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Review of Recent Trends in Sensing Methodologies and AI Techniques for Non-Cooperative Aerial Target Recognition

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Abstract
The proliferation of non-cooperative aerial targets, particularly low altitude-slow-speed small RCS drones, presents a complex challenge for airspace security. Detection and identification of non-cooperative aerial objects is an intensive area of research. The aim of this article is to carry out a structured review of UAV/drones, fixed wing aircraft and other non-cooperative aerial targets' detection and classification using machine learning (ML) algorithms. This article presents a systematic review of 184 recent studies (2019–2025) covering five key sensing modalities: Radar (RCS, Micro-Doppler, HRRP), Passive Sensing (5G/Wi-Fi/Radio Frequency (RF)), Acoustic sensing, Computer Vision and multi-modal sensing. Although individual sensing modalities have been extensively studied, existing reviews often lack a holistic operational assessment of multi-modal integration. Additionally, the review work introduces a novel operational suitability framework that maps each modality against critical deployment constraints, including detection range, Line of Sight (LOS) requirements, and environmental robustness. Furthermore, authors critically analyze the transition from classical statistical methods and outdated deep learning architectures to advanced deep learning architectures, specifically highlighting the emergence of vision transformers (ViT) and niche technologies such as integrated sensing and communications (ISAC). Finally, the review identifies persistent gaps in artificial intelligence (AI) based non-cooperative target

recognition research and proposes a roadmap for future research in multi-modal machine learning (MML) and sensor fusion pipelines. Moreover, this review work would direct the research effort for further enhancing the aerospace, human safety, and important installations' security.

Keywords- RCS, Micro-doppler, High range resolution profile, NCTR, MML.

1. Introduction

Recent technological advancements have led to a global rise in drone/UAV usage across various applications. Since the capabilities of the drones are continuously growing and the cost of the drones is reducing, it is also boosting the use of the drones in various civil and military applications. The use of drones makes things more convenient in most applications however, due to lenient regulations, enforcement issues and difficulty in detection and classification, these airborne objects may pose potential risks to flight safety. Due to the increase in commercial air traffic (Federal Aviation Administration, 2023) , the threat ranging from mid-air collision to air traffic disruption due to unidentified flying objects is increasing (BBC News, 2019; Manchester Evening News, 2020; Robin Radar, 2023). Unidentified flying objects can also potentially be used by non-state actors (BBC News, 2016; Al Jazeera, 2021). Misidentification of the unknown flying objects poses the risk of friendly fire incidents. Accurate aerial target identification is a key goal of modern air defense systems and is too complex for human operators. Several transponder-based technologies, such as IFF (Identification Friend or Foe)-Mk XII, are available to assist in identifying cooperative targets for airspace management and contingency response. A detailed description of IFF systems and procedures are described in (International Civil Aviation Organization, 2014). Automatic Dependent Surveillance-Broadcast (ADS-B) is another IFF transponder-based technology (Federal Aviation Administration, 2023). ADS-B offers detailed GNSS-based flight data, supported by a ground-based reception and broadcast system for sharing information. However, equipping all commercial and military aircraft with ADS-B is often unfeasible due to cost, technical or compatibility challenges. Even when onboard transponders (Mk-XII or ADS-B) are present, they may sometimes be non-operational. Additionally, microlight aircraft, drones, and UAVs often forgo IFF or ADS-B systems due to size, weight, cost, or intent. ADS-B also faces vulnerability to spoofing attacks (TajDini et al., 2021). As a result, some airborne objects provide no identification data to military or civil aviation centers. Further, as seen in recent conflicts, unidentified aerial targets such as UAVs and drones are hardly detectable with radars (Council on Foreign Relations, 2024). Airborne objects that do not communicate with air traffic control are grouped into the category of non-cooperative targets and identifying or classifying these targets is known as NCTR as described in one of the earliest overviews on the subject (Cohen, 1991). **Figure 1** illustrates both cooperative and non-cooperative targets. The problem of NCTR is not new and research has commenced as early as 1986 (Bhanu, 1986). The precision of classification depends on the types of airborne targets. Broadly, the system must differentiate between fighters, aircraft, helicopters, UAVs and drones. More detailed classification, such as distinguishing between birds, mini, and micro drones, requires greater accuracy.

To achieve higher accuracy in the identification of the airborne target the proper choice of the sensor is important. In some cases, a single type of sensor is good enough to provide accurate target identification while in other cases multi-sensor data is needed to accurately identify the target. Advanced objectives include identifying specific shapes, models, and sizes of airborne objects. Despite the availability of multiple sensor data sources and extensive collected information, achieving accurate target identification remains challenging. This difficulty primarily arises from the unpredictable reception and noise-afflicted, stochastic nature of real-time airborne target data, as well as the sheer volume of prerecorded sensor data to be processed. Utilization of AI algorithms helps to overcome these problems in the NCTR.

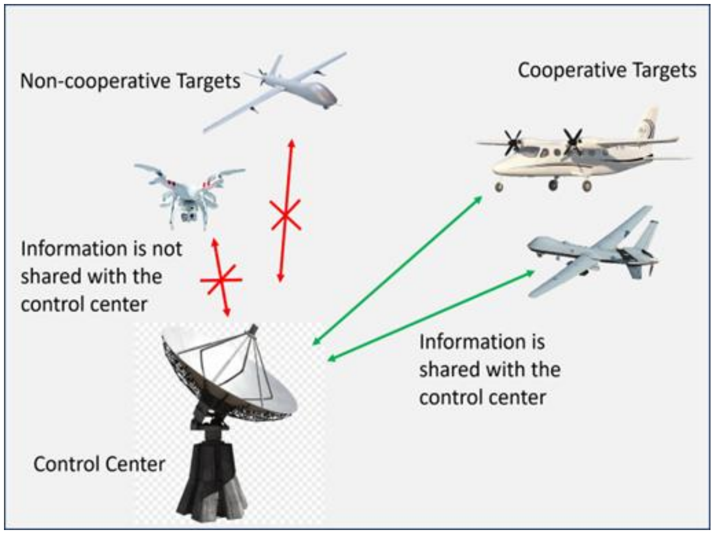

Figure 1. A general illustration distinguishing non-cooperative and cooperative targets.

ML a branch of AI builds predictive and classification models using historical and real-time data. It improves performance through experience and is effective in solving classification and regression problems. ML, which is widely applied across sciences, engineering, economics, and business, is also increasingly being used in NCTR to enhance recognition accuracy (Taha & Shoufan, 2019). A general framework for NCTR with application of AI is described in Melvin & Scheer (2014). Extensive application of ML is also found in radar signal processing (Lang et al., 2020). Over the years researchers have explored different types of sensors to identify and classify airborne non-cooperative targets such as radars, RF signature sensors, EO/IR sensors, acoustic sensors, and opportunity RF signal illuminators available in environment such as 5G/Wi-Fi networks. For longer ranges, target classification by primary surveillance radars across different frequency bands have been utilized (Lang et al., 2020; Geng et al., 2021). For intermediate ranges particularly for drone detection and classification, RF signature techniques (Soltanieh et al., 2020) find its application. For the non-cooperative target within line-of-sight, Electro-Optic/IR sensors (Huckridge & Ebert, 2008), high resolution optical cameras which utilize advances in computer vision techniques (Wang et al., 2024), acoustic sensors (Shi et al., 2020), illuminators of opportunity such as 5G/LTE signals (Maksymiuk, et al., 2023) or combinations of these sensing methodologies (Svanström, 2019; Kim et al., 2023) are utilized. Moreover, researchers have explored different ML algorithms such as K-Nearest Neighbor (kNN), Support Vector Machine (SVM), decision trees, random forest, Naïve's Bayes classifier and multiple types of neural networks for non-cooperative target recognition. The choice of sensor and ML algorithm is also based on target kinematic behavior, shape, modes of flying, optimum distances and timeframes required for detection/identification, environmental background involved (weather and lighting conditions, RF interference, urban vs clear sky background). These requirements are to be mapped onto the sensor capabilities and evaluated against sensor limitations. **Figure 2** provides an illustrative framework for NCTR using ML algorithms depicting target types, their feature variance and various ML paradigms.

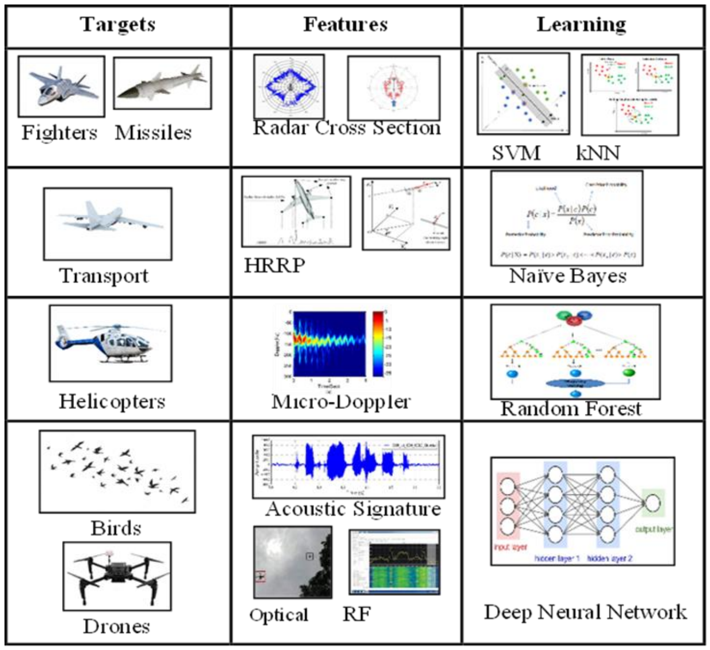

Figure 2. An illustrative framework for NCTR using ML algorithms, mapping specific target types to their dominant features and the ML paradigms used for classification.

This paper focuses on providing complete state-of-the-art review on sensing methodologies and AI techniques for identifying non-cooperative targets. The prominent aspects of this review paper are as follows:

- The review examines various sensing methodologies for airborne target signatures acquisition such as radars, RF signatures, computer vision, acoustic sensors, and their combinations for NCTR. It provides a structured review of recent studies (2019–2024), covering the integration of abovementioned modalities with cutting-edge deep learning techniques.
- The review highlights different feature extraction (RCS, micro-Doppler, high range resolution profile (HRRP), Kinematic) and data preprocessing techniques for NCTR and presents the effectiveness of different ML algorithms for identification of the targets.
- It introduces a novel operational suitability framework, evaluating the practical trade-offs of each sensor type regarding range, weather resilience, and computational cost.
- It assesses the performance of emerging AI architectures, specifically ViT and MML pipelines, in low-SNR environments. It outlines the limitations of current target sensing and classification methods and suggests future research directions in this field including ISAC for distributed detection and Physics-Informed Neural Networks (PINNs) for data-constrained classification.
- It aggregates and categorizes essential open-source datasets to support further development in non-cooperative target recognition using artificial intelligence.

To guide this systematic review, authors have formulated three primary research questions (RQs):

- RQ1: What are the operational boundaries and performance limitations of current single-modality sensing (Radar, RF, Acoustic, Vision) for NCTR.
- RQ2: How do emerging AI architectures, such as ViT and physics-informed neural networks, address the persistent challenges of low-SNR and data scarcity.

- RQ3: What are the architectural trade-offs (latency vs. accuracy) in multi-modal sensor fusion for real-time counter-UAS applications.

Although, some review papers on non-cooperative detection and classifications are available in the literature. These reviews are either focused on a specific type of sensing methodology or addressing a specific set of aerial targets. **Table 1** provides the key differences between this paper and other review paper available in literature.

Table 1. Key differences from previously published review papers.

Reference	**Scope of targets**	**Sensing modalities covered**	**ML/AI depth**	**Operational constraints analysis**	**Key gaps identified in prior work**
Seidaliyeva et al. (2025)	Drones only	Radar, RF, Acoustic, Vision	High (Survey of methods)	Medium	Does not address the limitations of radar technologies
Rahman et al. (2024)	UAVs only	RF-focused	Medium	High (Sync focus)	Narrow focus on UAVs; excludes fixed-wing and other non-cooperative threats
Park et al. (2021b)	Anti-Drone Systems	General Overview	Low (System level)	High (Threat assessment)	Focuses on mitigation (jamming/interdiction) rather than the sensing/classification algorithms
Jiang et al. (2023)	Radar Targets	Radar only (SAR/ISAR)	High (Deep Learning)	Low (Modality specific)	Restricted solely to radar; misses the multi-modal fusion aspect crucial for NCTR
Proposed Review	UAVs, Fixed-Wing, Birds, LSS	Radar (RCS, m-D, HRRP), RF, Acoustic, EO/IR, 5G	High (Transformers, GNN, Fusion)	High (Environmental & Compute)	Integrates all modalities; addresses adversarial AI, ISAC, and edge-computing constraints

The remainder of the paper is structured as follows: Section 2 explains the search strategy utilized for systematic review, Section 3 to 6 outlines different sensing methodologies with preprocessing and target detection and classification techniques. Section 7 briefly presents a fusion of different sensing modalities for target recognition. Section 8 presents the assessment of sensing methodologies while Section 9 presents the research challenges and directions of future work. Finally, Section 10 provides a conclusive remark.

2. Search Strategy

In this article, the authors employed a comprehensive search strategy to ensure the inclusion of all pertinent studies in the systematic literature review on sensing methodologies and AI techniques for NCTR. Targeted keywords such as "*non-cooperative targets*," "*UAV*," "*drones*," "*RCS*", "*hybrid sensing*", *"feature engineering", "deep learning", and "machine learning"* were used to search major scientific databases, including IEEE Xplore, ScienceDirect, Frontiers, MDPI, Taylor & Francis and Springer.

2.1 Inclusion and Exclusion Criteria

A total of 184 publications were included in the review paper. It generally aimed to include research conducted in the last five years. Accordingly, 986 papers were first selected which were published from 2019 onwards and till 2025. One article each from seminal work on fluctuating target RCS by Swerling (1960) and empirical mode decomposition by Huang (1998) were also referenced. The review encompassed journal and conference papers sourced from IEEE Xplore, ScienceDirect, and MDPI databases. Access to primary radars is limited to civil and military operators and R & D agencies. Therefore, the publications of Radar conferences and symposiums were also considered an important source for finding out the latest developments in the field. The research papers containing Synthetic Aperture Radar (primarily a space domain technique for imagery) based on NCTR were not included.

