Analysis of Asteroid Mining, using Machine Learning

Abstract

Accurate asteroid value estimation is essential for space mining decision-making as the exploration and the utilization of asteroids for rich minerals become more and more feasible. With an emphasis on M-type asteroids, this study suggests a technique for valuing asteroids according to their type and composition. Because M-type asteroids may be particularly rich in metals like gold, silver, platinum, and titanium, they are of special interest.

There are multiple steps in the process. In order to determine the asteroid's volume, it is first necessary to measure its diameter. The type of the asteroid is then determined by analyzing its albedo; those that lie between 0.1 and 0.3 are classified as M-type. The percentages of different metals are then ascertained by utilizing spectroscopic studies to identify the composition of the asteroid.

With this data, the market values for gold, silver, platinum, and titanium as well as their corresponding compositional percentages are taken into account to determine the asteroid's value. The suggested approach combines economic theory and scientific data analysis methods to offer a thorough framework for asteroid value estimation, supporting well-informed choices in space resource use programs. By providing a methodical and data-driven approach to assessing the economic potential of asteroids, this methodology advances space exploration and exploitation.

I. Introduction

Asteroid mining, represents a frontier of space exploration with profound implications for humanity's future. The concept involves extracting valuable resources, such as metals, minerals, and water, from asteroids and other celestial bodies for use on Earth or in space. This ambitious endeavor holds the promise of revolutionizing various industries, from space exploration and manufacturing to renewable energy and beyond [18].

At its core, asteroid mining taps into the vast potential of space resources to address pressing challenges on Earth and facilitate the expansion of human activities beyond our planet. With Earth's finite resources dwindling and the demand for rare metals and minerals steadily increasing, the ability to harness the abundant wealth of asteroids presents a compelling solution to resource scarcity. These celestial bodies are thought to contain vast quantities of precious metals like platinum, rare earth elements, and even water, which could be harvested and utilized to sustainably fuel humanity's technological progress [8].

The exploration and exploitation of asteroids offer numerous advantages over traditional terrestrial mining. Unlike on Earth, where accessing resources often requires extensive and environmentally disruptive excavation, asteroids provide a treasure trove of raw materials conveniently located in space. Moreover, the low-gravity environments of asteroids make extraction and transportation significantly more feasible, reducing the costs and logistical challenges associated with traditional mining operations. Additionally, the abundance of certain elements in asteroids, such as platinum-group metals, could potentially disrupt global markets and catalyze innovation in various industries.

Despite its immense potential, asteroid mining also presents formidable technical, economic, and ethical challenges as discussed [1]. Developing the necessary technology to identify, extract, and transport resources from asteroids requires significant investment and innovation. Moreover, the regulatory framework governing space mining activities remains uncertain, raising questions about property rights, environmental impacts, and international cooperation. Additionally, concerns about the potential militarization of space and the exacerbation of existing inequalities in resource distribution underscore the need for careful deliberation and ethical considerations in the pursuit of asteroid mining.

In conclusion, asteroid mining represents a bold frontier of exploration with the potential to reshape humanity's relationship with space and address critical challenges on Earth. By harnessing the vast resources of asteroids, we can unlock new opportunities for sustainable development, technological innovation, and space exploration. However, realizing this vision will require collaboration between governments, private industry, and the international community to overcome technical, economic, and ethical hurdles. As we venture further into the cosmos, the pursuit of asteroid mining holds the promise of a brighter future for generations to come.

Furthermore, asteroid mining has the potential to catalyze a new era of space exploration and colonization. By establishing infrastructure for resource extraction and utilization in space, we can create stepping stones for further human expansion beyond Earth. The abundance of water ice on certain asteroids, for example, could serve as invaluable resources for sustaining human life in space habitats or fueling spacecraft through the production of hydrogen and oxygen.

Moreover, the development of asteroid mining technologies could pave the way for ambitious ventures, such as the construction of space-based manufacturing facilities and the establishment of permanent settlements on celestial bodies. With continued advancements in robotics, artificial intelligence, and propulsion systems, the dream of a thriving space economy fueled by asteroid resources is becoming increasingly attainable [14]. In essence, asteroid mining represents not only a means of addressing present-day challenges but also a gateway to unlocking the boundless potential of the cosmos for future generations [17].

This paper's primary contribution is the presentation of an extensive methodology for valuing asteroids according to their type classification and composition, with a focus on M-type asteroids. Our approach offers a methodical framework for assessing the economic potential of asteroids by fusing scientific data analysis tools with economic concepts. This allows for well-informed decision-making in space resource exploitation activities. This study also emphasizes how mining asteroids has the potential to significantly alter how humans will interact with space in the future, from promoting technological innovation and sustainable development to encouraging space travel and colonization.

The importance of asteroid mining and its potential to transform resource utilization and space exploration are discussed in the Introduction. By going over the current status of asteroid mining research, including technological developments, financial concerns, and ethical ramifications, the literature review part gives background. The estimation of asteroid value based on composition and type classification is shown in the implementation section, along with a breakdown of the procedures involved in value calculation, composition analysis, type classification, and diameter estimation. The results of using the suggested method on a sample of asteroids are shown in the results section along with estimations of their value and implications for space mining activities. The paper's main conclusions and contributions are outlined in the conclusion, which also emphasizes the importance of asteroid mining and urges cooperation in overcoming obstacles to fully fulfill the technology's potential.

