Logistic Regression Model For Predictive Classification Of State Space Object Registration Compliance Under The United Nations Registration Convention

Jennifer Patrick[1]
Advanced Space Technology Applications Laboratory Uyo,
National Space Research and Development Agency,
Federal Capital Territory, Abuja, Nigeria

Uchua Christiana Member[2]
Advanced Space Technology Applications Laboratory Uyo,
National Space Research and Development Agency,
Federal Capital Territory, Abuja, Nigeria

Bethel-Wali Joy U.[3]
Advanced Space Technology Applications Laboratory Uyo,
National Space Research and Development Agency,
Federal Capital Territory, Abuja, Nigeria

***Abstract*—Performance evaluation of Logistic Regression model for predictive classification of State space object registration compliance under the United Nations Registration Convention is presented. Specifically, the work employed three different versions of Logistic Regression model to classify the different States with launched space objects as compliant and non-compliant with respect to their respective space object registration status in line with the United Nation Registration Convention. The classification results for each launched space object were then used to determine the overall compliance level and non-compliance level of the State. A five consecutive years (2020–2024) dataset was used in the study. The dataset was obtained from the official database maintained in pursuant to the UN Convention on Registration of Objects Launched into Outer. The results of descriptive analysis of the case study dataset show that there is an average of 330 launched space objects per State, average of 321 registered and 18 unregistered space objects per State which amounted to average compliance level of 82.74% and average non-compliance level of 17.26 % over the five rears period studied. The classification results showed that the LR_Baseline model has the best overall classification performance with integrated performance value of 0.969575. The results of the compliance level prediction show that about 5 out of the 10 States categories listed in the case study dataset have 100 % compliance record. In addition, the State with identification number 6 had the lowest compliance level of 33.3 % and conversely, the highest non-compliance level of 66.6 %. The ideas presented in this study will facilitate further discussion on the United Nation Registration Convention and the way forward to enhance compliance among the member States.**

Keywords—Spacefaring States, Logistic Regression model, Space Law Compliance Prediction, Synthetic Minority Over-sampling Technique (SMOTE), United Nations Space Object Registration Convention

1. Introduction

The rapid proliferation of artificial space objects, driven by the emergence of mega-constellations, commercial space actors, and small satellites, has made the sustainable use of outer space a critical global issue [1,2]. The foundational legal framework governing this activity, the 1975 United Nations Registration Convention, mandates that States establish registries to identify objects, allocate jurisdiction, and, consequently, ensure liability [3,4]. While the Convention provides the legal basis for maintaining a central register via the UN Office for Outer Space Affairs (UNOOSA), the increasing complexity of modern space operations—including on-orbit transfers, joint launches, and rapid deployment of small satellites—has introduced significant challenges, resulting in gaps in compliance and, at times, a decline in registration rates [5,6,7].

Effective compliance with the Registration Convention is essential not only for space traffic management but also for international security and the mitigation of space debris [8,9]. However, the current voluntary nature of compliance timelines, often interpreted as "as soon as practicable" leads to lags in registration. Furthermore, the sheer volume of data makes it challenging to identify in real-time which space objects are compliant and which are not.

Despite the mandatory nature of the Convention, the percentage of compliance—defined as the timely, accurate registration of space objects by the responsible launching State—fluctuates, with evidence suggesting a decline in recent years [10,11]. The increasing number of "unregistered" objects, particularly in lower orbits, creates substantial risks to space sustainability. Existing approaches to monitoring this compliance are often reactive. There is a pressing need for a predictive, proactive method to identify, categorize, and classify the likelihood of compliance, allowing for the early identification of potential risks in space object registration [12,13].

Accordingly, this paper aims to address these challenges by applying and evaluating a machine learning approach to predict state compliance with the 1975 Registration Convention. Specifically, this study utilizes Logistic Regression, a robust and interpretable binary classification model suitable for determining whether a space object will be registered (compliant) or not (non-compliant) based on key predictors.

The research evaluates the performance of the logistic regression model by utilizing data on launch state, operator country, and satellite type as predictor variables and also by assessing the classification accuracy, precision, recall, and the area under the receiver operating characteristic (ROC) curve to determine model efficacy. The findings presented herein aim to catalyse further dialogue on the United Nations Registration Convention, offering a roadmap for improving State adherence to its provisions

2. Methodology

This work presents the methodological framework adopted to investigate the predictive classification of space object registration compliance under the United Nations Registration Convention. Specifically, the work employed three different versions of Logistic Regression model to classify the different States with launched space objects as compliant and non-compliant with respect to their respective space object registration status in line with the United Nation Registration Convention. Thereafter, the level of compliance is computed based on the sum of the discrete classification result for each of the space object of the State. The architecture of the Logistic Regression model is given in Figure 1.

