Satellite Orbit Prediction using a Machine Learning Approach

Giridhar Jadala*, Gowri Namratha Meedinti and Radhakrishnan Delhibabu

Vellore Institute Of Technology, Vellore, India

Abstract

The most cutting-edge approaches for orbit prediction right now use physics-based models, which call for exceedingly precise information about the object's trajectory, its operating environment, and its intended course of action. We don't actually have access to this information. Our knowledge of space weather and air density is limited, trajectories are only seldom obtained from noisy ground-based radar systems, and satellite operators are reluctant to disclose their maneuvering intentions. Current orbit predictions that are only based on physics-based models may not achieve the required accuracy for collision avoidance and have already resulted in satellite collisions due to the lack of information regarding the state of the space environment and resident space objects' (RSOs') body characteristics. Two line element sets(TLE) made accessible to the public lack any related error or correctness information. The majority of TLE prediction techniques used today fit polynomials, which cannot capture periodic properties. This paper has presented a methodology for orbital prediction using curve fitting and LSTM on historical orbital data. The proposed machine learning approaches are used with various TLE parameters where the LSTM model is trained to learn through large amounts of historical TLE data. The fitted data is synthesized and then compared with the SGP4 predictions. The two proposed methods focus on reducing prediction errors. The results of the study demonstrate that the proposed machine learning approaches can improve orbital prediction accuracy with good performance in most cases. We go into further optimization and the computing needs for using all-on-all conjunction analysis on the whole TLE collection and visualize when and where conjunction may occur, both currently and in the near future.

Keywords

TLE, SGP4, Orbit, Prediction, Satellite Collisions, LSTM, Curve Fitting

1. Introduction

Spacecraft, astronauts, and the global commons of near-earth space are all at risk from collisions in orbit. Several collisions between spacecraft and debris have already occurred, with the Iridium 33/Cosmos 2251 collision in January 2009 being the first known satellite-satellite collision. The total number of collisions so far is consistent with the foresight of the runaway chain reaction [1].

The number of resident space objects (RSOs) is fast increasing, as is the frequency of collision warnings between RSOs. Improved orbit prediction accuracy is a major challenge for Space Situational Awareness (SSA). Iridium 33 and Cosmos 2251 collided in 2009, revealing the lack

ICAIW 2022: Workshops at the 5th International Conference on Applied Informatics 2022, October 27–29, 2022, Arequipa, Peru

*Corresponding author

jadala.giridhar2019@vitstudent.ac.in (G. Jadala); gowri.namratha2019@vitstudent.ac.in (G. N. Meedinti); r.delhibabu@vit.ac.in (R. Delhibabu)

of high-accuracy orbit prediction capability [2]. The majority of existing orbit prediction methods are physics-based. Fundamentally, the failure is due to a lack of required data, such as the state of the space object at the start of trajectory computation, environmental conditions such as atmospheric drag and solar radiation pressure, RSO body characteristics such as mass, geometry, and material, and maneuvering object intent information. Their success is contingent on a thorough understanding of forces including Earth's gravity, atmospheric drag, and solar radiation pressure. For high-accuracy forecasts, the RSO's maneuvering information, geometric information, and other aspects are also required. The analytical model is well-developed, but the RSO's data is limited or difficult to obtain. Satellite collision would produce orbiting fragments, every of which might increase the chance of more collision, resulting in the expansion of belt trash around the earth. Increased in-order collisions easily can reach the collisional cascading point called "Kessler's syndrome", because the random collision frequency is non-linear with debris accumulation rates, the development can eventually become the foremost necessary long supply of debris accumulation rates unless the buildup rate of larger, non-operational objects in earth orbit was considerably reduced.

In comparison to the physics-based method, machine learning (ML) offers a new modeling and prediction path. Without specifically describing the geometry of RSOs, movements, or the space environment, the forecast can be made. Instead, the models are created using a significant amount of historical data, much like how humans learn from their past experiences to predict future events. Machine learning approaches have proven their worth in a variety of applications [3], with many in the aerospace field [4, 5].

The orbits of RSOs are continually developing and are impacted by both conservative and non-conservative processes. As a result, learning orbit prediction errors is distinct from, and perhaps more difficult than, many other machine learning problems. Nonetheless, we believe that part of the information can be learned because the prediction mistakes are implicitly included in RSOs' historical data, such as measurements, estimations, and predictions errors. The orbits of tracked RSOs around Earth are specified and updated in the US space catalog as TLEs. TLE data is readily available for satellite owners and operators at Space-Track.Org published by US strategic command (USSTRATCOM). Numerous space companies (private and government) are launching their satellites into orbit for advancement in space exploration and communication. These satellite companies have inadequate technology and procedures to avoid close encounters between objects. So the only source of information at their fingertips from the spec of paint to the international space station is the publicly available TLE data. NORAD two-element sets are used for increasing the number of satellite operations and analyses. General perturbation element sets generated by NORAD can be used to predict the position and velocity of earth-orbiting objects. Around five mathematical models for the prediction of satellite position and velocity are available. Among these SGP4 model is widely used to generate NORAD element sets. It was developed by Kencrankford in 1970 and is used for near-earth satellites [6]. The analytical SGP4 model is computationally fast and efficient however its advantage within the computation potency is shaded by a lack of high accuracy in propagated orbits [7]. So operators can use the SGP4 algorithm to address this issue interestingly we demonstrated two machine learning approaches for predicting and improving RSOs orbit information.

The machine learning methodology provides unique modeling and prediction capability compared to physics-based approaches. One of the approaches used is based on various TLE parameters such as Inclination (i) is an independent mean element of a TLE that defines the orientation of the orbital plane with respect to the Earth [8]. The right ascension of the ascending node (ω) is a mean element of a TLE that defines the orientation of an orbit with respect to the ^z axis, which is parallel to the rotation axis of the Earth [8], Argument of perigee (ω) is a mean element of a TLE that defines the orientation of the orbital plane with respect to the Earth around the axis parallel to the angular momentum vector of the orbit, Mean anomaly (m) is a mean element of a TLE that defines the position of a space object in its orbit [8], eccentricity (e) is a mean element of a TLE that defines the shape of the orbit while semi-major axis (a) defines the size of the orbit, mean motion (n) is one of the 6 independent mean elements, which include the inclination, right ascension of the ascending node, the argument of perigee, mean anomaly and eccentricity, that is required for computations of TLEs [9]. Curve fitting is used for some parameters such as right ascension of the node, argument of pedigree, mean anomaly, and eccentricity, to look at the standardized data and extract physical parameters. Curve fitting tries to adjust a smooth and balancing model function to provide the best-optimized fit for the data. A non-linear least square minimization process is used to find a plausible minimization quantity. LSTM layers are used to fit the data of some TLE parameters as these are more efficient in the case of time series data. First, the model is trained with historical TLE data, and then validation is done which outputs loss value and metric values for the model. Finally, the actual predictions for the future epochs which output the fitted data with higher accuracy, and then new synthesized TLE can be computed. This work considers each orbital parameter individually. LSTM networks are a sort of recurrent neural network that can learn order dependence in sequence prediction issues. This is an essential behavior in difficult problem areas like machine translation, speech recognition, and more complex problems such as orbital prediction.