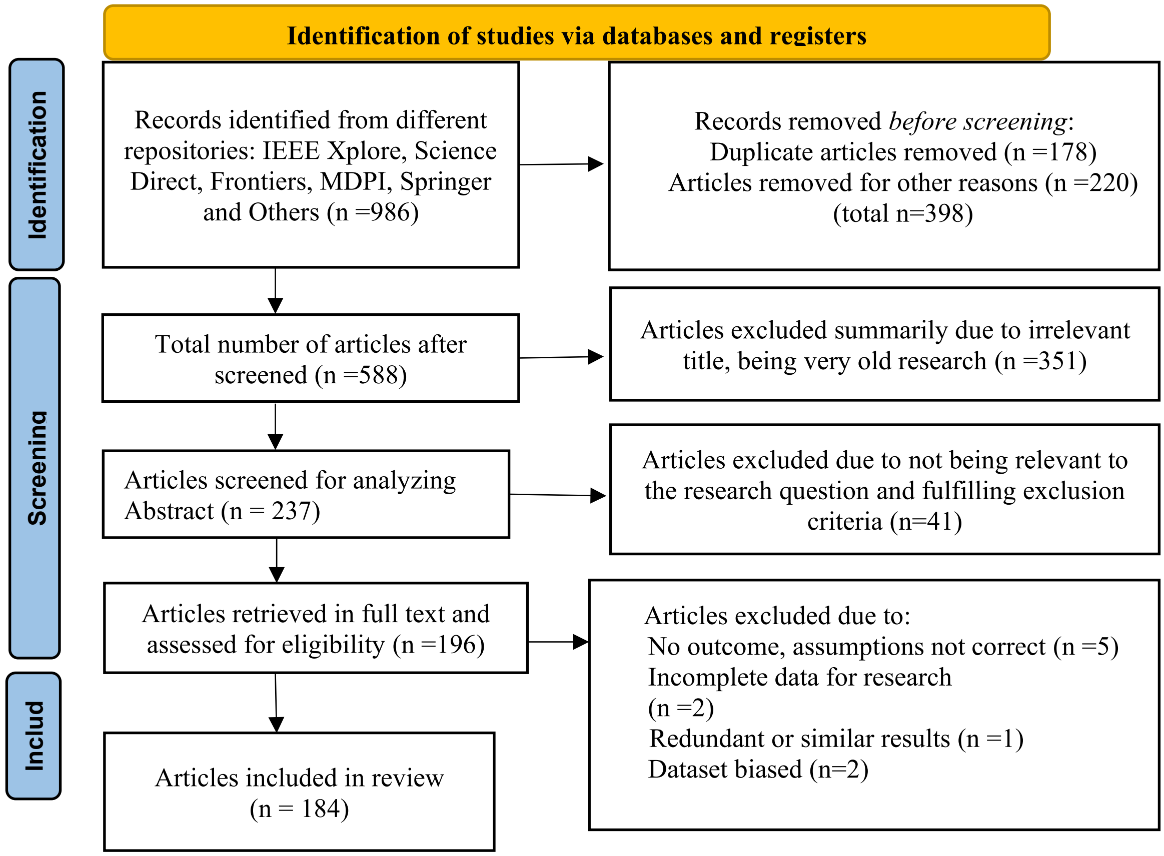

Figure 3. PRISMA flow diagram for searching the articles.

2.2 Screening of Research Articles

The authors started search by executing an orderly query over important databases with additional search criteria applied based on timeframe (last five years for recent research) as well as without timeframe (for reputed journal and conference papers covering seminal research articles). Relevant search strings used for exploring research databases were 'Non-Cooperative Target identification', 'RCS based target identification', 'UAV identification', 'Aerial target classification using machine learning', 'Artificial intelligence for Radar target classification', 'Convolutional Neural Network for target classification', 'Computer Vision based drone identification', 'Acoustic signature based drone identification', ' Artificial intelligence techniques for RF signature based drone identification' and similar relevant combination of search words other than abovementioned words which filtered out 986 articles. The complete selection process is summarized in the PRISMA flow diagram presented in **Figure 3**.

3. Radar Sensors

Primary surveillance radars provide various features of the target such as kinematic features (Jochumsen et al., 2014; Doumard et al., 2022), RCS (Ezuma et al., 2022), High Range Resolution Profile (Wan et al., 2019) or micro-Doppler (Rahman & Robertson, 2020; Roldan et al., 2020), signatures. With the recent advancements of the technology in the millimeter-waves, millimeter-wave radars have been utilized for short range detection and classification of drones (Solaiman et al., 2023). This section covers the detailed review of feature sets obtained from primary surveillance radars and their application in NCTR as follows:

3.1 Kinematic Features

Kinematic features of an aerial target are the most common feature obtained through any surveillance radar. The kinematic feature includes velocity, heading or azimuth vector, altitude, and rate of climb and Doppler velocity. Different aerial targets display unique kinematic behavior based on their lift/thrust mechanisms, power-to-weight ratio, glide ratio, and aerodynamic design. These factors affect their velocity, acceleration, climb rate, descent, and turn radius. Many studies have used kinematic data and derived features for ML-based airborne target classification (Garg & Singh, 2014; Jochumsen et al., 2014; Ginoulhac et al., 2019; Sarikaya et al., 2019; Doumard et al., 2022). It is possible to derive multiple kinematic features like acceleration in three axes, rate of turn, mean and variance of above quantities as attempted from flight trajectories (Garg & Singh, 2014; Doumard et al., 2022). Feature extraction can be performed over the full trajectory or using a sliding window approach (Doumard et al., 2022). A sliding window is used to extract features at every few steps and make classifications using small windows of the track trajectory.

3.2 Radar Cross Section

The IEEE dictionary of Electrical and Electronic Terms (IEEE Standard Dictionary of Electrical and Electronics Terms, 2008) defines the RCS as the measure of the reflective strength of the target. More precisely it is the limit of the squared ratio of scattered electric field intensity E_s to the incident electric field intensity E_i as the distance from radar to target reaches infinity. The RCS is defined as:

$$\sigma = \lim_{R\to\infty} 4\pi R^2 \frac{|E_s|^2}{|E_i|^2} \tag{1}$$

where, R is the distance from the radar to the target. The RCS of a target depends on the following factors (Vaitheeswaran et al., 2017):

(a) Target geometry (size, shape) and material composition, paint characteristics
(b) Aspect Angle (Angular orientation of target relative to radar)
(c) Frequency or wavelength of radar
(d) Antenna polarization

RCS of an object can be determined either by using an electromagnetic (EM) simulator or from measurements. The IEEE recommended practice outlines detailed procedures, techniques, and setup for RCS testing (1502-2020 - IEEE Recommended Practice for Radar Cross-Section Test Procedures, 2020). **Figure 4** shows a typical setup for Near Field Test Range (NFTR) of RCS measurement.

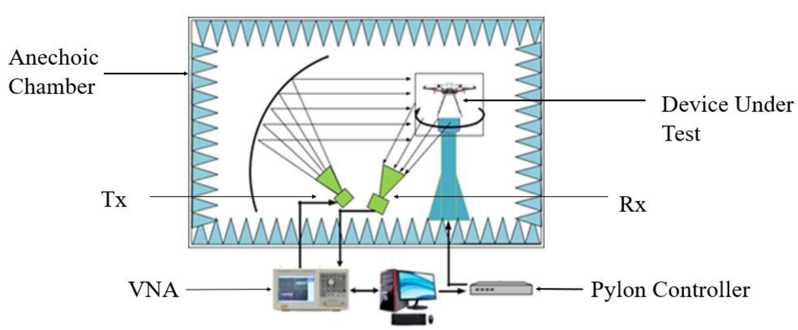

Figure 4. Typical RCS measurement setup.

For non-cooperative targets, having highly unpredictable movements makes it difficult to model their RCS using fixed angles and poses. Therefore, dynamic RCS measurements with high update rates through sensors or high-fidelity simulations are crucial. Low RCS, low speed targets like small drones pose additional challenges. The procedure for the standard RCS simulation setup of a target is provided in (Development Committee of the IEEE Electromagnetic Compatibility Society, 2009). Physical optics and physical theory of diffraction-based asymptotic techniques (Zhuang et al., 2014; Pienaar et al., 2015; Vaitheeswaran et al., 2017; Mao et al., 2018) are used for Dynamic RCS simulation of electrically large objects due to their better simulation speed and acceptable accuracy as compared to Multilevel Fast Multipole Method (MLFMM) (Smit et al., 2012).

3.2.1 Dynamic Radar Cross Section

Dynamic RCS statistical distribution models were first studied in the seminal work by Swerling (1960). In this study, RCS signatures were treated as random variables with corresponding probability density functions. Swerling proposed four target models: two based on target shape and size, and two on target behavior (also known as temporal models). The first model assumed RCS as the result of multiple distributed scatterers, each with similar reflective strength. The joint probability density function for target RCS was proposed as a $\chi 2$ distribution having two degrees of freedom. The second target model assumed uneven scatterer strength with dominating point scatterer having a much larger magnitude. The joint pdf in this case is again a $\chi 2$ distribution having four degrees of freedom. The distribution is shifted to higher mean RCS values for higher frequencies. The two remaining models, based on temporal behavior, explained how pulse-to-pulse echo fluctuations affect pulse amplitude correlation. In the first model, the target was assumed to be electrically small, causing minimal RCS variation between pulses. The second model described an electrically large, fast-turning target, leading to greater pulse-to-pulse RCS fluctuations. However, these Swerling models are not ideal for describing modern, highly maneuverable, or stealth targets like UAVs and drones. Modern surveillance radars, operating at higher frequencies, experience significant RCS decorrelation for large targets with slight changes in aspect angles during coherent pulse integration (Hughes, 2017). The target's RCS depends on aspect angle (azimuth and elevation) with respect to illuminating radar wavefront. The target's reflectivity therefore becomes highly dependent on instantaneous pitch, yaw and roll angle of the aerial target with respect to the radar. Multiple RCS statistical models have been proposed by measuring the RCS data and then fitting this data empirically to possible distributions (Ezuma et al., 2022). Dynamic RCS has been researched with the aim of classifying the NCTR targets in (Tian et al., 2015; Lee et al., 2016; Sehgal et al., 2019; Ardon et al., 2020; Fu et al., 2021; Ye et al., 2021). Availability of real flight paths for the purpose of construction of dynamic RCS has been possible with the help of ADS-B flight data gleaned from OpenSky network or other websites providing access to such data (Rozel et al., 2022).

3.2.2 Feature Extraction and Dimensionality Reduction from Dynamic RCS Data

Target RCS measurement data observed for aspect angle dependency may exhibit multiple peaks with high probability mass at certain angles (Wang et al., 2021a) whereas dynamic RCS often appears as non-stationary time series data (Ardon et al., 2020). Most of the time the raw dynamic RCS data may not contain sufficient information to classify different targets. Feature extraction is therefore undertaken to get feature vectors that can improve classification performance from the RCS data. Normalization, denoising, and dimensionality reduction are key data preprocessing techniques that enhance classification accuracy, reduce runtime, and minimize misclassification. Dimensionality reduction is crucial in ML and data mining, with principal component analysis (PCA) often being used to extract meaningful features and eliminate redundant information that does not contribute to the classifier. In Gökkaya & Günel (2019) PCA has been used with RCS as initial data set. Singular value decomposition (SVD) (Uzhga-Rebrov & Kuleshova, 2020; Kim & Youn, 2024) has been used for feature extraction in PCA based radar target recognition in (Lee et al., 2008). Various feature extraction methods have been used, including statistical model-based approaches and data-driven adaptive methods. The Dynamic RCS has mostly been modelled by statistical distributions such as log-normal, gamma distribution and Gaussian Mixture Models (Espindle & Kochenderfer, 2009). Indicators that have been used to obtain fitting performance of RCS Statistical Models in literature are SSE (Sum of Squared Errors), RMSE (Root Mean Squared Error) and Kolmogorov Smirnov test (Zhuang et al., 2015). The underlying assumption in statistical model-based approach is that knowing the statistical models behind airborne object's dynamic RCS and their variation patterns can help in discriminating between targets. Statistical model-based approach attempts to estimate RCS statistical parameters like CDF, peak, mean, variance, standard deviation etc. of a particular model (Ezuma et al., 2021). The goodness of fit of the dynamic RCS to a particular model can be provided by using the Kolmogorov–Smirnov (KS) test (Rosamilia et al., 2022). Post model determination of statistical model, Maximum a Posteriori (MAP) rule can be applied for target classification. Ezuma et al. (2021) explored RCS signatures of six commercial UAVs, obtained in an anechoic chamber that has been used to train 15 different classification algorithms such as statistical learning (SL), kNN, SVM, Ensemble, Naïve Bayes, classification, and discriminant analysis (DA), and deep learning (Squeezenet, Googlenet, Nasnet, and Resnet 101) techniques. The study showed that statistical models show better performance in comparison to other models. The most relevant statistical distributions that have been considered for dynamic RCS are as follows:

- Log normal distribution: The Dynamic RCS of airborne targets such as missiles can be modeled as a log-normal random variable. The PDF of Log normal distribution is given by Equation (2):

$$\rho(x) = \frac{1}{xs\sqrt{2\pi}} exp\left[\frac{-(\ln x - \ln \mu)}{2s^2}\right], x > 0 \tag{2}$$

- Weibull distribution: Weibull and piecewise Weibull Modelling of RCS has been studied in Hughes (2017). Weibull distribution is given by Equation (3):

$$F(x; \mu, k) = 1 - e^{-(x/\mu)^k}, x \geq 0 \tag{3}$$

where, μ decides scale and k decides shape of distribution.

- Gaussian mixture distribution: The Gaussian mixture model (GMM) is a probabilistic mixture model that uses a combination of Gaussian (Normal) probability distributions. This entails the estimation of the mean and standard deviation parameters for each pdf. It combines the statistical and data driven approach. The pdf of GMM is given as in Equation (4):

$$f(x, \theta) = \sum_{i=1}^{M} \frac{w_i}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(x-\mu_i)^2}{2\sigma_i^2}\right) \tag{4}$$

where, $\theta = \left(w_1, w_2, \dots, w_M; \mu_1, \mu_2, \dots, \mu_M; \sigma_1^2, \sigma_2^2, \dots, \sigma_M^2\right)$ and w_i is the weight of i^{th} component, and it meets the condition $\sum_{i=1}^{M} w_i = 1$. The variables μ_i and s_i represent the mean and variance of the i-th element. The parameter estimation of GMM can be done by using Expectation Maximization (EM) method. The Expectation-Maximization algorithm is an approach for maximum likelihood estimation in the presence of latent variables. In Roychowdhury & Ghosh (2021) kNN, Linear Discriminant Analysis (LDA), Naïve Bayes, RNN, SVM, Decision tree and Ensemble Model techniques have been applied for classification of RCS data of various UAVs. Ensemble model and SVM yield classification accuracy of 87% and 83% respectively.