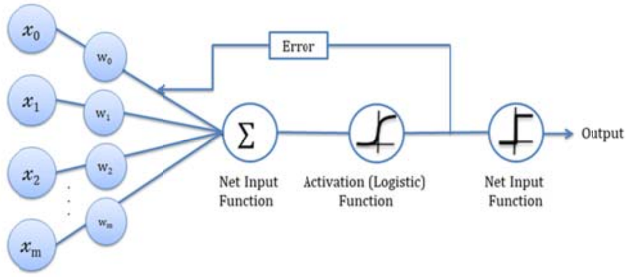
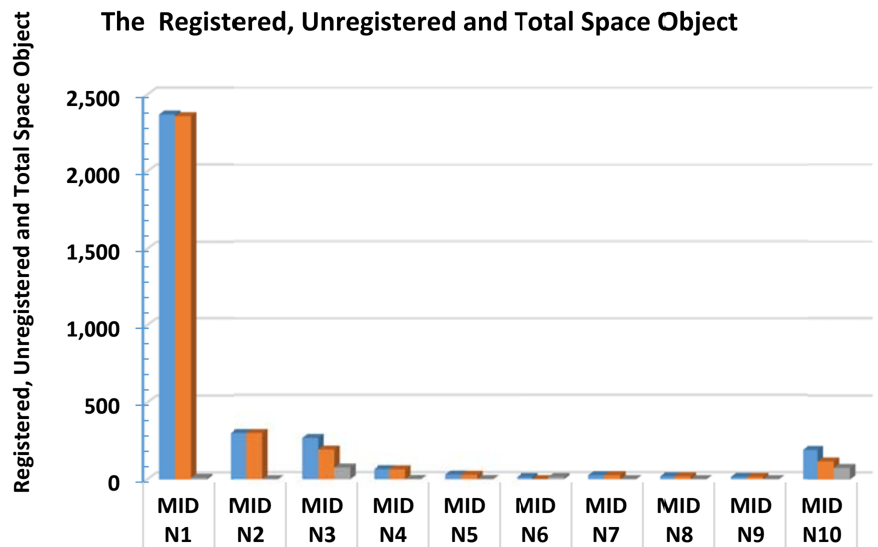


Figure 1 The architecture of the Logistic Regression model [14]

The study employed three configurations of classification for the Logistic Regression algorithm, which include the Baseline Logistic Regression (LR_Baseline), the Logistic Regression with SMOTE balanced dataset (LR_SMOTE) and Logistic Regression with Class Weight dataset (LR_ClassWeight). The Baseline Logistic Regression (LR_Baseline), is the case where the Logistic Regression is trained and validated using the case study dataset which is not subjected to any data balancing process. The Logistic Regression with SMOTE (LR_SMOTE) is the case where the dataset is balanced using the SMOTE approach. Lastly, the Logistic Regression Class Weight (LR_ClassWeight) is the version of the model where the data imbalance issue is addressed by using different weights for the majority and minority classes. The model implementation pipeline is entirely reproducible and executed in Python program.

This dataset used was obtained from the official database maintained in pursuant to the UN Convention on Registration of Objects Launched into Outer Space (1975) and General Assembly Resolution 1721B (XVI) [15,16,17]. The dataset comprises of annual records covering five consecutive fiscal cycles (2020–2024). The State listed in the dataset are encoded using MIDN which stands for model identification number. The summarized data records showing the registered, the unregistered and the total space object for the ten identified and encoded States with launched space objects within the study years is shown in Figure 2. Again, the procedure used to classify launched space objects and hence predict the compliance level and non-compliance level of the States with launched space objects is shown in Figure 3.



	MID N1	MID N2	MID N3	MID N4	MID N5	MID N6	MID N7	MID N8	MID N9	MID N10
Total Number of Space object	2,371	301	269	65	30	14	26	19	15	192
Number of Space object Registered	2,360	301	193	64	29	0	26	19	15	117
Number of Space object Unregistered	11	0	76	1	1	14	0	0	0	75

