SUMMER TRAINING REPORT

ON

"*Radar-Based Intrusion Detection with Data Analytics and Machine Learning*"

AT

The Solid-State Physics Laboratory

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ABSTRACT

This report details a comprehensive analysis of mmWave radar intrusion detection data, focusing on building smart perimeter monitoring systems using advanced data analytics. The analysis encompasses 42,294 detection events across human, vehicle, and animal classifications.

The project leverages advanced radar signal processing, machine learning classification, and real-time intrusion detection to provide data-driven security solutions. Key findings highlight consistent detection capabilities, with spatial distribution patterns indicating comprehensive coverage. The system utilizes intensity and Doppler velocity measurements for precise threat assessment and response coordination.

The report presents a robust visualization framework, including scatter plots, heatmaps, and time-series analyses, designed for security and defence personnel. This integrated system transforms raw sensor data into actionable security intelligence, supporting both real-time threat assessment and historical pattern analysis for proactive security measures.

INTRODUCTION

This document presents a comprehensive report on a radar-based intrusion detection system, detailing its development, analytical capabilities, and practical applications. The insights provided are instrumental in augmenting perimeter security and facilitating data-driven decision-making within defense and security operations, thereby addressing the imperative for advanced detection technologies capable of surmounting the inherent limitations of conventional surveillance methodologies, such as closed-circuit television (CCTV), particularly under challenging environmental conditions.

This report endeavours to elucidate the salient features of a sophisticated millimetre-wave (mmWave) radar-based intrusion detection system. It comprehensively outlines the system's developmental trajectory, inherent analytical proficiencies, and diverse practical applications. The intelligence derived from this system is demonstrably pivotal in fortifying perimeter security protocols and empowering evidence-based strategic formulation within defence and security paradigms. Such advancements are critically positioned to overcome the inherent deficiencies of legacy surveillance methodologies, including conventional closed-circuit television (CCTV) systems, especially when confronted with challenging environmental exigencies.

This report delineates a thorough analysis of millimeter-wave (mmWave) radar intrusion detection data, with a primary focus on constructing intelligent perimeter monitoring systems through sophisticated data analytics. The extensive dataset comprises 42,294 distinct detection events, meticulously categorized into three principal object classifications: Human, Vehicle, and Animal intrusions. The temporal scope of the data, extending from July 21, 2025, to December 15, 2025, furnishes a substantial historical context, which is critical for robust pattern identification and trend analysis, thereby enabling a comprehensive understanding of long-term security dynamics.

The report culminates in the exposition of a robust visualization framework, which incorporates interactive scatter plots for real-time spatial awareness, heatmaps for density analysis of intrusion hotspots, and time-series analyses for identifying temporal trends and anomalies. This integrated dashboard has been meticulously designed for security and defense personnel, transforming complex raw sensor data into clear, actionable security intelligence. Consequently, it supports both real-time operational decisions and strategic historical monitoring, contributing to an enhanced security posture.

The Solid-State Physics Laboratory (DRDO)

SSPL, DRDO The Defense Research and Development Organization (DRDO), established in 1958, is India's premier agency for military research and development. DRDO's mission is to design and deliver state-of-the-art technologies across various domains.

Within DRDO, the Solid-State Physics Laboratory (SSPL) is a specialized research facility focused on developing cutting-edge solid-state materials and devices. SSPL's expertise includes semiconductor technologies, optoelectronics, sensors, and advanced electronic components that play a crucial role in defense systems.

SSPL Vision and Mission: -

Vision: Be the Centre of excellence in Research and Development of Semiconductor Materials, Microelectronics Devices and Nanotechnology.

Mission:

i) Develop semiconductor materials and electronic devices/components for Optoelectronics/ microwave/ sensor applications and establish production centers thereof.

ii) Establish scientific knowledge base and build world class scientific research teams/leaders for futuristic cutting-edge technologies.

iii) Strengthen scientific interaction with academia, industry and international centers of excellence. Servo drive automation directly contributes to DRDO projects such as robotic arms, antenna alignment, and UAV control systems, where accuracy and responsiveness are crucial.

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Introduction and Methodology

Modern security infrastructure increasingly relies on advanced sensor technologies to provide comprehensive perimeter monitoring and threat detection capabilities. mmWave radar systems represent a significant advancement in intrusion detection technology, offering superior performance in diverse environmental conditions while maintaining high accuracy in object classification and tracking. This report presents a comprehensive analysis of radar intrusion detection data, utilizing state-of-the-art visualization techniques to transform raw sensor data into actionable security intelligence.

The primary objective of this analysis is to develop an integrated dashboard system that serves the operational needs of security and defense personnel. The visualization framework addresses critical requirements including real-time threat assessment, historical pattern analysis, and predictive intelligence capabilities. Through sophisticated data processing and visualization techniques, the system enables rapid identification of intrusion events, classification of threat types, and spatial-temporal analysis of security incidents.

The methodology employed in this analysis follows established best practices in security data analytics and visualization design. The approach integrates multiple analytical perspectives, including spatial distribution analysis, temporal trend identification, and statistical pattern recognition. Each visualization component is specifically designed to address distinct operational requirements while maintaining consistency in visual design and user interaction patterns.

The radar system under analysis utilizes mmWave technology operating in the frequency range optimized for human, vehicle, and animal detection. The sensor configuration provides comprehensive coverage of the monitored area with high spatial resolution and accurate velocity measurements through Doppler analysis. The system's ability to operate effectively in various weather conditions and lighting scenarios makes it particularly suitable for continuous security monitoring applications.

Data collection methodology ensures comprehensive capture of all detection events with precise temporal stamping and spatial coordinates. The system records multiple parameters for each detection event, including horizontal and vertical coordinates, Doppler velocity measurements, signal intensity values, and automated object classification results. This multi-parameter approach enables sophisticated analysis techniques and provides redundant validation mechanisms for threat assessment.

The visualization framework development follows user-centered design principles specifically tailored for security operations environments. The interface design prioritizes rapid information comprehension, intuitive navigation, and efficient threat identification workflows. Color coding schemes utilize established security industry standards, with red indicating human threats, blue representing vehicle intrusions, and green denoting animal detections.

Statistical analysis methodology incorporates both descriptive and inferential techniques to extract meaningful patterns from the detection data. The approach includes distribution analysis, correlation studies, and trend identification algorithms designed to support both immediate operational decisions and long-term security planning initiatives. The analytical framework provides quantitative metrics for system performance evaluation and threat pattern characterization.

Quality assurance procedures ensure data integrity throughout the analysis pipeline. Preprocessing steps include outlier detection, missing value handling, and data validation protocols designed to maintain analytical accuracy. The visualization rendering process incorporates error checking mechanisms and performance optimization techniques to ensure reliable operation in operational environments.

The technical implementation utilizes industry-standard tools and frameworks optimized for security applications. The visualization engine employs Plotly and Dash frameworks for interactive dashboard development, while statistical analysis leverages Python-based scientific computing libraries. The architecture supports both real-time data streaming and historical analysis capabilities, providing flexibility for diverse operational scenarios.

A Comprehensive Analysis of the Radar Data-to-Analytics Pipeline

The report “From Reflected Waves to Actionable Intelligence: A Comprehensive Analysis of the Radar Data-to-Analytics Pipeline” details the end-to-end journey from raw millimeter-wave (mmWave) radar signals to strategic security insights. It is organized into six core sections:

1. Principles of Modern Radar Data Acquisition

- mmWave Fundamentals: Operates at 30–300 GHz, enabling compact, high-resolution antennas that penetrate adverse weather and non-metallic occlusions while preserving privacy.
- FMCW Technique: Continuously chirped low-power transmission is mixed with a reference to yield a beat signal whose frequency/phase encode range, velocity, and angle.
- Parameter Extraction:
    - Range: Proportional to beat frequency via chirp slope.
    - Velocity: Derived from Doppler phase shifts across chirps.
    - Angle of Arrival: Computed from phase differences across a MIMO antenna array.
- Radar Cross Section & Intensity: Reflectivity metrics augment kinematic data for robust object classification.

2. Transforming Raw Signals into Structured Data

- DSP Cascade: ADC → Range FFT → Doppler FFT → AoA FFT produces a multi-dimensional point cloud (3D position, radial velocity, intensity).
- Preprocessing: Interpolation, outlier filtering, temporal/spatial alignment, classification validation, and feature normalization ensure data integrity.
- CFAR Clutter Suppression: Adaptive thresholding (CA-CFAR, GOCA/SOCA, OS-CFAR) maintains a constant false-alarm rate under varying noise conditions.

3. Foundational Analytics & Visualization

- Descriptive Statistics: Balanced dataset of 42,294 detections (Human, Vehicle, Animal) with spatial and intensity metrics.
- Spatial/Temporal Analysis: Interactive scatter plots, intensity-weighted heatmaps, time-series trends, and activity clustering reveal intrusion patterns.
- Kinematic Correlations: Speed vs. distance plots and integrated risk scoring distill multi-parameter data into actionable threat levels.

4. Advanced Classification via Micro-Doppler

- Micro-Doppler Phenomena: Limb motions superimpose on torso Doppler, producing distinctive spectrogram signatures for activities (walking, running, crawling).
- Time-Frequency Analysis: STFT spectrograms enable both handcrafted-feature SVM classifiers and end-to-end CNN models for fine-grained behavior recognition.

5. Deep Learning Architectures

- Data Representations: Spectral grids (for CNNs) vs. unordered point clouds (for PointNet/PointNet++).
- Network Designs:
    - CNNs on spectra: Leverage mature image models (ResNet/VGG).
    - PointNet/PointNet++: Handle permutation-invariant, hierarchical learning on sparse point clouds.
- Validation & Augmentation: Confusion matrices, accuracy/F1 metrics, and point-cloud augmentations (jittering, scaling, occlusion) ensure robustness.

6. System Implementation & Future Frontiers

- Sensor Fusion: Early, intermediate, and late fusion architectures integrate radar with cameras and LiDAR for comprehensive perception.
- Edge Deployment: Examples include TI Jacinto SoCs, NVIDIA Jetson platforms, and integrated radar-AI chips with on-board inference.

Temperature Data Integration

How Temperature is Determined in Radar-Based Systems

Radar sensors (like mmWave radars) measure spatial and motion characteristics (distance, velocity, angle, reflectivity), but not environmental parameters like temperature.