Analysis of nonstationary data with model-oriented approach is not effective. Therefore, data driven nonstationary time series investigation methods have been examined by researchers. One such data driven technique is Empirical Mode Decomposition (EMD). In Huang et al. (1998), authors described decomposition of signal or time series results in a set of oscillating components. The decomposed components of the signal are called the Intrinsic Mode Functions (IMFs) of the given signal. The IMFs are representative of different oscillating scales underlying the signal or time series data. The first IMF is the highest frequency component whereas the last IMF is the lowest frequency component. These IMFs in turn are the basis function of EMD. The residual signal is the trend of the time series data. EMD techniques have been used for feature extraction from RCS time series data (Ardon et al., 2020).

3.2.3 Target Classification from RCS Features

In the subsequent subparagraphs the target classification from RCS features using ML is enumerated. In shells of different sizes have been chosen for classification. Shells require a very short time for classification due to very high velocity therefore conventional full RCS time series analysis methods will fail. Authors have used neuro-fuzzy classifiers which are based on a very short time series of collected RCS values as compared to the constructed RCS database of shells. It results in improvement of classification accuracy which has also been presented as a plot of SNR for gaussian, trapezoidal and triangular membership function (MF). Particle swarm optimization (PSO) is employed to extract MF parameters. In Ye et al. (2021), multi-axis symmetric targets, like missiles, were chosen. It is argued that traditional ML methods such as SVM, kNN, and backpropagation neural networks find it challenging to identify discriminative attributes from dynamic RCS data such targets. As a result, these methods are less effective in utilizing the statistical features of RCS for NCTR. In Chen et al. (2018), authors extracted twenty-six different features from the RCS time series data to train an elaborately constructed CNN. In total 512 RCS time series points were considered as input. The extracted features include eleven statistical features, twelve wavelet features, and one spectral feature. In Abd-Elfattah et al. (2022), central moments are obtained from RCS values and thereafter PCA is applied to these moments. Then the features extracted in this way are classified by SVM. In Zhang et al. (2021a), intelligent utilization of five technologies suitable for the midcourse recognition of the warhead, such as the RCS sequence in conjunction with HRRP, ISAR, micro-Doppler and polarization have been used to establishes a Bayesian network model for midcourse recognition of warhead. In Ardon et al. (2020), Empirical Mode Decomposition (EMD) has been used to decompose the RCS time-series into low-frequency and high-frequency components to classify different types of aircraft. It is executed with the assumption that the low frequencies correspond to the elevation angle and measurement errors, while the higher frequencies are related to the target's geometry and aspect angles relative to the radar. Therefore, the high frequency IMF components in the RCS time series could be used to characterize the targets. In Gökkaya & Günel (2019), central moments are obtained from RCS values and PCA is explored for dimensionality reduction, thereafter SVM is used for classification. A detailed study of drone classification using RCS feature was identified in Ezuma et al. (2021). The authors compared statistical learning, ML and Deep learning approaches for drone recognition. Anechoic chamber-based RCS measurements of commercial drones were used for target recognition. The study showed that ML algorithms gave the best results among the three learning paradigms.

- ***Millimeter Wave Radar and LiDAR for Drone Detection and Classification***

Millimeter wave radars operating in frequency range of 30-300 GHz are generally being used as automotive radars, missile guidance, industrial applications are also being proposed for low altitude airspace surveillance and drone recognition. Due to their fine spatial resolution, they can be effectively used for drone detection and classification. These systems frequently use CNN to extract representative features. A framework for simultaneous tracking and recognition of drones using millimeter wave radar was proposed in Solaiman et al. (2023). In this work CNN combined with LSTM was used for spatio-temporal feature extraction and recognition. In Ye et al. (2023) the mm-wave acquired RCS data was represented on a Gramian Angular Field and a 2D Resnet-10 was designed for Radar target recognition. A Gramian angular field (GAF) is a method used to transform one-dimensional time series data into a two-dimensional image.

This helps in capturing the temporal relationships and correlations between different points in the time series by representing them on a polar coordinate system, where each point is encoded as an angle based on its value. Represented image is subjected to deep learning techniques like CNN. This representation has the capability to recognize space targets as identified in Zhai & Wang (2023). LiDAR is a technology which works like the radar but uses laser instead of radar waves. Authors demonstrated 3D LiDAR systems capability for Drone detection and tracking (Abir et al., 2023). ML and DL approaches in drone detection have been reviewed in Seidaliyeva, et al. (2024). LiDAR based detection of UAVs was also practically demonstrated in Dogru & Marques (2022).

3.3 Micro Doppler Signatures

Radar systems operating at X band and above can extract good quality Micro Doppler Signatures. Helicopter blades, drone rotors and jet engine blades are the parts in aerial targets which have additional movements like rotational or vibrational motion which are other than the target translational movement with respect to sensor. These movements can generate micro frequency modulations around the main doppler shift. These modulations are commonly referred to as micro-Doppler (m-D) modulations (Chen et al., 2014). A review of micro-Doppler modulations-based radar target recognition is provided in Hanif et al. (2022). More details about micro-Doppler effect in radar signatures and its mathematical analysis can be found in Chen (2011). **Figure 5** depicts the translational and rotation motion of a point scatterer P with respect to radar.

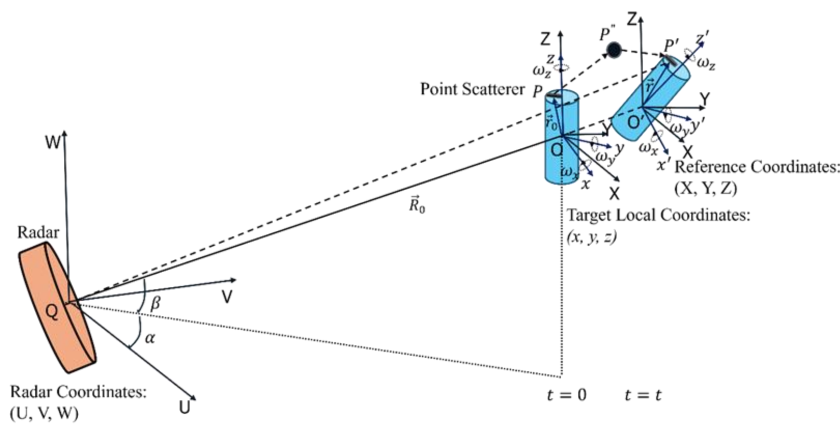

Figure 5. Geometry of a radar and a point scatterer having translation and rotations.

The movement of P can be considered as, first, a translation from P to P'' with velocity v, or $OO' = vt$, and then, a rotation from P'' to P' with an angular velocity ω.

Thus, the scalar range of point scatterer is:

$$R(t) = \|\vec{R}_0 + \vec{v}\mathrm{t} + R_{ot}(\mathrm{t}) \cdot \vec{\mathrm{r}_0}\| \tag{5}$$

where, the rotation matrix $\mathrm{Rot}(t)$ can be written in terms of the matrix $\hat{\omega}$ as

$$R_{ot}(t) = \exp\{\hat{\omega}t\} \tag{6}$$

where,

$$\hat{\omega} = \begin{bmatrix} 0 & -\omega_Z & \omega_Y \\ \omega_Z & 0 & -\omega_X \\ -\omega_Y & \omega_X & 0 \end{bmatrix} \tag{7}$$

Therefore, the Doppler frequency shift is given by:

$$f_D = \frac{2f}{c}[\vec{v} + \widehat{\omega} \times \vec{r}]_{\text{radial}} \tag{8}$$

where, the first term within brackets represents the Doppler shift caused by the translational motion of the target's main body toward the radar, while the second term corresponds to the micro-Doppler component arising from the rotational motion of the point scatterer. To extract micro-Doppler features very high Pulse Repetition Frequency (as per Nyquist-Shannon theory limitations), large SNR, narrow beamwidth, long dwell times or high track update rates are needed. This limits the usage of conventional Track-While-Scan (TWS) radars for micro-Doppler based target classification.

3.3.1 Feature Extraction and Target Classification from Micro-Doppler Signatures

The goal of micro-Doppler feature extraction is to create feature set that ease subsequent classification processes, thus identifying motion types within the original micro-Doppler data eventually leading to target recognition. Time-Frequency Analysis (TFA) is a common approach which is applied to the micro-Doppler signal's feature extraction. TFA includes Short-Time Fourier Transform (STFT), Continuous Wavelet Transform (CWT), and Wigner-Ville Distribution (which chooses the window adaptively rather than a fixed window like STFT or CWT). Techniques like adaptive kernel-based sparse time-frequency distribution are shown to improve feature resolution for classification tasks as brought out in (Qin et al., 2022; Hong et al., 2024; Yang et al., 2024). Some techniques bypass TFA and focus only on intrinsic signal properties, such as Discrete Cosine Transform (DCT) coefficients or Cepstrum coefficients analysis. DCT transforms the signal into a sum of cosine functions at different frequencies (Dai et al., 2022). It is effective in reducing dimensionality and capturing the essential features of the micro-Doppler signal while discarding noise thus making it useful in applications requiring compact feature representation, such as in real-time UAV detection. The other technique, Cepstrum coefficients analysis involves taking the inverse Fourier transform of the logarithm of the spectrum of a signal. This technique emphasizes the periodic components of a signal, such as the rotational frequency of UAV blades or turbines. It is particularly useful for identifying subtle repetitive patterns in micro-Doppler signatures caused by rotating parts in airborne targets. These methods are often combined with classification algorithms like SVMs or neural networks to improve detection and identification performance.

3.4 High Range Resolution Profile (HRRP)

HRRP represents the coherent summation of the received SNR from a target's major scattering centers in each range cell onto the radar LOS in the time domain, as shown in **Figure 6**. This one-dimensional signature provides basic geometric information about the target, making it useful for recognition. In modern radars, the range resolution is much finer than the target size, dividing the target into multiple range cells along the radar LOS. The return pattern from each cell forms a unique signature. The spatio-temporal variation of HRRP offers insight into point scatterer distribution, aiding in target identification. This has been studied widely in applications particularly for target recognition (Wan et al., 2019; Liu et al., 2022c).

3.4.1 Feature Extraction and Target Classification from HRRP Signatures

Time sequential feature extraction is very crucial for HRRP signatures due to their spatio-temporal as well as target attitude dependent variation as the target moves with respect to the radar sensor. After initial ML based (SVM, Random Forest) classifier implementations, recently the research has picked up pace in application of Neural networks based HRRP feature extracting and learning (Sagayaraj et al., 2021). The main advantage is that the neural network integrates feature extraction with target classification and continuously refines the extracted features through iterative training. Besides CNN (Liu et al., 2022c), recurrent neural networks (RNN) (Liu et al., 2019) have also been employed to extract time sequential features between HRRP range cells for its efficacy in processing and memorizing time sequential data. To solve the low SNR problem in training and testing data authors (Chen et al., 2021) have proposed using domain knowledge as side information layer. In Lian et al. (2021), the central moment and waveform entropy features of Time Reversal HRRP signature are extracted and introduced into SVM as classification features. In Jia et al. (2023) HRRP signatures of four array type targets were obtained through FEKO simulation and efficacy of CNN-BiLSTM (a Bidirectional Long Short-Term Memory variant of CNN) was shown to have better classification accuracy.

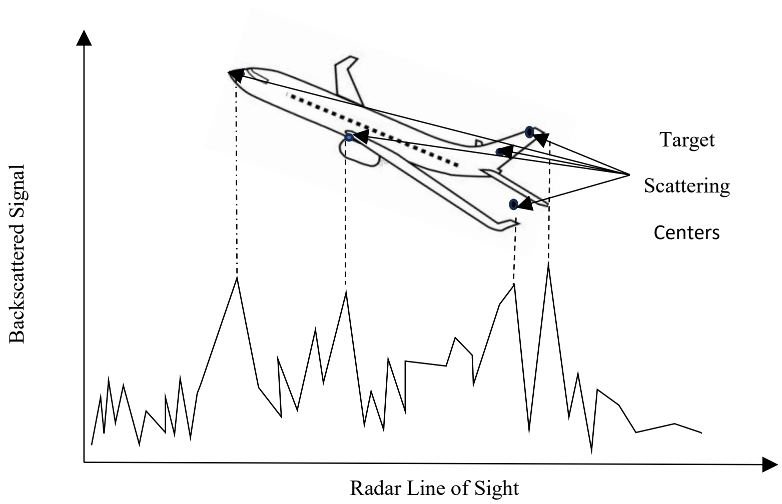

Figure 6. High range resolution profile representation.

3.5 Passive Radar Sensors

Passive radar systems utilize transmitters of opportunity like FM transmission, GNSS signals like GPS, GLONASS etc. (Clemente et al., 2015) and 5G signals (Liu et al., 2022a). The use of 5G base stations as illuminators for detecting unauthorized drones has recently become a focus of research, driven by the global expansion of 5G. With shorter wavelengths, small objects like amateur drones, nearly invisible in the microwave domain, achieve significant reflectivity in the millimeter wave domain. 5G signals in combination with Wi-Fi signals have been used for drone detection and localization (Teo et al., 2021).

3.5.1 5G Signal based Drone Detection/Classification

Narrow steerable beams of 5G base stations can act as passive radar illuminator for drone targets. Variable RF resource allocation is inherent to the 5G network, and it is the main challenge of 5G based passive radar as variability affects the signal time and bandwidth occupancy. The signal characteristics depend on the network load and the user demand, which may show temporal and spatial variance. Therefore, conventional integration methods, such as coherent or non-coherent integration, do not work for 5G based passive radar systems. As a result, the passive radar system for drone detection must be adaptive to changing signal environment and select the optimal time frames for signal integration. In Solomitckii et al. (2018) 5G millimeter wave cellular infrastructure has been utilized to detect the presence and localize the drone. The features of Non-Line-of-Sight (NLOS) transmissions by 5G radar along-with kNN and received signal strength indicator (RSSI) of 5G signal reflected by drone have been used to predict the location of the drone. **Table 2** presents the Radar sensor based NCTR.

Table 2. Structured review for radar sensor based NCTR.