Figure 2 The Registered, Unregistered and Total Space Object

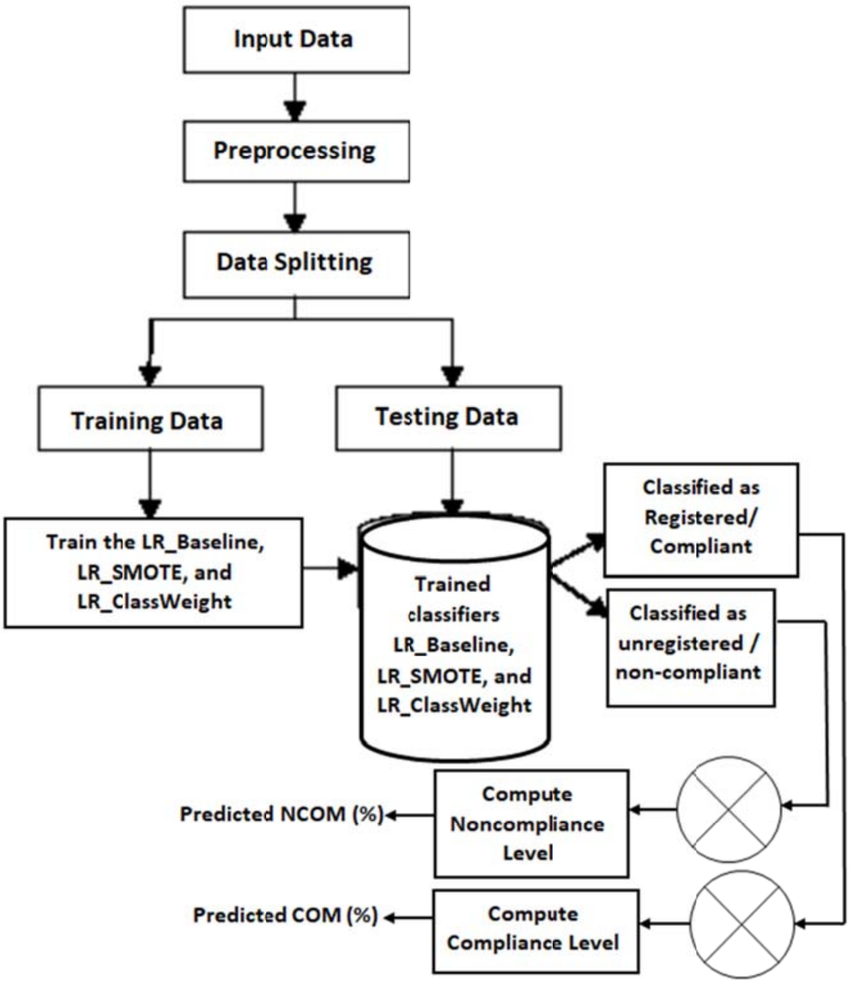


Figure 3 The procedure used to classify launched space objects and hence predict the compliance level and non-compliance level of the States with launched space objects

3. Results and Discussion

3.1 The results of the actual compliance and non-compliance level computation

The summary of the actual compliance and non-compliance computations conducted on the preprocessed five years (2020 to 2024) case study data compiled from the UNOOSA (United Nations Office for Outer Space Affairs) [18] Online Index Search portal (https://www.unoosa.org/oosa/osoindex/search-ng.jspx) is presented in Table 1. In the detailed dataset used, each of the State's launched space object has its separate record which is used to categories it as registered (compliant) or as unregistered (non-compliant). In Table 1, the States in the original dataset are represented by Model Identification number (MIDN). The results show that there is an average of 330 launched space objects per State, average of 321 registered and 18 unregistered space objects per State which amounted to average compliance level of 82.74% and average non-compliance level of 17.26 % over the five rears period studied.

Table 1 The summary of the five years (2020 to 2024) case study data results for compliance and non-compliance level for each of the encoded State

MIDN (Model Identification number) for the State / Organisation	Total Number of Space object	Number of Space object Registered	Number of Space object Unregistered	Non-Compliance Level, NCOM (%)	Compliance Level, COM (%)
MIDN1	2,371	2,360	11	0.46%	99.54%
MIDN2	301	301	0	**0.00%**	**100.00%**
MIDN3	269	193	76	**28.25%**	**71.75%**
MIDN4	65	64	1	1.54%	98.46%
MIDN5	30	29	1	3.33%	96.67%
MIDN6	14	0	14	**100.00%**	**0.00%**
MIDN7	26	26	0	**0.00%**	**100.00%**
MIDN8	19	19	0	**0.00%**	**100.00%**
MIDN9	15	15	0	**0.00%**	**100.00%**
MIDN10	192	117	75	**39.06%**	**60.94%**
MEAN	330	312	18	**17.26%**	**82.74%**

3.2 The classification results of the three Logistic Regression classification model configurations

The results for the three Logistic Regression model configurations and presented present a clear gradient from conservative (LR_Baseline) to aggressive minority-class orientation (LR_SMOTE and LR_ClassWeight).

3.2.1 The results for the Baseline Logistic Regression (LR_Baseline) Model

The results for the Baseline Logistic Regression (LR_Baseline) model is presented in Table 2 and Figure 4. The LR_Baseline achieves a Class 0 F1 of 0.7059 (Precision = 0.7500, Recall = 0.6667), correctly identifying 24 of 36 non-compliant objects while generating 8 false alarms against the registered class. Class 1 performance is strong (F1 = 0.9838, Precision = 0.9804, Recall = 0.9872), reflecting the model's natural tendency to over-predict the majority class. The ROC-AUC of 0.9793 indicates strong ranking ability despite the suboptimal decision boundary calibration.

Table 2: The LR_Baseline Classification Results (Test Set, n = 661)

Class	Precision	Recall	F1-Score	Support	Accuracy	ROC-AUC
Class 0 — Unregistered (Non-Compliant)	**0.7500**	**0.6667**	**0.7059**	**36**	**0.9697**	**0.9793**
Class 1 — Registered (Compliant)	0.9804	0.9872	0.9838	625		
Macro Average	*0.8652*	*0.8270*	*0.8449*	*661*	—	—
Weighted Average for the LR_Baseline	*0.9695*	*0.9697*	*0.9694*	*661*	—	—

Where Class 0 = Unregistered (Non-Compliant, n = 36). Class 1 = Registered (Compliant, n = 625). Accuracy and ROC-AUC are model-level statistics.