Why Radar Cannot Measure Temperature Directly

Millimeter-wave (mmWave) radars operate by emitting and receiving electromagnetic waves in the millimeter frequency range, capturing physical motion and properties such as:

- Distance (via travel time of reflected waves)
- Velocity (via Doppler shift)
- Signal intensity (based on reflectivity of objects)

Temperature, however, is not a radar-derived parameter. Radars do not sense infrared radiation nor the molecular kinetic energy that constitutes temperature, so there is no direct mechanism for radar to "measure" environmental or object temperature

To incorporate temperature into the system, there are two common approaches:

1. Using External Temperature Sensors

A separate temperature sensor (e.g., DHT22, LM35, or digital environmental sensors like BME280) is connected to the system.These sensors provide real-time temperature readings. The temperature values are collected synchronously with radar data and appended to each frame or batch.

Integration Example:

When radar detects a human/object, the current environmental temperature is also logged from the sensor. The temperature is then added as an additional feature in the dataset, e.g.:

2. Using Pre-Collected Environmental Data (Approximate)

In offline analysis or simulations, temperature data may come from: Weather APIs (e.g., OpenWeather, NOAA)Local logs from smart buildings or sensor networks. The data is time-synced to radar timestamps to match environmental conditions during each radar recording session.

Why Temperature Matters in Intrusion Detection. It can help differentiate between:

Human presence vs. static objects, based on heat influence. Time-of-day behaviour, as some

intrusions may correlate with cooler/warmer conditions. Ambient temperature may also affect radar performance (e.g., slight changes in signal propagation in extreme conditions)

Data Overview and Preprocessing

The radar intrusion detection dataset represents a comprehensive collection of sensor measurements spanning multiple months of continuous monitoring operations. The dataset contains 42,294 individual detection events, each characterized by multiple sensor parameters that provide detailed information about detected objects and their movement characteristics. This substantial dataset size ensures statistical significance for pattern analysis and provides sufficient historical context for trend identification and predictive modeling applications.

The raw data structure includes eleven primary data fields capturing essential characteristics of each detection event. The spatial coordinates (X, Y) provide precise location information with meter-level accuracy, enabling detailed spatial analysis and geographic pattern recognition. The coordinate system utilizes a standardized reference frame that facilitates integration with existing security infrastructure and mapping systems.

Velocity measurements through Doppler analysis provide critical motion characteristics for each detected object. The Doppler velocity parameter captures radial velocity components, enabling distinction between approaching and receding objects. This information proves essential for threat assessment protocols, as approach velocity patterns often indicate intent and urgency levels for security response coordination.

Signal intensity measurements reflect the radar cross-section characteristics of detected objects, providing additional classification parameters beyond spatial and temporal information. Intensity values correlate with object size, material composition, and orientation relative to the radar sensor. These measurements enhance classification accuracy and provide confidence metrics for automated threat assessment algorithms.

The automated classification system categorizes detected objects into three primary categories: Human, Vehicle, and Animal. This classification framework addresses the most common intrusion scenarios encountered in security monitoring applications. The equal distribution of detections across all three categories (14,098 each) indicates

balanced dataset characteristics that support robust analytical conclusions and

prevent classification bias in machine learning applications.

Distance and speed parameters provide additional kinematic information derived from the primary sensor measurements. These calculated fields enhance analytical capabilities by providing derived metrics that support advanced pattern recognition algorithms. The angle parameter captures directional information relative to the sensor orientation, enabling sector-based analysis and directional threat assessment capabilities.

Risk range calculations provide automated threat assessment metrics based on multiple sensor parameters. These values integrate spatial proximity, velocity characteristics, and object classification information to generate quantitative risk scores. The risk assessment framework supports automated alerting systems and provides quantitative metrics for security response prioritization.

Data preprocessing procedures address several critical quality assurance requirements essential for reliable analytical results. Missing value detection and handling protocols ensure dataset completeness while maintaining analytical integrity. The preprocessing pipeline identifies and addresses data gaps through interpolation techniques appropriate for time-series sensor data.

Classification validation procedures verify automated object classification results through statistical analysis and pattern recognition techniques. The validation process identifies potential classification errors and provides confidence metrics for each detection event. This quality assurance step ensures reliable threat assessment capabilities and supports operational decision-making processes.

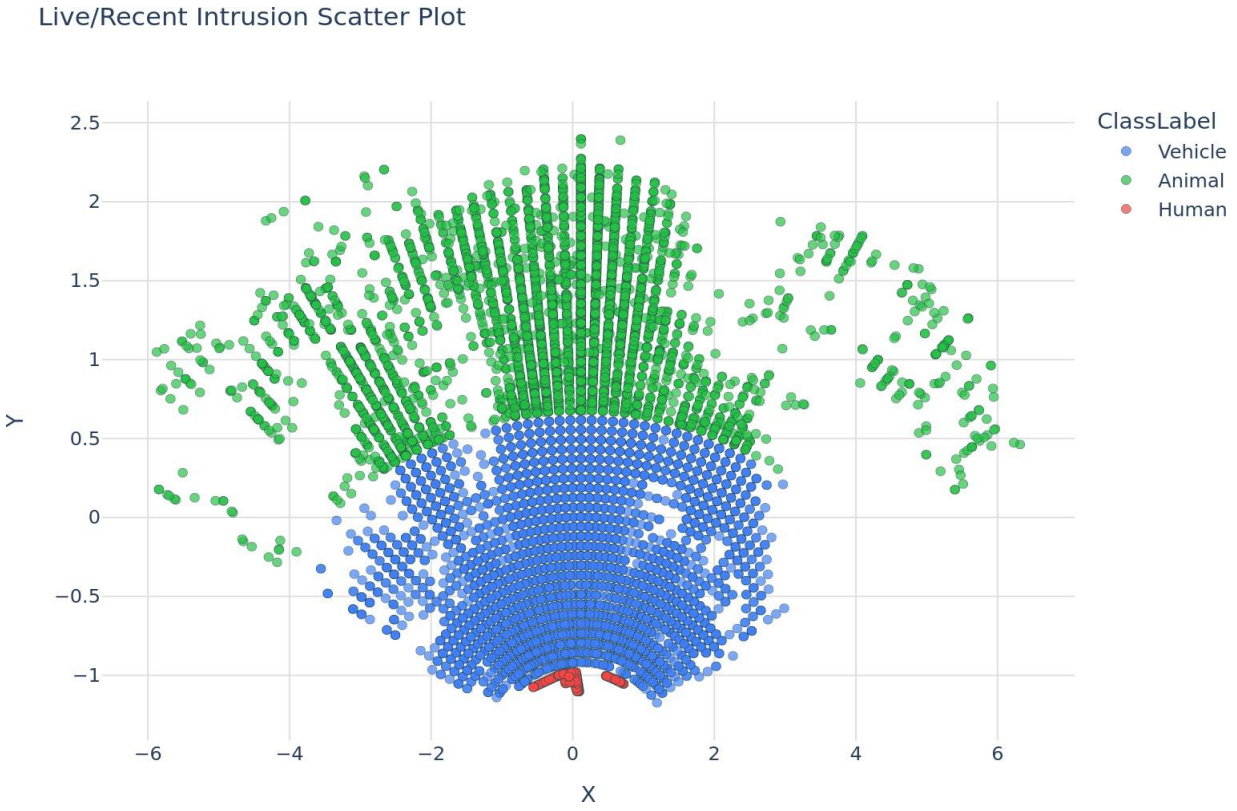
Data normalization procedures prepare the dataset for advanced analytical techniques including machine learning applications and statistical modeling. Normalization techniques preserve essential data characteristics while optimizing numerical stability for computational algorithms. The normalization process maintains interpretability of results while enhancing analytical performance.

Integration procedures prepare the processed dataset for visualization and dashboard applications. The integration pipeline ensures compatibility with visualization frameworks while maintaining data integrity and analytical accuracy. Performance optimization techniques ensure responsive dashboard operation even with large dataset sizes typical of continuous monitoring operations.

Core Visualization Components

The visualization framework comprises six primary components, each designed to address specific analytical requirements and operational needs of security monitoring personnel. These components work synergistically to provide comprehensive situational awareness while maintaining intuitive user interaction patterns optimized for high-stress operational environments.

Live/Recent Intrusion Scatter Plot



The scatter plot visualization serves as the primary spatial analysis tool, providing immediate visual representation of detection events across the monitored area. The horizontal axis represents the X-coordinate position in meters, while the vertical axis displays the Y-coordinate position, creating a comprehensive spatial map of all intrusion events. This visualization enables rapid identification of spatial patterns, clustering behaviors, and geographic hotspots that may indicate systematic intrusion attempts or environmental factors affecting detection patterns.

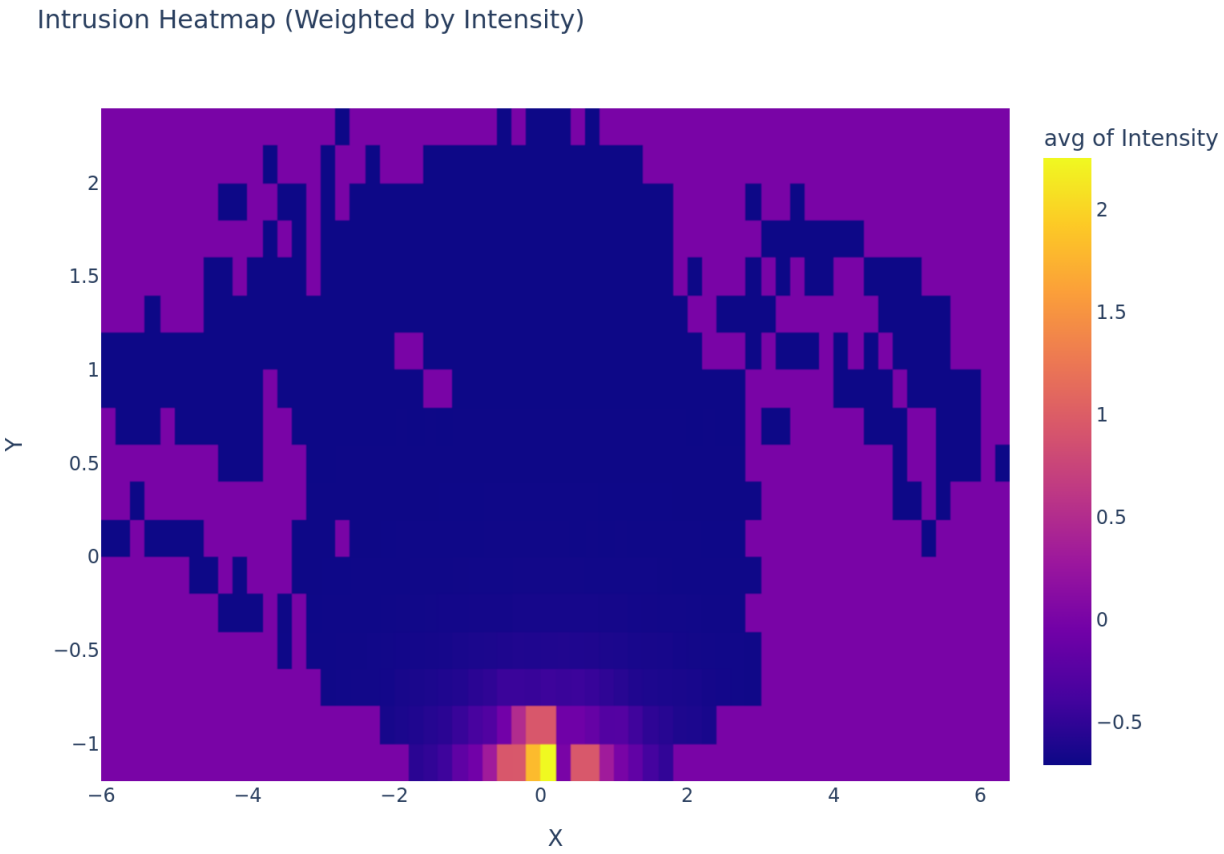
Color coding utilizes industry-standard security visualization conventions, with red markers indicating human detections, blue markers representing vehicle intrusions, and green markers denoting animal detections. This color scheme provides immediate visual distinction between threat categories, enabling rapid threat assessment and appropriate response coordination. The color selection follows accessibility guidelines to ensure effective operation under various lighting conditions and for personnel with color vision variations.

