

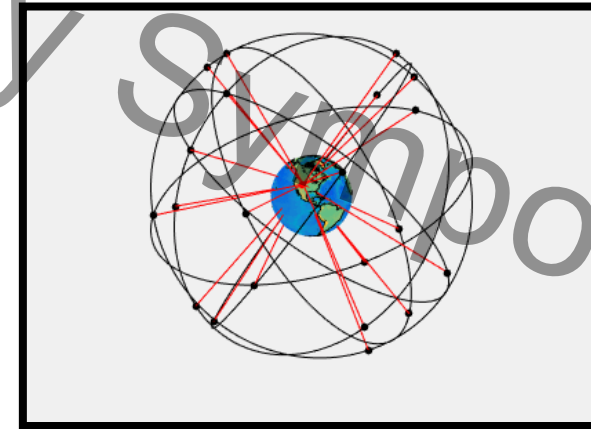
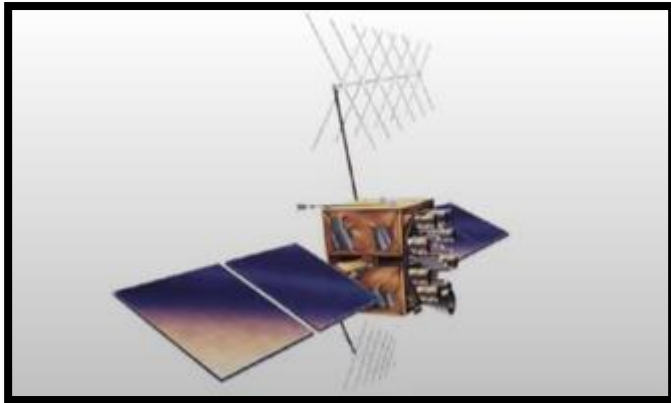
# GPS spoofing: challenges, detection strategies, and training through real scenarios

*CAE Cybersecurity Symposium – Charleston, South Carolina  
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# What is Global Positioning System (GPS) ?

- Constellation of space vehicles (SVs) and ground control stations managed by the US Space Force
  - Provides **position, navigation, and timing (PNT)** data to military and civilian users globally 24/7/365
- GPS satellites (currently 31 satellite in orbit): transmit time, satellite location to the user
- User needs at least four satellites in view to determine time error; three after correcting



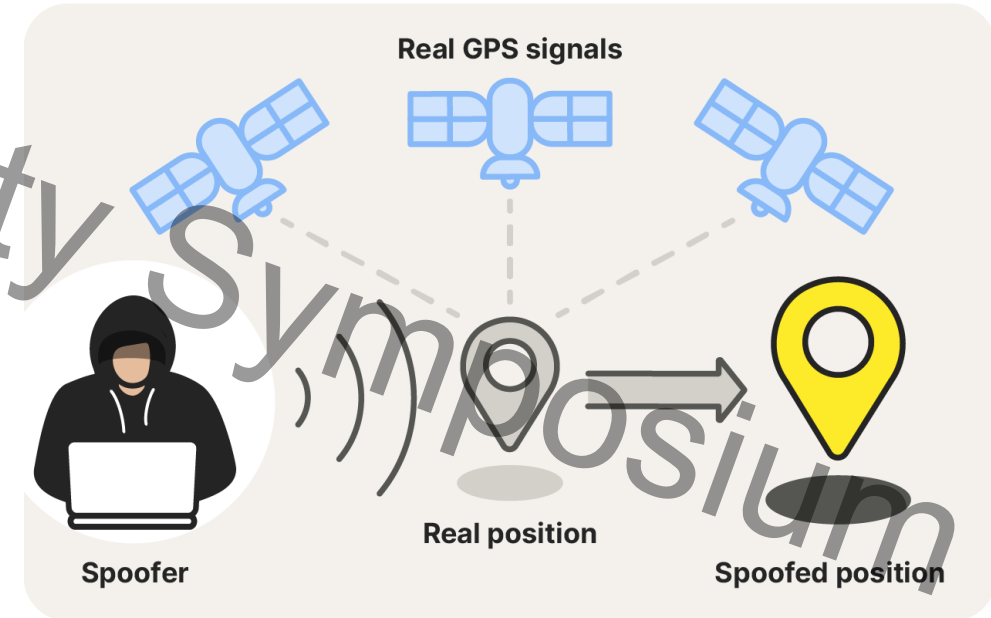
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# What is GPS Spoofing?

**Spoofing:** Generation of fake signals that mimic those from GPS satellites causing GPS receivers to calculate incorrect PNT information

## Techniques:

- Source signal spoofing
  - Alter the characteristics (amplitude, frequency, phase shift, etc.) of the incoming signal from satellite
- Receiver spoofing
  - Attack the receiver's ability to decode the signal





# Real-World GPS Spoofing Incidents

FORBES > BUSINESS > AEROSPACE & DEFENSE

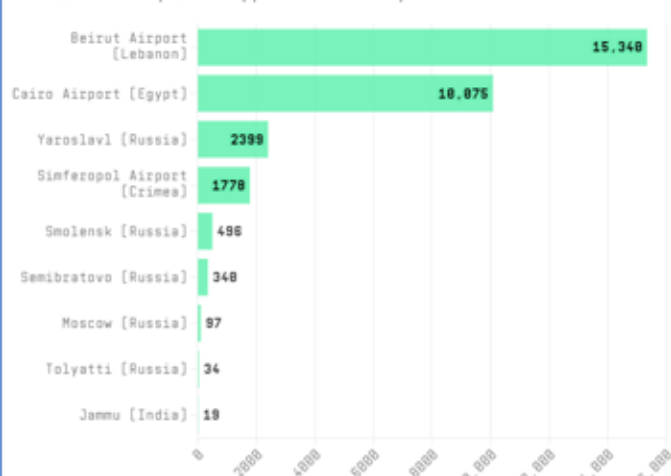
## GPS Spoofing in the Middle East Is Now Capturing Avionics



Avionics like those equipping Bombardier's Global 7500 business jet and other commercial aircraft are being "captured" by false GPS broadcasts in the Middle East. [-] BOMBARDIER