The prime contributions of this study are summarised as follows:

- Using LSTM and curve fitting for making predictions of satellite's TLE (The proposed ML approach orbit is closer to the true orbit. This concept is illustrated in Figure 1).
- Obtaining a comparable accuracy to the SGP4 model.

2. Background

2.1. SGP4

Simplified perturbation models (SGP, SGP4, SDP4, SGP8, and SDP8) are a series of five mathematical models for calculating orbital state vectors of satellites and space debris relative to the Earth-centred inertial coordinate system. Because of its widespread use, especially with two-line element sets provided by NORAD and NASA, this group of models is commonly referred to as SGP4.

The influence of perturbations induced by the Earth's form, drag, radiation, and gravitational forces from other bodies such as the sun and moon is predicted by these models. Simplified General Perturbations (SGP) models are used to calculate the orbital period of near-earth objects having orbital periods of less than 225 minutes. Simplified Deep Space Perturbations (SDP) models are applicable to objects with an orbital period of more than 225 minutes, which corresponds to an altitude of 5,877.5 km in a circular orbit.

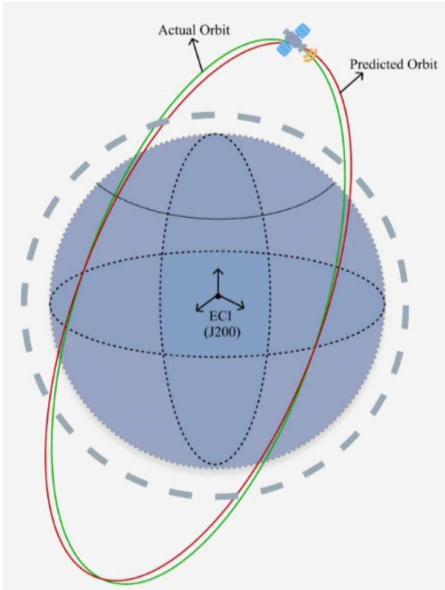

Figure 1: Predicted ML approach orbit vs Actual Orbit

The TLE sets include mean orbital elements that were derived by specifically eliminating periodic fluctuations. These periodic changes must be recreated by the prediction model precisely in the same manner as they were eliminated in order to produce accurate forecasts. One of these orbit models for satellites in near-Earth space (period 225 minutes) is the SGP4 model.

Using 'ideal' TLE data sets that were created based on the precise orbit information available for the operational satellites, it was first determined whether the SGP4 analytical orbit model's intrinsic modeling accuracy could be improved.

Current SGP4 implementations are based on Brouwer's gravity solution [1] and Lane's atmospheric model [10], but with Lyddane's adjustments to avoid loss of precision in the assessment of periodic correlations [3], which are also significantly simplified to improve evaluation efficiency. The NORAD mean element sets can be used for prediction with SGP.

The unit orientation vectors are calculated by:

$$U = M sinU_k z + N_{cosU_k} \tag{1}$$

$$v = M cosU_k - N_{sinU_k} \tag{2}$$

Where

$$M = \begin{cases} M_x = -sin\Omega_k cosi_k \\ M_y = cos\Omega_k cosi_k \\ M_z = sini_k \end{cases} \tag{3}$$

$$N = \begin{cases} N_x = cos\Omega_k \\ N_y = sin\Omega_k \\ N_z = 0 \end{cases} \tag{4}$$

Then the position and velocity are calculated by

$$r = r_k U \tag{5}$$

$$\dot{\Gamma} = \dot{r}_R U + (r\dot{f})_k v \tag{6}$$

2.2. LSTM

Long short-term memory, LSTM algorithm, which is a type of Recurrent Neural Network (RNN). An input layer, a hidden layer, and an output layer make up the three layers. By constructing weight coefficients between hidden layers, LSTM solves the problem of long-distance dependence that RNNs cannot manage. It indicates that while forecasting satellite telemetry parameter time series data, LSTM can develop long-term connections between distant nodes in the time series, improving the accuracy of time series data prediction [11].

Our intuition to use LSTM was because of its effectiveness on the time series. We have only used linear regression in some cases where data looked linear. Looking closely at the linear data points, one would notice they usually return back to a value after some time abruptly. Like a modulo operation so delinearize helps with taking a linear result and applying a modulo operation to the result.

2.3. Curve Fitting

The process of creating a curve, or mathematical function, that best fits a set of data points, sometimes subject to constraints, is termed curve fitting. Either interpolation, where an exact fit to the data is required or smoothing, where a "smooth" function is generated that roughly fits the data, can be used to fit a curve. Fitted curves can be used to explain the relationships between two or more variables, to infer values of a function when no data are available, and as a tool for data visualization. Extrapolation is the use of a fitted curve outside the range of the observed data, and it carries some risk because it could represent the construction process of the curve just as much as it does the actual data.

2.4. Dataset

The TLE dataset was employed in this study. A two-line element set (TLE) is a standardized format for describing a satellite's orbit and trajectory. Below is an example of the International Space Station. There are 14 fields in a TLE; however, our method only needs 9 of them. The 9 fields are Epoch Year - The year the TLE was calculated, Epoch Day - The day and fraction of the day the TLE was calculated, B- star - The drag term or radiation pressure coefficient, Inclination - Satellite orbit tilt between 0 and 180 degrees, Right Ascension of the Ascending Node - Ranging from 0 to 360 degrees, Eccentricity - A measure of how circular the orbit is

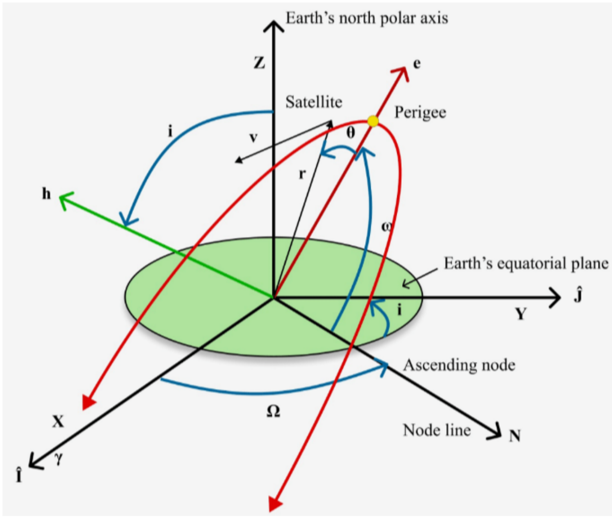

Figure 2: An orbit in 3D defined by TLE parameters

ranging from 0 to 0.25 for LEO satellites, Argument of Perigee - The angle from the ascending node ranging from 0 to 360 degrees, Mean Anomaly - The angular position measured from pericenter if the orbit was circular ranging from 0 to 360 degrees, Mean Motion - The angular speed necessary to complete one orbit measured in revolutions per day with a minimum of 11.25 for LEO satellites.

