of Pakistan (Malakand Region)," *Mediterranean Journal of Social Sciences*, 6(4S2), pp. 678–688, 2015. doi: 10.5901/mjss.2015.v6n4s2p678.

[4] Shang, J., Liu, Y. and Yan, S., "A System for Data Fusion of Multi-Source Wireless Monitoring Devices and Identification of Illegal FM Broadcast Signals," in *Proc. 10th IEEE International Conference on High Performance and Smart Computing (HPSC)*, Shenzhen, China, pp. 120–125, 2024. doi: 10.1109/HPSC62738.2024.00029.

[5] Wu, P.W., Huang, L., Ramírez, D., Xiao, Y.H. and So, H. C., "One-Bit Spectrum Sensing for Cognitive Radio," *IEEE Transactions on Signal Processing*, 72(1), pp. 549–564, 2024. doi: 10.1109/TSP.2023.3343569.

[6] Malmstedt, J., "Speaking Amplitudes: Dynamical Variation in Swedish Radio Broadcasting, 1980–1998," *Journal of Radio & Audio Media*, (ahead-of-print): pp. 1–17, 2025. doi: 10.1080/19376529.2025.2469248.

[7] Ma, J., Liu, H., Peng, C., and Qiu, T., "Unauthorized Broadcasting Identification: A Deep LSTM Recurrent Learning Approach," *IEEE Transactions on Instrumentation and Measurement*, 69(9), pp. 5981–5983. 2020. doi: 10.1109/TIM.2020.3008988.

[8] Huang, Z., Liu, W., Li, Z., Shao, Z. and Dong, C., "Intelligent Identification of Illegal Broadcast Based on Distributed Spectrum Monitoring," in *IET 8th International Conference on Wireless, Mobile & Multimedia Networks,* Beijing, China, pp. 5–11, 2019.

[9] Cortès̆, G, Fonollosa, J., Serrà, J., Pascual, S., and Serra, X., "Baf: an Audio Fingerprinting Dataset for Broadcast Monitoring",Zenodo, Version 1, 2022. doi: 10.5281/zenodo.6868083.

[10] Guo, S., Xu, Y., Huang, W. and Liu, B., "An SEI-Based Identification Scheme for Illegal FM Broadcast*," in Proc. IEEE 23rd Int. Conf on High Performance Computing & Communications; 7th Int Conf on Data Science & Systems; 19th Int Conf on Smart City; 7th Int Conf on Dependability in Sensor, Cloud & Big Data Systems & Application (HPCC/DSS/SmartCity/DependSys)*, Hainan, China, pp. 517–524, 2021. doi: 10.1109/HPCC-DSS-SmartCity-DependSys53884.2021.00092.

[11] Cortes, C. and Vapnik, V., "Support-vector networks," *Machine Learning*, 20(3), pp. 273–297, 1995. doi: 10.1007/BF00994018.

[12] Wang, K., Chen, Y., Bo, D. and Wang, S. "A novel multi-user collaborative cognitive radio spectrum sensing model: Based on a CNN-LSTM model," *PLoS One*, 20(1), pp. 1-27, 2025. doi: 10.1371/journal.pone.0316291.

[13] Abdelbaset, S., Kasem, H., Khalaf, A., Hussein, A. and Kabeel, A., "Deep Learning-Based Spectrum Sensing for Cognitive Radio Applications," *Sensors*, 24(24): pp. 1–22, 2024. doi: 10.3390/s24247907.

[14] Li, L., Xie, W. and Zhou, X. "Cooperative Spectrum Sensing Based on LSTM-CNN Combination Network in Cognitive Radio System," *IEEE Access*, 11, pp. 87615–87625, 2023. doi: 10.1109/ACCESS.2023.3305483.

[15] Wu, J., Qiu, Z., Dai, M., Bao, J., Xu, X. and Cao, W. "Distributed Sequential Detection for Cooperative Spectrum Sensing in Cognitive Internet of Things," *Sensors*, 24(2): pp. 1–20, 2024. doi: 10.3390/s24020688.

[16] Kim, J., Parikh, K. and Mason, G. "Distribution of the Analog or Digital FM Composite Multiplex Signal across IP Networks," in *Proc. NAB Show Broadcast Engineering Conference*, Las Vegas, NV, USA, pp. 1–8, 2016.