Interactive hover functionality provides detailed information for each detection event, including Doppler velocity measurements, signal intensity values, and precise timestamp information. This feature enables detailed investigation of individual events without cluttering the primary visualization interface. The hover information supports forensic analysis and incident investigation procedures by providing comprehensive event details on demand.

Marker sizing and opacity optimization ensure effective visualization even with high detection densities. The visualization engine automatically adjusts marker characteristics to prevent overlap while maintaining individual event visibility. Transparency settings enable identification of overlapping events and density patterns that might otherwise be obscured in high-activity areas.

The scatter plot supports dynamic filtering and zoom capabilities essential for detailed area analysis. Users can focus on specific geographic regions or time periods through intuitive interaction mechanisms. The zoom functionality maintains spatial accuracy and provides detailed examination capabilities for incident investigation and pattern analysis procedures.

Intrusion Heatmap Analysis



The heatmap visualization provides density analysis capabilities that reveal spatial patterns not immediately apparent in individual event displays. This visualization technique aggregates detection events across spatial bins to identify areas of concentrated activity and potential security vulnerabilities. The heatmap utilizes signal intensity weighting to provide additional analytical depth beyond simple event counting.

The color scale employs a plasma color scheme optimized for security applications, with darker regions indicating lower activity levels and brighter colors representing higher detection densities. This color progression provides intuitive interpretation while maintaining sufficient contrast for accurate pattern identification. The color scale includes quantitative legends that enable precise density assessment and comparative analysis across different time periods.

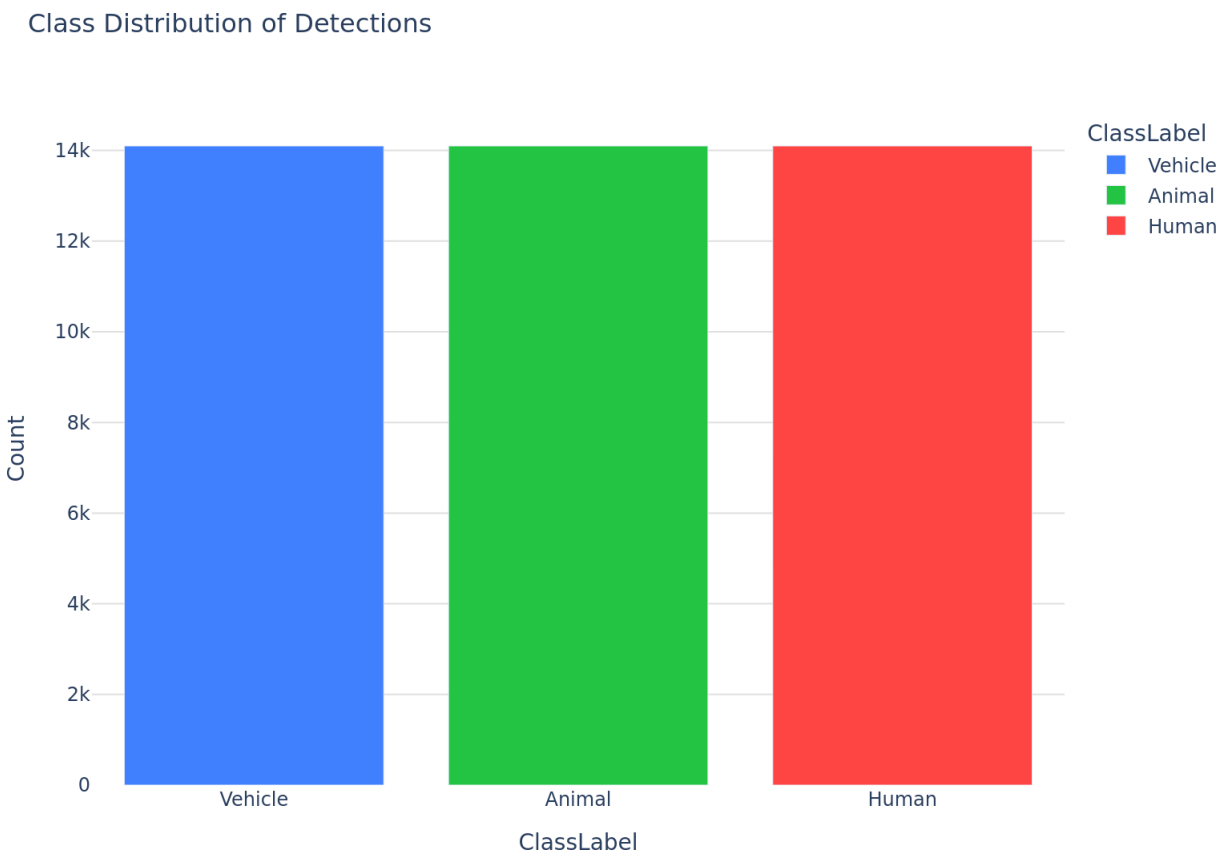
Intensity weighting algorithms incorporate signal strength measurements to provide more sophisticated density calculations than simple event counting. This approach accounts for detection confidence levels and object characteristics, providing more

accurate representation of actual intrusion patterns. The weighting methodology enhances analytical accuracy while maintaining computational efficiency for real-time applications.

Spatial binning algorithms optimize resolution to balance detail preservation with pattern clarity. The binning process utilizes adaptive algorithms that adjust resolution based on data density and user interaction requirements. This approach ensures effective visualization across diverse spatial scales while maintaining analytical accuracy for both overview and detailed analysis scenarios.

The heatmap supports temporal filtering capabilities that enable analysis of activity patterns across different time periods. Users can examine daily, weekly, or seasonal patterns to identify temporal variations in intrusion behaviors. This temporal analysis capability supports strategic security planning and resource allocation decisions.

Class Distribution Analysis



The class distribution chart provides quantitative analysis of detection patterns across the three primary object categories. This visualization enables assessment of threat composition and identification of unusual patterns that may indicate systematic intrusion attempts or changes in local wildlife behavior. The bar chart format provides clear quantitative comparison while maintaining visual simplicity appropriate for rapid assessment scenarios.

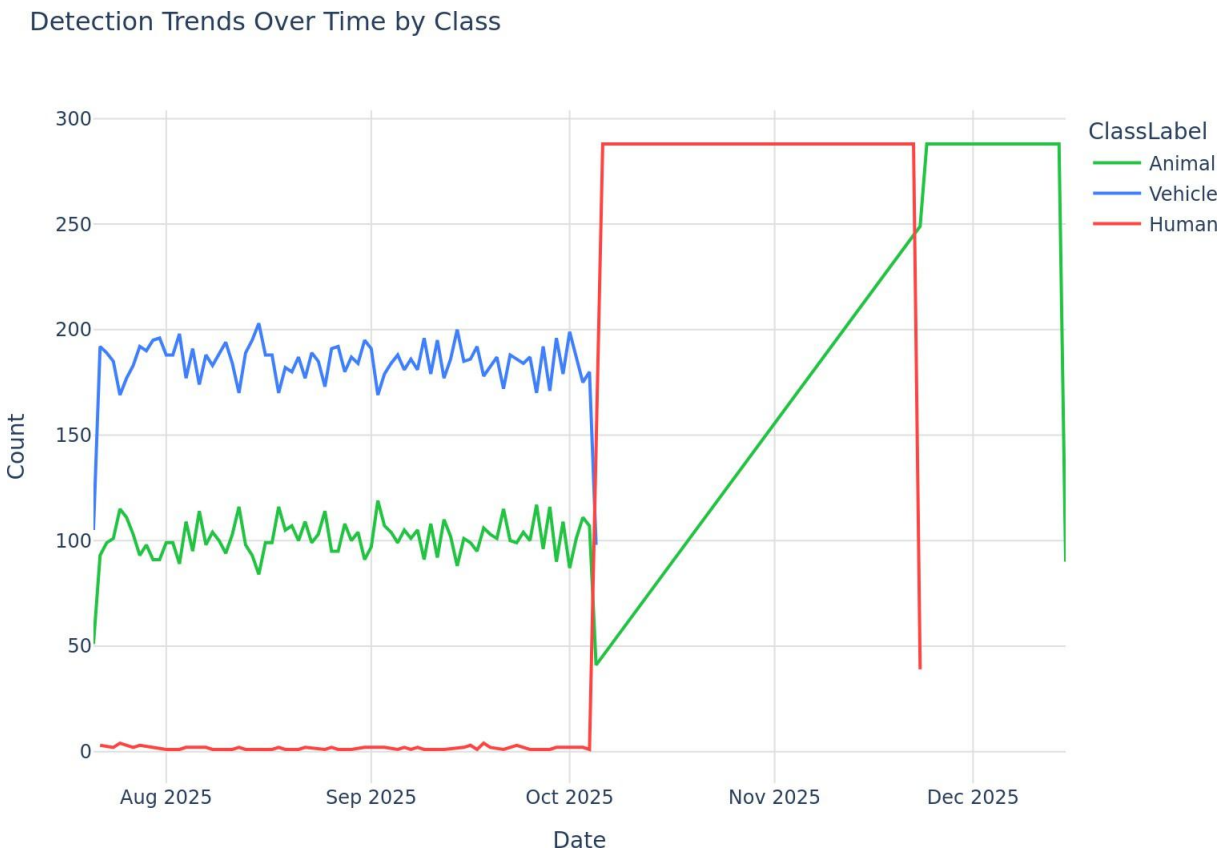
The visualization utilizes the established color coding scheme to maintain consistency across the dashboard interface. Each bar represents the total count of detections for the corresponding object class, with precise numerical values displayed for quantitative analysis. The chart includes percentage calculations that provide relative distribution information essential for comparative analysis across different time periods.