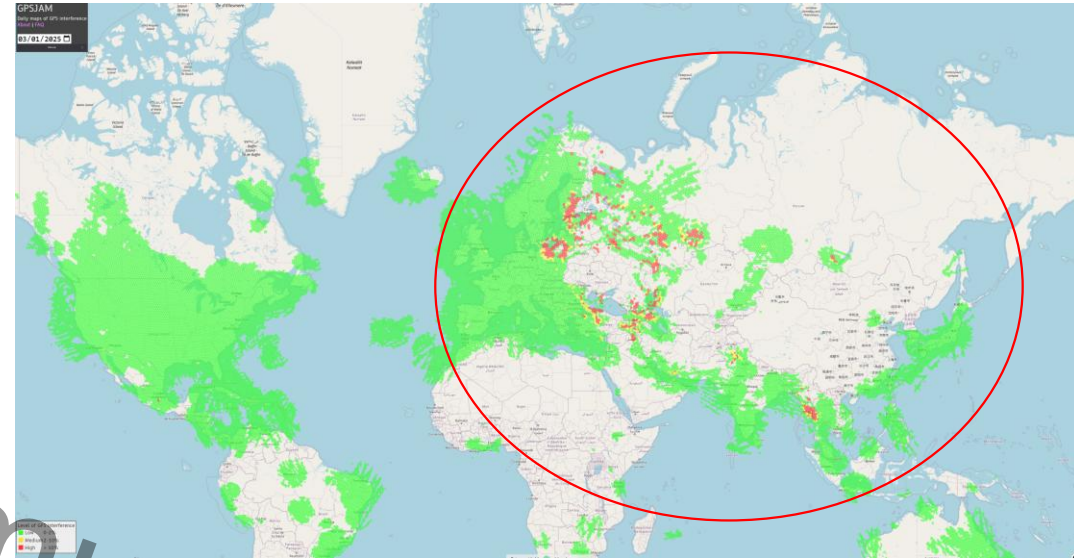
"What we've seen since late September," University of Texas researchers say, "is unprecedented. We have never seen commercial aircraft captured by GPS spoofing before."

**Number of Planes Experiencing GPS Spoofing in April 2024**  
The locations planes appeared to be spoofed to.



Source: GPS Spoofing Map by Skat Data Services, Zurich University, OpenSky Network

WIRED



Credit: INCD / El Al

# Detection of GPS Spoofing ?

## Spoofing Detection

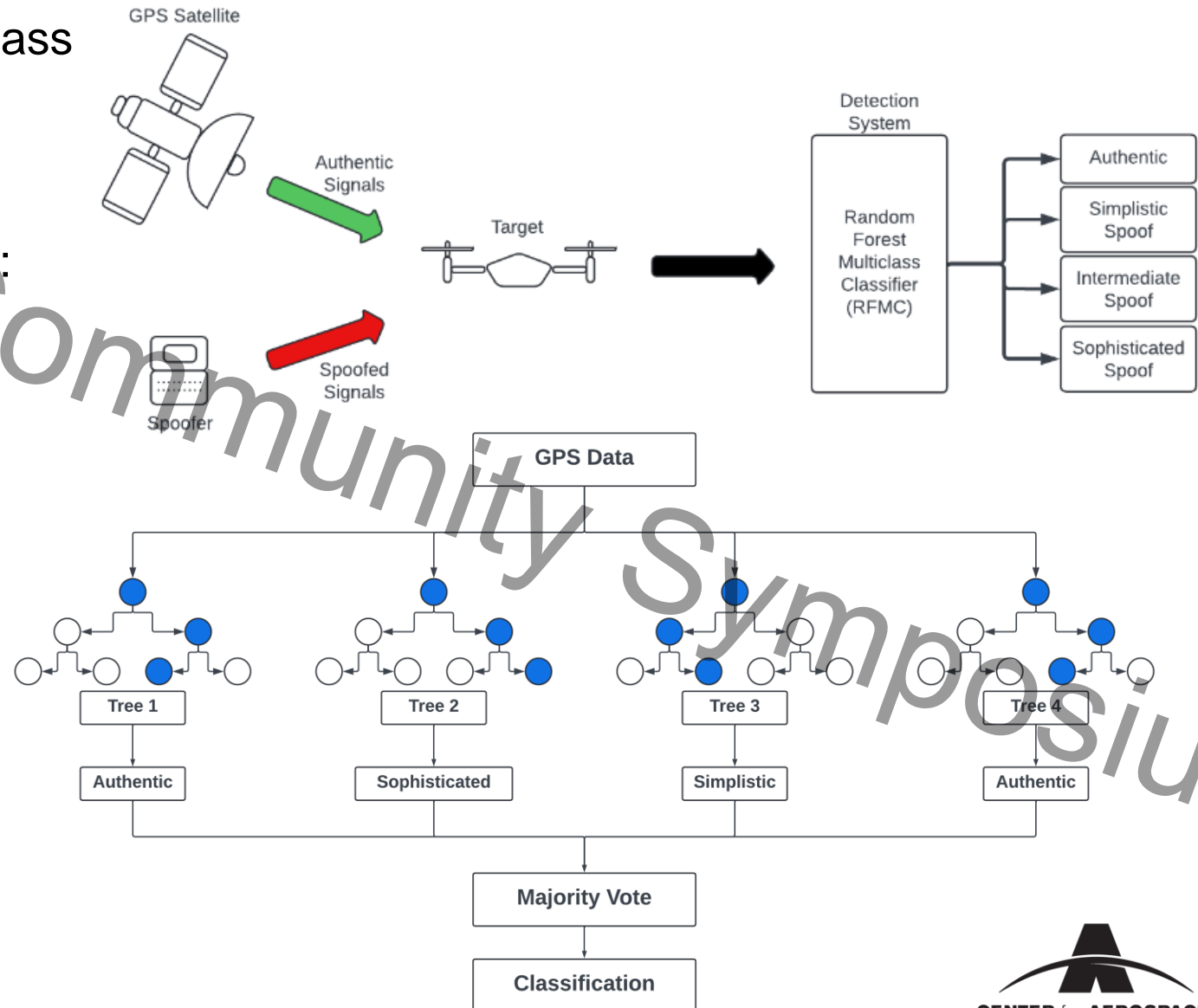
- Dual/multi-band receivers (to compare signals from different bands)
- Global Navigation Satellite System (GNSS) receivers (compare signals from different constellations)
- Signal to Noise Ratio Analysis
- Power Level Checks