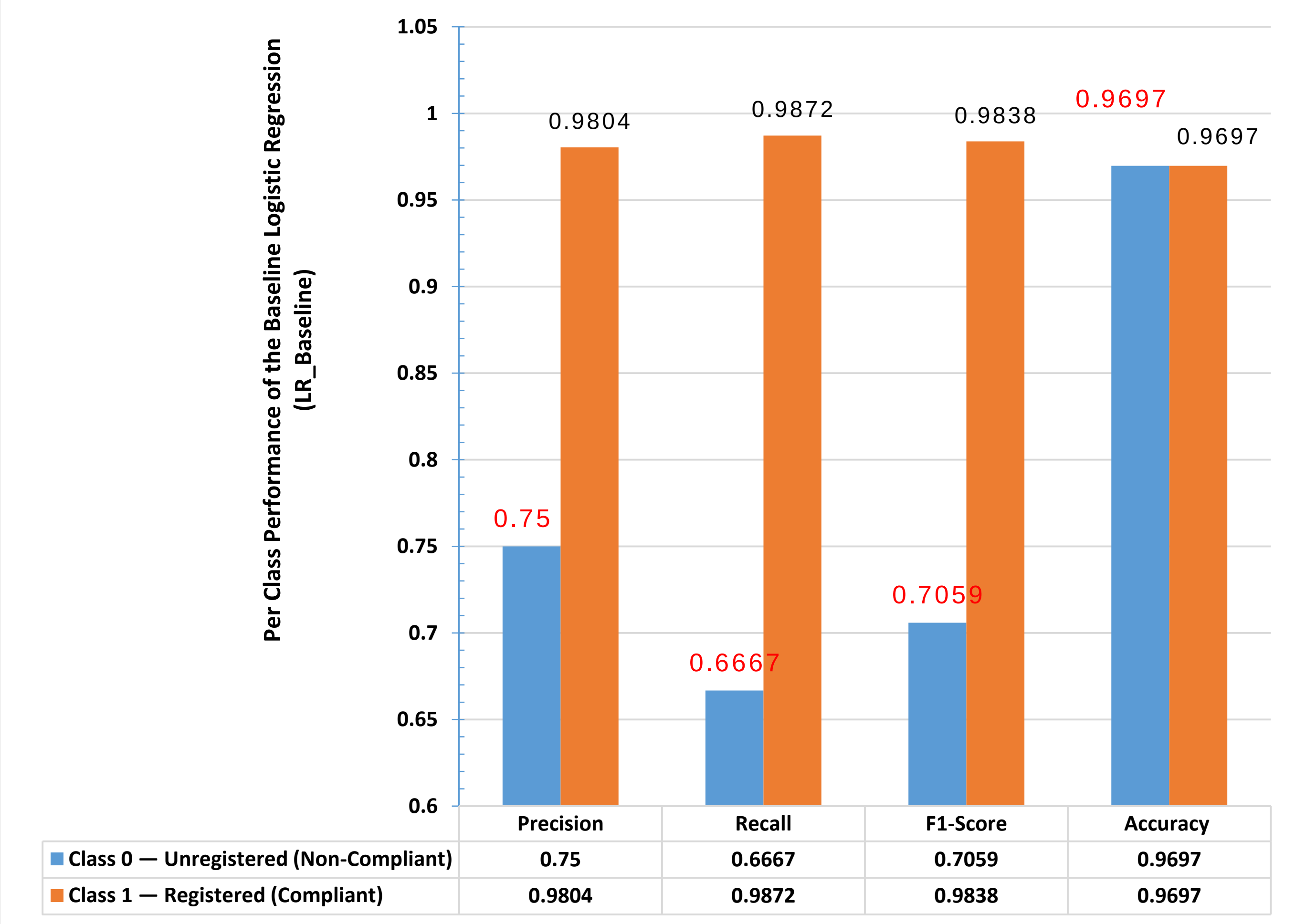


Figure 4 The Per Class Performance of the Baseline Logistic Regression (LR_Baseline)

3.2.2 The results for the Logistic Regression Model with SMOTE balanced dataset (LR_SMOTE)

The results for the Logistic Regression Model with SMOTE balanced dataset (LR_SMOTE) is presented in Table 3 and Figure 5. The results show that the LR_SMOTE achieves high Class 0 Recall value (0.9722), correctly flagging 35 of 36 non-compliant objects. However, Precision falls sharply to 0.4321, as 46 of the 625 registered objects are incorrectly classified as non-compliant. The Class 1 Recall drops to 0.9264 as a result. The macro-averaged F1 of 0.7796 masks this severe Class 0 precision deficit.

Table 3: Classification Report — LR_SMOTE (Test Set, n = 661)

Class	Precision	Recall	F1-Score	Support	Accuracy	ROC-AUC
Class 0 — Unregistered (Non-Compliant)	**0.4321**	**0.9722**	**0.5983**	**36**		**0.9814**
Class 1 — Registered (Compliant)	0.9983	0.9264	0.9610	625		
Macro Average	*0.7152*	*0.9493*	*0.7796*	*661*	—	—
Weighted Average for the LR_SMOTE	*0.9714*	*0.9289*	*0.9424*	*661*	—	—

Note: LR_SMOTE achieves high Class 0 Recall at the cost of 46 false alarms — flagging 7.4% of compliant objects as non-compliant.