[17] Ajdani, M. and Ghaffary, H. "Design Network Intrusion Detection System Using Support Vector Machine," *International Journal of Communication Systems*, 34(3), e4689**,** 2021. doi: 10.1002/dac.4689.

[18] Rajagopal, S., Kundapur, P. P. and Hareesha, K. S., "A Stacking Ensemble for Network Intrusion Detection Using Heterogeneous

https://dx.doi.org/10.4314/njt.v45i1.13

Datasets," *Security and Communication Networks*, pp. 1–9, 2020. doi: 10.1155/2020/4586875.

[19] Çiftci, B., Çetin, N., Günaydın, S. and Kaplan, M., "Machine Learning Approaches for Binary Classification of Sorghum (Sorghum bicolor L.) seeds from image color features," *Journal of Food Composition and Analysis*, 140, p. 107208, 2025. doi: 10.1016/J.JFCA.2025.107208.

[20] Bazzana, F., Bee, M. and Hussin Adam Khatir, A. A., "Machine Learning Techniques for Default Prediction: An Application to Small Italian Companies," *Risk Management*, 26(1), pp. 1–28, 2024. doi: 10.1057/s41283-023-00132-2.

[21] Furuse, Y. and Tran, G. K., "Localization of Radio Sources Using High Altitude Platform Station (HAPS)," *Sensors*, 25(6), p. 1935, 2025. doi: 10.3390/s25061935.

[22] Jagannath, A., Jagannath, J. and Kumar, P. S. P. V., "A Comprehensive Survey on Radio Frequency (RF) Fingerprinting: Traditional Approaches, Deep Learning, and Open Challenges," *Computer Networks*, 219: pp. 1–24, 2022. doi: 10.1016/j.comnet.2022.109455.

[23] Nandom, S. S., Abe, G. T. and Gambo, I. P., "Application of Random Forest and Hierarchical Clustering Models for Crop and Fertilizer Recommendation to Farmers," *Nigerian Journal of Technology*, 44(1), pp. 114–122, 2025. doi: 10.4314/njt.v44i1.13.

[24] Yang, K., Zhao, L. and Wang, C., "A New Intelligent Bearing Fault Diagnosis Model Based on Triplet Network and SVM," *Scientific Reports*, 12(1), pp. 1–15, 2022. doi: 10.1038/s41598-022-08956-w.

[25] Zhang, Y. and Luo, Z., "A Review of Research on Spectrum Sensing Based on Deep Learning," *Electronics (MDPI)*, 12(21), pp. 1–28, 2023. doi: 10.3390/electronics12214514.

[26] Senol, N. S., Baza, M., Rasheed, A. and Alsabaan, M., "Privacy-Preserving Detection of Tampered Radio-Frequency Transmissions Utilizing Federated Learning in LoRa Networks," *Sensors*, 24(22), pp. 1–20, 2024. doi: 10.3390/s24227336.

[27] Sujithra, C and Thandapani, K., "CitZO-SVM: Machine Learning-Based Spectrum Sensing and Channel Allocation for Cognitive Radio Networks," *International Journal of Communication Systems*, 38(7), e70053, 2025. doi: 10.1002/dac.70053.

[28] Zheng, W., Rong, X., Bao, X. and Dong, Y., "Adaptive Support Vector Machine for Time-Variant Failure Probability Function Estimation. Reliability Engineering & System Safety," *Reliability Engineering & System Safety*, 253, pp. 1–12, 2025.

[29] Alnuaimi, A. F. A. H. and Albaldawi, T. H. K., "An Overview of Machine Learning Classification Techniques," *BIO Web of Conferences*, 97, p. 00133, 2024. doi: 10.1051/bioconf/20249700133.

[30] Elreedy, D., Atiya, A. F. and Kamalov, F., "A Theoretical Distribution Analysis of Synthetic Minority Oversampling Technique (SMOTE) for imbalanced learning," *Machine Learning*, 113(7), pp. 4903–4923, 2024. doi: 10.1007/s10994-022-06296-4.