**Machine Learning?**

# Machine Learning-Based GPS Spoofing Detection

# Random Forest Multiclass Classification

- Apply the Random Forest Multiclass Classification Approach for the detection of the GPS spoofing signals
- Categorizing the GPS signals as:
  - Authentic Signal
  - Spoofed Signal
  - Simplistic
  - Intermediate
  - Sophisticated



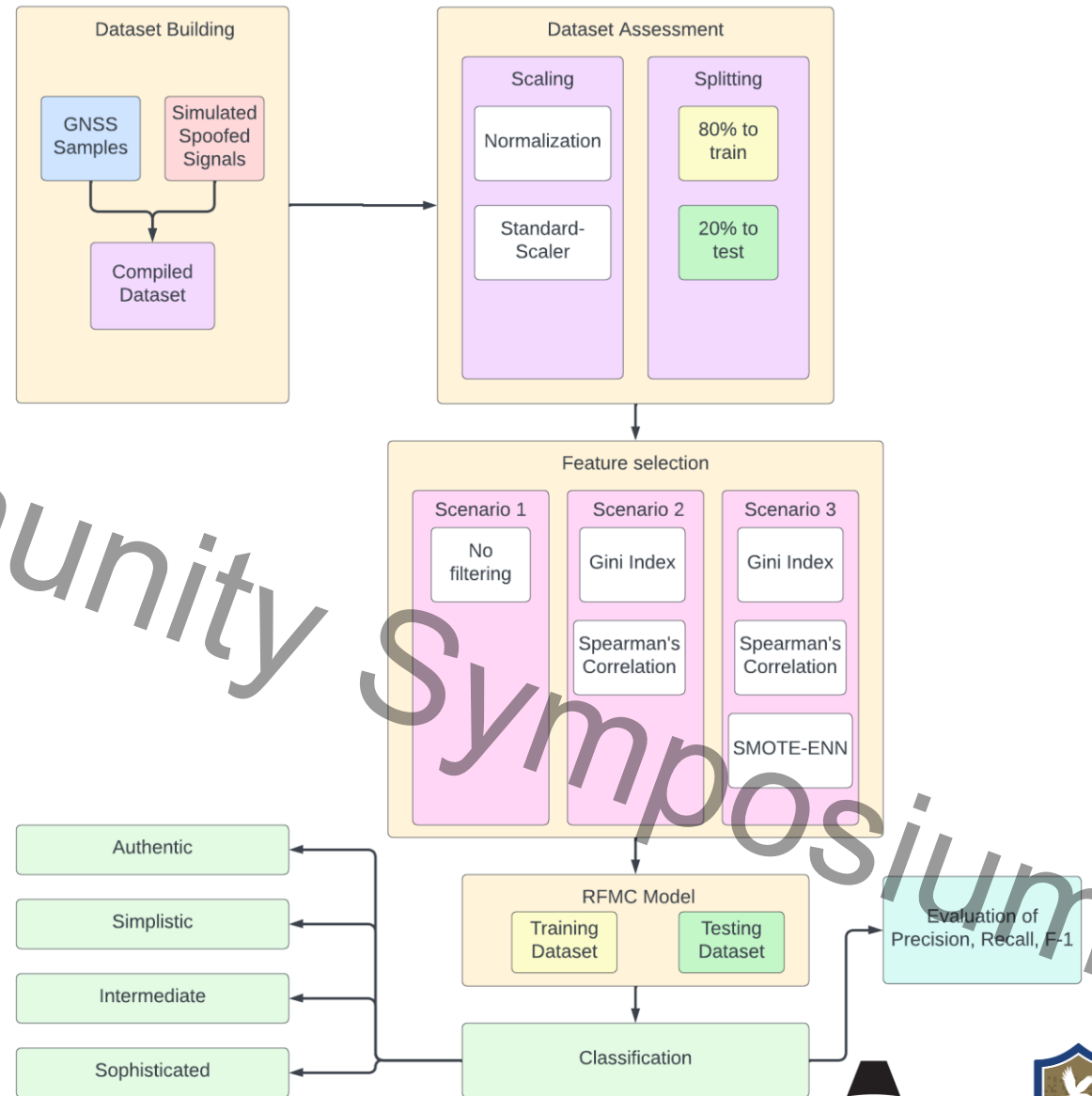
# Methodology Overview

1. GPS Data
2. Data Scaling and Splitting
3. Feature Selection
4. Random Forest Classifier Model
5. Performance Evaluation

## GPS Data

Collected by the School of Electrical Engineering and Computer Science, University of North Dakota; 510,530 samples, 13 features

Sample Type	Number of Samples	Percentage
Authentic signal	397825	78%
Simple spoofing	36458	7%
Intermediate spoofing	44232	9%
Sophisticated spoofing	32015	6%





# Features in GPS Dataset

Extracted features	Abbreviations
Carrier to Noise Ratio	C/N <sub>0</sub>
Early Correlator	EC
Late Correlator	LC
Prompt Correlator	PC
Prompt in-phase correlator	PIP
Prompt Quadrature component	PQP
Carrier Doppler in Tracking loop	TCD
Carrier Doppler	DO
Pseudo-range	PD
Receiver Time	RX
Time of the week	TOW
Carrier Phase Cycles	CP
Satellite vehicle number	PRN