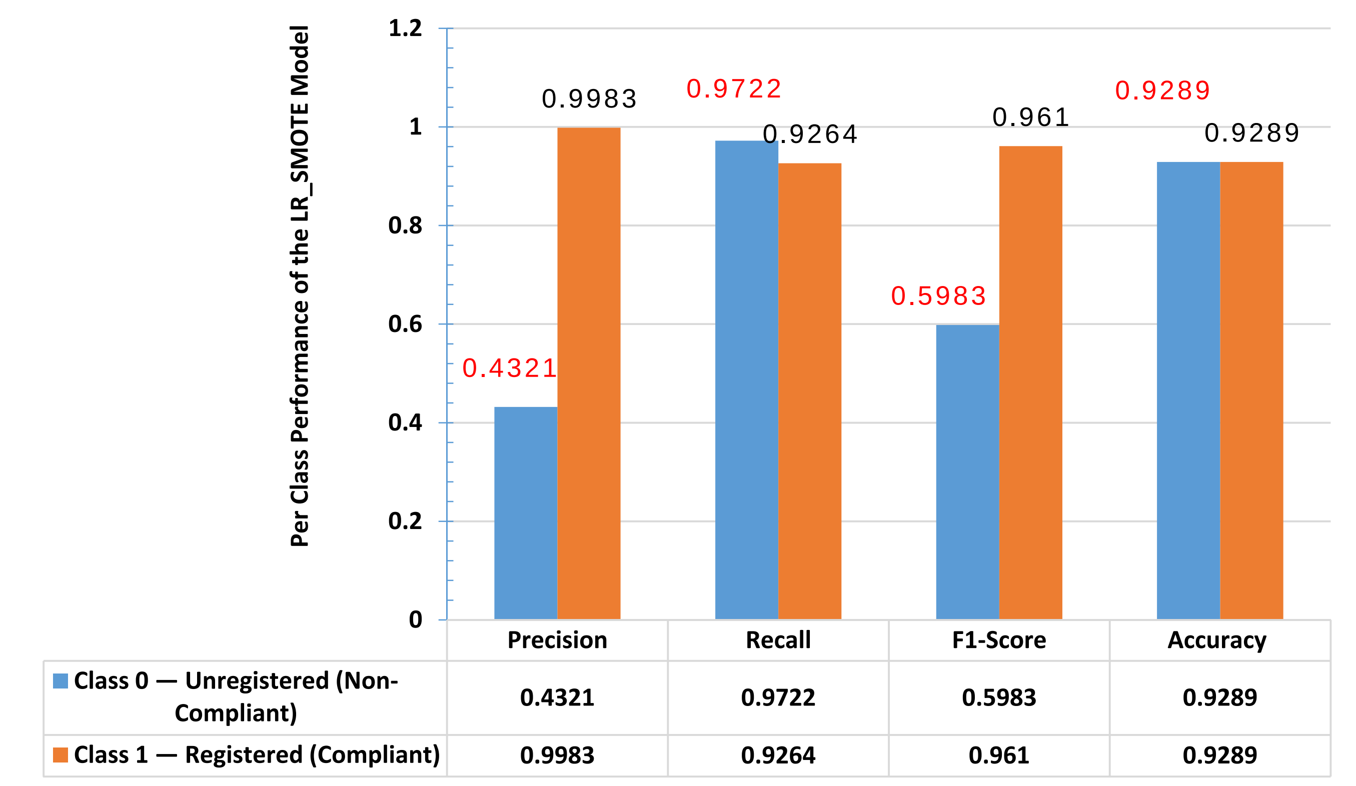


Figure 5 Per Class Performance of the LR_SMOTE Model

3.2.3 The results for the LR_ClassWeight — Classification Report

The results for the LR_ClassWeight is presented in Table 4 and Figure 6. The results show that the LR_ClassWeight produces results identical to LR_SMOTE on the test set (Class 0 F1 = 0.5983, Recall = 0.9722, Precision = 0.4321). This convergence reflects a structural feature of Logistic Regression: both SMOTE and class weighting shift the effective decision threshold in the same direction — toward more aggressive minority-class prediction — and the magnitude of this shift is sufficient in both cases to produce the same prediction boundary on this test partition.

Table 4: Classification Report — LR_ClassWeight (Test Set, n = 661)

Class	Precision	Recall	F1-Score	Support	Accuracy	ROC-AUC
Class 0 — Unregistered (Non-Compliant)	0.4321	0.9722	0.5983	36	0.9289	0.9812
Class 1 — Registered (Compliant)	0.9983	0.9264	0.9610	625		
Macro Average	*0.7152*	*0.9493*	*0.7796*	*661*	—	—
Weighted Average for the LR_ClassWeight	*0.9714*	*0.9289*	*0.9424*	*661*	—	—

Note: LR_ClassWeight and LR_SMOTE produce identical test-set predictions. Both sacrifice Class 1 Recall (0.9264) to maximise Class 0 Recall (0.9722).