[31] Aygül, M. A., Çırpan, H. A. and Arslan, H. "Machine Learning-Based Spectrum Occupancy Prediction: A Comprehensive Survey," *Frontiers in Communications and Networks,* 6, pp. 1–35, 2025. doi: 10.3389/frcmn.2025.1482698.

[32] Buchwald, J., Yeang, C. P., Stemeroff, N., Barton, J. and Harrington, Q., "What Heinrich Hertz Discovered about Electric Waves in 1887–1888," *Archive for History of Exact Sciences*, 75(2), pp. 125–171, 2021. doi: 10.1007/s00407-020-00260-1.

[33] Irfan, M., Sciancalepore, S. and Oligeri, G. "On the Reliability of Radio Frequency Fingerprinting," 2024, [Online]. Available: http://arxiv.org/abs/2408.09179

[34] Akram, J., Akram, A., Ingle, P., Jhaveri, R. H., Anaissi, A. and Akhunzada, A. "Privacy-Preserving Spatial Crowdsourcing Drone Services for Postdisaster Infrastructure Monitoring: A Conditional Federated Learning Approach," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 18, pp. 16272–16291, 2025. doi: 10.1109/JSTARS.2025.3577648.

[35] International Telecommunication Union, "Radio Regulations, Edition of 2024, Geneva", Switzerland, 2024. Accessed: 22, 2025. [Online]. Available: https://www.itu.int/pub/R-REG-RR

[36] Bharati, R. K. *Handbook on the Information Technology Act, 2000: Offences, Penalties, and the Impact of New Criminal Laws*, Deep Science Publishing, New Delhi, India, 2025. doi: 10.70593/978-93-7185-183-1.

[37] Gupta, M. S., Srivastava, A. and Kumar, K. "PORA: A Proactive Optimal Resource

Allocation Framework for Spectrum Management in Cognitive Radio Networks," *IEEE Transactions on Network and Service Management*, 22(4), pp. 3249–3261, 2025, doi: 10.1109/TNSM.2025.3540717

[38] Brown, C. and Rutagemwa, H., "Revolutionizing Spectrum Management: Data-Driven Strategies," *IEEE Wireless Communications*, 32 (4): pp. 1–9, 2025. doi: 10.1109/MWC.004.2500029

[39] Lahrouni, K., Semlali, H., Andrieux, G., Diouris, J.F. and Ghammaz, A., "A Systematic Literature Review on Spectrum Detection for Cognitive Radio-Internet of Things Networks," *Ad Hoc Networks*, 175, 103857, 2025. doi: 10.1016/j.adhoc.2025.103857.

[40] Labsis, L., Teguig, D., Lassami, N. and Chikh Touami, H., "An Advanced Blind Cyclostationary Spectrum Sensing Algorithm for Cognitive Radio Networks," *Physica Scripta*, 100(6), 065502, 2025. doi: 10.1088/1402-4896/adcfd0.

[41] Casmin, E. and Oliveira, R., "Survey on Context-Aware Radio Frequency-Based Sensing," *Sensors*, 25(3), 602, 2025, doi: 10.3390/s25030602

[42] African Telecommunications Union, "Framework for Harmonized Spectrum Management in Africa," Nairobi, Kenya, 2023. Accessed: 2025. [Online]. Available: https://atuuat.africa/en/documents

[43] United Nations, "Transforming Our World: The 2030 Agenda for Sustainable Development ," New York, NY, USA: United Nations, 2015.

[44] Shalev-Shwartz, S., "Online Learning and Online Convex Optimization," *Foundations and Trends in Machine Learning*, 4(2), pp. 107–194, 2011. doi: 10.1561/2200000018.

[45] Ahmed, Md. T., Haque, M., Sugiura, Y. and Shimamura, T. "Machine Learning Approach to Energy Detection Based Spectrum Sensing for Cognitive Radio Networks," *IEEJ Transactions on Electrical and Electronic Engineering*, 20(6), pp. 910–919, 2025. doi: 10.1002/tee.24261.

[46] Zhou, K., Li, Q., Cai, P., Cai, Z., Shi, X., and Wang, F., "Lightweight and Efficient Hybrid Network for UAV Identification Using Radio Frequency Fingerprinting," *IEEE Internet of Things Journal*, (early access): pp. 1–13, 2025. doi: 10.1109/JIOT.2025.3594571.