Reference	Targets for classification	Data source	Feature extraction and data preprocessing techniques	ML classification algorithm	Results/Remark
Wan et al. (2019)	Ogive targets of different shapes	FEKO EM software, Pytorch	RCS Time series/ 12 statistical features like mean, std dev, min, max, variance was extracted	Sliding window Statistical Gated Recurrent Unit (SW-S-GRU)	97.2% classification accuracy of SW-S-GRU reported as compared to 95.2% ,94% and 93.1% of ResNet-18, SVM and kNN
Garg & Singh (2014)	Helicopter, Transport/ Fighter aircraft	Radar Track Data	Kinematic data like Velocity, Acceleration/ Derived x, y, z components of velocity and acceleration from track data	Classification and regression tree	Classification accuracy ranges from 66% to 100% as the number of features is increased from 2-10
Lee et al. (2016)	Shells of different sizes	FEKO EM Simulation software for RCS, Fire finder radar for track data	RCS time series, Track data	Fuzzy Classifier with three membership functions (MF) for classification/optimization of parameters of MF by Particle Swarm Optimization for maximizing classification capability	Approx 75% classification accuracy at 20dB SNR
Fu et al. (2021)	Drones (6 small and 4 large)	RCS measurements at mmWave frequencies (26-40 GHz) in anechoic chamber using VNA	Conversion of RCS signatures into images, preprocessing using LSTM-ALRO model	Long Short-Term Memory (LSTM) with Adaptive Learning Rate Optimization (ALRO)	Achieved 99.88% accuracy, better than CNN and GoogLeNet
Ye et al. (2021)	Warhead and Decoy of the same shape	CAD models, FEKO EM software	RCS time series, Simulated missile trajectory/ Statistical derivatives like average, max, min, median, range, Std Dev, skewness, kurtosis of RCS time-series	Custom built CNN RCSNet having total 43 layers with 08 convolution and seven pooling layers, SVM, classification tree and kNN	95% accuracy for RCSNet, less value for other algorithms
Sumari et al. (2022)	F-16C, Su-30MKK/MK2, C-130 Hercules, Boeing 737-200, and Boeing 737-900	Synthetic dataset generation from multiple open-source references	Not used	Decision Tree, K-Nearest Neighbors (kNN), Random Forest, SVM, and Backpropagation Neural Network (BPNN)	100%, however dataset size is very limited (100 for each target type)
Fix et al. (2021)	Three classes of airliner (small, medium and large)	FEKO EM software simulations for Bistatic RCS	Not used	2D-CNN classifier of the sparse BS-RCS, a 1D-CNN classifier of the BS-RCS time series and angles, and an RNN taking as input only the BS-RCS time series	95.27 % for three fold Cross Validation
Kumawat et al. (2022)	Three-short-blade rotor, three-long-blade rotor, quadcopter, bionic bird, and mini helicopter + bionic bird.	X Band CW Radar at 10 GHz	Micro-Doppler Signatures, Noise Reduction to improve the quality of the micro-Doppler signatures. Normalization Segmentation Transform (STFT) to analyze the time-varying frequency content of the radar signals	Custom made Deep Convolutional Neural Network (DCNN) model named DIAT-RadSATNet	The model achieved high classification accuracy across the six different types of SUAVs (97.3% multiclass accuracy)

Table 2 continued…

Sun et al. (2021)	Small UAVs (micro helicopter and quadcopter)	Patch antennas-based transceivers working with 2-kHz bandwidth centered at 915 MHz.	Spectral subtraction, filtering, Empirical Mode Decomposition (EMD), STFT, PCA	CNN, SVM,LSTM	LSTM performed better than CNN, SVM for detection, classification, and localization (93.9% with EMD for short distance)
Park et al. (2021a)	Three types of UAVs and two different types of human activities	micro-Doppler signature acquired through FMCW Radar 9.6-10 GHz	Generation of spectrogram images through STFT, Data augmentation	ResNet-SP (based on ResNet-18)	Accuracy: 83.39%, Training Time: 242s

4. RF Signature Sensors

RF sensing and fingerprinting techniques for airborne targets, particularly drone detection and identification, are active research areas as described in (Ozturk et al., 2020; Kılıç et al., 2022; Sazdić-Jotić et al., 2022). A review of fundamentals and research literature of RF fingerprinting based drone detection and classification is given in Jurn et al. (2024). Drone controllers typically use wireless transmissions in the unlicensed ISM band, ranging from 2.4 GHz to 5.8 GHz. Wi-Fi-based controllers operate at 2.4-2.483 GHz or 5.725-5.825 GHz, while 5G drones generally use the 3.5 GHz range, with sub-6 GHz options depending on the area's 5G deployment. This makes it feasible for engineers to develop a low-cost SDR-based RF capture device for monitoring the relevant spectrum (Flak, 2021). Regulatory restrictions may make packet sniffing of wireless traffic illegal in many countries. However, SDR-based RF receivers can legally detect only the RF spectrogram, which can then be used to train ML models for drone detection and classification. Frequency-hopping RF scanners are typically used to quickly tune across different frequencies to capture drone-controller communications (Kaplan et al., 2021). RF scanning method has also been productized and a few commercials off the shelf systems are available such as DJI AeroScope, Drone Defense and Air Warden. In Zhang (2021), six ML algorithms XGBoost, AdaBoost, decision tree, random forest, kNN, and multilayer perceptron have been evaluated using an open-access dataset to detect drones via RF signals.

4.1 Feature Extraction and Target Classification from RF Sensor Data

In RF physical layer, features such as the amplitude envelope spectral shape, modulation and symbol rate correlation can be extracted from the received data. For RF MAC layer (drone controller signal), the extracted features can be MAC address, Wi-Fi packet length, packet duration, mean packet inter-arrival time etc. MFCC as described in above section has also been used in non-acoustic signals like RF controller signals for the purpose of discriminating feature extraction techniques (Kılıç et al., 2022). Signal processing techniques are also frequently used by researchers and practical application developers. The raw RF signal may not be directly suitable for learning. In Zhang et al. (2023), authors computed DFT to generate spectrogram which was further segmented and augmented to generate high quality dataset. In Kılıç et al. (2022), authors elaborated handcrafted feature extraction using power spectral density (PSD), MFCC and linear frequency cepstral coefficients (LFCC) were undertaken for low and high frequency bands of the open-source DroneRF dataset (Allahham et al., 2019) and SVM multiclass classifier was used. In Ezuma et al. (2020), a multistage detector, which estimates the bandwidth and modulation features of the detected RF signals was designed to operate in the presence of interference from Wi-Fi and Bluetooth sources. Post isolation of interference, the UAV controller signal was detected and sent to RF fingerprints classification system using ML based classification techniques. In Sazdić-Jotić et al. (2022), author elaborate the method for generating drone RF dataset using three types of drones and five different drone flying modes (OFF, connecting, hovering, flying, and flying & recording video) using real time spectrum analyzer and ISM band RF sensors. Time frequency analysis tool based on STFT of MATLAB was used. FC DNN obtained impressive performance of 96.1% in classifying drones using RF signatures. In Ozturk et al. (2020), RF fingerprints of UAVs with low SNR levels have been explored for classification. Spectrogram representations of RF emissions from 15 commercial drone controllers have been extracted, and CNN has been trained on both screenshots of time-series representation of RF signals and the spectrogram. The spectrogram approach has been found to work better in low SNR paradigm. Classification accuracy of 92% has been achieved, which steadily increases to 100% as SNR improves from −10 dB to 30 dB. **Table 3** outlines the structured review of RF signature sensor based NCTR.

Table 3. Structured review for RF signature sensor based NCTR.

Reference	Targets for classification	Data source	Feature extraction and data preprocessing techniques	ML classification algorithm	Results/Remark
Zhang et al. (2023)	Five representative drone types, including Parrot ANAFI, FIMI X8SE, DJI Phantom 4 Pro V2.0, DJI Mavic Air, and DJI Mavic Mini 2	Universal software radio peripheral (USRP) X310 for downlink radio-signal acquisition	Spectrogram using DFT, data augmentation, spectrogram segmentation	Resnet Neural Network	Accuracy reported for various cases of data preprocessing and SINR conditions, best being 96% for SINR > 15 dB
Ezuma et al. (2019)	Different types of UAV	RF signal receiver	RF signature	Detection using Markov-based Naïve Bayes, K-Nearest Neighbors, Discriminant Analysis, Support Vector Machine, and Neural Networks	Accuracy of 95%, 96.84%, 88.15% and 58.49% using different techniques
Al-Sa'd et al. (2019)	Detection of UAV type and flight mode	Experimental setup for the drone RF signature database development used	RF signatures/Segmentation and FFT	DNN	Accuracy of 99.7% for 2, 84.5% for 4, and 46.8% for 10 classes, F1score: 99.5% for 2, 78.8% for 4, and 43.0% for 10 classes
Alam et al. (2023)	UAV detection using RF	Preexisting CardRF dataset	RF signature (UAS controller in the presence of Bluetooth, WiFi of different SNR)	End-to-End CNN Model	Accuracy: 97.53%, Precision: 98.06%, Recall: 98.00%, and F1score: 98.00%, computational time performance also reported.
McCoy et al. (2023)	UAVs, Thunder, Birds, and Planes are broken up into two sections.	Integrated two publicly available datasets one for image (Kaggle SonainJamil) and other DroneRF dataset	Mel spectrogram representation of sound for RF signals integration	Ensemble deep learning approach	Weighted average ensemble method gave accuracy of 96.88%
Basak et al. (2021, 2022)	Drone and WiFi signals	RF signals from commercial drones and WiFi routers using USRP X 310 SDR	Spectrogram representation, DFT, AWGN noise addition,	YOLO-lite, DRNN, Goodness of Fit based spectrum sensing	YOLO-lite showed better detection performance, DRNN provided better classification
Basak et al. (2021)	Drone RF signals	Nine commercial drones and WiFi signals	Spectrogram dataset, AWGN and multipath fading introduced	Deep Residual Neural Network (DRNN)	Achieved nearly 99% classification accuracy at 0 dB SNR, 5% better F1 score at −10 dB SNR
Nemer et al. (2021)	UAV Presence, Type (three classes of commercial UAV) and flight mode	Public UAV RF Dataset (not mentioned)	Filtering, Noise Reduction, FIR Filter	Hierarchical Learning Approach	Accuracy: 94.20%, F1 Score: 96.10%

Table 3 continued…

Lofù et al. (2023)	Identify, classify, and track UAVs (commercial DJI models)	NATO UAV flight measurements dataset	Standardization, One-hot Encoding, Label Encoding	Multilayer Perceptron (MLP), Random Forest (RF)	MLP model attained 90% accuracy, RF model showed MSE ≈ 0.29, MAE ≈ 0.04, and $R^2 \approx 0.93$.
Sazdić-Jotić et al. (2022), Shi & Li (2020)	7 different DJI Drone Types	Drone Detect Dataset (Contains raw I/Q samples collected by using a Nuand BladeRF SDR)	Spectrogram generation using STFT, annotation strategies	YOLOv5	Improved precision, recall, and mAP with second annotation strategy

Most of the researchers have used commercial SDR based systems for wideband RF sensing and subsequent preprocessing. **Figure 7** illustrates the end-to-end SDR-enabled RF sensing and deep learning–based classification pipeline for drone detection, highlighting the progression from raw RF signal acquisition to feature extraction and learning-based inference.

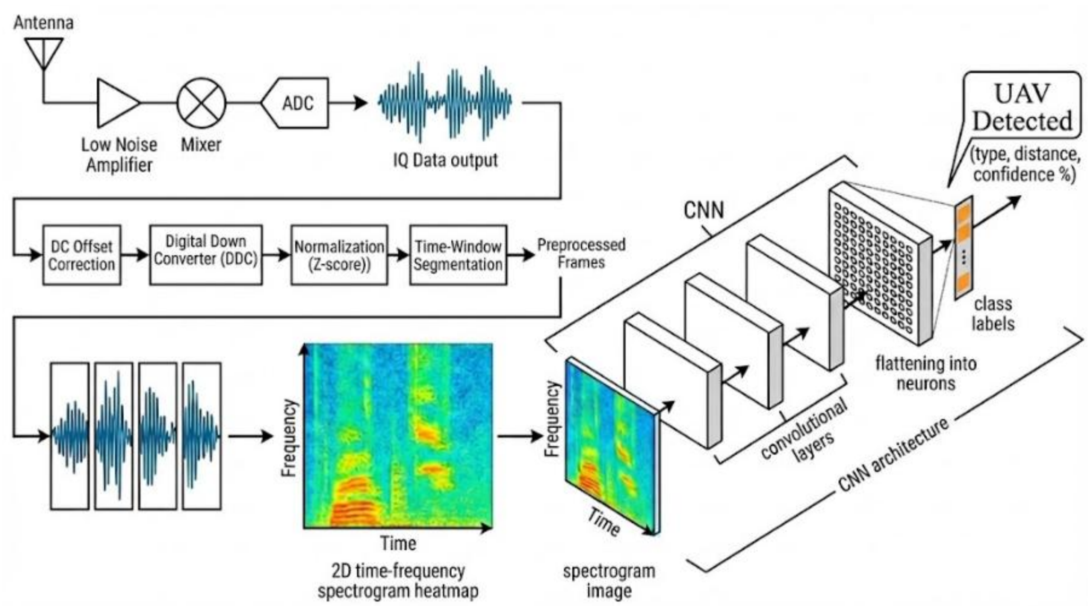

Figure 7. SDR and deep learning-based RF sensing and classification pipeline for drones.

5. Acoustic Sensors

Acoustic-based drone detection and classification is a method of detecting and classifying aerial targets such as drones with sound signals using AI (Ohlenbusch et al., 2021). Acoustic sensing offers a passive, low-cost approach for drone detection, particularly effective in situations where radar visibility is obstructed or RF links are disabled. Acoustic data collection is usually done by recording from acoustic sensor array or microphones (Strauss et al., 2018) and extracting useful features using signal processing and statistical techniques as utilized in creating a Dataset DREGON (Drone EgoNoise and localization). More recent studies have adopted dataset enhancement using Generative Adversarial Networks and then using deep learning (Al-Emadi et al., 2021). DL models such as stacked BiLSTM CNN, a variation of Long Short-Term Memory (LSTM) have been used to learn and store temporal variations in the acoustic signals

(Utebayeva et al., 2020). The advantage of acoustic based detection is that they do not require LOS and work very well in silent areas while being relatively cheaper. Acoustic based drone detection systems are constrained by low detection range depending on microphone array sensitivity, high sensitivity to background noise and wind conditions affecting acoustic based systems.