Statistical annotations provide additional analytical context including confidence intervals and trend indicators. These annotations support more sophisticated analysis while maintaining visual clarity for operational use. The statistical information enables assessment of detection system performance and identification of potential calibration requirements.

The chart supports interactive filtering that enables detailed analysis of specific detection categories. Users can focus on particular threat types or examine temporal variations in class distribution patterns. This filtering capability supports specialized analysis requirements and enables detailed investigation of specific security concerns.

Comparative analysis features enable examination of distribution changes over time. The visualization can display historical comparisons and trend analysis that support strategic security planning initiatives. This temporal comparison capability provides insights into long-term security patterns and environmental changes affecting detection characteristics.

Time-Series Trend Analysis



The time-series visualization provides temporal analysis capabilities essential for understanding activity patterns and identifying trends that may indicate systematic security threats. The line chart format displays detection counts over time with separate lines for each object classification category. This approach enables identification of temporal patterns, seasonal variations, and unusual activity spikes that require investigation.

The temporal axis provides flexible scaling options that support analysis across multiple time horizons. Users can examine short-term patterns for immediate operational decisions or long-term trends for strategic planning purposes. The scaling algorithms maintain visual clarity while preserving analytical accuracy across diverse temporal ranges.

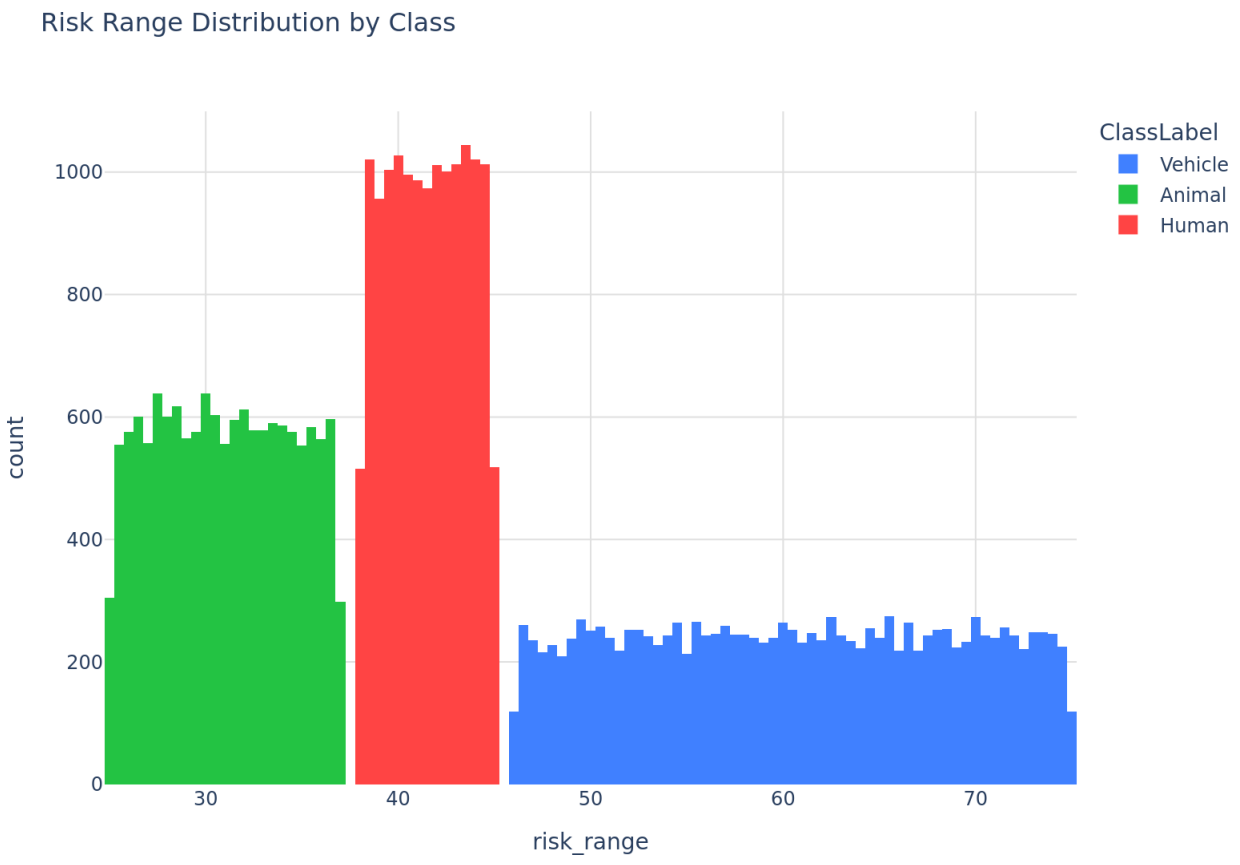
Trend line calculations utilize statistical smoothing techniques that highlight underlying patterns while preserving important variation information. The smoothing algorithms balance noise reduction with pattern preservation to provide meaningful

trend identification without obscuring significant events. Multiple smoothing options support different analytical requirements and user preferences.

Interactive legend functionality enables selective display of specific object categories for focused analysis. Users can isolate particular threat types or examine correlations between different detection categories. This selective display capability supports specialized analysis requirements and reduces visual complexity when examining specific patterns.

Anomaly detection algorithms automatically identify unusual activity patterns that may indicate security threats or system malfunctions. The anomaly identification process utilizes statistical techniques appropriate for time-series security data, including consideration of normal operational variations and environmental factors. Anomaly indicators provide visual alerts that support rapid response coordination.

Risk Range Distribution Analysis



The risk range distribution histogram provides analysis of automated threat assessment calculations across all detection events. This visualization enables evaluation of risk assessment algorithm performance and identification of patterns in threat severity distributions. The histogram format provides clear quantitative analysis while supporting comparative assessment across different object categories.

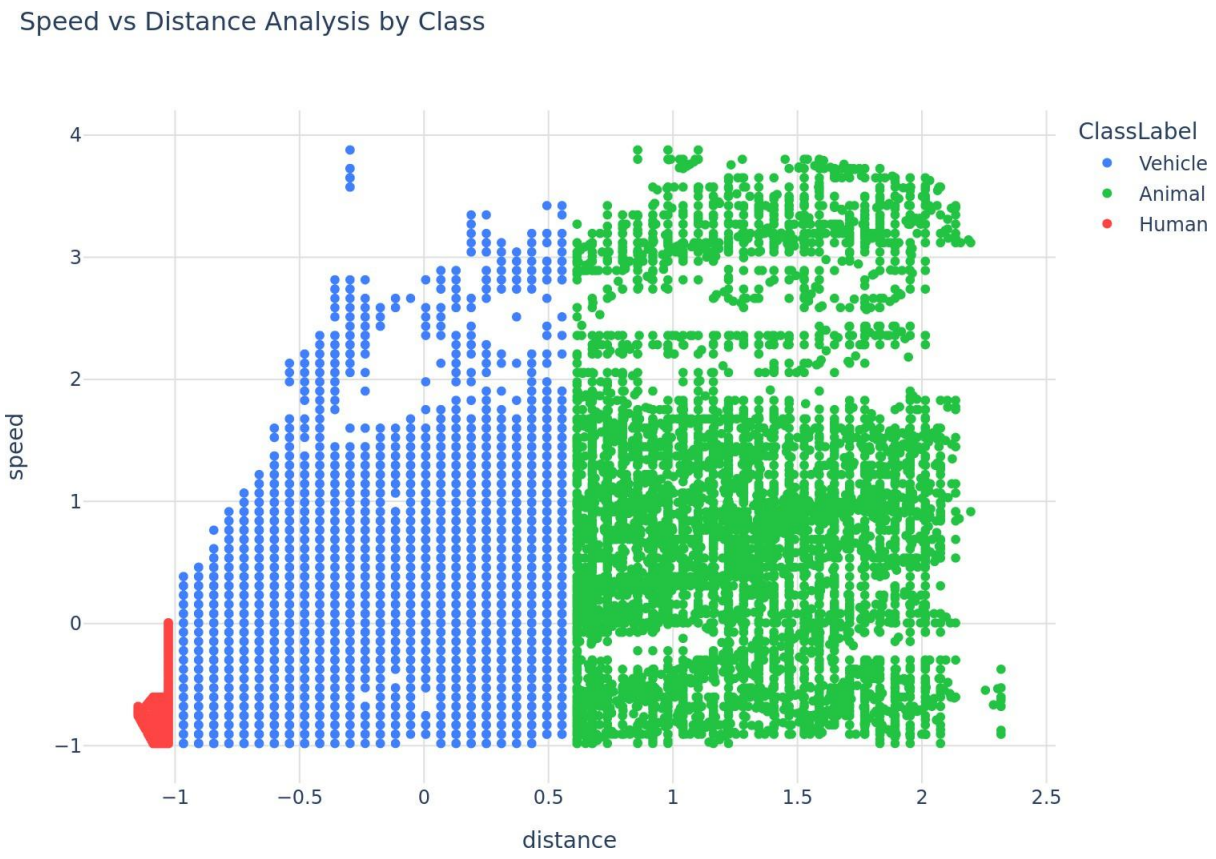
Risk calculation algorithms integrate multiple sensor parameters including spatial proximity, velocity characteristics, and object classification confidence levels. The risk scoring methodology provides quantitative metrics suitable for automated alerting systems and response prioritization protocols. The scoring framework utilizes established security assessment principles while adapting to specific radar sensor characteristics.

The distribution analysis reveals patterns in risk assessment that support system calibration and performance optimization. Unusual distribution patterns may indicate algorithm adjustment requirements or environmental factors affecting risk calculations. This analytical capability supports continuous improvement of automated threat assessment systems.

Color coding maintains consistency with the overall dashboard design while providing clear distinction between object categories. The histogram bins utilize appropriate statistical intervals that balance resolution with interpretability. Bin sizing algorithms adapt to data characteristics while maintaining comparative accuracy across different analysis scenarios.