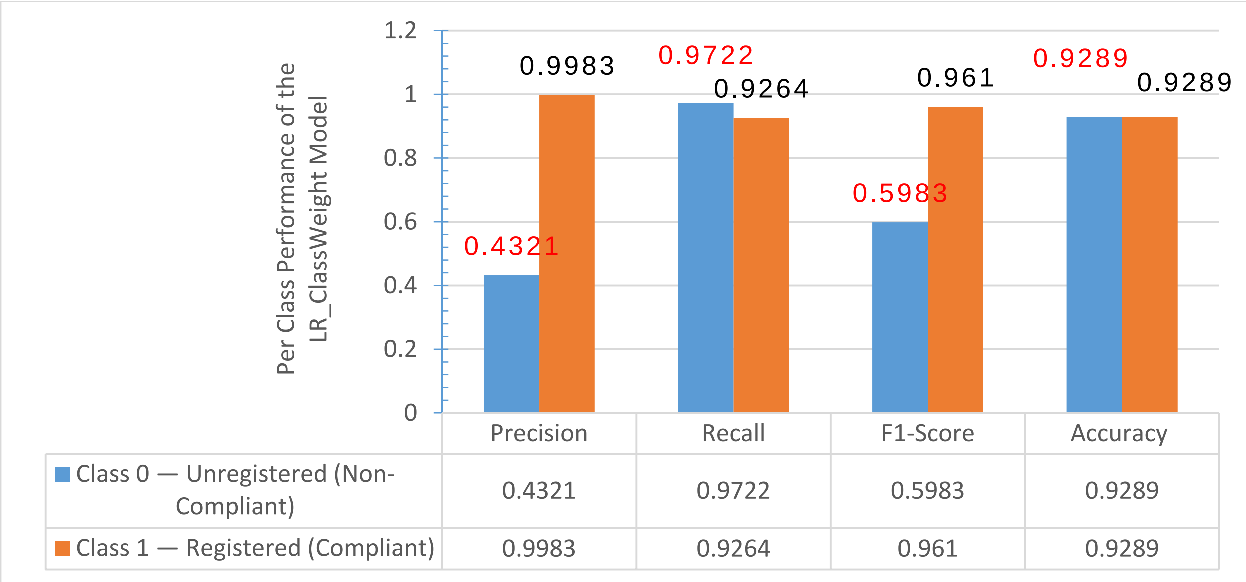


Figure 6 Per Class Performance of the LR_ClassWeight Model

3.2.4 The overall classification performance of the three Logistic Regression classification model configurations

The results of the overall classification performance of the three Logistic Regression classification model configurations are presented in Table 5 and Figure 7.The results showed that the LR_Baseline model has the best overall classification performance with integrated performance of 0.969575. The other two models have the same performance values. Consequently, the LR_Baseline model is selected for the compliance level prediction. The results of the actual and the LR_Baseline predicted compliance and non-compliance levels are presented in Table 5, Figure 8 and Figure 9.

The results of the compliance level prediction show that State 6 has the lowest compliance level of 33.3 % and conversely, the non-compliance level of 66.6 %. Also, about 5 out of the 10 States categories considered have 100 % compliance record.

Table 5: The overall classification performance of the three Logistic Regression classification model configurations

Class	Precision	Recall	F1-Score	Accuracy	Integrated Performance (Mean of the 4 Metrics)
Weighted Average for the LR_Baseline	*0.9695*	*0.9697*	*0.9694*	**0.9697**	**0.969575**
Weighted Average for the LR_SMOTE	*0.9714*	*0.9289*	*0.9424*	**0.9289**	**0.9429**
Weighted Average for the LR_ClassWeight	*0.9714*	*0.9289*	*0.9424*	0.9289	**0.9429**