3. Methodology

3.1. Methods and Procedure

There are a few studies that investigate different approaches to estimating TLEs. USSTRATCOM publishes TLE data on the spacetrack.org website. We retrieve TLE data of RSOs by their SATNAME within a specific period of time. After getting the data, we then used it to visualize over time. We observed various dependencies inTLE data propagation. TLEs, by their nature, can only be converted to position data using SGP4. TLEs include the mean states estimated by fitting observations to the dynamics provided by SGP4, and they can only be used with SGP4. As a result, we attempted to use curve fitting to ensure that our models were invariant with respect to the dependencies. To construct a linear or non-linear function based on the data, we tried different fitting methods. We tried polynomial fitting and sinusoidal fitting on the data.

The linear or non-linear curve fitting method is a mere global minimization of the weighted sum of squares. So in our study, for some parameters such as the right ascension of the node, the argument of perigee, mean anomaly, eccentricity, the weighted sum of squares, and root mean squared error is used to assess the goodness of fit. TLE data is input to either adjust a smooth and balancing model function that describes the data adequately or train a special kind of recurrent neural network that is capable of learning long-term dependencies in data. Applying this method to all parameters produced disappointing results. So curve fitting worked with

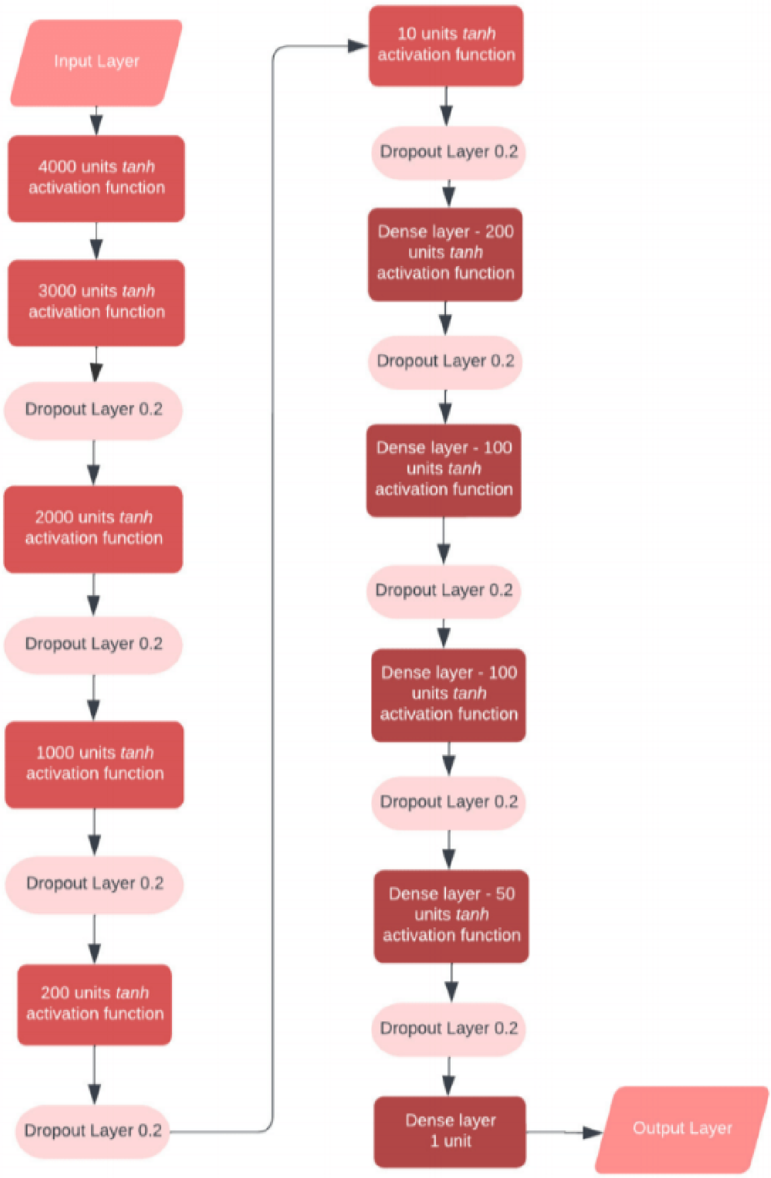

Figure 3: LSTM Model

some parameters, but for others, such as inclination, mean motion, etc, it gave some reasonable deviations. So we tried LSTM (Figure 3) to fit the data. LSTM is a special kind of recurrent neural network and it is good at predicting sequential and temporal data. A fully connected neural network architecture is trained with 9 hidden layers using tanh as an activation function. To modify each epoch weight and the loss function efficiently, we have used the Adamax optimizer, a variant of Adam based on the infinity room [12]. As this problem is large in terms of data parameters, the Adam optimizer is a primary algorithm for optimization to estimate lower-order moments.

Training the model would continue by comparing the output with the target, calculating the error, and optimizing the weights, reiterating the process again and again. We believe that we did a thorough hyper-parameter search and optimization in order to seek the best overall parameters in order to minimize our loss on the validation set.