13 total features are present in the dataset

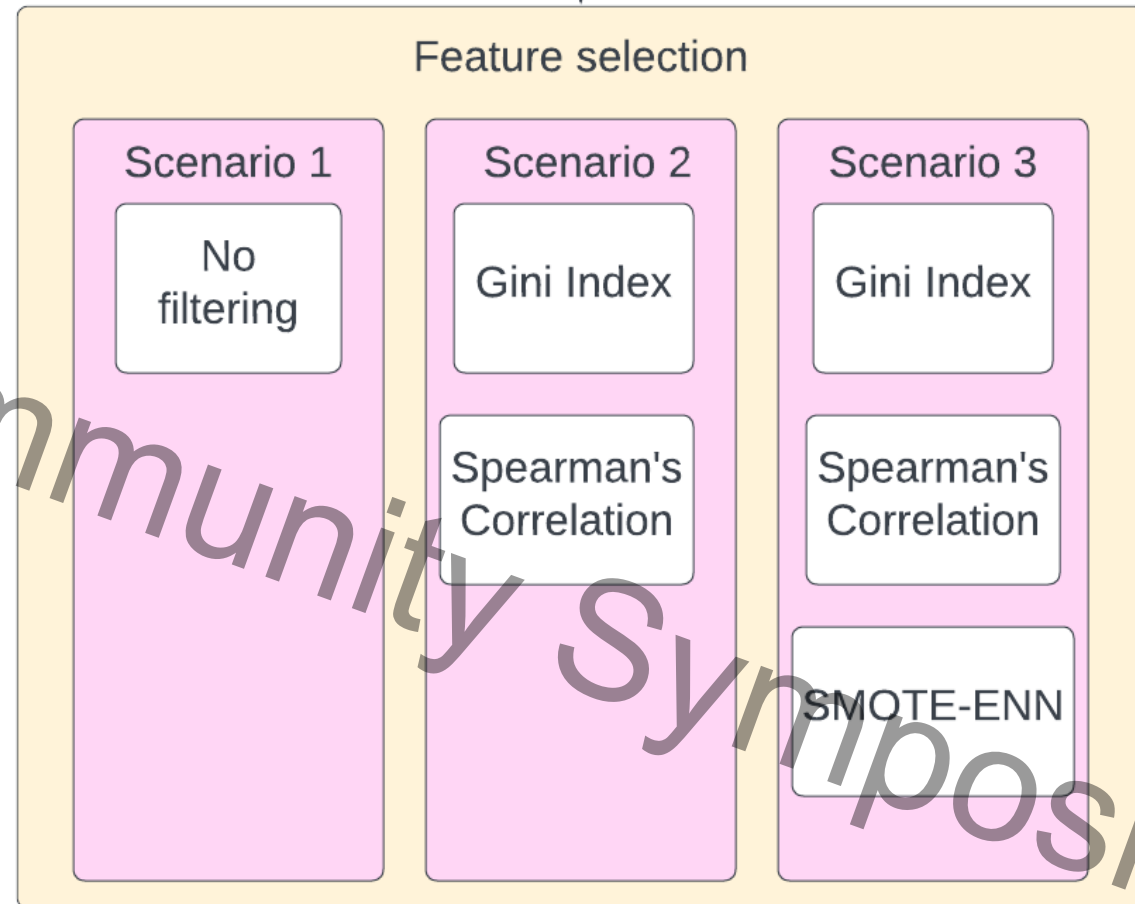
# Features Selection

**Scenario 1:** All 13 features using Standard-Scaler

**Scenario 2** Utilized 9 features, identified using the Gini index and utilized Spearman's correlation.

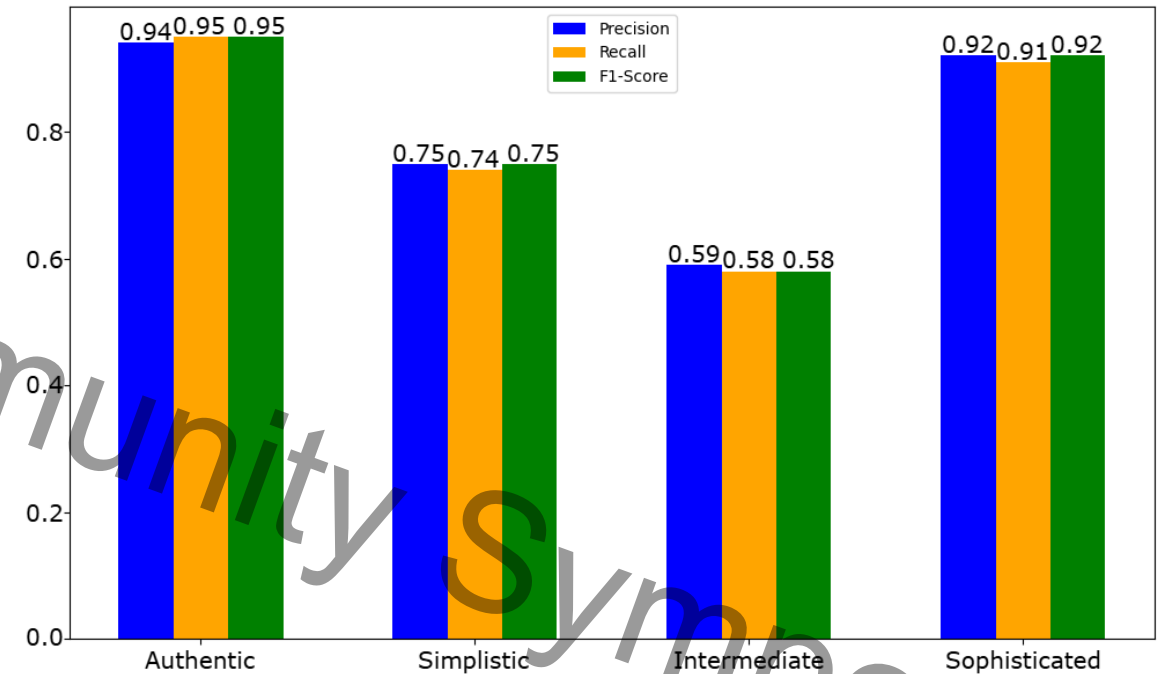
**Scenario 3** Utilized 9 features collected from scenario two and used the SMOTE-ENN sampling technique to balance the dataset

*SMOTE-ENN oversamples minority classes and under samples the majority class to address class imbalance*



# Results: Scenario 1

- Was accurately able to distinguish authentic and sophisticated signals ( $>0.90$ )
- Was moderate at classifying simplistic spoofing signals ( $\sim 0.75$ )
- Demonstrated poor accuracy in classifying intermediate spoofing signals ( $\sim 0.58$ )