5.1 Feature Extraction and Target Classification from Acoustic Sensor Data

Raw data from acoustic sensors for training ML model may not produce desired classification performance, therefore features extraction from raw sound data is essential. Useful features for classification include Power Spectral Density (PSD), RMS of PSD, Mel-Frequency Cepstral Coefficients (MFCC) (Abdul & Al-Talabani, 2022), and acoustic STFT. MFCC is a non-linear mapping of the received audio frequency signal which replicates the auditory response of the human ear. MFCC extraction has been used for drone sound characterization and classification. It is based on Mel scale. The Mel scale is a scale that relates the perceived frequency of a tone to the actual measured frequency. It scales the frequency to match more closely what the human ear can hear. The Mel scale to the response frequency and vice versa is computed by the following equations:

$$\begin{aligned} m &= 2595\log_{10}\left(1+\frac{f}{700}\right) \\ f &= 700(10^{m}/2595-1) \end{aligned} \tag{9}$$

where, *m* is Mel scale frequency and *f* is actual frequency.

The required number of triangular band pass Mel filter banks are constructed using the value of *m*. To remove the correlation in filter bank coefficients as computed in the previous step can apply Discrete Cosine Transform (DCT) to decorrelate the filter bank coefficients and yield a compressed representation of the filter banks. The feature extraction process for MFCC is shown in **Figure 8**. The complete process of acoustic sensors based drone detection and classification pipeline using DL is depicted in **Figure 9**. The pipelines include a direction and distance finding branch integration with detection and classification system.

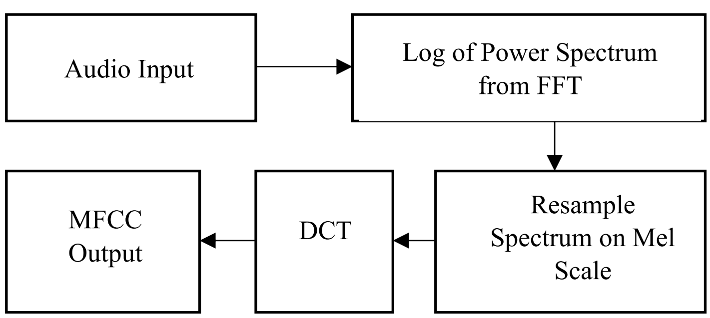

Figure 8. Feature extraction process for MFCC.

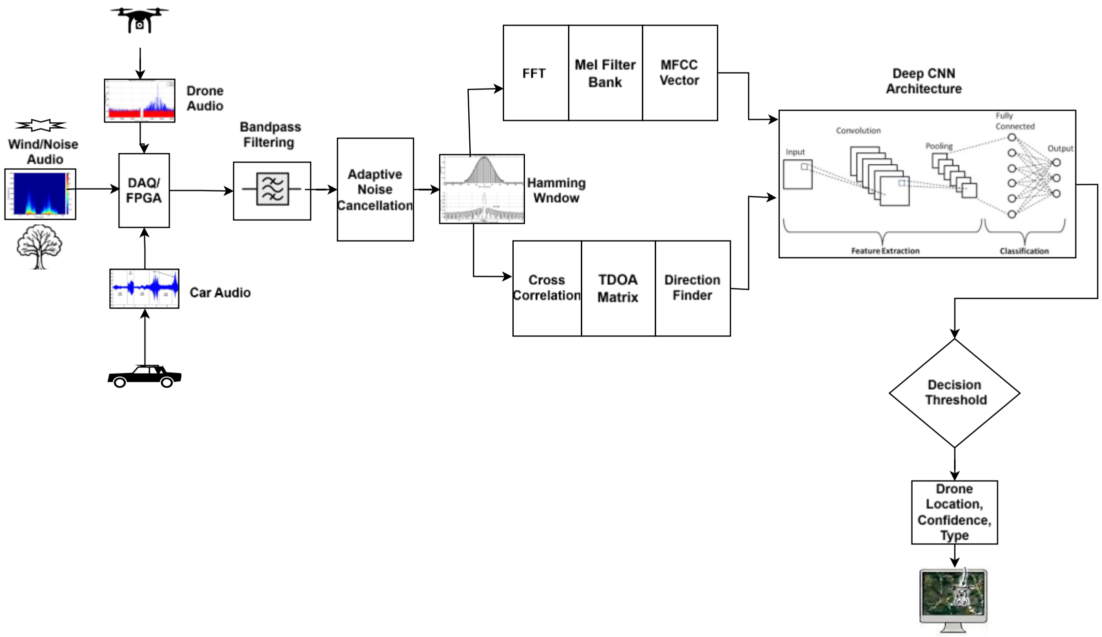

Figure 9. Acoustic based drone detection and classification pipeline.

In Shi et al. (2020), authors use SVM along with object localization technique called time difference of arrival (TDOA) for detection and localization of drones. Eight microphones arranged in two tetrahedron arrays along with data acquisition cards have been used. STFT has been used to analyze the features contained in acoustic signals. Harmonics features have been captured by a cepstral coefficient extraction. Drone presence is confirmed by distinguishing whether extracted features belong to drone or background noise. In Lacava et al. (2022), a publicly available dataset of Drone EgoNoise and localization (DREGON) (Strauss et al., 2018; Anwar et al., 2019). Various audio features like chromogram, spectral centroid spectral bandwidth and MFCC were extracted. Eight ML models (SVM, kNN, gradient boosting, decision tree, naive bayes, random forest, logistic regression, neural network) were used in the training phase. It was reported that logistics regression and SVM gave acceptable classification accuracy of 90%. In Ohlenbusch et al. (2021), authors have attempted to use both temporal and spectral features. They have utilized block-wise time domain features such as block RMS, the temporal centroid (TC) and the zero-crossing rate (ZCR). In the spectral domain, the spectral centroid, spectral Roll-Off, spectral bandwidth, spectral flatness, skewness and kurtosis and 13 MFCCs were extracted. One class SVM based classification was used. Instead of using the features themselves, the authors have used the normalized mid-term statistics for each block-wise feature. The kernel function used are radial basis functions (RBF), also known as Gaussian kernels. The classification accuracy achieved was 92.63 %. In Anwar et al. (2019), necessary features from amateur drone sound like MFCC and linear predictive cepstral coefficients (LPCC) have been extracted. SVM with different types of kernels were thereafter utilized to classify these sounds. Using an SVM with a cubic kernel on MFCC features yields higher accuracy than the LPCC-based method. Accuracy of 96.7% for amateur drone detection was achieved by using drone sound features. **Table 4** presents the structured review of Acoustic sensor based NCTR.

Table 4. Structured review for acoustic sensor based NCTR.

Reference	Targets for classification	Data source	Feature extraction and data preprocessing techniques	ML classification algorithm	Results/Remark
Al-Emadi et al. (2021)	Multiple Commercial Drone Detection and Identification	Microphone-captured drone sounds alongside GAN-generated synthetic drone audio samples	Reformatted audio files, divided into one-second segments, converted to spectrograms, Data augmentation with background noise, pitch shifting	CNN, RNN, CRNN	CNN and CRNN models were effective, GANs improved detection of new and unfamiliar drones
Uddin et al. (2020)	Single or Multiple Amateur Drones	Acoustic signals in the presence of interference (e.g., birds, airplanes, thunderstorm, rain, wind) from publicly available databases	Independent Component Analysis (ICA), MFCC, PSD, RMS of PSD	SVM, kNN	RMS values of PSD with SVM and kNN performed better (96.1,99.1%) than MFCC with SVM and kNN (88.2, 98.4%)
Anwar et al. (2019)	Amateur Drone Sounds	Real-time acoustic data (birds, drones, thunderstorm, airplanes) using array of microphones	Mel Frequency Cepstral Coefficients (MFCC), Linear Predictive Cepstral Coefficients (LPCC)	SVM with various kernels	MFCC with SVM cubic kernel achieved 96.7% accuracy, outperforming LPCC method
Aydın & Kızılay (2022)	Amateur Drones, Birds, Airplanes, Helicopters, Storms, Background Noises	Audio signals from Parrot Anafi, Bebop and Tello drones, background sounds from public databases	Mel Frequency Spectrum, Z-score normalization	Light-Weight Convolutional Neural Network (LWCNN), SVM	98.8% accuracy for Cubic kernel SVM, 95.6% for Light weight CNN, effective in noisy environments
Dumitrescu et al. (2020)	Commercial quadcopter drone detection and classification	Acoustic signals from UAVs gathered from spiral microphone array	Filtering, Segmentation, Windowing, Mel Frequency Cepstrum Coefficients (MFCC), Adaptive Filtering, Time Frequency Analysis (Cohen's class)	Concurrent Neural Networks (CoNN) are a type of neural network architecture designed to process multiple sequences of data simultaneously, Self-Organizing Map (SOM), Multi-layer Perceptron (MLP), Time-Delayed Neural Network (TDNN)	Higher accuracy in recognition compared to non-competitive cases
Wang et al. (2021b)	Audio recordings of DJI Phantom 4 and Evo 2 Pro	1191 Audio and noise samples using microphones	Python library Librosa used for 5 different audio feature extraction	SVM, kNN, Gaussian Naïve Bayes and NN	Combination of features shows enhancement in accuracy for all algorithms. Multiple results show improvements.

6. Optical/EO/IR Sensors and Computer Vision for NCTR

Autonomous non cooperative targets/drones cannot be detected by RF signature detectors as they do not rely on RF signals for navigation. For such targets, optical PTZ cameras, Electro-Optical/ Infra-Red (EO/IR) cameras and Thermal Imaging (TI) sensors can be used for detection and classification of drones in conditions of poor visibility such as fog or night-time, detecting the IR signatures emitted by the drone is a better option. Computer vision is a field of AI that enables computers and systems to derive meaningful information from digital images, videos, and other visual inputs through application of DL. In recent years, numerous commercial applications including face recognition, optical character recognition, biometrics, and video surveillance have emerged, driven by deep learning-based computer vision. Commercial availability and capability of edge computing devices and software stack have improved a lot as evident in products. Object detection techniques based on DL can be categorized as either one-stage or two-stage methods. One-stage methods use CNNs to directly predict target categories and positions through regression. A detailed review of one-stage networks for object detection is presented by the author in Zhang et al. (2021b). Two-stage object detectors are basically R-CNNs (Region-based Convolutional Neural Network). A two-stage object detection algorithm that uses a region proposal algorithm to propose several regions that might contain an object and then apply a CNN to each of these regions to classify them. R-CNN was introduced by Girshick et al. (2014). The R-CNN algorithm consists of three main modules: the region proposal, the feature extraction, and the object detection module. The region proposal module generates a set of object proposals using selective search. The feature extraction module extracts a fixed-length feature vector from each object proposal using CNN. Finally, the object detection module classifies each object proposal into one of the pre-defined classes and refines its bounding boxes. Fast R-CNNs, Faster R-CNNs, and Mask R-CNNs are the progressively better neural networks to speed up such computation. Object detection, which is one of the most basic functions in computer vision based on DL and its variations (Alam et al., 2021) has been applied to airborne drone detection with optical, EO/IR or pure IR images having diverse background. In Isaac-Medina et al. (2021) a performance benchmark study evaluated the performance of four detector architectures for UAV detection and tracking. These architectures were Faster R-CNN (which achieved the highest mAP of 98.6% for visual detection and tracking), SSD (Single Shot Detector) which is known for its computational efficiency. YOLO (You Only Look Once) has evolved into a preeminent real-time object detection system used in counter drone applications and autonomous vehicles. Authors at Terven et al. (2023) provide an extensive review of the YOLO architecture, detailing its development from YOLOv1 to the latest advancements such as YOLOv8. The authors analyse significant innovations and changes in the network architecture, training techniques, and performance metrics across various versions, emphasizing the trade-off between speed and accuracy in real-time object detection applications.

The architecture improvements in YOLO models include the incorporation of anchor boxes, batch normalization, and features like multi-scale predictions to enhance detection accuracy YOLO frameworks offer a balance between algorithm run time and accuracy, making them well-suited for real-time applications, though detecting small or overlapping objects remains challenging. In Dewangan et al. (2023), one of the recent object detection and classification algorithm YOLOv7 has been used. More optimal network structure, loss function, etc. increase accuracy without decreasing detection speed in YOLOv7. It uses a multi-scale feature pyramid network. DL architecture has been extensively used in drone detection and classification due to its inherent advantages in dealing with optical and EO/IR imagery. In Garcia et al. (2020), a publicly available dataset *SafeShore* has been utilized for computer vision-based drone detection using faster R-CNN (Region-based Convolutional Neural Network) with ResNet-101 (Residual Neural Network-101) as the base network for the detection of drones. Faster R-CNN with ResNet 50 is a model that combines two key computer vision techniques i.e. faster R-CNN (Region-based Convolutional Neural Networks) and ResNet (Residual Networks). Accuracy of 93.40% has been achieved and the model has successfully detected the drone in safe-shore dataset. In Zheng et al. (2021), a data set of 13271 images of a flying UAV acquired by another flying UAV (DJIM210) has been constructed and subjected to eight DL algorithms for training and testing. Authors have also analyzed the impact of environmental background, target scales, viewing angles, and other challenging conditions on the detection performance. A manually labeled large dataset has been created by Pawełczyk & Wojtyra (2020). **Table 5** outlines the structured review of selected articles for NCTR using computer vision techniques. Recent advancements in ViT-based architecture show marked improvements in image classification in the presence of noise (Maurício et al., 2023), which is a key requirement for drone identification.

Table 5. Structured review for computer vison based NCTR.

Reference	Targets for classification	Data Source	Feature extraction and data preprocessing techniques	ML classification algorithm	Results/Remark
Dewangan et al. (2023)	UAV Detection	Dataset available on Kaggle and self-captured images	Image preprocessing like RGB, Grayscale, Hue Augmentation, Edge Enhancement	YOLOv5, YOLOv7	Highest accuracy with YOLOv5 and hue augmentation (mAP: 96.7%)
Samadzadegan et al. (2022)	Drones and Birds	Publically available Quadcopetr, Hexacopter, Helicopter, Birds images Dataset (10,000 images)	Ground truth bounding box, normalization, data augmentation (CutMix, Mosaic, DropBlock, label smoothing)	YOLOv4, Deep Convolutional Neural Network	Accuracy: 83%, mAP: 84%, IoU: 81%, Average Recall: 84%, Average Accuracy: 83%, Average F1-score: 83%
Liu et al. (2021)	Small UAV detection using image	Camera	Optical imagery/ small object augmentation (insertion of multiple copies of same objects) to enhance the detection capability for small drones and compensate for accuracy loss	Pruned yolov4	Model achieved a precision of 30.7%, recall of 72.6%, mean average precision of 90.5%, and an F1-score of 45.2%
Singha & Aydin (2021)	UAV detection using images	Google and Kaggle images approx. 2400 for birds and drones	Optical Imagery	YOLOv4	Precision = 0.95, Recall = 0.68, F1-score = 0.79, mAP = 74.36%
Jamil et al. (2022)	Five different classes (i.e., aeroplanes, birds, helicopters, drones, Multiple Drone Images as malicious droens)	Open source dataset	HOG (Histogram of Oriented Gradients), LBP (Local Binary Patterns), Noise resistant LBP, GLCM	ViT, Deep CNN, SVM, kNN, NB, Decision Tree	98.28 %, best with ViT

Figure 10 presents the computer vision–based drone detection and classification pipeline, outlining the sequential stages from image/video acquisition to preprocessing, feature extraction and learning-based inference.