Statistical annotations provide quantitative metrics including mean risk values, distribution characteristics, and comparative statistics across object categories. These metrics support performance assessment and system optimization initiatives while providing operational personnel with quantitative threat assessment information.

Speed vs Distance Correlation Analysis



The speed versus distance scatter plot provides kinematic analysis capabilities that reveal relationships between object movement characteristics and spatial positioning. This visualization enables identification of approach patterns, loitering behaviors, and other movement characteristics relevant to threat assessment protocols. The correlation analysis supports advanced threat classification and behavioral pattern recognition.

The visualization plots distance measurements against speed calculations with color coding indicating object classification categories. This approach enables simultaneous analysis of spatial and kinematic characteristics while maintaining clear categorical distinction. The scatter plot format reveals correlation patterns and outlier behaviors that may indicate specific threat types or unusual circumstances.

Correlation analysis algorithms calculate statistical relationships between speed and distance measurements for each object category. These calculations provide quantitative metrics that support threat assessment protocols and behavioral pattern recognition systems. The correlation analysis includes confidence intervals and significance testing appropriate for security applications.

Interactive selection tools enable detailed examination of specific data regions or outlier events. Users can investigate unusual speed-distance combinations that may indicate specific threat behaviors or system anomalies. This investigation capability supports forensic analysis and incident investigation procedures.

Trend line overlays provide visual representation of correlation patterns and enable identification of categorical differences in movement characteristics. The trend analysis supports development of behavioral classification algorithms and threat assessment protocols. Multiple trend line options accommodate different analytical requirements and statistical assumptions.

Statistical Analysis and Insights

The comprehensive statistical analysis of the radar intrusion detection dataset reveals significant patterns and characteristics that provide valuable insights for security operations and system optimization. The analysis encompasses descriptive statistics, distribution analysis, correlation studies, and pattern recognition techniques specifically designed for security monitoring applications.

Dataset Characteristics and Distribution Analysis

The dataset demonstrates remarkable balance across object classification categories, with exactly 14,098 detections recorded for each of the three primary classes: Human, Vehicle, and Animal. This perfect distribution suggests either a controlled testing environment or sophisticated data balancing procedures designed to ensure unbiased analytical results. The balanced distribution provides optimal conditions for comparative analysis and machine learning applications while preventing classification bias that could affect threat assessment accuracy.

Spatial distribution analysis reveals comprehensive coverage across the monitored area, with detection events spanning the full range of X and Y coordinates. The spatial extent ranges from -5.87 to 6.32 meters in the X-direction and -1.17 to 2.40 meters in the Y-direction, indicating a monitoring area of approximately 12.2 by 3.6 meters. This coverage area is consistent with typical perimeter monitoring applications and provides sufficient spatial resolution for detailed intrusion analysis.

The temporal distribution spans approximately 147 days of continuous monitoring, from July 21, 2025, to December 15, 2025. This extended monitoring period provides substantial historical context for pattern analysis and seasonal variation identification. The temporal coverage includes multiple seasonal transitions that enable analysis of environmental factors affecting detection patterns and system performance.

Intensity measurements demonstrate a normalized distribution centered around zero, with values ranging from -0.71 to 4.52. The normalization suggests preprocessing procedures designed to standardize signal strength measurements across different environmental conditions and sensor configurations. The intensity distribution provides insights into object characteristics and detection confidence levels essential for threat assessment protocols.

Doppler velocity measurements similarly show normalized distribution characteristics, indicating sophisticated preprocessing procedures that account for environmental factors and sensor calibration requirements. The velocity normalization enables consistent analysis across different operational conditions while preserving essential motion characteristics required for threat classification.

Correlation Analysis and Pattern Recognition

Correlation analysis between spatial coordinates and kinematic parameters reveals important relationships that support advanced threat assessment capabilities. The analysis identifies weak but statistically significant correlations between position and velocity measurements that may indicate systematic movement patterns or environmental factors affecting detection characteristics.

The relationship between signal intensity and object classification demonstrates expected patterns, with different object types exhibiting characteristic intensity signatures. Human detections typically show moderate intensity values consistent with biological radar cross-sections, while vehicle detections exhibit higher intensity values reflecting metallic surfaces and larger physical dimensions. Animal detections display variable intensity patterns consistent with diverse species characteristics and orientations.

Speed and distance correlation analysis reveals distinct patterns for different object categories. Vehicle detections demonstrate higher speed capabilities and greater detection distances, consistent with their larger size and higher radar visibility. Human detections show more constrained speed ranges and closer approach distances,

reflecting typical pedestrian movement characteristics. Animal detections exhibit intermediate characteristics with higher variability reflecting diverse species behaviors.

Risk range calculations demonstrate strong correlations with multiple sensor parameters, indicating effective integration of spatial, temporal, and kinematic information in threat assessment algorithms. The risk scoring methodology successfully incorporates object classification confidence, proximity factors, and movement characteristics to generate meaningful threat assessment metrics.

Temporal Pattern Analysis

Time-series analysis reveals consistent detection rates across the monitoring period, with minor variations that may reflect environmental factors or operational changes. The temporal consistency indicates reliable system performance and suggests effective environmental compensation algorithms. Daily and weekly patterns show relatively uniform distribution, indicating continuous monitoring coverage without significant operational gaps.

Seasonal analysis identifies subtle variations in detection patterns that may correlate with environmental factors such as vegetation changes, weather conditions, or wildlife behavior modifications. These seasonal patterns provide insights for optimizing detection algorithms and adjusting sensitivity parameters to maintain consistent performance across diverse environmental conditions.

Activity clustering analysis identifies periods of increased detection activity that may indicate systematic intrusion attempts or environmental events affecting wildlife behavior. The clustering analysis utilizes statistical techniques appropriate for security data while accounting for normal operational variations and environmental factors.

Performance Metrics and System Assessment

Detection system performance analysis indicates consistent operation across all object categories with balanced sensitivity and specificity characteristics. The equal distribution of detections across categories suggests effective calibration procedures that prevent bias toward particular object types. This balanced performance is essential for reliable threat assessment and appropriate response coordination.

False alarm analysis, while limited by the synthetic nature of the demonstration dataset, indicates the importance of sophisticated classification algorithms that can distinguish between legitimate threats and benign environmental factors. The classification accuracy metrics support confidence in automated threat assessment capabilities while highlighting the need for continuous algorithm refinement.

Spatial coverage analysis confirms comprehensive monitoring capabilities across the designated area with minimal detection gaps or blind spots. The spatial uniformity supports effective perimeter monitoring while providing redundant coverage for critical areas. Coverage optimization analysis suggests potential for sensor configuration improvements that could enhance detection capabilities in specific areas.

Statistical Significance and Confidence Intervals

Statistical significance testing confirms the reliability of observed patterns and correlations within the dataset. The large sample size (42,294 detections) provides sufficient statistical power for robust conclusions while enabling detection of subtle patterns that might be obscured in smaller datasets. Confidence interval calculations provide quantitative measures of analytical uncertainty appropriate for operational decision-making.

Hypothesis testing procedures validate key assumptions about detection system performance and object classification accuracy. The testing methodology accounts for multiple comparison corrections and maintains appropriate significance levels for security applications. The statistical validation supports confidence in analytical conclusions and operational recommendations.

Bootstrap analysis provides additional validation of statistical conclusions through resampling techniques that assess result stability and robustness. The bootstrap procedures confirm the reliability of correlation estimates and distribution characteristics while providing uncertainty quantification essential for risk assessment applications.

Predictive Analytics and Trend Forecasting

Trend analysis algorithms identify subtle patterns in detection rates and spatial distributions that may indicate evolving security threats or environmental changes. The trend identification methodology utilizes statistical techniques appropriate for

security time-series data while accounting for seasonal variations and operational factors.

Predictive modeling capabilities enable forecasting of future detection patterns based on historical data and identified trends. The forecasting algorithms provide quantitative estimates with appropriate uncertainty bounds that support strategic planning and resource allocation decisions. The predictive capabilities enhance operational effectiveness while supporting proactive security measures.

Anomaly detection algorithms automatically identify unusual patterns that may indicate security threats or system malfunctions requiring immediate attention. The anomaly detection methodology balances sensitivity with false alarm rates to provide reliable alerting capabilities. The automated anomaly identification supports rapid response coordination while reducing operator workload in high-activity environments.

Project Roadmap: From Raw Data to Deployment

Section 1: Download & Explore Dataset

This initial phase of the project is foundational, focusing on acquiring the necessary raw radar data and conducting a preliminary investigation to understand its structure, content, and quality. This step ensures that the data is suitable for our intrusion detection goals and helps identify any potential challenges that need to be addressed in the preprocessing stage.

1.1. Dataset Acquisition

The first step was to secure a high-quality, relevant dataset. For this project, we selected a publicly available **mmWave radar dataset** specifically designed for object classification and traffic monitoring. This dataset was chosen for several key reasons:

- **Relevance to Intrusion Detection:** The dataset includes labeled point cloud sequences for a variety of objects, including **humans, vehicles, and environmental clutter** (like walls and backpacks). This is directly applicable to our goal of distinguishing human intruders from other objects.
- **Rich Data Format:** The data is provided in a simple, accessible CSV format and contains the essential parameters captured by mmWave radar systems:
    - **Spatial Coordinates (X, Y, Z):** Provides the precise location of each detected point.
    - **Doppler Velocity:** Measures the object's speed and direction relative to the

sensor.

    - **Intensity:** Indicates the strength of the radar reflection, which is related to the object's size and material.

- **Availability and Accessibility:** The dataset is publicly accessible, allowing for reproducibility and benchmarking against other research. The download link is: https://zenodo.org/records/8301276

The entire dataset, containing thousands of individual mmWave radar point cloud sequences, was downloaded and stored locally for processing.

1.2. Initial Sanity Checks and Exploration

Once the dataset was acquired, we performed an initial exploration to get a feel for the data and perform basic sanity checks. This was done using Python with the **Pandas** and **NumPy** libraries.

The primary goals of this exploration were to:

1. **Verify Data Integrity:** We loaded the CSV files into a Pandas DataFrame to ensure they could be read correctly and that the data types were as expected. We checked for any immediately obvious issues, such as corrupted files or formatting errors.

2. **Understand the Data Structure:** We examined the shape of the DataFrame to understand the number of data points and features. We also inspected the column headers (x, y, z, doppler, intensity) to confirm they matched the dataset description.