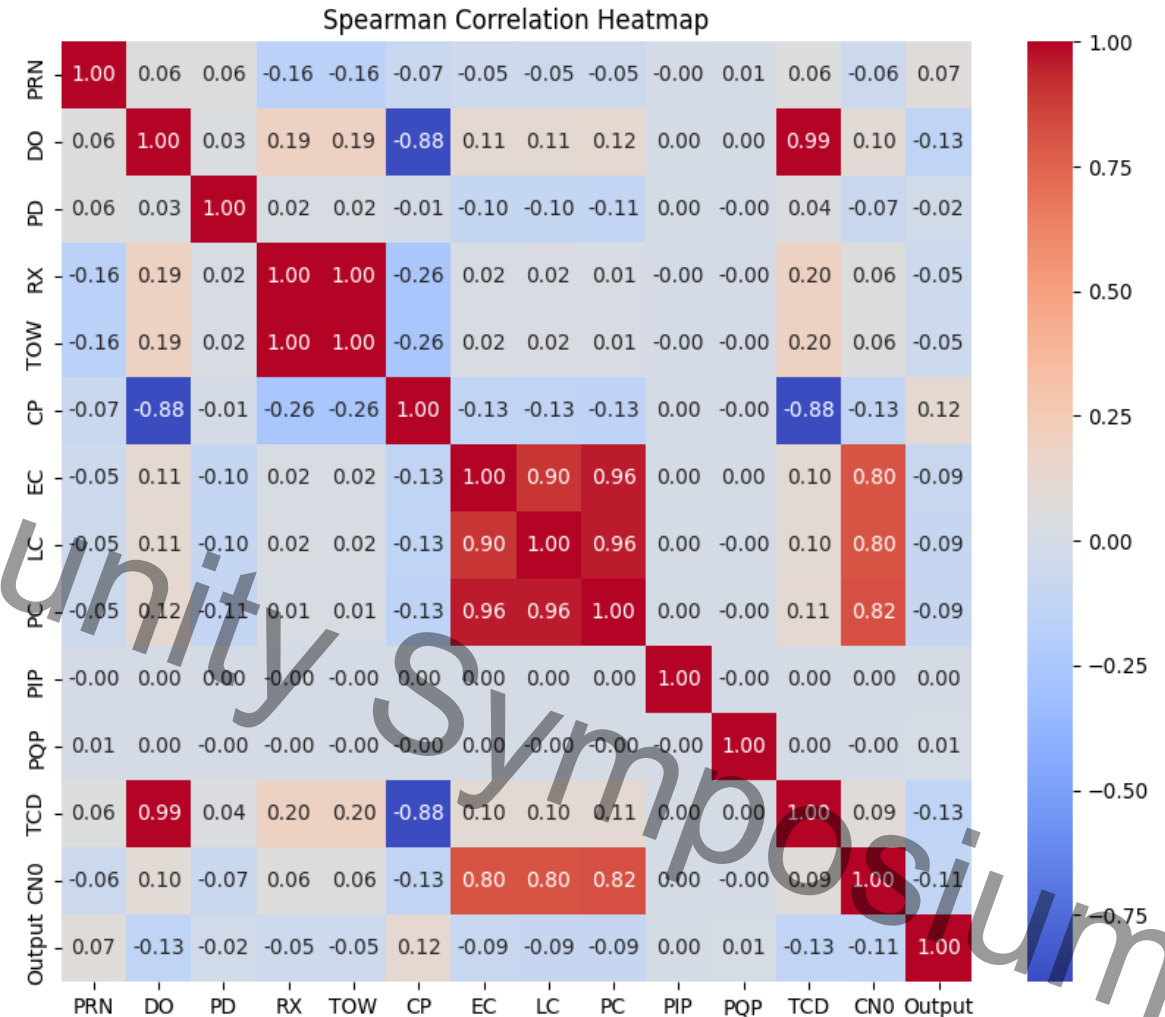
# Feature Filtering using Spearman's Correlation

## Feature Selection Filtering

Feature correlation using Spearman's Correlation

Highly correlated:

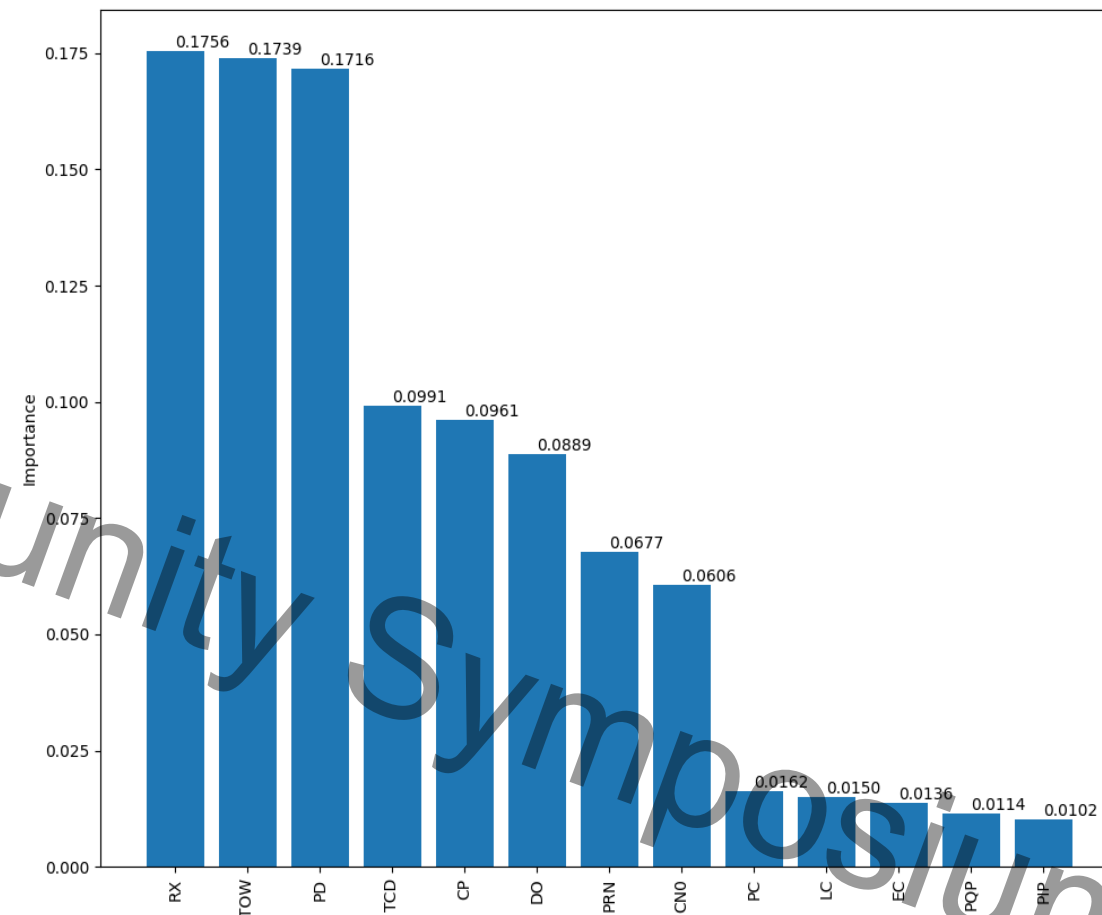
- (TCD, DO)
- (TOW, RX)
- (PC, EC)
- (PC, LC)
- (EC, LC)