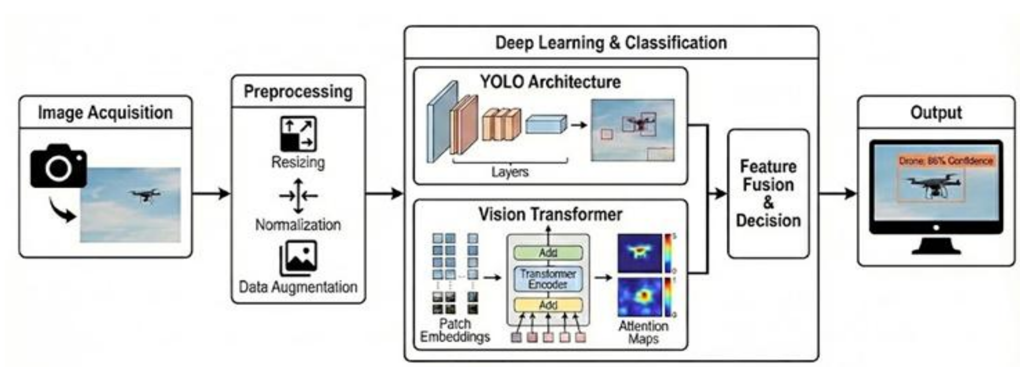

Figure 10. Computer vision-based drone detection and classification pipeline.

7. Fusion of Different Sensing Modalities

Multimodal machine learning (MML) aims to build models by using the sensing modalities which can pertain to multiple sensors. MML is an active research area (Barua et al., 2023). It becomes a necessity when a feature set from one domain is not sufficient to accurately classify or predict with desired accuracy. MML working in parallel or sequential mode can be used for detecting and/or classifying non cooperative targets in various operational scenarios. In Kim et al. (2023), a two-pronged approach using vision and acoustic based sensing was used. DJI Mavic 2 Pro, containing a built-in camera and microphone, was used as a detecting drone, and DJI Matrice 200 V2 was defined as a target drone. For image features, YOLOv5 backbone network was used for feature extraction while MFCC was explored for sound feature extraction and CNN was used for classification. The computer vision-based model achieved classification accuracy of 90.26% and the acoustic based model achieved accuracy of 88.96%. The author explored OR function to the result of vision and acoustic models, which result in improvement of accuracy to 92.53%. In other works where one or more detections and modalities have been used for sensor fusion based classification have been explored (Liu et al., 2017; Svanström et al., 2020). Often, one sensing modality can act as the cue for other sensing modalities. NLOS detection schemes like RF sensing and Radar signatures can be used to cue the other sensors having lesser detection range (Optical or Acoustic) to adjust its direction, tilt, zoom level etc. to confirm the detection and classify accurately. The main constraints of multimodal detection for NCTR are increased complexity for realization, sensor imperfections and background uncertainties. When joint detection/classification by multiple sensors is attempted, issues related to synchronization, contradictory classification, false sensing, overshooting of time, range budget by one sensing modality, cueing and handoff without impacting other modalities can also arise. In Svanström et al. (2020) a sensor fusion based approach was used with visible, thermal and acoustic sensors. IR camera and optical camera data sets were processed with YOLOv2 for learning and detection whereas audio sensor used MFCC features and LSTM classifier. An information gain using sensor fusion resulted in increased classification accuracy from 67% from visual only to 78% when using all three types. **Figure 11** presents the schematic representation of multi sensor fusion based NCTR data processing and AI pipeline. The pipeline demonstrates the aggregation of feature vectors from Radar, RF, and EO/IR sensors into a shared concatenation layer for final classification. **Table 6** presents structured reviews of important articles using sensor fusion and ML approach for non-cooperative target identification.

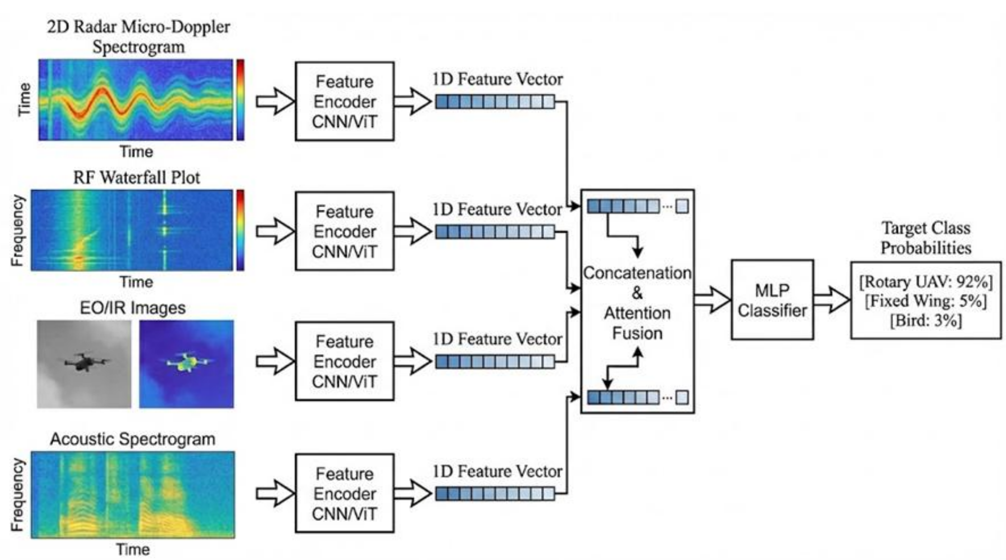

Figure 11. Schematic representation of multi sensor fusion based NCTR data processing and AI pipeline.

Table 6. Structured review of sensor fusion based NCTR.

Reference	Targets for classification	Data sources/Sensors	Feature extraction and data preprocessing techniques	ML classification algorithm	Results/Remark
Mehta et al. (2023)	Various Small DJI Drones, birds	FMCW Radar, HD PTZ Camera	Not applied	YOLOv 5, RNN	98% for drones, 94% for birds
Lee et al. (2023)	Various small DJI drones	FMCW Radar, HD Camera, microphone	Range doppler map for radar and Mel spectrogram by windowing and STFT for acoustic signals	GoogLeNet used as a pre-trained CNN model	99% combined accuracy when using all three sensors
Jamil et al. (2020)	Five image classes: birds, airplanes, kites, balloons, and drones	Array of microphones, High Resolution cameras	AlexNet for Visual feature extraction, MFCC for audio	SVM classifier (various kernels used)	98.5% for combined sensors
Frid et al. (2024)	Nine Small drones and interference	Opensource datasets (Drone RF dataset, Drone Audio dataset), XBeeSDR	PSD, Gamma Tone Cepstral Coefficient (GTCC), Mel Freq. Cepstral Coeff. (MFCC), Wavelet Packet Decomposition	CNN, LSTM, RNN, SVM	91% at an SNR of −10 dB using the LSTM
Svanström et al. (2022)	Three different Make and models of commercial drones, airplane, birds, helicopters	Infra-Red Camera, Video Camera, FishEye lens camera, Microphone, ADS-B	MFCC for audio, GMM background subtraction	Kalman filter for sensor fusion, LSTM classifier, YOLOv2	78% combined accuracy

8. Assessment and Evaluation of Sensing Methodologies and Artificial Intelligence Techniques for NCTR

This section presents the assessment and evaluation of sensing methodologies and AI applications in recent research works for NCTR. The count of research articles in the last five years has been presented. A histogram analysis as per sensing methodologies is presented in **Figure 12**. Nearby ranges provide more varied types of sensing and data collection opportunities. This includes RF scanners, Acoustic sensors and Computer vision based NCTR. This variety of sensing methods available for near ranges is reflected in large article count for these sensor-based research works. The research articles utilizing more than one sensing domain are separately annotated as multimodal in the histogram.

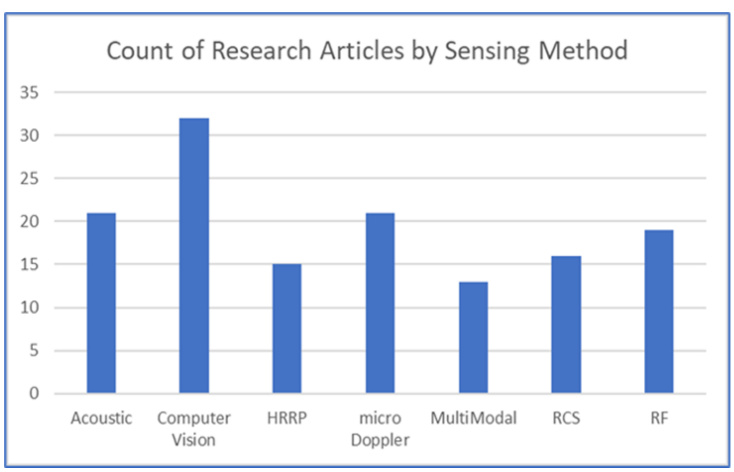

Figure 12. Analysis of NCTR as per sensing methodologies.

Moreover, due to the availability of open-source dataset researchers are motivated to explore different ML and DL algorithms for non-cooperative target detection and classification. **Table 7** summarizes important publicly available data sets for NCTR.

Table 7. Important publicly available data sets for NCTR.

S. No.	Data set	Target type	Data acquisition / sensor methodology	Description of dataset	Dataset accessible link
1.	Cardinal Radio Frequency (CARDRF) Dataset	Drones (DJI Inspire, DJI Matrice 600, and DJI Phantom, Beebeerun FPV RC drone mini quadcopter)	RF Sensor	Dataset contains UAV, UAV RF Controller, Bluetooth, Wi Fi Sampled Signals (raw and processed). The Processed CardRF directory has sliced steady signals from LOS with respective class or label. Each signal in the processed CardRF directory has 1024 sampling points	https: //aerpaw.org/
2.	Drone RCS Data Set (Semkin et. al.)	Custom built hexacopter, DJI Matrice M100, HMF Y600, Walkera Voyager 4, DJI Mavic Pro, DJI Phantom 4 Pro, DJI F450	Anechoic Chamber, VNA	Various dimensions and material-based Drones' RCS were measured at 26-40 GHz. Targets were rotated through stepper motor for azimuth and elevation angle variations	https://ieee-dataport.org/open-access/drone-rcs-measurements-26-40-ghz
3.	Drone RF dataset	Three types of small drone by different manufacturers	Broadband RF receivers.	The dataset comprises 227 RF activity recordings collected from three different drones, along with background RF recordings captured in the absence of drones	https://data.mendeley.com/datasets/f4c2b4n755/1
4.	Fredrik (Svanström et al., 2022)	Hubsan H107D+, DJI Phantom4 Pro, DJIFlameWheel	The thermal infrared camera for IR images, HDR Video camera for video recording, directional microphone for sound capture, SDR based ADS-B receiver	The database contains 90 audio clips and 650 videos (365 IR and 285 visible of ten seconds each), with a total of 203328 annotated images. The IR videos have a resolution of 320×256 pixels, whereas the visible videos have 640×512. The greatest sensor to-target distance for a drone in the dataset is 200m.	https://github.com/DroneDetectionThesis/Drone-detection-dataset
5.	Det-Fly Dataset	flying target UAV (DJI Mavic)	Onboard Camera	Dataset of 13271 images of target UAV acquired by another flying UAV (DJI M210). The relative distance of the target UAV varies from 10 m to 100 m, and the flight altitude from 20 m to 110 m.	https://github.com/Jake-WU/Det-Fly
6.	UAV Detection Tracking Benchmark dataset	Three distinct types of UAV datasets.	other drones, ground-based surveillance cameras and handheld mobile devices.	This GitHub repository contains the code and dataset for Unmanned Aerial Vehicle Visual Detection and Tracking using Deep Neural Networks: A Performance Benchmark submitted to IROS 2021.	https://github.com/KostadinovShalon / UAV Detection Tracking Benchmark
7.	IEEE data port Drone Detect Dataset	7 distinct types of DJI Drones	commercial SDR and open-source software GNU Radio.	There are 4 subsets of data included in this dataset, the UAS signals in the presence of Bluetooth interference, in the presence of Wi-Fi signals, in the presence of both and with no interference. 3 flight modes are captured - switched on, hovering and flying.	https://ieee-dataport.org/open-access/dronedetect-dataset-radio-frequency-dataset-unmanned-aerial-system-uas-signals-machine
8.	Drone Audio Dataset	Two types of drones (Bebop and Mambo)	iPhone embedded microphone	Consists of drone audio dataset which has been recorded of drone propellers noise in an indoor environment by Sara Al-Emadi and artificially augmented with random noise clips using Generative Adversarial Network	https://github.com/saraalemadi/DroneAudioDataset

Table 7 continued…

9.	University of Southern California Dataset	Single Drone model	High Resolution Camera	USC drone dataset comprises 30 video clips, all captured using a single drone model. Covers various backgrounds, camera angles, drone appearances, and weather conditions, and in fast motion, extreme illumination, and occlusion	https://mcl.usc.edu/mcl-drone-dataset/
10.	RDRD database – Kaggle	drones, cars, and people	FMCW Radar at 8.75 GHz with 500 MHz Bandwidth	Composed of CSV files with 17,000 samples of drones, cars, and people. The RDRD database contains an 11×61 matrix representing the power in dBm of each of the cells.	https://www.kaggle.com/datasets/iroldan/real-doppler-raddar-database

8.1 Assessment of Radar based Methodologies

Radar remains the cornerstone of long-range aerial surveillance due to its day/night and all-weather capabilities. However, the detection/classification of small consumer drones (Low-Slow-Small or LSS targets) presents unique challenges that traditional air defense radars optimized for fast, fighter class aircraft struggle to meet. In the radar-based sensing methodology the RCS, HRRP, and micro-Doppler signatures vary with target orientation and Radar system state thereby necessitating extensive training data for robust classification. However, techniques such as data augmentation (Dieter et al., 2023), invariant feature learning, and attention mechanisms or their variants can enhance the capturing of complex temporal dependencies in radar signals, improving target classification based on dynamic RCS variations. Like many other domains, the adoption of transformer architecture and attention mechanism has improved performance in radar based DL models (Chen et al., 2024). The core concept in micro-Doppler based radar target recognition is to treat micro-Doppler data as a discriminative signature unique to different targets. LSTM based RNNs (Sherstinsky, 2020) excel at capturing sequential dependencies in time series micro-Doppler signatures (Sun et al., 2021). It was demonstrated by authors in Sun et al. (2021) that LSTM neural network outperformed other ML models (CNN, SVM, SVR, GPR, RFR) in detection, classification, and localization tasks. The seminal paper "Attention Is All You Need" by Vaswani et al. (2017) introduced the Transformer which marked a paradigm shift in DL by replacing recurrent and convolutional structures with a self-attention–based mechanism for sequence modeling (Yang et al., 2024). Its foundational design enabled global dependency modeling, parallel computation, and improved scalability compared to RNNs and CNNs. The core concepts of multi-head self-attention and positional encoding have since become fundamental building blocks across learning tasks. This breakthrough has profoundly influenced modern DL, underpinning advances in natural language processing, computer vision, and multimodal intelligence. Transformers, utilizing self-attention mechanisms, are better at capturing the long-range temporal dependencies and sequences of micro-motions across the Coherent Processing Interval (CPI) than CNNs, leading to higher classification accuracy even in low-SNR conditions. In HRRP-based methods, which describe a target's range-dependent scattering characteristics, research has mainly focused on employing RNN, such as LSTMs and GRUs, to capture temporal variations in target signatures. However, with the advent of transformer architecture, it is being leveraged to overcome the inherent limitations of CNN- and RNN-based HRRP sequence recognition, particularly their inability to model long-range dependencies and global spatiotemporal context information. By employing multi-head self-attention, the Transformer adaptively captures long-range correlations across HRRP sequences, enabling the model to focus on discriminative scattering features while suppressing redundant and noisy regions.