We have also chosen an ideal number of epochs after which the accuracy stopped increasing. When determining optimized weights for the trained model, the loss function is the most important factor to consider. The MAE loss function is used as it is more robust to outliers. This fully-connected neural network learns the mapping between the input and output by connecting all neurons available, and it has 201,052,641 trainable parameters (total number of weights and biases). The LSTM architecture is shown in (Figure 3). To reduce the over-fitting of the model, I used a dropout of 0.2, which significantly reduced the complex co-adaptions of training data. Neural networks are sensitive to the scaling of the input data; therefore, the input data is either standardized or normalized based on the resultant performance of the model. For this neural network model, normalization is done through Z-score normalization. The arithmetic mean and standard deviation of the given input data are calculated first. The standard Z-score is calculated as follows: The Z-score indicates how many standard deviations the data element is from the mean. As follows, min-max normalization is done for each data element. It is observed that input data for neural network standardization outperforms normalization:

$$z_n = \frac{x - min(x)}{max(x) - min(x)} \tag{7}$$

$$z_s = \frac{x - u(x)}{\sigma} \tag{8}$$

Table 1 shows the parameters which are used to standardize and normalize the input data. A ratio of 80/20 is used for data splitting, such that 80% goes to the training subset and 20% goes to the testing subset. The input to LSTM is a 3-dimensional array to train and predict the output. The model is tested with n data points from the TLE dataset so that the rest of the TLE data can be used for validation and testing. The fitted data is returned for every parameter of the input TLE data for n data points. The reliability of conjunction messages and collision risk estimation is largely dependent on the accuracy of the fitted data to estimate the orbit and associated covariance information.

Table 1
Parameters to normalize and standardize the input data for LSTM model

S.No	Parameter	Mean	Std
1	First time derivative of mean motion	-5.8e-13	2.8e-12
2	Ballistic drag coefficient	1.2e-05	5.9e-05
3	Mean motion	0.062	1.5e-05
4	Inclination	0.0639	2.07e-5

3.2. Proposed model

Figure 4 depicts the overall framework of the model proposed in this paper. The framework of the orbit prediction through machine learning is shown in Figure 4. The components and the process is explained in their respective section.

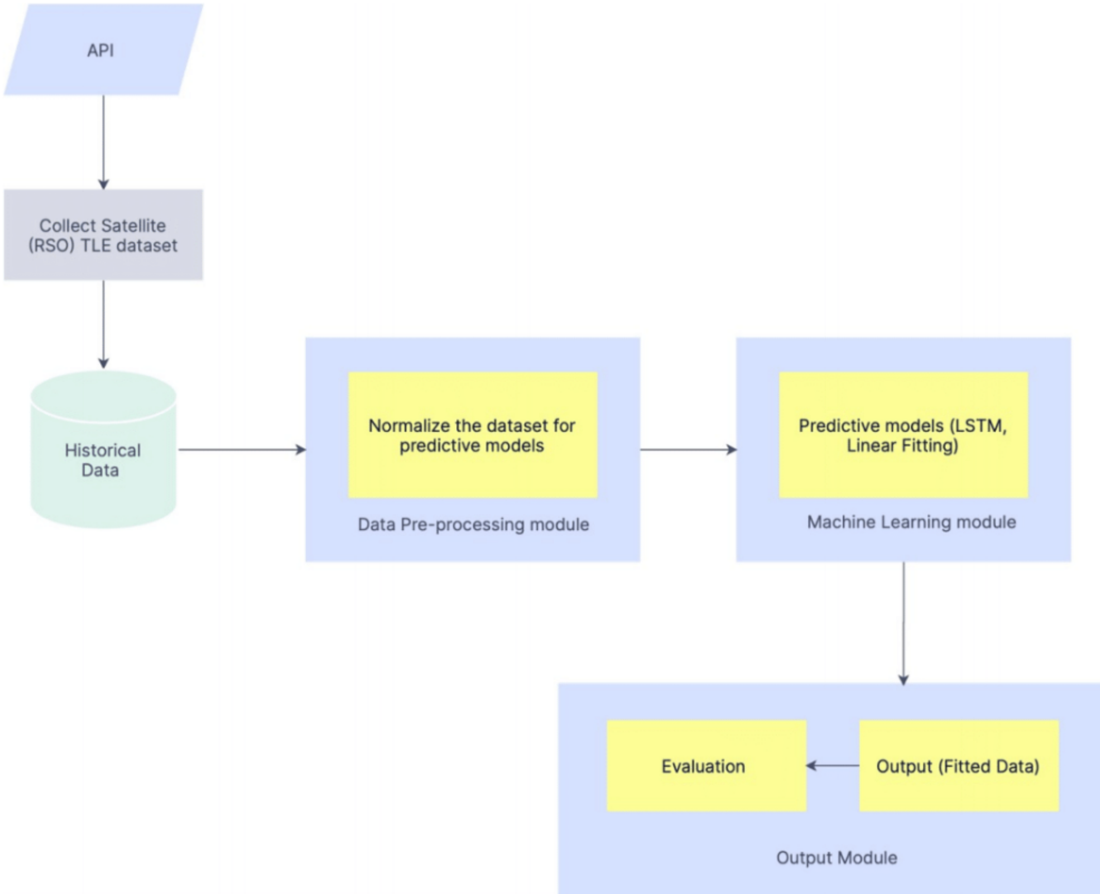

Figure 4: Framework

3.3. Task Flow

Figure 5 depicts the task flow diagram of the proposed method.

4. Results

4.1. Residual plots and Scatter Plots

The absolute residual plots and the scatter plots with regression of the TLE parameters prediction made using machine learning models are presented below Figures (6, 7, 8, 9, 10, 11, 12, 13). The