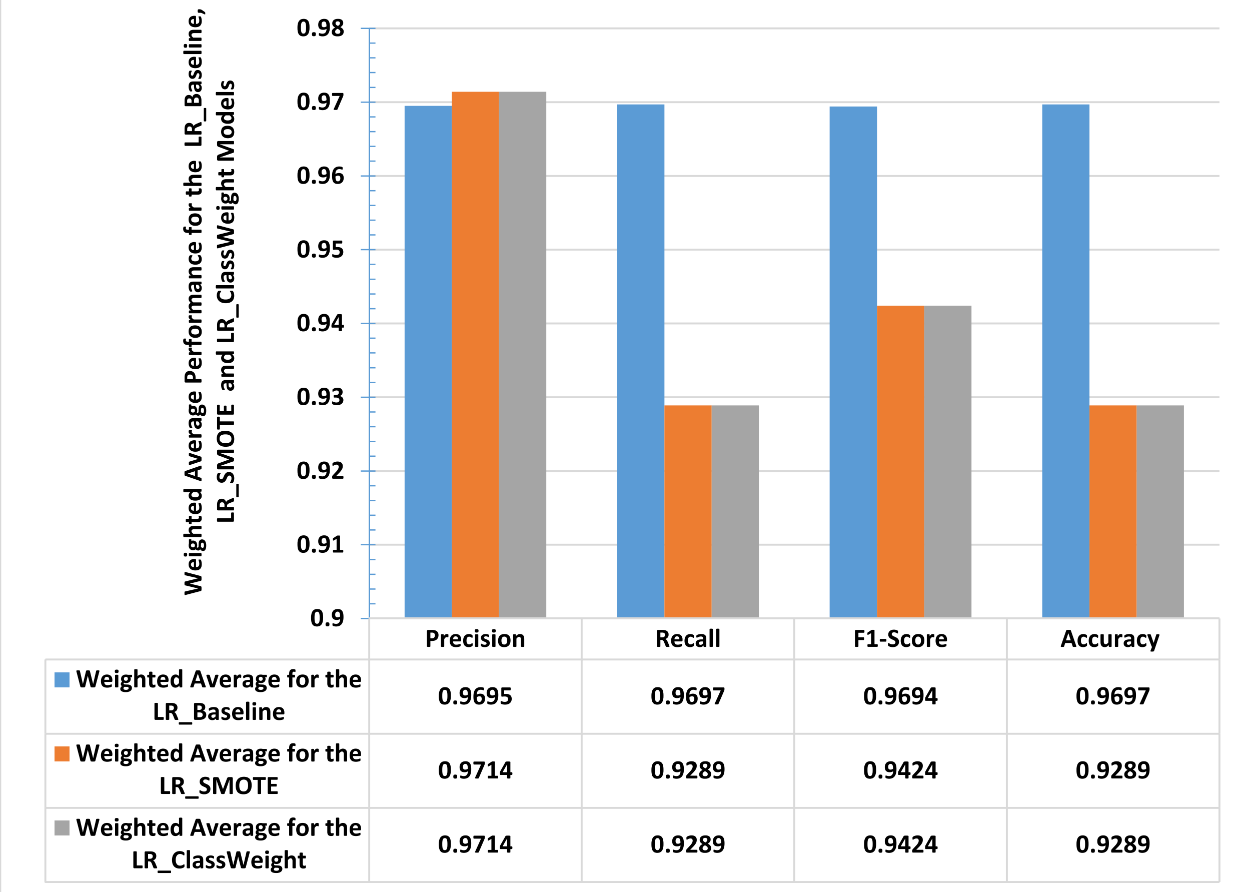


Figure 7 The Weighted Average Performance for the LR_Baseline, LR_SMOTE and LR_ClassWeight Models

Table 6 The actual and the LR_Baseline predicted compliance and non-compliance levels

State / Organisation Model Identification Number (MIDN)	Actual NCOM (%)	Actual COM (%)	Predicted NCOM (%)	Predicted COM (%)
MIDN1	0.46%	99.54%	**0.00%**	**100.00%**
MIDN2	**0.00%**	**100.00%**	**0.00%**	**100.00%**
MIDN3	**28.25%**	**71.75%**	21.31%	78.69%
MIDN4	1.54%	98.46%	**0.00%**	**100.00%**
MIDN5	3.33%	96.67%	**0.00%**	**100.00%**
MIDN6	**100.00%**	**0.00%**	**66.67%**	**33.33%**
MIDN7	**0.00%**	**100.00%**	**50.00%**	**50.00%**
MIDN8	**0.00%**	**100.00%**	**50.00%**	**50.00%**
MIDN9	**0.00%**	**100.00%**	**0.00%**	**100.00%**
MIDN10	**39.06%**	**60.94%**	**35.90%**	**64.10%**