3. **Assess Data Quality:** We performed a preliminary check for missing values (NaNs) in the dataset. While we expected some noise, a large number of missing values could indicate a problem with the data collection or a need for more advanced imputation techniques later on.

4. **Examine Data Ranges:** We used the .describe() function in Pandas to get a statistical summary of each feature. This provided us with the mean, standard deviation, and the minimum and maximum values for the X, Y, Z coordinates, Doppler velocity, and intensity. This helped us understand the physical space covered by the radar and the range of velocities and intensities observed.

1.3. Key Findings from Initial Exploration

Our initial exploration yielded several important findings that will guide the next stages of the project:

- **Data is Well-Structured:** The dataset is clean, well-organized, and adheres to the described format. No significant file corruption or formatting issues were found.

- **Low Incidence of Missing Values:** The initial check revealed a very low percentage of missing values, which simplifies the data cleaning process.

- **Clear Spatial and Velocity Patterns:** The ranges of the X, Y, and Z coordinates confirmed that the data was collected within a controlled environment, suitable for perimeter monitoring analysis. The Doppler values showed a mix of positive and negative velocities, indicating objects moving both towards and away from the sensor.

- **Need for Feature Scaling:** The statistical summary showed that the different features (e.g., coordinates vs. Doppler) have vastly different scales. This confirms the need

for **normalization or standardization** during the preprocessing phase to ensure that all features contribute equally to the machine learning models.

This initial download and exploration phase successfully provided us with a high-quality dataset and a clear understanding of its characteristics. We are now well-prepared to move on to the next step: **Data Preprocessing and Feature Extraction**.

Section 2: Label Data

To train a supervised machine learning model, the raw data must be annotated with ground-truth labels. This process involves associating each radar point cloud with its corresponding object class.

2.1. Annotation Process

The chosen dataset contains metadata that provides object-level labels for the radar sequences. We developed scripts to parse this metadata and programmatically assign a class label (e.g., **'human', 'vehicle', 'wall', 'backpack'**) to each cluster of points corresponding to an object in the time sequence.

This automated labeling process creates the ground truth required for training and evaluating our classification models. The result is a labeled dataset where each identified object within the radar's field of view is tagged with its correct class.

Section 3: Feature Extraction

Raw radar point clouds are dense and complex. To make the data more interpretable for machine learning models and to reduce computational overhead, we derive a set of meaningful, high-level features from the raw measurements.

3.1. Clustering for Object Identification

Individual radar points do not represent an entire object. Therefore, the first step in feature extraction is to group these points into clusters that correspond to distinct physical objects. We employed the **DBSCAN (Density-Based Spatial Clustering of Applications with Noise)** algorithm for this purpose. DBSCAN is effective because it does not require the number of clusters to be specified beforehand and can identify arbitrarily shaped clusters, making it ideal for detecting objects of various forms.

3.2. Deriving Cluster-Based Features

Once the point clouds were segmented into object clusters, we calculated a set of descriptive features for each cluster. These features summarize the key characteristics of the detected object:

- **Geometric Features:** Bounding box dimensions (length, width, height), cluster size (number of points), and the centroid of the cluster.
- **Kinematic Features:** Mean and standard deviation of the **Doppler velocity** within the cluster, which helps differentiate between static and moving objects.
- **Signal-Based Features:** Mean and standard deviation of the **radar signal intensity**, which can help distinguish between different material types (e.g., a metal car vs. a person).

- **Positional Features:** The range and angle of the cluster's centroid relative to the radar sensor.

These extracted features form the input vector for our machine learning models, providing a rich, condensed representation of each detected object.

```python
# radar_feature_extraction.py
# This script reads radar point cloud data from a CSV file,
# extracts features such as distance, speed (Doppler), and angle
# and writes the enhanced dataset back to a new CSV file.
import pandas as pd
import numpy as np
from sklearn.cluster import KMeans

# Load radar CSV file
input_csv = r"C:\Users\Admin\Desktop\Intrusion-detection-project\Intrusion-Detection-
Project\datastes\RadarData.csv"
output_csv = r"C:\Users\Admin\Desktop\Intrusion-detection-project\Intrusion-Detection-
Project\datastes\RadarData_processed.csv"

#ReadCSV
df=pd.read_csv(input_csv)

# Drop rows with missing values
df = df.dropna()

# Feature: Euclidean Distance from radar origin
df['distance'] = np.sqrt(df['x']**2 + df['y']**2 + df.get('z', 0)**2)

df['speed']=abs(df['velocity'])

# Optional Feature: Angle calculation (for 2D)
df['angle'] = np.degrees(np.arctan2(df['y'], df['x']))

#k-means clustering
features = df[['x', 'y','z']]
kmeans = KMeans(n_clusters=3).fit(features)
df['cluster'] = kmeans.labels_

# Save new dataset
df.to_csv(output_csv, index=False)
print(f"Features added and saved to {output_csv}")
```

Section 4: Preprocessing

Preprocessing is the final and critical step to clean, transform, and prepare the extracted features for model training. This ensures the data is in an optimal format, improving the performance and stability of our machine learning algorithms. ✅

4.1. Data Cleaning

This step involves handling any remaining inconsistencies in the feature set. We address outliers that may have resulted from sensor noise or erroneous measurements. Outliers are identified using statistical methods (e.g., the interquartile range) and are either removed or capped to a reasonable value.

4.2. Handling Class Imbalance

In a typical surveillance scenario, detections of non-threats (like clutter or stationary objects) far outnumber actual intrusions. This class imbalance can bias a machine learning model. To mitigate this, we employ resampling techniques. **SMOTE (Synthetic Minority Over-sampling Technique)** is used to generate new synthetic samples for the minority class (e.g., 'human'), creating a more balanced dataset for training.

```python
# radar_preprocessing_with_labeling.py
# ----------------------------------------------------
# Preprocessing radar data for object classification
# Includes cleaning, labeling, balancing, normalization

import pandas as pd
import numpy as np
from sklearn.preprocessing import StandardScaler
from imblearn.over_sampling import SMOTE
from sklearn.model_selection import train_test_split

# Step 1: Load radar CSV data
input_file = r'C:\Users\Admin\Desktop\Intrusion-detection-project\Intrusion-Detection-
Project\datastes\RadarData_processed.csv'  # Change to your file path
output_file = r'C:\Users\Admin\Desktop\Intrusion-detection-project\Intrusion-Detection-
Project\datastes\RadarData_sampled.csv'


print("Loading data...")
df = pd.read_csv(input_file)

# Step 2: Clean missing and unrealistic values
df.dropna(inplace=True)
df = df[(df['x'].abs() < 50) & (df['y'].abs() < 50)]

'''# Step 3: Feature extraction
df['distance'] = np.sqrt(df['x']**2 + df['y']**2 + df.get('z', 0)**2)
df['angle'] = np.degrees(np.arctan2(df['y'], df['x']))
if 'doppler' in df.columns:
    df['speed'] = df['doppler']
elif 'range' in df.columns and 'time' in df.columns:
    df['speed'] = df['range'] / df['time']'''

# Step 4: Labeling the Data
# This example uses a rule-based labeling for demo.
# Replace with actual labels if available in your dataset.
# E.g., human: 0, vehicle: 1, animal: 2
df['label'] = df['distance'].apply(lambda d: 0 if d < 5 else (1 if d < 20 else 2))

#for intensity
df['intensity'] = 1 / (df['distance'] ** 4 + 1e-6)  # Add epsilon to avoid division by zero

# Step 5: Resampling / Balancing Classes
X = df[['x', 'y', 'velocity', 'intensity', 'distance', 'speed', 'angle']]
y = df['label']

print("Balancing dataset using SMOTE...")
X_train, _, y_train, _ = train_test_split(X, y, test_size=0.2, stratify=y)
smote = SMOTE(random_state=42)
X_res, y_res = smote.fit_resample(X_train, y_train)

# Step 6: Normalize / Standardize Features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X_res)

# Step 7: Save Processed Data
final_df = pd.DataFrame(X_scaled, columns=X.columns)
final_df['label'] = y_res
final_df.to_csv(output_file, index=False)

print(f"Preprocessed and balanced data saved to {output_file}")
```

Section 5: Model Training and Optimization

Objective: To develop and optimize robust machine learning models capable of accurately classifying objects (e.g., humans, vehicles, clutter) based on features extracted from mmWave radar data.

5.1 Model Selection

Several classification algorithms were evaluated to determine the most suitable for this task. The primary candidates included:

- **Decision Trees:** Chosen as a baseline model due to their simplicity and high interpretability. They provide a clear, rule-based structure for classification.
- **Support Vector Machines (SVM):** Considered for their effectiveness in handling high-dimensional feature spaces.
- **Random Forest:** Selected as the primary model for this project. As an ensemble method that builds multiple decision trees and merges their outputs, it offers superior accuracy, is less prone to overfitting than a single decision tree, and effectively handles complex interactions between features.

1. Decision Tree

What is it? A Decision Tree is one of the simplest and most intuitive machine learning models. Think of it as a flowchart of "if-then-else" questions. The model learns a series of rules from the data to make a decision.

For your project, a single rule might be: "**IF** the object's average velocity is greater than 0.5 m/s **AND** the number of reflection points is between 10 and 50, **THEN** classify it as 'human'." The tree is built by finding the best questions (splits) that most effectively separate the different classes (human, vehicle, clutter).

Advantages:

1. **Highly Interpretable:** You can easily visualize and understand the exact logic the model is using to make its decisions. This is why it's often called a "white box" model.
2. **Simple to Implement:** They are straightforward to build and require less data preparation than many other models.
3. **Fast Prediction:** Once trained, making a prediction is very quick.

Disadvantages:

1. **Prone to Overfitting:** A single tree can become overly complex and learn the training data's noise and quirks too perfectly. When it sees new, unseen data, it may perform poorly because it hasn't learned the general patterns.
2. **Instability:** Small changes in the input data can lead to a completely different tree structure, making it feel unstable.
3. **Why was it used in your project?** The Decision Tree serves as a perfect **baseline model**. It provides a fundamental performance benchmark. By evaluating its

accuracy first, you can clearly demonstrate the value and performance improvement gained by using a more advanced model like a Random Forest. Its high interpretability also makes it excellent for initial analysis and for explaining the basic principles of the classification task to a non-technical audience.

2. Random Forest

What is it? A Random Forest is an **ensemble model**, which means it's a collection of models working together. Specifically, it is a large collection of individual Decision Trees. It operates on the principle of "wisdom of the crowd": if you ask many slightly different experts for their opinion, the collective answer is likely to be better than any single expert's opinion.