# Feature Filtering using Gini Index

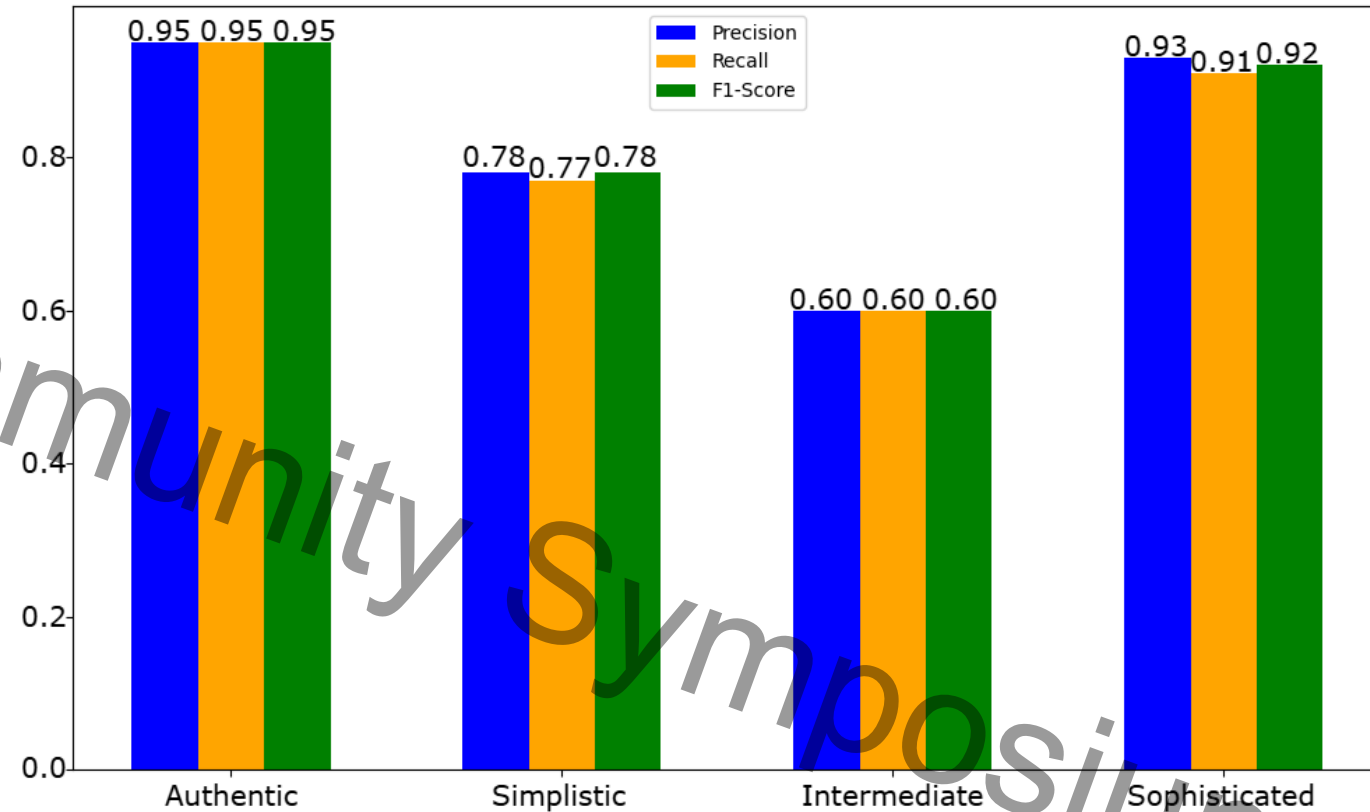
- Feature Importance Using Gini Index  
RX > TOW, TCD > DO, PC > LC, and PC > EC
- Removed the less important and highly correlated features: TOW, DO, LC, EC
- Selected Features: TCD, PRN, PD, RX, CP, PC, PIP, PQP, and C/N0