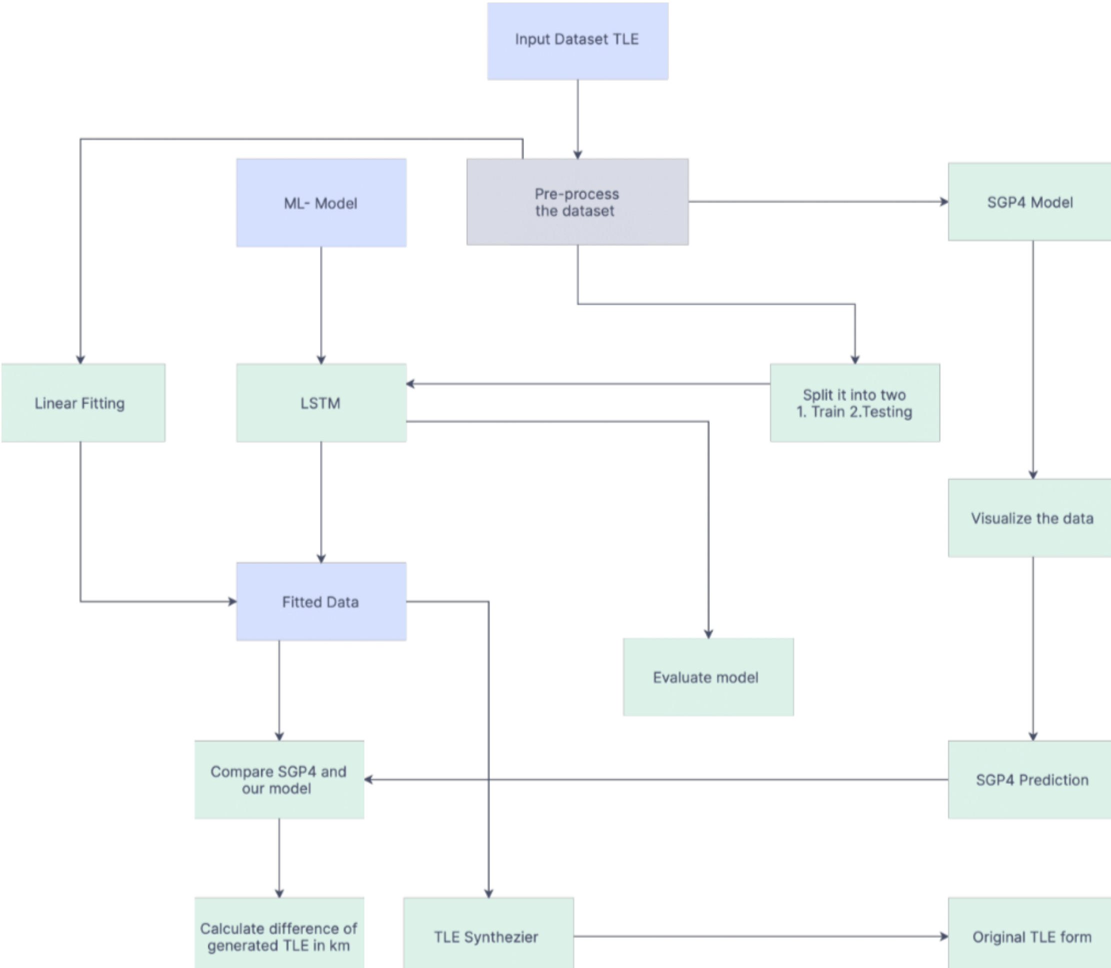

Figure 5: Process Flow

absolute residual plot detects incorrect behavior of residuals, the graph depicts the density of residuals predicted by ML models and their values are displayed along the x-axis for every TLE parameter. The residuals are concentrated close to 0.00001(rad/min) and their mean is scattered approximately between 0.0000 and 0.0001, hence the predictions are not biased and uncorrelated. The percentage of residuals smaller than 0.0001 is 31.9% and residuals smaller than 0.0007 is 89.2% for B* model. The peak outside the confidence interval for particular lag k means the output y(t) that originates from the input u(t-k) is not properly described by the LSTM model. The residuals smaller than 0.0001 are 90.1% for mean motion and the RMSE observed is 2.2e-07. Table 3 shows the mean and standard deviation of the residuals of the predictions for the machine learning model.

The patterns of both predicted output and actual output (1/Earth Radius) are close to the regressed diagonal line. The first-time derivative of motion model including other TLE parameter models has high goodness of fit so that the predicted values are not heavily dispersed away from

Table 2
RMSE of TLE parameters

S.No	Training Approach	RMSE of the proposed model	RMSE of Gradient boosting tree model
1	First time derivative of mean motion	1.7e-12	-
2	Ballistic drag coefficient	2.3e-05	2.4e-05
3	Right ascension of ascending node	0.004	0.01
4	Argument of perigee	0.998	0.22
5	Mean anomaly	1.2741	0.3
6	Mean motion	2.2e-07	5.3e-9
7	Inclination	2.06e-6	9.8e-5
8	Eccentricity	7.5e-6	2e-7

Table 3
Mean and standard deviation of residuals for the given parameters

S.No	Parameter	Mean of proposed model	Std of proposed model	Mean of gradient boosting trees	Variance of gradient boosting trees
1	First time derivative of mean motion	4.766425e-13	2.943803e-12	-	-
2	Ballistic drag coefficient	8.627849e-06	5.971809e-05	0.0002	0.0009
3	Right ascension of ascending node	-0.009	0.011680	0.0045	0.0029
4	Argument of perigee	0.320074	101.875286	0.24	1.898
5	Mean anomaly	1.049211	8.9800481	0.19	0.23
6	Mean motion	-7.972256e-08	1.668083e-05	6.5e-5	1.8e-8
7	Inclination	4.01e-6	5.14e-6	0.002	1.6e-5
8	Eccentricity	7.82378080292368e-05	0.000078	0.008	1.23e-5

the line, this indicates the values are non-random around the line. The machine learning models output the values close to the target values. The points are located around the diagonal line which means that the proposed model predicted well. The regression plot of actual vs predicted output shows that the RMSE predictions of the LSTM model are quite smaller compared to other naive and Bayesian neural networks and Gradient Boosting Tress as shown in Table 2. The density plot of residuals and scatter plot with regression of Right ascension of ascending node