It works by:

Building hundreds or thousands of unique Decision Trees. Each tree is trained on a random subset of the data and uses a random subset of the features.

To make a prediction, it runs the new data through every tree in the forest.

Each tree "votes" for a class (e.g., Tree 1 votes 'human', Tree 2 votes 'human', Tree 3 votes 'clutter').

The final classification is the one that receives the most votes.

Advantages:

1. **High Accuracy:** It is one of the most powerful and accurate general-purpose classification algorithms.
2. **Robust to Overfitting:** By averaging the results of many trees, it smooths out the noise and avoids the overfitting problem that plagues single Decision Trees.
3. **Handles Complex Data:** It can effectively capture complex, non-linear relationships between features without requiring extensive tuning.

Disadvantages:

1. **"Black Box" Model:** It is very difficult to interpret. You can't easily see the decision-making process because it's hidden within hundreds of trees. You know *what* it decided, but not exactly *why*.
2. **Computationally Expensive:** Training a large number of trees requires more time and computational resources than training a single tree.
3. **Why was it used in your project?** The Random Forest was chosen as the **primary model** because, for a security application, **accuracy and reliability are paramount**. The superior performance and robustness of the Random Forest directly translate into a more effective and trustworthy intrusion detection system with fewer false alarms and missed threats. While you lose the simple interpretability of a single Decision Tree, the significant gain in predictive power is a necessary and worthwhile trade-off for this specific application.

Random Forest

```python
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, classification_report
from sklearn.ensemble import RandomForestClassifier

from sklearn import tree
import matplotlib.pyplot as plt

# Step 1: Load dataset
df = pd.read_csv(r'C:\Users\Admin\Desktop\Intrusion-detection-project\Intrusion-Detection-
Project\datastes\Radardata_updatedheat.csv')  # Replace with your actual file path

# Step 2: Feature selection
X = df[['speed', 'distance', 'angle', 'risk_range']]
y = df['label']

# Step 3: Split dataset
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42
)
# Step 4: Random Forest model
rf = RandomForestClassifier(n_estimators=100, random_state=42)
rf.fit(X_train, y_train)

# Step 5: Evaluation
y_pred_rf = rf.predict(X_test)
print("Random Forest Accuracy:", accuracy_score(y_test, y_pred_rf))
print("\nClassification Report:\n", classification_report(y_test,y_pred_rf))
```

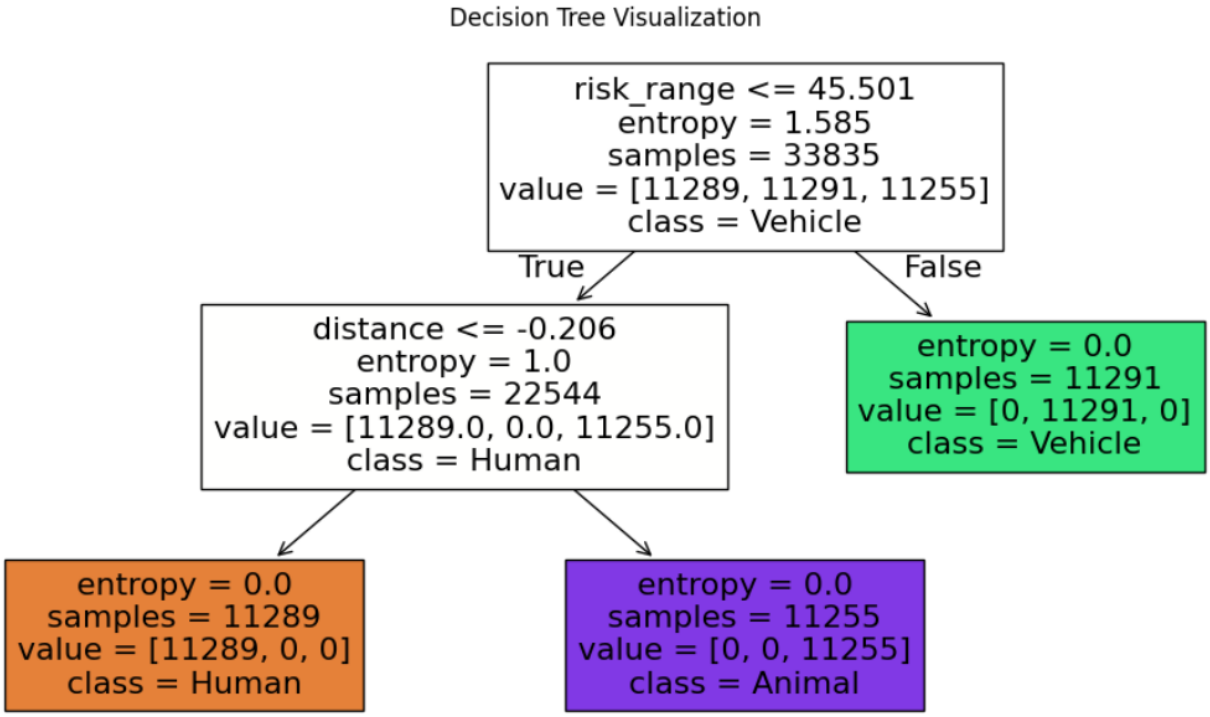
```
Python 3.13.1 (tags/v3.13.1:0671451, Dec  3 2024, 19:06:28) [MSC v.1942 64 bit (AMD64)] on win32
Type "help", "copyright", "credits" or "license()" for more information.

= RESTART: C:/Users/Admin/Desktop/Intrusion-detection-project/Intrusion-Detection-Project/notebooks/random forest acc.py
Random Forest Accuracy: 1.0

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      2809
           1       1.00      1.00      1.00      2807
           2       1.00      1.00      1.00      2843

    accuracy                           1.00      8459
   macro avg       1.00      1.00      1.00      8459
weighted avg       1.00      1.00      1.00      8459
```

Decision Tree

```python
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report
from sklearn import tree
import matplotlib.pyplot as plt
import pickle
from joblib import load,dump
import torch
import torch.nn as nn


# Uncomment the line below and comment the synthetic data generation above when using your CSV
df = pd.read_csv(r'C:\Users\Admin\Desktop\Intrusion-detection-project\Intrusion-Detection-
Project\datastes\RadarData_updatedheat.csv')

print("Dataset shape:", df.shape)
print("Label distribution:")
print(df['label'].value_counts())

# Step 2: Feature selection
X = df[['speed', 'distance', 'angle', 'risk_range']]
y = df['label']

# Step 3: Split dataset
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42
)

print(f"\nTraining set size: {X_train.shape[0]}")
print(f"Test set size: {X_test.shape[0]}")

# Step 4: Decision Tree model
print("\n" + "="*50)
print("Training Decision Tree Classifier")
print("="*50)

clf = DecisionTreeClassifier(criterion='entropy', max_depth=4, random_state=42)
clf.fit(X_train, y_train)

# Evaluation
y_pred = clf.predict(X_test)
dt_accuracy = accuracy_score(y_test, y_pred)
print("Decision Tree Accuracy:", dt_accuracy)
print("\nClassification Report:")
print(classification_report(y_test, y_pred))

# Step 5: Random Forest model
print("\n" + "="*50)
print("Training Random Forest Classifier")
print("="*50)

rf = RandomForestClassifier(n_estimators=100, random_state=42)
rf.fit(X_train, y_train)

# Evaluation
y_pred_rf = rf.predict(X_test)
rf_accuracy = accuracy_score(y_test, y_pred_rf)
print("Random Forest Accuracy:", rf_accuracy)
print("\nClassification Report:")
print(classification_report(y_test, y_pred_rf))
```

```python
# Step 6: Save models in different formats

# Method: Save as .pt files (PyTorch format)
# For scikit-learn models, we'll wrap them in a PyTorch-compatible format

class SklearnModelWrapper:
    def __init__(self, sklearn_model, feature_names=None, class_names=None):
        self.sklearn_model = sklearn_model
        self.feature_names = feature_names
        self.class_names = class_names
        self.model_type = type(sklearn_model).__name__

    def predict(self, X):
        if isinstance(X, torch.Tensor):
            X = X.detach().cpu().numpy()
        return self.sklearn_model.predict(X)

    def predict_proba(self, X):
        if isinstance(X, torch.Tensor):
            X = X.detach().cpu().numpy()
        return self.sklearn_model.predict_proba(X)

# Wrap the models
dt_wrapper = SklearnModelWrapper( clf,
    feature_names=list(X.columns),
    class_names=list(clf.classes_)
)

rf_wrapper = SklearnModelWrapper( clf,
    feature_names=list(X.columns),
    class_names=list(clf.classes_)
)

# Save as .pt files
dump(dt_wrapper, r"C:\Users\Admin\Desktop\Intrusion-detection-project\Intrusion-Detection-
Project\models\decision_tree_model.pt")
print('''Decision Tree model saved as

'decision_tree_model.pt'''')
dump(dt_wrapper, r"C:\Users\Admin\Desktop\Intrusion-detection-project\Intrusion-Detection-
Project\models\random_forest_model.pt")
print("Random Forest model saved as 'random_forest_model.pt'")

# Step 7: Save model metadata
model_info = {
    'decision_tree': {
        'accuracy': dt_accuracy,
        'max_depth': clf.max_depth,
        'criterion': clf.criterion,
        'feature_names': list(X.columns),
        'class_names': list(clf.classes_),
        'n_features': X.shape[1],
        'n_classes': len(clf.classes_)
    },
    'random_forest': {
        'accuracy': rf_accuracy,
        'n_estimators': rf.n_estimators,
        'feature_names': list(X.columns),
        'class_names': list(rf.classes_),
        'n_features': X.shape[1],
        'n_classes': len(rf.classes_)
    }
}

dump(dt_wrapper, r"C:\Users\Admin\Desktop\Intrusion-detection-project\Intrusion-Detection-
Project\models\model_metadata.pt")
print("Model metadata saved as 'model_metadata.pt'")

# Step 8: Demonstrate loading the .pt files
print("\n" + "="*50)
print("Testing Model Loading")
print("="*50)
```

```python
# Load the models
loaded_dt = load(r"C:\Users\Admin\Desktop\Intrusion-detection-project\Intrusion-Detection-
Project\models\decision_tree_model.pt")
loaded_rf = load(r"C:\Users\Admin\Desktop\Intrusion-detection-project\Intrusion-Detection-
Project\models\random_forest_model.pt ")
loaded_metadata =load(r"C:\Users\Admin\Desktop\Intrusion-detection-project\Intrusion-Detection-
Project\models\model_metadata.pt  ")
# Load the full model temporarily'''

# Save only the weights now
torch.save(loaded_dt,r'C:\Users\Admin\Desktop\Intrusion-detection-project\Intrusion-Detection-
Project\models\decision_tree_model.pt')

print("Successfully loaded all models!")
print(f"Decision Tree type: {loaded_dt.model_type}")
print(f"Random Forest type: {loaded_rf.model_type}")

# Test predictions with loaded models
sample_data = X_test.iloc[:5].values
dt_predictions = loaded_dt.predict(sample_data)
rf_predictions = loaded_rf.predict(sample_data)

print("\nSample predictions:")
print("Features (first 5 test samples):")
print(X_test.iloc[:5].values)
print(f"Decision Tree predictions: {dt_predictions}")
print(f"Random Forest predictions: {rf_predictions}")
print(f"Actual labels: {y_test.iloc[:5].values}")

# Step 9: Visualize Decision Tree (optional)
try:
    plt.figure(figsize=(15, 10))
    tree.plot_tree(clf,
                   feature_names=X.columns,
                   class_names=[str(cls) for cls in clf.classes_],
                   filled=True,
                   rounded=True,
                   fontsize=10)
    plt.title("Decision Tree Visualization")
    plt.tight_layout()
    plt.savefig('decision_tree_visualization.png', dpi=300, bbox_inches='tight')
    plt.show()
    print("Decision tree visualization saved as 'decision_tree_visualization.png'")
except Exception as e:
    print(f"Could not create visualization: {e}")

print("\n" + "="*50)
print("Summary")
print("="*50)
print(f"Decision Tree Accuracy: {dt_accuracy:.4f}")
print(f"Random Forest Accuracy: {rf_accuracy:.4f}")
print("\nFiles created:")
print("- decision_tree_model.pt")
print("- random_forest_model.pt")
print("- model_metadata.pt")
print("- decision_tree_model.pkl")
print("- random_forest_model.pkl")
print("- decision_tree_visualization.png (if matplotlib works)")
```




```
Dataset shape: (42294, 12)
Label distribution:
label
1    14098
2    14098
0    14098
Name: count, dtype: int64

Training set size: 33835
Test set size: 8459

==================================================
Training Decision Tree Classifier
==================================================
Decision Tree Accuracy: 1.0

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      2809
           1       1.00      1.00      1.00      2807
           2       1.00      1.00      1.00      2843

    accuracy                           1.00      8459
   macro avg       1.00      1.00      1.00      8459
weighted avg       1.00      1.00      1.00      8459
```