# Results : Scenario 2

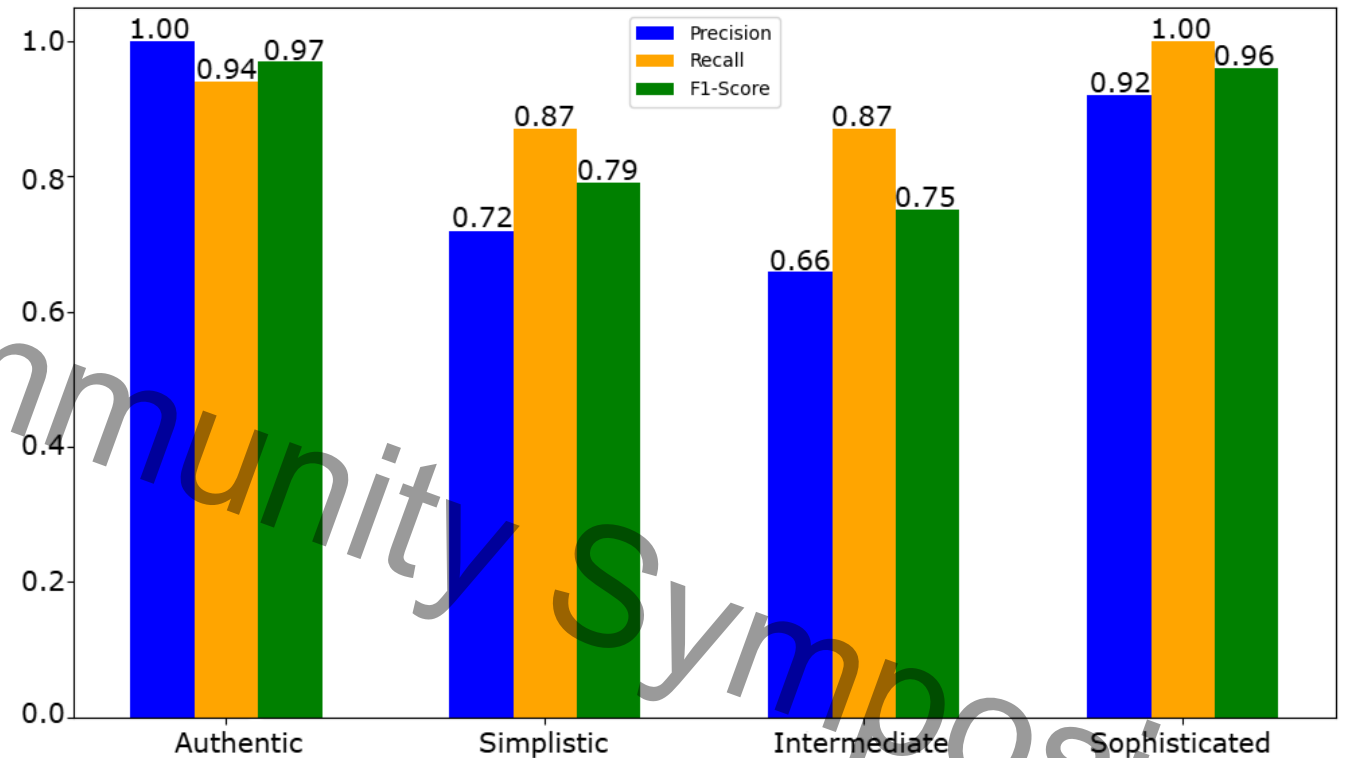
Was accurately able to distinguish authentic and sophisticated spoofed signals ( $>0.90$ )

Slightly improved performance in classifying simplistic ( $\sim 0.77$ ) and intermediate spoofed signals ( $\sim 0.60$ )



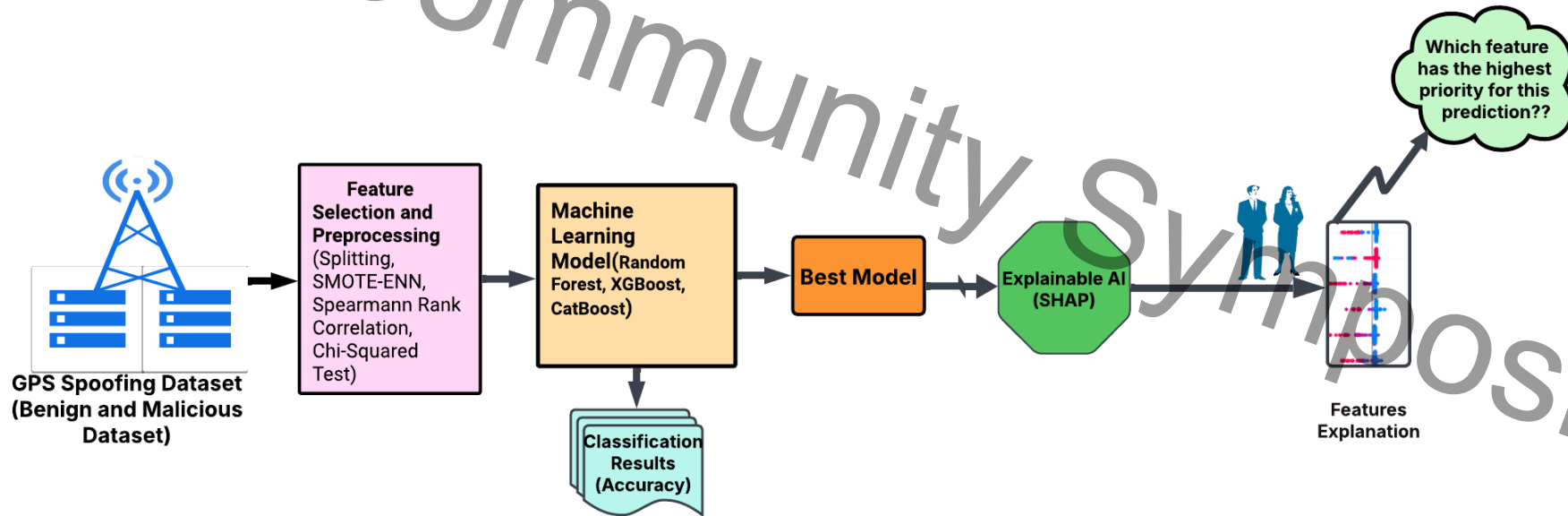
# Results: Scenario 3

- Improved classification of authentic and sophisticated signals ( $>0.95$ )
- Greatly improved metrics for simplistic and intermediate signals



# Explainability of GPS Spoofing Results

- Is the performance of ML model trustworthy?
- Which features contribute the most for the prediction of the performance of the ML model?