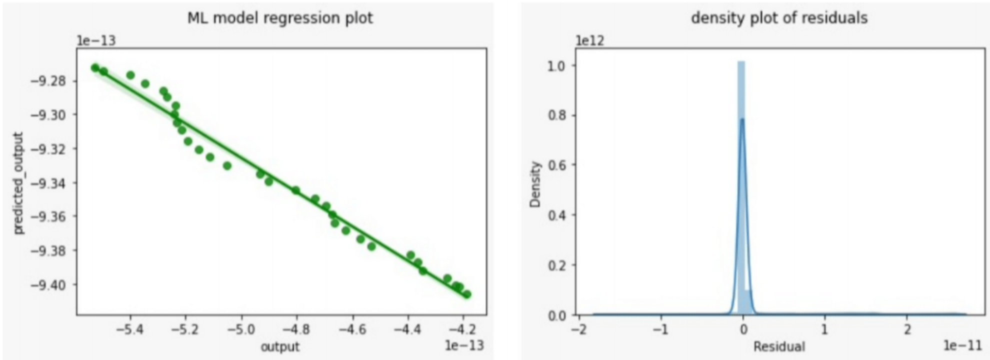

Figure 6: Performance of first time derivative of the mean motion

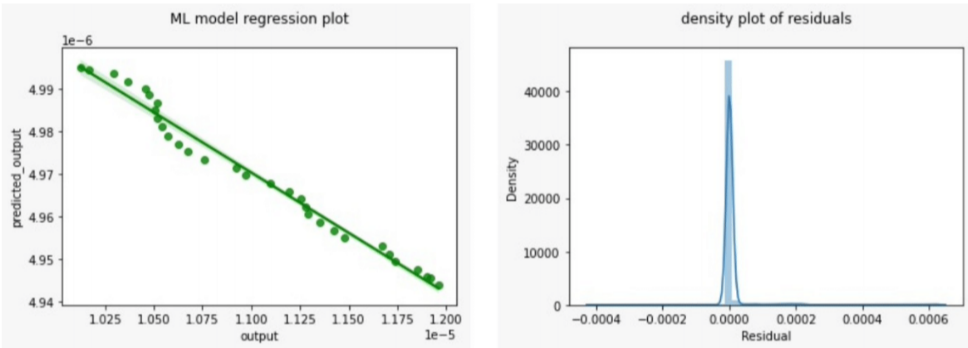

Figure 7: Performance of Ballistic drag coefficient B* in inverse earth radii

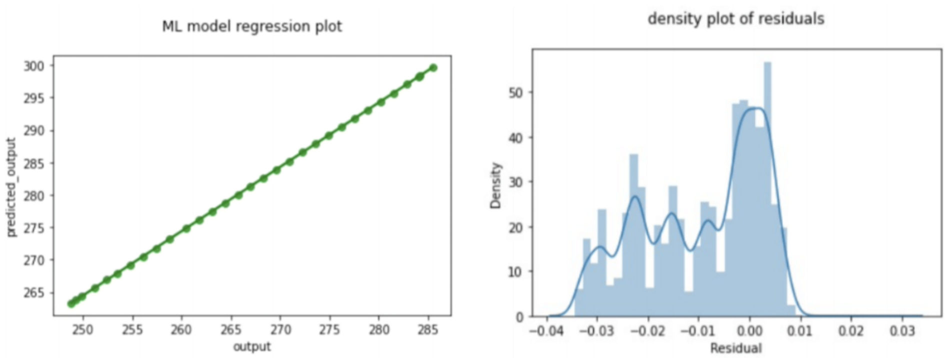

Figure 8: Performance of Right ascension of ascending node

is shown in Figure 8. The absolute mean of residuals is 0.009 radians and the standard deviation is 0.0116. The larger variance is due to the ineffectiveness of the machine learning model to recognize the cyclic behavior when the mean element switches values between 2π and 0 as the orbit propagate in time. Due to similar performances in residuals of their predictions both the argument of perigee and the mean anomaly machine learning models have relatively poor

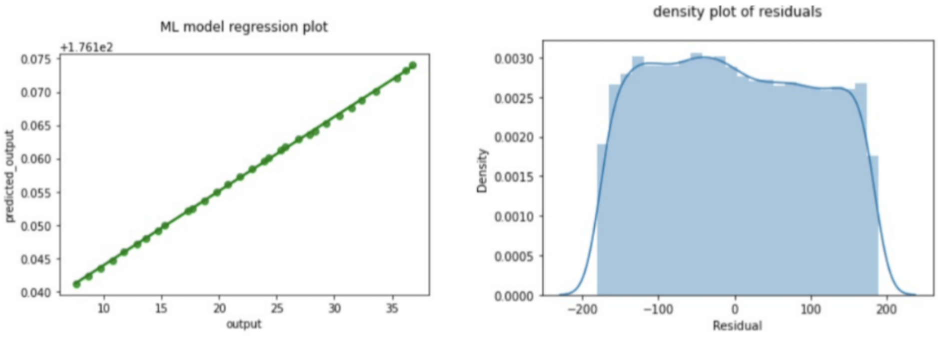

Figure 9: Performance of Argument of perigee

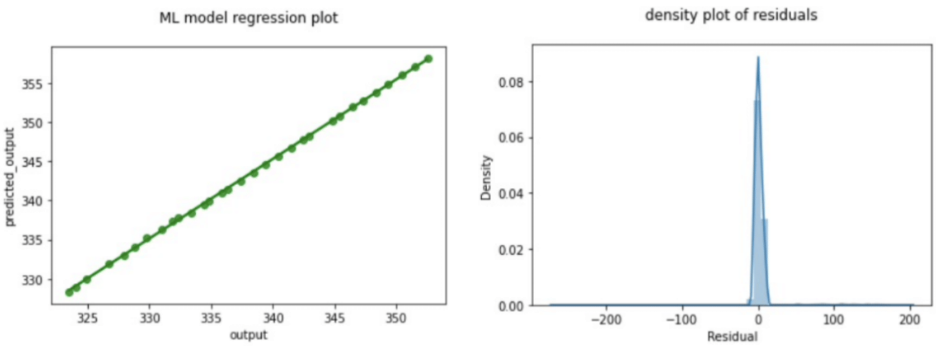

Figure 10: Performance of Mean Anomaly

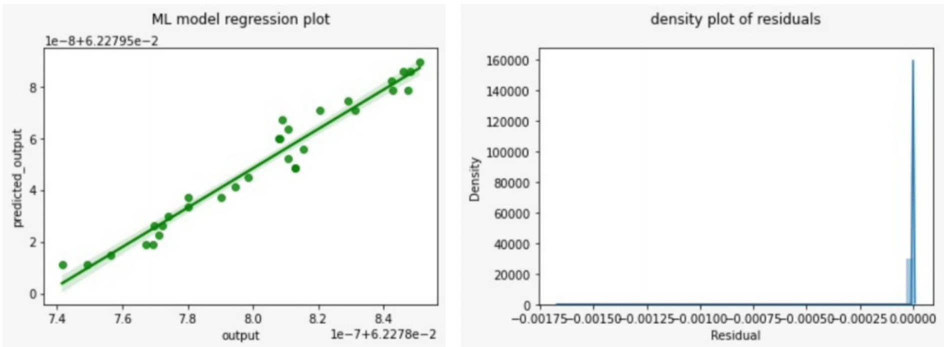

Figure 11: Performance of Mean Motion

performance in determining the decision boundary that can map the orbital evolution to the mean elements accurately. As discussed above for the right ascension of ascending node, due to difficulty in capturing the cyclic behavior of the angle between 0 and 2π due to Lv (Ω, w, v) feature i.e. equinoctial element, all machine learning models learn a representation that has large fluctuations in the residuals of its predictions and this may very well signify that argument