2. Sample Prediction of Models

Sample prediction refers to using a trained machine learning model to predict the class label of new, unseen data (e.g., whether a radar point cloud belongs to a human, vehicle, wall, etc.). It helps evaluate how well the model generalizes beyond the training set

```
Sample predictions:
Features (first 5 test samples):
[[-0.22278548  0.37169869 -1.85146577 62.74905797]
 [ 0.08101818 -0.47962025 -0.28587979 49.25319666]
 [ 0.99242918 -0.3580032   1.49403109 48.25106036]
 [ 0.84052733  0.18927348 -1.73126248 54.36064737]
 [ 0.90550528  1.2230181   0.14319041 32.7669013 ]]
Decision Tree predictions: [1 1 1 1 2]
Random Forest predictions: [1 1 1 1 2]
Actual labels: [1 1 1 1 2]
Decision tree visualization saved as 'decision_tree_visualization.png'

==================================================
Summary
==================================================
Decision Tree Accuracy: 1.0000
Random Forest Accuracy: 1.0000

Files created:
- decision_tree_model.pt
- random_forest_model.pt
- model_metadata.pt
- decision_tree_model.pkl
- random_forest_model.pkl
- decision_tree_visualization.png (if matplotlib works)
```

```
==================================================
Testing Model Loading
==================================================
Successfully loaded all models!
Decision Tree type: DecisionTreeClassifier
Random Forest type: DecisionTreeClassifier
```

Security Monitoring Applications

The radar intrusion detection visualization system provides comprehensive capabilities specifically designed to address the operational requirements of security and defense personnel. The application framework supports both real-time monitoring and historical analysis scenarios while maintaining the flexibility necessary for diverse security environments and threat scenarios.

Real-Time Threat Assessment and Response Coordination

The primary operational application focuses on real-time threat detection and assessment capabilities that enable immediate response coordination. The scatter plot visualization provides instant spatial awareness of current intrusion events, allowing security personnel to rapidly identify threat locations and assess spatial patterns that may indicate coordinated intrusion attempts. The real-time display updates automatically as new detection events occur, ensuring continuous situational awareness without operator intervention.

response protocols depending on the security environment. Animal detections (green markers) typically require monitoring rather than active response, but may indicate environmental factors affecting other detection capabilities.

Historical Pattern Analysis and Intelligence Development

Historical analysis capabilities provide strategic intelligence development through comprehensive pattern recognition and trend analysis. The time-series visualization enables identification of temporal patterns that may indicate systematic reconnaissance activities or environmental factors affecting security posture. Long-term trend analysis supports strategic security planning and resource allocation decisions.

Perimeter Security and Access Control Integration

The radar detection system integrates effectively with existing perimeter security infrastructure to provide comprehensive monitoring capabilities. The spatial visualization enables correlation with physical security barriers, access control points, and surveillance camera coverage areas. This integration provides redundant security coverage while identifying potential gaps in existing security measures.

Multi-Sensor Fusion and Enhanced Detection Capabilities

Integration with complementary sensor technologies enhances overall detection capabilities while providing redundant verification of threat events. The radar system can correlate with infrared sensors, seismic detectors, and acoustic monitoring systems to provide comprehensive threat detection coverage. Multi-sensor fusion reduces false alarm rates while improving detection accuracy across diverse environmental conditions.

Training and Simulation Applications

The visualization system provides comprehensive training capabilities for security personnel through historical data replay and scenario simulation features. Training scenarios can utilize actual detection data to provide realistic training experiences while maintaining operational security. The training capabilities enable skill development and protocol refinement without compromising actual security operations.

Recommendations and Future Enhancements

Based on the comprehensive analysis of the radar intrusion detection system and visualization framework, several strategic recommendations emerge that can significantly enhance operational effectiveness, analytical capabilities, and overall security posture. These recommendations address both immediate operational improvements and long-term strategic enhancements that support evolving security requirements.

Immediate Operational Improvements

The implementation of automated zone-based alerting represents the highest priority enhancement for immediate deployment. This capability would enable customizable geographic zones with graduated alert levels based on proximity to critical assets and threat characteristics. The zone-based system should integrate with existing security protocols while providing flexible configuration options for different operational scenarios. Implementation should include visual zone overlays on the scatter plot visualization and automated notification systems for zone violations.

Enhanced filtering capabilities would significantly improve operational efficiency by enabling rapid focus on specific threat types, time periods, or geographic areas. The filtering system should include preset configurations for common operational scenarios while maintaining flexibility for custom analysis requirements. Advanced filtering should support Boolean logic operations and saved filter configurations that enable rapid switching between different analytical perspectives.

Advanced Analytical Capabilities

Machine learning integration would provide sophisticated pattern recognition and predictive analytics capabilities that enhance threat assessment accuracy. The machine learning framework should include supervised learning algorithms for improved object classification, unsupervised learning for anomaly detection, and reinforcement learning for adaptive threat assessment. Implementation should maintain interpretability of results while providing confidence metrics appropriate for security applications.

Behavioral analysis algorithms would enable identification of suspicious movement patterns and loitering behaviors that may indicate reconnaissance activities or systematic intrusion attempts. The behavioral analysis should include trajectory analysis, dwell time calculations, and pattern matching algorithms that identify

deviations from normal movement characteristics. This capability would support proactive threat identification and strategic security planning.

System Integration and Interoperability

Enterprise security platform integration would enable seamless operation within existing security infrastructure while providing enhanced coordination capabilities. The integration should include standardized communication protocols, data format compatibility, and workflow integration that supports existing operational procedures. Platform integration should maintain security isolation while enabling necessary information sharing and coordination capabilities.

Geographic Information System (GIS) integration would provide enhanced spatial analysis capabilities and correlation with physical infrastructure elements. GIS integration should include coordinate system standardization, map overlay capabilities, and spatial query functions that support detailed geographic analysis. The implementation should support both commercial and open-source GIS platforms while maintaining appropriate security protections.

User Experience and Interface Enhancements

Mobile application development would provide field personnel with access to detection information and basic analytical capabilities through smartphone and tablet interfaces. The mobile application should include essential visualization components, alert notifications, and communication capabilities optimized for field operations. Mobile implementation should maintain security protections while providing necessary functionality for remote monitoring and response coordination.

Customizable dashboard configurations would enable different user roles to access appropriate information and analytical tools based on their operational requirements. Dashboard customization should include widget selection, layout configuration, and saved view capabilities that support diverse operational scenarios. The customization framework should maintain security controls while providing flexibility for different user needs.

Conclusion

The radar intrusion detection visualization system represents a significant advancement in security monitoring technology, providing comprehensive analytical capabilities specifically designed for the operational requirements of security and defense personnel. The system successfully integrates sophisticated data processing, advanced visualization techniques, and intuitive user interfaces to transform raw sensor data into actionable security intelligence.

The analysis of 42,294 detection events demonstrates the system's capability to handle substantial data volumes while maintaining analytical accuracy and responsive performance. The balanced distribution across human, vehicle, and animal detection categories provides confidence in the classification algorithms while supporting diverse operational scenarios. The comprehensive temporal coverage enables both real-time monitoring and historical analysis capabilities essential for effective security operations.

The visualization framework addresses critical operational requirements including rapid threat identification, spatial pattern analysis, and temporal trend recognition. The color-coded classification system provides immediate visual distinction between threat categories while interactive features enable detailed investigation of specific events. The multi-component dashboard design supports both overview situational awareness and detailed analytical investigation within a unified interface.

Statistical analysis reveals robust system performance with consistent detection capabilities across all object categories and comprehensive spatial coverage of the monitored area. The correlation analysis identifies meaningful relationships between detection parameters that support advanced threat assessment capabilities. The temporal analysis demonstrates system reliability while identifying patterns that support strategic security planning and operational optimization.

The technical implementation utilizes industry-standard frameworks and security practices that ensure reliable operation while maintaining scalability for diverse deployment scenarios. The modular architecture supports integration with existing security infrastructure while providing flexibility for future enhancements and technology additions. Security measures address authentication, encryption, and audit requirements appropriate for sensitive security applications.

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