8.2 Assessment of RF Signature based Methodologies

In RF signature-based drone detection and identification ML algorithms analyze radio frequency signals, including control and communication transmissions. This approach is highly useful for security applications, as it operates effectively day or night and in all weather conditions. The main concern is that it does not work in detecting or classifying fully autonomous non-cooperative aerial targets. Recent studies present significant progress in RF signature-based techniques, particularly in enhancing feature extraction, leveraging DL models, and enabling real-time processing through edge AI to effectively manage noise and signal variability including low SNR conditions. Moreover, researchers are also exploring transfer learning, leveraging pre-trained models on large RF datasets and fine-tuning them for specific drone detection tasks. However, challenges arise due to similarities between drone controller signals and the ubiquitous Wi-Fi, Bluetooth spectrum which operates in the same range, prompting ongoing research efforts to improve signal differentiation and classification accuracy (Alam et al., 2023). The primary operational challenge is the severe congestion of the ISM bands (2.4/5.8 GHz). In urban environments, legitimate Wi-Fi and Bluetooth traffic creates a high noise floor and co-channel interference (Ezuma et al., 2020). Simple energy detectors fail in these scenarios. Research indicates that RF classifiers trained on clean data suffer significant performance degradation (over 20%) when deployed in real-world environments with active Wi-Fi interference. Addressing this requires robust source separation algorithms and the training of neural networks on datasets augmented with realistic interference profiles. The system must distinguish the specific packet preambles and inter-arrival times of drone protocols from standard 802.11 traffic (Zhang et al., 2023). The commercial drone market evolves rapidly, with new models and protocols released frequently. This can lead to static threat libraries quickly become obsolete. Transfer Learning can be utilized to address this. By taking a deep model pre-trained on a RF dataset (like Cardinal RF), researchers can "fine-tune" the network on a small number of samples from a new drone model.

8.3 Assessment of Acoustics based Methodologies

Drone identification using acoustic signatures remains in an early stage, with several persistent limitations reported in the literature. Multirotor UAVs generate aero-acoustic signatures dominated by rotor harmonics and broadband turbulence, typically spanning 500 Hz to 10 kHz. These high-frequency components experience rapid atmospheric absorption and scattering, leading to a steep reduction in signal-to-noise ratio (SNR) as the range increases. Experimental studies demonstrate that, while drone presence may still be detected at 300–500 m under favorable conditions, reliable classification typically deteriorates beyond 150–200 m as the acoustic signal approaches the ambient noise floor (Al-Emadi et al., 2021; Kang et al., 2025). Consequently, acoustic modalities are best positioned for short-range “last mile” detection, gap-filling surveillance, and perimeter defense rather than wide-area tracking. Urban environments impose complex acoustic channel effects, including ground reflections, building-induced reverberation, and scattering from vegetation. These mechanisms distort the harmonic structure and spectro-temporal features necessary for machine-learning-based identification, reducing detection precision and increasing confusion between drone classes. Additionally, background sources such as road traffic, wind, rain, industrial machinery, and human activity elevate the noise floor, masking low-amplitude rotor harmonics and degrading classification robustness. Traditional MFCC, Mel-spectrogram, and time–frequency representations continue to serve as information rich features for feeding into convolutional and RNN. To improve resilience under diverse noise and SNR conditions, researchers are incorporating aggressive data augmentation strategies, including pitch modification, time-stretching, spectral warping, and additive noise mixing using large collections of environmental recordings (Kümmritz, 2024). More recently, Generative Adversarial Networks (GANs) have been exploited to synthesize realistic drone audio and drone–noise mixtures, significantly improving generalization to unseen UAV models, flight states, and environmental conditions. To reduce false alarms and enable spatial tracking, single-microphone systems are being replaced by spatially distributed microphone arrays. These systems rely on Beamforming (Delay-and-Sum, MVDR, SRP-PHAT) to enhance SNR in a given direction and on Time Difference of Arrival (TDOA) estimation for 2D/3D localization (Shi et al., 2020). Distributed arrays deployed across rooftops, masts, or vehicles enable multi-baseline triangulation but require precise time synchronization (microseconds or better), careful geometric calibration, and significant networking overhead, increasing system complexity and power consumption. Recent research indicates that while UAV acoustic-based NCTR remains constrained by propagation physics, it is rapidly maturing into a complementary modality within fusion-driven counter-UAS architectures.

8.4 Assessment of Computer Vision based Methodologies

Computer vision has emerged as a crucial component of drone classification pipelines due to its intuitive verification capability, rich semantic information, and the ability to identify UAV types, payloads, and behavioral anomalies. Recent progress in visual NCTR is driven largely by three pillars: advanced object detectors, edge-enabled deployment, and dataset enhancement (Bala et al., 2025). Modern UAV detectors predominantly rely on the YOLO (You Only Look Once) family due to its favorable speed–accuracy trade-off and scalability. Progress from YOLOv5 to YOLOv9 has introduced increasingly sophisticated mechanisms, including anchor-free detection heads, multi-scale feature aggregation, and attention-enhanced hierarchies. Particularly, YOLOv9 architectures integrate Programmable Gradient Information (PGI) and decoupled heads, improving localization consistency and robustness for small distant drones that occupy only a few pixels in a high-resolution frame (Hakani & Rawat, 2024). Generative Adversarial Network (GAN)-based data augmentation has further improved performance by synthesizing realistic drone imagery under occlusion, motion blur, fog, and illumination variations. While CNNs dominate operational deployments, ViTs and hybrid transformer-CNN frameworks (e.g., DETR, RT-DETR) are gaining traction. Unlike CNNs that focus on local receptive fields, ViTs incorporate global self-attention, allowing the network to model entire-scene relationships, thereby reducing false positives from birds, kites, and airborne debris (Zhang, 2023). Attention modules such as CBAM, ECA-Net, and Transformer encoder blocks have been shown to significantly improve performance in small target recognition, especially in low-SNR imaging with clouds, twilight, and atmospheric scattering. However, transformer-based pipelines generally incur heavier computational loads, creating challenges for deployment on real-time low-SWaP platforms. Operational counter-UAS platforms often rely on embedded computing devices such as NVIDIA Jetson Nano, Xavier NX, TX2, and Orin AGX. Edge deployment requires real-time inference (>30 FPS) under constrained power budgets, necessitating compression methods such as quantization (FP32→INT8), structured pruning, neural architecture search (NAS), and lightweight backbones (e.g., MobileNetV3, ShuffleNet, GhostNet). Research demonstrates that well-optimized quantized YOLO/Transformer models can retain >95% of baseline accuracy while reducing latency by up to 60% and power consumption by>40% on Jetson-class devices (Hakani & Rawat, 2024). Dynamic environmental challenges such as fog, rain, dust, snow, glare, overcast backgrounds, and low-light nighttime conditions degrade detection reliability and induce higher false-alarm rates (Coluccia et al., 2021). Synthetic dataset generation via GANs, physics-based rendering, drone swarm simulation, infrared augmentation, and domain adaptation techniques have been investigated to address dataset scarcity and environmental bias (Dieter et al., 2023). Multispectral and thermal imaging has also been shown to significantly improve drone detection under night and fog conditions, expanding applicability beyond daylight-only optical surveillance (Svanström et al., 2022). Recent studies have begun leveraging spatiotemporal vision techniques, including 3D CNNs, optical flow, trajectory analysis, and skeleton-based motion descriptors, enabling differentiation of drone types by flight dynamics rather than appearance alone (Doumard et al., 2022). This motion-based behavioral classification offers resilience to camouflage, weather-induced visibility losses, or visual spoofing, and can serve as a complement to appearance-based detectors in multimodal fusion systems. Overall, while state-of-the-art visual NCTR methods have matured substantially through YOLO and transformer-driven pipelines, operational robustness still depends heavily on environmental modeling, dataset realism, edge optimization, and integration with complementary sensing modalities.

8.5 Assessment of Sensor Fusion based Methodologies

Analysis of the literature reveals that the key ideas in sensor fusion based approaches have been to integrate diverse modalities to leverage their complementary strengths, enhancing detection/identification robustness across varied conditions. For instance, thermal infrared sensors excel in low-visibility scenarios e.g., night, fog, while radar provides long-range detection, and RF sensors detect communication signals unaffected by weather. In hybrid sensor-based drone identification there is perceptible shift towards using more sophisticated AI models like Transformers for hybrid sensor data fusion. These models excel at processing multi-modal data e.g., radar, RF, acoustic, visual by capturing complex relationships across modalities. Deploying lightweight models on edge devices for real-time drone detection is a growing trend. The integration of asynchronous sensors e.g., a Radar updating at 10 Hz and a Camera at 60 Hz requires rigorous Temporal Alignment. Data must be time-stamped precisely and often interpolated using predictive filters like Kalman Filters to align the streams. Spatially, Extrinsic Calibration (determining the rotation/translation matrix between sensors) is critical. Automated calibration methods using motion correspondence are replacing tedious manual processes. Fusion increases the computational burden. Processing high-bandwidth Radar I/Q data alongside 4K video streams introduces latency. In a kinetic C-UAS scenario, a processing delay of 500ms can mean missing a fast-moving FPV drone. This is driving a trend toward Hybrid Fusion, where sensors perform local processing extracting tracks or boxes and a lightweight central processor performs the final association and classification, minimizing data bandwidth and latency.

8.6 Operational Suitability Framework

While individual sensing modalities have been extensively studied in isolation, a critical gap remains in understanding their comparative operational boundaries. To address this, authors propose an operational suitability framework that maps each sensing paradigm against critical deployment constraints. As detailed in the previous subsections, no single sensor is robust across all conditions. **Table 8** provides a comparative analysis of these methodologies, evaluating them against Detection Range, LOS requirements, environmental sensitivity (Weather/Noise), and computational cost. This framework highlights that while sensor fusion offers the highest robustness, it imposes significant computational and latency penalties that must be mitigated through edge-optimized architectures.

Table 8. Comparative analysis of different sensing methodologies.

Modality	Detection range	LOS required	Weather sensitivity	Computational cost	Key strength	Key challenge
Radar	Long (>1 km)	Yes	Low (All-weather)	High (Pre-processing)	Accurate range and velocity; day/night capable	Micro-Doppler classification requires high dwell time; confusion with birds
RF Sensing	Medium (1–3 km)	No	Low	Low (Edge-capable)	Detects controller presence before takeoff; identifies specific protocols	Ineffective against autonomous (silent) drones; high interference in urban ISM bands
Acoustic	Short (<300 m)	No	Medium (Wind/Rain)	Low	Low cost; passive; gap-filling in blind spots	Low SNR; high false alarm rate in noisy urban environments
Computer Vision	Short to Medium	Yes	High (Fog/Darkness)	High (CNN/ViT inference)	Visual verification; payload and type classification	Fails in low visibility; high latency for high-resolution video processing
Sensor Fusion	Variable	Partial	Low (Complementary)	Very High	Maximum robustness; mitigates single-sensor failure	Spatio-temporal alignment issues; high latency overhead

There are certain interoperability issues for operational deployment and effectiveness beyond algorithmic accuracy. The operational viability of NCTR frameworks depends critically on practical interoperability with broader Counter-UAS (C-UAS) ecosystems. First, fusion architectures must actively ingest cooperative surveillance data, specifically ADS-B and Remote ID streams to serve as a dynamic 'friend-or-foe' filter, thereby instantly validating authorized air traffic and significantly reducing false alarm rates. Second, the sensing pipeline requires robust spectral coordination with Electronic Warfare (EW) subsystems; this necessitates the implementation of cognitive blanking or synchronization protocols to ensure that high-power jamming countermeasures do not saturate RF sensors or 'blind' the detection algorithms during kinetic engagement. Finally, to close the sensor-to-shooter loop, NCTR outputs must evolve from simple classification labels to standardized, low-latency state vectors (comprising precise azimuth, elevation, and velocity) that can be immediately consumed by kinetic effector systems, ensuring that detection leads to rapid and effective mitigation.

9. Research Challenges and Directions for Future Work

This section outlines the research challenges of NCTR using AI algorithms arranged as per the limitations of specific sensing methodology followed by miscellaneous other challenges.

9.1 Addressing Limitations of Radar based Sensing Technologies

While FMCW radars offer advantages like lower peak power and minimum range, their effectiveness for drone detection can be hampered by leakage signals, phase noise, and challenges in isolating slow-moving or high-speed drone signatures (Sayed et al., 2024; Sen et al., 2024). Dynamic RCS simulations are performed by most of the researchers who consider only azimuth angle, whereas in a realistic flight profile scenario, the target elevation angle with respect to radar as well as roll angle will also continuously change which can reveal or hide major scattering centers (Sen et al., 2024). Further, the real NCTR applications in a modern radar may require computation of dynamic RCS by utilizing available SNR of a given at radar receiver. This may be significantly different than computation of RCS done by simulation. Often the radar automatic gain control circuitry may artificially suppress the SNR of targets at nearby ranges thus reducing the target specific SNR information available for training the AI models.