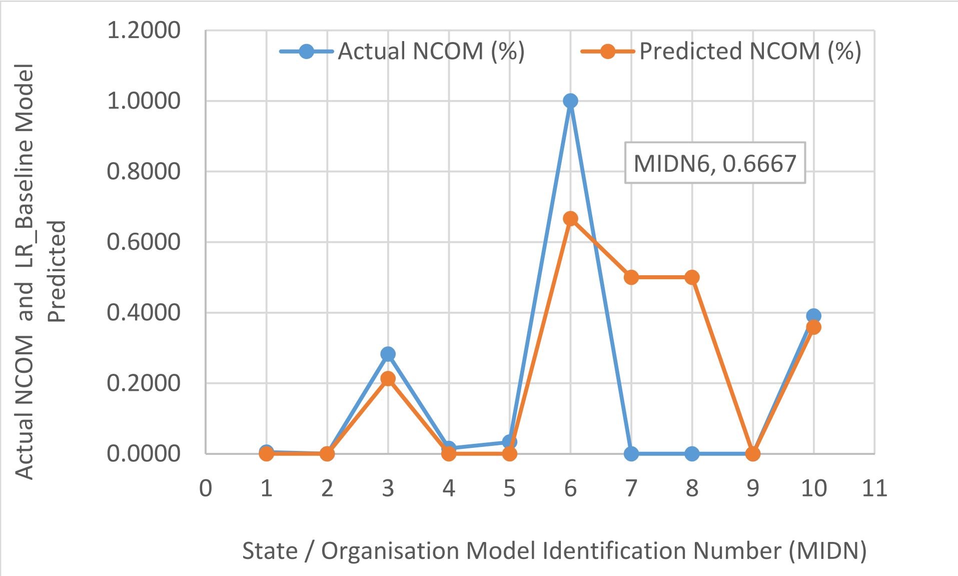


Figure 8 The Actual NCOM and LR_Baseline Model Predicted NCOM

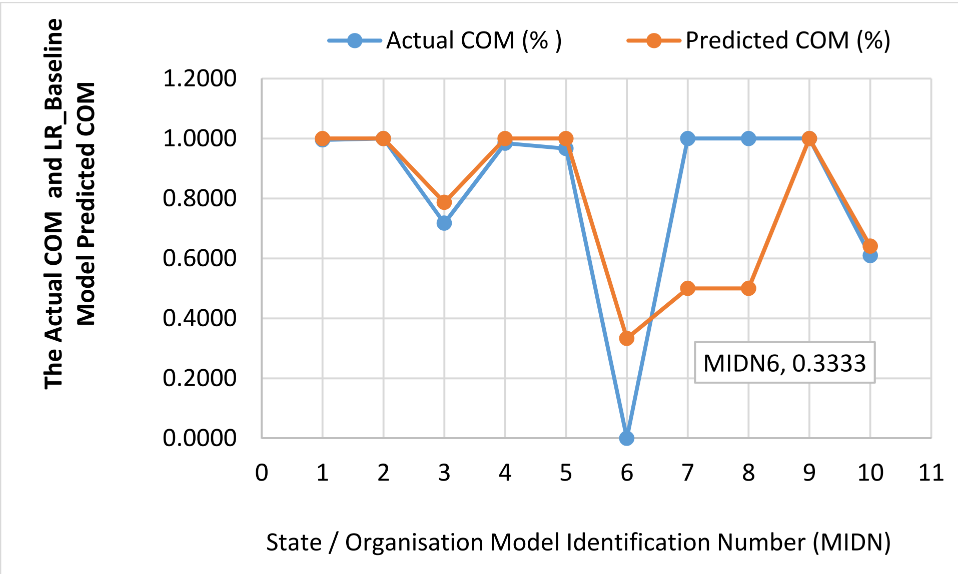


Figure 9 The Actual COM and LR_Baseline Model Predicted COM

4. Conclusion

The study supervised learning approach to classify and hence predict the compliance level of State to the space object registration requirement based on the United Nations Registration Convention. Specifically, three different versions of Logistic Regression model are employed to classify the different States with launched space objects as compliant and non-compliant with respect to their respective space object registration status in line with the United Nation Registration Convention. The study utilized 5 year data records and the results showed that the baseline configuration of the Logistic Regression model gave the best classification results and hence was selected as the best model. The overall compliance and non-compliance level was then computed for each of the States studied and the results showed that while about 50 percent of the States have fully complied with the UN conventions, few States are still maintaining high level of non-compliance status. The ideas presented in this study will facilitate further discussion on the United Nation Registration Convention and the way forward to enhance compliance among the member States.

References

1. Erkel, D. (2023). *The success of emerging space actors: effective strategies in the NewSpace Era* (Doctoral dissertation, Massachusetts Institute of Technology).

2. DE, L. S. Y. L. S., & ÓRBITA, L. (2024). AI in outer space: reinforcing the sustainability and safety of the low-earth orbit in the new space era. *Revista Española de Derecho Aeronáutico y Espacial*, 195.

3. Becerra, J., Martinez, J. R., & Almario, D. (2016). The convention on registration of objects launched into outer space and its implementation in Colombia's national legal system. In *Proceedings of the international institute of space law*.

4. Jakhu, R. S., Jasani, B., & McDowell, J. C. (2018). Critical issues related to registration of space objects and transparency of space activities. *Acta Astronautica*, *143*, 406-420.

5. O'Donnell, S. S. (2023). *International Responsibility for Activities in Outer Space in the Modern Space Age: Article VI of the Outer Space Treaty in the context of international space law and public international law* (Vol. 1). Lund University.

6. Hasin, G. (2023). From" space law" to" space governance": A policy-oriented perspective on international law and outer space activities. *Harv. Int'l LJ*, *64*, 385.

7. Sanchez, M. (2025). Advancements in space law: Satellite communications industry regulations and obligations for orbital debris mitigation. *International Journal of Legal Information*, *53*(1), 52-63.

8. Frandsen, H. O. (2022). Looking for the rules-of-the-road of outer space: A search for basic traffic rules in treaties, guidelines and standards. *Journal of Space Safety Engineering*, *9*(2), 231-238.

9. Yang, K., & Wu, Y. (2023). Improving international governance of space debris in the era of large constellations of small satellites and China's response. *Advances in Space Research*, *72*(7), 2607-2615.

10. Cinelli, C. (Ed.). (2024). *Regulation of outer space: international space law and the state*. Taylor & Francis.

11. Nunes Tartari, P. (2022). Outer Space Regime and the Issue of Space Debris, An analysis on the Committee on the Peaceful Uses of Outer Space on space debris from 2006 to 2019.

12. Ogedengbe, A. O., Jejeniwa, T. O., Olawale, H. O., Friday, S. C., & Ameyaw, M. N. (2023). Enhancing Compliance Risk Identification Through Data-Driven Control Self-Assessments and Surveillance Models.

13. Patnala, S., & Abdin, A. (2024). Spacecraft collision avoidance: Data management, risk assessment, decision planning models and algorithms. In *Space Data Management* (pp. 15-45). Singapore: Springer Nature Singapore.

14. Hossain, M. S., & Arefin, M. S. (2019). Development of an Intelligent Job Recommender System for Freelancers using Client's Feedback Classification and Association Rule Mining Techniques. *J. Softw.*, *14*(7), 312-339.

15. Jasentuliyana, N. (2023). *International space law and the United Nations*. Brill.

16. Marinich, V. K., & Myklush, M. I. (2023). Space Law, Subjects and Jurisdictions: pre-1963 period.

17. Hurwitz, B. A. (2024). *State liability for outer space activities: in accordance with the 1972 Convention on International Liability for Damage Caused by Space Objects*. Martinus Nijhoff Publishers.

18. Millwood, S. (2023). *The urgent need for regulation of satellite mega-constellations in outer space*. Springer.