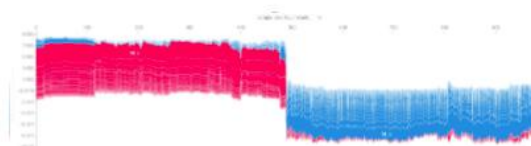
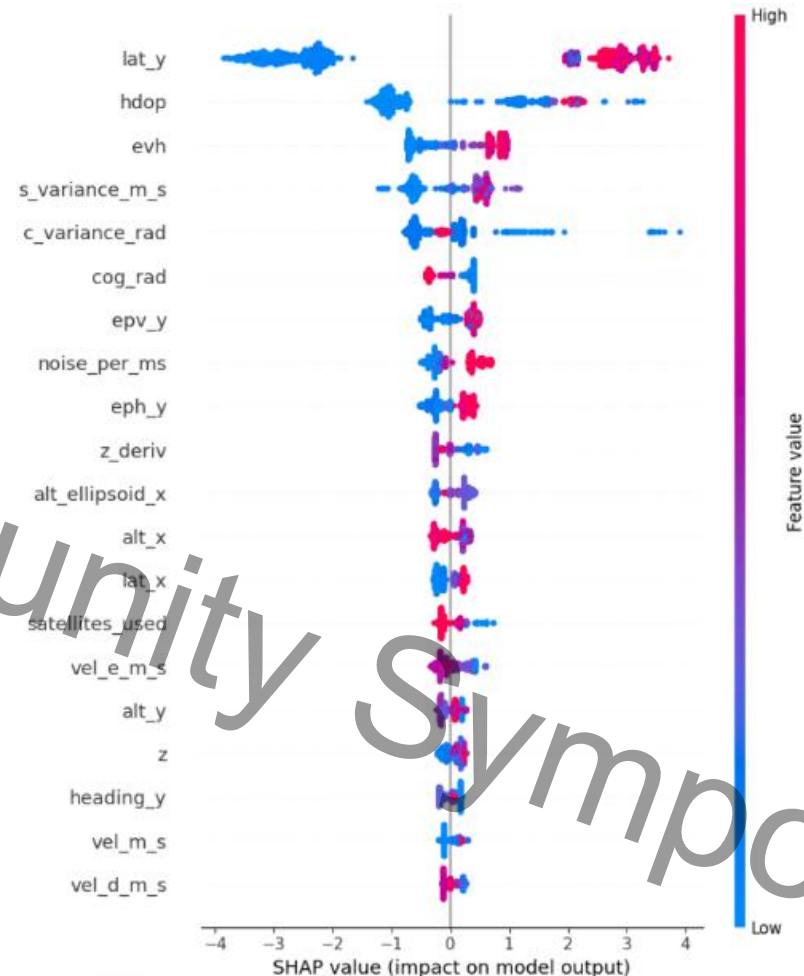


# Explainability of GPS Spoofing Results

Classifier	Hyperparameters	Accuracy (%)
<b>XGBoost</b>	n_estimators=50, max_depth=10, learning_rate=0.1, cv=5-fold	99.89
<b>Random Forest (RF)</b>	n_estimators=50, min_samples_split=10, min_samples_leaf=1, max_features=sqrt, max_depth=None	99.86
<b>CatBoost</b>	iterations=100, leaf_estimation_iterations=5, learning_rate=0.2, depth=6	99.87
<b>LightGBM</b>	metric=binary_logloss, learning_rate=0.05, feature_fraction=0.9, bagging_fraction=0.8, bagging_freq=5, objective=binary	99.87

## Extracted Feature

Short term	
hdop	Horizontal dilution of precision (Higher HDOP, lower the accuracy [37].
lat_y	ordinates(y axis position); Sudden changes in latitude may indicate errors.
evh	Elapsed Vehicle Hour; low EVH may indicate poor routing.
s_variance_m_s	Speed variance; may have speed fluctuation due to spoofing.
c_variance_rad	change in direction variance.
cog_rad	Course over ground in radians;direction of movement inconsistency .
epv_y	Vertical position error in y axis.
noise_per_ms	Signal noise per millisecond.
eph_y	Horizontal position error (y axis).
z_deriv	Change in altitude over time
alt_ellipsoid	Altitude in IE-3 above ellipsoid model(in millimeters).
alt_x	Altitude measurement; altitude measurement may altered by spoofing.
lat_x	latitude coordinate measurement; variation may cause by spoofing.
satellites_used	Number of satellites used for positioning; few satellites may have poor accuracy.
vel_e_m_s	GPS velocity in east direction; unusual speed may have spoofing.
alt_y	Measurement of altitude in y axis.
z	general altitude measurement
heading_y	direction of movement on the y axis; Inconsistent heading may have spoofing
vel_m_s	GPS ground speed.
vel_d_m_s	GPS Down velocity; large downward speeds manipulated signals.



# Gap in GPS Spoofing Detection

2025 CAE Community Symposium

Human factors aspect is often neglected, even though pilots are the integral part of aircraft operation and control!

# 2025 CAE Community Symposium

## Studying Pilot Reaction to GPS Spoofing

# Current CARS Flight Deck Equipment Benches

**Basic aircraft scenario using typical patch antenna.**

Center for Aerospace Resilient Systems (CARS) flight deck test bench during a GPS spoofing experiment (1).

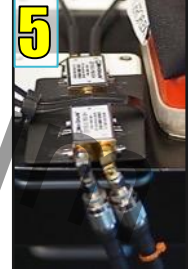
**3D position dynamically simulated via GPS/Galileo positional simulators (4).**

Multi-leg waypoint paths, SV modeling, SBAS for WAAS/EGNOS.

**Off-the-shelf King Air 200 and Citation Jet XLS avionics (1,3,7).**

“Real” signal from first GPS simulator while a spoofed signal is generated on a second.

Both signals are combined and fed to both GPS antennas on the aircraft. (2, 5).





# ACI Cyber Rodeo & CTF, Daytona Beach Campus

Capture The Flag Competition: Government / Industry / Students & Faculty



# Conclusion

- Machine Learning algorithms such as random forest and CatBoost are effective tools for spoofing detection
  - Provide approx. 99.89 % spoofing detection accuracy
- The result shows lat y, hdop, and evh are considered the three most important features having significant impact on model's prediction
- Additionally, pilot training is a critical aspect of mitigating GPS spoofing, as it enhances the ability to recognize and respond to spoofing attempts