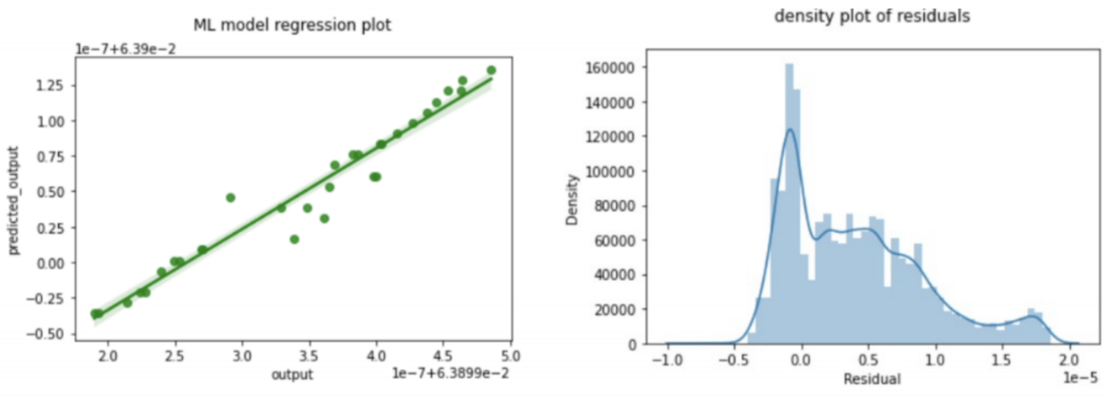

Figure 12: Performance of Inclination

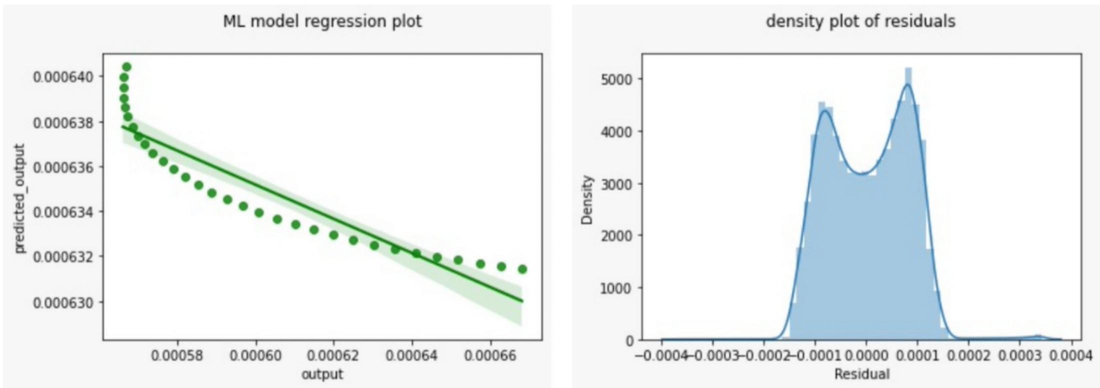

Figure 13: Performance of Eccentricity

of perigee and mean anomaly is modified to fit the perturbed orbit. The RMSE values of the proposed machine learning model output values close to the average of all target value There are outliers observed in the data which are kept between a comparable range of - 0.1000 to 0. 1000. For these parameters which behave randomly with LSTM it is observed that linear fitting works well. If one looks at the linear data points, one would notice that they usually return to a value at some time abruptly.

Large fluctuations in the residuals of predictions are a feature of every machine learning model, and this may signify that, like in the case of B*, the mean anomaly and the argument of perigee have been altered to fit the perturbed orbit. Unlike the other parameters, eccentricity has no significant relationship with the machine learning models so the polynomial sin fitting function can approximate $sin(x)$ between 0 and 2π. The development of value in the above-mentioned mean elements between 0 and 2π occur for about 0.73% of the test data. Future research will solve this problem by incorporating other characteristics into the features such as (Ω, w, v) by utilizing data transformations.

4.2. RMSE results of Proposed Model vs Gradient Boosting trees

Table 2 summarises the RMSE results of the proposed model with gradient boosting trees, the values tell you how concentrated the data is around the line of best fit. As you can observe the RMSE values of the argument of perigee have a high error which gives relatively high weight. Depending on the features chosen, different machine learning techniques perform differently. The proposed machine learning model outperforms the gradient-boosting trees regarding prediction accuracy unless the absolute difference between the prediction of the proposed model and the prediction of gradient-boosting trees is larger than the threshold value. The LSTM machine learning model is trained to predict each of the respective mean elements of a TLE and the model is chosen to be validated by the errors in the orbital evolution. The error in the orbital evolution is computed by propagating TLEs estimated by the selected best machine learning models and the associated Standard TLEs backward in time using SGP4 for 150 orbital periods. Figure 14 shows the comparison of orbital propagated using SGP4 model satellite TLE data with the proposed machine learning model predictions of TLE data. The below propagations of TLE data compare the actual RASAT RSO's TLE data with the predicted TLE data of our proposed model.

4.3. Evaluation of Prediction Error and Error Handling of the proposed model

From Table 4 we can see that the prediction accuracy using the proposed model significantly outperforms that using TLE/SGP4 [Space-track.org]. For the RASAT satellite, the absolute maximum error for 50 days in the along-track direction is 35.6 km using TLE/SGP4, while it is 3.8km using the proposed machine learning model. A reduction of 89.325% for the absolute maximum along track error is achieved using the proposed machine learning model. For Starlette, the absolute maximum prediction error for 50 days in the along-track direction is 13.9 km using TLE [spacetrack.org] and 2.9 km using the proposed model. The absolute maximum along track error is decreased by 79.1367% using the proposed model.

Table 4
Averages of the maximum 50-day position prediction error from 150 computations (in Kilometres)

S.No	Satellite	TLE (space track.org)	Proposed Model	Average Improvement Percentage
1	RASAT	35.6	3.8	89.3258%
2	STARLETTE	13.9	2.9	79.1367%
3	STELLA	2.7	1.1	59.2593%
4	GOKTURK-2	11.3	3.9	65.4867%

Table 4 gives the averages of maximum 50-day position prediction errors using the proposed machine learning models and TLE [spacetrack.org] from 50 computations. Compared with spacetrack.org TLE, the averages of the maximum 50-day position prediction errors of the proposed model propagated orbits are 3.8 km, 2.9 km, 1.1 km, and 3.9 km for Rasat, Starlette, Stella, Gokturk-2, which have been improved by 89.32%, 79.1367%, 59.2593%, 64.4867%, respectively. These findings suggest that the proposed model's TLE generated from the accurate orbit predictions may be able to provide even more precise orbit predictions. Further examination shows that prediction errors in the along-track, cross-track, and radial directions have periodic properties. This indicates that the predicted errors could be modeled by proper correction functions and the absolute relative errors can be improved by non-linear least squares and differential correction methods. For example, it is determined that n = 10 is suitable for the error fitting for the 50-day forecast period. The unknown coefficients ai, bi, and ci I = (1, 10) are estimated using the nonlinear least square technique using the prediction errors at each epoch as observations. The prediction errors at any epoch are estimated using a correction function after calculating the coefficients in the correction functions and are then used to correct the predicted orbits to provide more accurate orbit predictions. The amount and variance of the prediction errors are drastically decreased when the adjustments from the correction function are used. In conclusion, the performance of our model for different parameters of TLE is very precise and accurate this allows our proposed model to provide an estimate of the TLE data at various epochs. Our proposed LSTM has significant regression capabilities due to its more flexible structure so when dealing with different aspects of error handling with very large measurement noise it shows stable performance. So this ML approach can be applied without knowing the accurate noise in the dataset.