HRRP data exhibits sensitivity to amplitude, attitude, and translation due to the way it is acquired (Liu et al., 2022bc). Amplitude sensitivity arises from factors like radar-to-target distance and radar gain. Attitude sensitivity is influenced by the target's azimuth and the radar's viewing angle, which causes changes in the HRRP waveform. Translation sensitivity occurs as target movement causes shifts in the radar's echo position within the range window, complicating the recognition process. Despite the success of Deep and RNN based approaches in HRRP target recognition, two major challenges persist. First, training data typically consist of high-SNR samples, while real-world testing often involves low-SNR conditions, leading to performance degradation. Second, during training, the network performs feature extraction over the entire input, without distinguishing between target and noise regions.

9.2 Limitations in Application of Machine Learning for NCTR

9.2.1 Classification and Detection Performance

In non-cooperative target alert systems, high false negative is not tolerable as a false negative target can rapidly become a potential threat without operator being aware about its proximity. More research is required for optimum classification metrics selection when high false negative rates are not acceptable. In Terven et al. (2025), a comprehensive survey of loss functions and metrices has been discussed and the researchers can find various tradeoffs in selecting different metrices and loss functions. In Kim and Youn (2024), authors focus on drone-based object detection in urban environments, proposing the F-beta score as a versatile metric that adjusts the weights based on application needs. The F2-score (beta = 2) is highlighted as ideal for scenarios where minimizing false negatives is critical, such as disaster response and security applications. In De Cubber et al. (2025), authors outlined appropriate performance metrices identified in pursuit of evolving a standard detection, tracking and identification framework. In Ahmad et al. (2024), authors outlined performance metrices such as Classification Time Delay (CTD), True Positive Confidence (TPC), False Positive Confidence (FPC) for drone classification using Radar. The classification performance deteriorates as the number of classes increases due to closeness in features. This is more evident in RF sensing based drone classification systems where RF controller signals in different drone types from the same manufacturer resemble each other. Quality of data in ML is reviewed in Kariluoto et al. (2021). This is specially relevant in RF based drone detection as the poor quality of training data of RF controller signals can also reduce classification accuracy.

9.2.2 Explainability of Machine Learning for NCTR

AI based NCTR system may ultimately feed into a safety critical decision support system. The presence of explainability in such systems is essential (Wang & Chung, 2022). Any lack of explainability of the DNN models remains a limitation in practical applications of ML algorithms, such as military target recognition. Due to the high stakes involved, even rare failures in target recognition may put the entire DL based model into question and limit their future use. Therefore, the inner structure of the DL network which includes the number of layers, neurons and activation function should be explainable for NCTR applications (Kinger & Kulkarni, 2024).

9.3 Emerging AI Architectures: Vision Transformers and Beyond

While CNNs have served as the backbone of NCTR for the past decade, future research must focus towards architectures that address the inherent limitations of CNNs, specifically their inability to capture long range temporal dependencies and global context. Here the ViT approach is gaining ground. Unlike CNNs, which process images via local receptive fields, ViT utilize self-attention mechanisms to process the entire image as a sequence of patches. This allows the model to understand the global context. This can for instance distinguish, a drone from a bird not just by shape, but by the contextual relationship between the object and its background environment. Recent research on Event-based Streaming Vision Transformers (ESVT) has demonstrated that these architectures can significantly outperform standard object detectors in high-speed drone detection scenarios by leveraging asynchronous visual data (Jing et al., 2025). Future work should focus on optimizing Lightweight ViTs that can retain this high accuracy while running on SWaP-constrained edge devices.

9.3.1 Application of Transformers for Performance Enhancement

The application of Transformers is revolutionizing the processing of 1D spectral data. In the Radar domain, researchers have recently introduced "Interpretable Target-Aware Vision Transformers" (ITAViT) for Polarimetric HRRP, which use novel attention losses to align the model's focus with the physical scattering centers of the target, achieving superior noise robustness compared to ResNet-based approaches (Gao et al., 2024). Similarly, for Radar Cross Section (RCS) based target recognition, new Transformer-based sequence modeling has proven effective in mitigating the aspect-angle sensitivity issues that plague traditional statistical classifiers (Xie et al., 2025). Here, the Transformer architecture mitigates aspect sensitivity by modeling the structure of the fluctuation across all angles, rather than just measuring the intensity of the fluctuation.

Dual stream cross attention network adopts hybrid architecture. It processes input images through two parallel streams, a CNN branch to extract fine-grained local textures and a Swin Transformer branch to capture long-range temporal dependencies. In the RF domain, dual-stream cross-attention networks developed recently have shown the ability to fuse local recursive features with global evolutionary features, achieving 98.6% accuracy on drone controller signals and outperforming standard ViT and ResNet50 baselines (Li et al., 2025). As NCTR moves toward sensor fusion, Transformers offer a unified architecture for processing disparate data types. For acoustic detection, Hybrid CNN plus Transformer models have recently demonstrated detection accuracies exceeding 98% by effectively modeling the long-range harmonic dependencies of drone rotors that CNNs often miss (Jasim & Hreshee, 2025). Furthermore, "Multimodal Transformers" are now solving the complex synchronization issues of sensor fusion. An application developed for visually impaired persons named "FusionSight" can have cross domain application for NCTR (Ikram et al., 2025). For visual inputs, a Vision Transformer (ViT) was used to extract high-level features, enabling the model to capture fine details as well as long-range relationships that are important for a CNN to learn spatial and temporal characteristics such as range, speed, and velocity which are crucial for understanding the dynamic behavior of objects.

9.4 Integrated Sensing and Communications (ISAC) for Distributed UAV Detection

IEEE standard P3383 defines ISAC as a system that integrates sensing (object detection, range/ velocity estimation, classification) and communication (voice/video/data) functions by efficiently utilizing wireless resources such as spectrum, hardware, and waveforms. While current non-cooperative sensing systems rely on active monostatic radar illumination, emerging 5G/6G networks offer new affordable modalities through ISAC. These networks custom-design waveform resources and intelligently perform beamforming so that a single transmission jointly supports communication and sensing tasks (Liu et al., 2022b). The key outcome from this foundational ISAC frameworks is that communication waveforms can be repurposed without modifying hardware, enabling radar-like capabilities through network coordination. Recent surveys indicate that ISAC is moving from coexistence to full waveform sharing, particularly in multi-cell massive MIMO infrastructures (Zhang et al., 2022). The Perceptive Mobile Network (PMN) architecture generalizes this concept by enabling the cellular network itself to operate as a distributed radar sensor. Unlike ISAC, which specifies the dual-function signaling techniques, PMN is the network-level practical system realization where uplink, downlink, and channel state information (CSI) are exploited to obtain range and Doppler measurements without emitting dedicated radar pulses (Rahman et al., 2020). Experimental results demonstrate that 5G downlink signals can detect UAV micro-motions passively. However, a key challenge in 5G is signal variability. To overcome this (Maksymiuk et al., 2023) use Renyi entropy to identify specific moments when the 5G traffic is "dense" enough (high bandwidth and duration) to be useful for radar processing and then uses cross ambiguity function to compare reference signal and the signal copy received as reflected from drone (Ai et al., 2021). These developments can motivate future researchers to come out with NCTR frameworks that exploit dense 6G cellular infrastructures to build scalable, covert, distributed UAV detection systems.

9.5 Physics-Informed Neural Networks (PINNs) for Data Constrained NCTR

Physics-informed ML combines real-world noisy data and established mathematical models embedding both directly into neural networks so that learning is guided not just by data, but also by the underlying physics (Karniadakis et al., 2021). Non-cooperative classification inherently suffers from sparse labels and limited dataset availability. To mitigate this dependence, Physics-Informed Neural Networks (PINNs) embed governing physics directly into the loss function, reducing reliance on extensive labeled datasets. In the seminal PINN framework by Raissi et al. (2019) the loss function is augmented with differentiable PDE residuals, forcing the network to satisfy physical constraints even at unlabeled sample locations. In radar-based NCTR, electromagnetic propagation is governed by Maxwell’s equations, requiring accurate treatment of boundary conditions, RCS diversity, and multipath effects. Recent EM-focused PINN efforts demonstrate that full field evolution can be learned directly from PDE constraints, eliminating the need for lookup tables or handcrafted solvers. In Oh & Hong (2025) authors introduce a Physics-Informed Neural Network (PINN) that integrates the time-domain Helmholtz equation directly into the loss function, enabling the model to simulate 2D transient electromagnetic fields without needing labeled training data. As a future research direction, trained PINN can be used to generate vast amount of synthetic RCS signatures for different angles, frequencies, or material properties that were not originally measured. This can enrich the training dataset for classification models without expensive flight tests or slow full-wave simulations. This concept can be extended to the learning of kinematics of airborne targets. Motion-related features such as velocity, turn rate, acceleration, and climb rate must satisfy nonlinear PDEs derived from rigid-body dynamics and aerodynamic force-moment relations. These approaches can be tried by future researchers for NCTR work.

9.6 Adversarial Robustness and Counter-Spoofing for RF Sensing and Radar based NCTR

Traditional jamming techniques such as Digital RF Memory (DRFM) generate time-shifted replicas of genuine radar echoes, fabricating deceptive targets (Davidson & Bray, 2020). DL techniques can both enhance and degrade DRFM deception, depending on architectural choices, highlighting the need for robust Radar-AI based NCTR (Wang et al., 2025). Radar-specific adversarial research further demonstrates that CNN-based NCTR using HRRP signatures can be compromised through imperceptible perturbations requiring far less power than classical ECM (Huang et al., 2020). This suggests that future NCTR pipelines must integrate counter-spoofing and adversarial defense in the overall system design.

9.7 Benchmarking Challenges for Non-Cooperative Aerial Target Recognition

The development of benchmarking and standards for NCTR and C-UAS systems is currently in an evolutionary phase. It is moving from ad-hoc, single-sensor based testing toward standardized, multi-modal frameworks. The field remains challenged by the physics of LSS (Low-altitude, Slow-speed, and Small RCS) targets, the complexity of urban environments, and the rapid pace of adversarial innovation. Effective benchmarking is required to now address the following gaps:

9.7.1 Methodological and Standardization Gaps

A major methodological challenge is balancing the need for controlled, repeatable tests (to statistically validate NCTR or C-UAS system) with the need to evaluate these systems in unpredictable, real-world environments (weather, time of day, urban obstacles, RF congestion). The need is to evolve standardized methods for assessing NCTR performance, whereas currently end-users rely on manufacturer claims that are often based on ideal laboratory conditions. In one of the attempts to address this, the EU-funded COURAGEOUS project developed a standardized test methodology (CWA 18150). This framework introduces standard user-defined scenarios (e.g., airport security, prison protection, stadium/important buildings) and specific performance metrics such as Detection Probability, positional accuracy, False Alarm Rate, and Response Time (De Cubber et al., 2025).

9.7.2 Dataset Heterogeneity

The development of robust multimodal artificial intelligence algorithms for NCTR is challenged by the lack of high-quality, diverse, and standardized datasets. This includes annotation inconsistencies and sensor synchronization (Dong et al., 2025). For instance, some computer vision datasets use bounding boxes while others use trajectory points, making cross-comparison of algorithms invalid. Further, there is often lack of factoring in adversarial actions and realistic noise scenarios. Most open-source datasets feature drones flying in clear conditions with high signal-to-noise ratios regime. There is a critical shortage of data representing stealth scenarios, night-time operations, adverse weather, or electronic warfare (jamming) conditions.

9.7.3 Operational and Environmental Benchmarking Issues

Operational benchmarking reveals that a system's effectiveness is often dictated by its False Positive Rate (FPR) apart from its maximum detection range. High FPRs may cause alarm fatigue thereby leading security teams to hesitate or ignore alerts. In urban environments, improperly tuned radar systems can report large number of potential targets per hour, the vast majority being clutter or birds. Another challenge is to benchmark the degree of RF Congestion under which the CUAS systems operate (Dong et al., 2025). RF sensors operating in the 2.4–5.8 GHz bands must discriminate between drones and countless consumer devices (Wi-Fi, Bluetooth). Benchmarking this capability requires testing in spectrally dense environments, which is difficult to replicate in controlled ranges.

10. Conclusion

This review has presented a systematic analysis of the evolving landscape of sensing methodologies and AI Techniques for NCTR, specifically addressing the detection and classification of UAVs, drones, and other aerial targets using AI. The survey of recent publications confirms that NCTR has transitioned from reliance on single-sensor, manual feature extraction approaches to complex, multi-modal systems driven by deep learning architectures. The assessment of sensing methodologies reveals distinct evolutionary paths for each domain. In radar-based NCTR, research has moved beyond basic RCS and kinematic features to the exploitation of Transformer architecture in micro-Doppler signatures and HRRP. Literature review reveals that newer models demonstrated superior capability in capturing long-range temporal dependencies in radar returns compared to traditional RNNs or CNNs, particularly in low-SNR environments. For non-radar modalities, the review identifies critical trade-offs. RF signature analysis remains highly effective for detecting controller-drone communication but faces severe performance degradation in congested urban ISM bands (Wi-Fi/Bluetooth interference). Future success in RF sensing depends heavily on robust source separation algorithms and the integration of channel-state information. Similarly, while acoustic sensors offer a cost-effective, NLOS solution, they require advanced noise-robust feature engineering, such as MFCC combined with Deep Neural Networks, to mitigate environmental noise and wind interference. Computer vision has benefited most from the explosion of real-time object detection models, with the YOLO architecture (v5 through v9) becoming the dominant framework for optical and IR-based detection due to its balance of speed and accuracy on edge devices. Despite these advancements, several research gaps persist. A primary challenge is the lack of "Explainable AI" (XAI) in NCTR systems. As DL models become more complex, their "black box" nature poses a barrier to deployment in safety-critical air defense and traffic management systems, where understanding the rationale behind a classification is as vital as the result itself. Furthermore, the review notes a lack of standardization in performance metrics; adopting the F-beta score is recommended to prioritize the minimization of false negatives in security applications. Looking forward, the trajectory of NCTR research points toward Multi-Modal Learning. Single-sensor systems are increasingly insufficient for handling diverse environmental conditions (e.g., fog affecting optical sensors or radio silence affecting RF detection). Future frameworks must leverage sensor fusion combining Radar, EO/IR, and Acoustic data to create unified, robust classification pipelines. Consequently, future work should prioritize the development of lightweight, edge-deployable transformer models capable of real-time sensor fusion, alongside the creation of comprehensive, multi-sensor open-source datasets to benchmark these advanced algorithms.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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