

# ORBITAL ANOMALIES CLASSIFICATION BY MACHINE LEARNING TECHNIQUES

MARRAKECH

ضاید ربضاقاا قده اج

UNIVERSITÉ CADI AYYAD



H.IDELBACHA\*, O.Beltramo-Martin\*\*, M.Kaab\*, Z. Benkhaldoun\*, A.Boskri\*, and A. ABDOU\*
\*Cadi Ayyad University, Oukaimeden Observatory, Faculty of Sciences Semlalia, High Energy
Physics, Astrophysics and Geoscience Laboratory, Marrakech, Morocco
\*\*SpaceAble, Paris, France.

## Abstract

Given the continual increase in the number of satellites in orbit, there is an escalating need to enhance trajectory models and operational risk management to gain a deeper understanding of orbital anomalies, such as unexpected changes in a satellite's orbit, which can have a significant impact on satellite operations and threaten human and financial resources. This study aims to employ machine learning techniques to identify abnormal or divergent changes in satellite trajectories from datasets containing multiple sets of Two-Line Elements (TLEs). Once anomalies are detected, it is interesting to categorize them based on their causes using supervised machine learning methods, namely Random Forest, SVM, and artificial neural networks.

### Data Acquisition

The database consists of various Two-Line Elements (TLEs) of satellites classified as abnormal, encompassing all known satellite fragmentations. It is published by the NASA Johnson Space Center's Orbital Debris Program Office (ODPO). These anomalies fall into four distinct classes: Deliberate, Accident, Battery, and Propulsion.

#### Experiments & Methodology

We have chosen to use three different Machine Learning models for classification: Random Forest, Support vector Machines, and Neural network.

## **Results**

After data preprocessing, we train three models. The first step in evaluating their performance is constructing a confusion matrix, which summarizes the classification results on the test dataset. Additionally, various evaluation metrics, including precision, recall, and F1-score, are presented in the figure below.

Metrics Models	Accuracy	Precision	Recall	f1-score
$\mathbf{RF}$	91%	87 %	87%	86%
$\mathbf{SVM}$	86%	88%	87%	87%
MLP	84%	87%	87%	86%

## Conclusion

We used 70% training data and 30% test data to evaluate the effectiveness of different machine learning-based approaches. The overall accuracy, precision, recall, and F1-score were used to evaluate the results, as shown in Table above. As we see in Table above, The Random Forest method outperforms the others in overall accuracy. The three models achieved similar performance in terms of overall precision, recall, and F1-score.

## References

[1] Phillip Anz-Meador, John Opiela, and Jer-Chyi Liou.History of on-orbit satellite fragmentations. Technical report, 2023.

[2] Leo Breiman. Random forest, vol. 45. Mach Learn, 1, 2001.

[3] Hak-Keung Lam and Hung T Nguyen. Computational intelligence and its applications: evolutionary computation, fuzzy logic, neural network, and support vector machine techniques. World Scientific, 2012.