4.4. Comparison and Evaluation of proposed Machine Learning model with other models

This work is the first effort to use a unique machine learning methodology to predict satellite TLE data to improve the orbit prediction accuracy of the RSO at future epochs and focuses on reducing prediction errors. Depending on the TLE parameters, machine learning techniques function differently. The mean components of TLE are predicted by two different machine learning techniques and the performance of the models is compared with other models based on errors in orbital evolution. In Table 5 we have presented the comparison of the percentage of improvement for position prediction errors of the satellites with generalized polynomial algorithm [6] and data-driven model.

Table 5
Comparison of Improvements of Prediction Errors

S.No	Satellite	Our Proposed Model	Other Model - Gen-TLE [13]	Other Model - Data-Driven Model [14]
1	STARLETTE	79.1367%	74.9%	61.87%
2	STELLA	59.2593%	NA	51.267%
3	AJISA	71.275%	74.285%	41.98%
4	LARETS	77.110%	70.611%	NA

After performing predictions on different LEO satellites, the summary statistics say that the typical prediction error of our method is 1.1 km at 30 days out corresponding to $\sim$28 m/day prediction error growth. The worst case is observed in STELLA where the median error grows <90 m/day and the best case is observed in RASAT at 9m/day. These are compared to typical

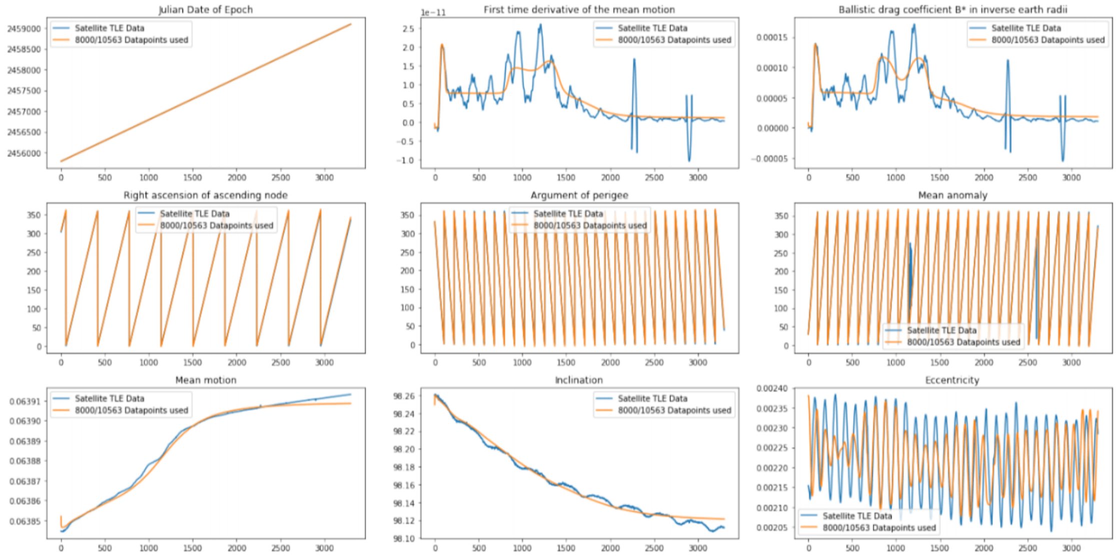

Figure 14: Comparison of fitted data with actual TLE Datapoints

growth of 1500m/day for TLEs propagated with SGP4 for these satellites and 200m/day when compared to other ML and data-driven approaches as shown in Table 6. This table comparatively indicates that there is no secular error growth(10-180m/day) in the orbital evolution of TLEs predicted by our machine learning model. The proposed method exhibits approximately three orders of magnitude improvement in prediction accuracy over TLEs propagated with SGP4 and one order of magnitude improvement in prediction accuracy over data-driven approaches. The trained model can reduce more than half of the prediction error as shown in Table 4. With this prediction, we have estimated the error and limited the maximum error we can have in the prediction. It allows us to know the current position of the satellite, and to predict the final position with a bounded error. The intersection of both curves in Figure 14 shows that for around 80% of the testing data, the residual error percentage is less than 100%, indicating that our trained model has been effective in lowering their prediction errors. In general, the orbit prediction accuracy for the majority of future epochs can be improved by the suggested ML technique.

Table 6
Comparison of accuracies (error growth in meters/day) with other Prediction Methods

S.No	Prediction Methodology	Accuracy [in meters/day]
1	Our proposed model	10-180
2	TLE + SGP4 Model [15]	100-3000
3	TLE + Fitted Model [14]	50-200
4	Least Square Model [16]	10-300
5	Bayesian Neural Network Model [17]	10-200
6	High Accuracy Catalog + SP Model [15]	50-200

5. Conclusion

In this paper, a new and unique approach for estimating the TLE parameters of an RSO has been developed. We have presented a prediction technique that allows us to more accurately estimate the satellite TLE parameters in the future. As a general evaluation, the pros of this paper are the distinctive study that we have performed to predict new data parameters in base on the data we had with comparable accuracy and limiting error in such prediction. Using RASAT and STELLA as an example, the results show that the performance is stable on testing data and this prediction technique is effective for RSOs for most position and velocity components. RSOs in low earth orbit are simulated to examine the performance of the machine learning models. After the corrections to the predicted orbit, the final prediction accuracy can also be improved significantly With the obtained results, it is possible to conclude that Curve fitting and Long short-term memory are promising machine learning approaches for estimating TLE parameters. The machine learning model's projected TLEs can accurately determine the reference orbit. Different machine learning architectures, non-discontinuous transformations of cyclic parameters, and more input parameters might all improve model performance.

The efficiency of the proposed ML technique varies with the orbit's RSO and further research is required to shed light on their relationship among various TLE parameters.

Further research is suggested to combine physics and machine learning models to enhance the capabilities of the model. To improve the orbit propagation accuracy it is suggested to model the orbit propagation errors for the biased results. Future research will also examine the viability of utilizing physics-integrated machine learning models to improve predictions of the right ascension of the ascending node and the inclination, as well as the conjunction search component for collision avoidance.

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