II. Literature Survey

Paper [1] analyzes global equity and future of asteroid mining. It defines global equity and evaluates it using 9 indicators. It uses entropy weight method and group decision method for evaluation. Establishes two-dimensional vector evaluation model for global equity classification. Uses K-means clustering to categorize countries and evaluate global equity. A two-dimensional spatial model was established to measure global equity. Four equitable conditions were defined: equitable, relatively equitable, inequitable, and extremely inequitable. Six representative countries were selected for validation through cluster analysis. The EP and IP of the selected six representative countries were evaluated. The paper provides a comprehensive evaluation of global equity based on regional development.

Paper [2] develops a CNN-based IP algorithm for centroid estimation. The algorithm is applied to the HERA mission with the binary asteroid Didymos. It successfully estimates the centroid of the primary body with high accuracy. The algorithm is not affected by the presence of the secondary body or illumination. It can also estimate the centroid of the secondary body when both bodies are in the same image. Developed CNN-based IP algorithm successfully estimates centroid of primary body. Algorithm is robust to adverse illumination conditions and presence of secondary body. HRNet-based IP algorithm provides higher accuracy than MCLS IP algorithm. Algorithm can estimate centroid of secondary body even in eclipse conditions. Future work includes exploring other utilizations for HRNet-based IP algorithm.

Paper[3] uses machine learning to classify asteroids as hazardous or non-hazardous. Dataset from NASA-Nearest Earth Objects on Kaggle is used. Visualization figures are used to analyze the dataset. Goal is to design an efficient prediction model with good generalization. Classification report and confusion matrix are generated to evaluate models. Visualization of NASA Nearest Earth Objects dataset using various plots and charts. Classification of asteroids into hazardous and non-hazardous categories using machine learning techniques. Comparison of performance of different classification algorithms. Random forest algorithm outperforms other classification algorithms.

Paper [4] aims to classify Near-Earth Asteroids as potentially hazardous or non-hazardous. Deep neural networks used to learn patterns in asteroid orbital data. Automatic potentially hazardous asteroid detector can speed up asteroid characterization. Construction of a data corpus with essential features for training the model. Use of Keplerian elements to define asteroid orbits. PHAC hybrid classifier achieved 90% accuracy, 99% precision, and 80% recall. The model is cost-effective and can save computational resources. The proposed model took 2.54 hours to train and can make predictions within 0.001597s.

Paper [5] performs a study on motion control of low thrust spacecraft for near-Earth asteroid flight. Focus on small celestial bodies with stable Earth orbits. Use of electric propulsion to reduce mission costs. No methods developed for control programs and spacecraft trajectories. It Obtains optimal duration control program for flight to asteroid 2016HO3. The paper analyzes optimal transition between nonplanar orbits of a spacecraft with low-thrust engines. The spacecraft can be directed by the binormal or transversal. Small disturbing forces lead to significant deviations from calculated trajectory. Developed method for modeling controlled motion of spacecraft with low-thrust engines. Explored non-planar flights between low-earth orbit and near-earth asteroid 2016NO3.

In paper [6] Global mapping analysis tool for asteroid exploration introduced. Supports trajectory design and coverage analysis. Can import external orbit data. Future plans to add more analysis tools and navigation module. Introduction of global mapping analysis tools for asteroid explorations. Software provides different types of dynamical models. Use of depth buffer method in computer figureics for surface visibility. Support for trajectory design and coverage analysis in asteroid exploration. Future plans to add analysis tools for observation data and develop navigation and maneuver modules.

Paper [7] uses a two-stage binary classifier to detect asteroids. The current classifier has more false positives than true positives. The paper proposes an extended classifier that incorporates dynamic motion data. The new classifier decreases false positives by 59% with a low false negative rate. The extended classifier combines pixel-based classifier output with engineered features. The pixel-based classifier uses only pixel information and not dynamic motion data. Developed two new features to incorporate dynamic tracklet data. Built a new classifier to combine these features with the output scores of the pixel-based classifier. The new classifier reduces false positives by 59%. Maintains a false negative rate of 0 on the test set.

Paper [8] focuses on quantifying asteroid resource accessibility for space missions. Lambert's problem is solved to determine optimal transfer orbit between Earth and asteroid. Genetic algorithm used to determine minimum energy for transfer with varying flight durations and launch dates. Physical properties and spectral classifications used to estimate quantity and composition of accessible resources. Method applied to asteroids with assigned taxonomic classifications. Overall distribution of asteroid types and energy requirements presented. Developed method successfully analyzed asteroid resource accessibility to Earth and other planets. Method includes three-dimensional impulsive transfer optimization scheme for asteroid database. Future work will apply method to different asteroid sets and planetary bodies. Feasibility of complete resource retrieval mission can be assessed.

Paper [9] discusses the use of AI in analyzing hazardous asteroids. Proposes a supervised ML method to detect hazardous asteroids. Random forest classifier performs best with 99.99% accuracy and 99.22% F1-score Multiple classification algorithms were used to detect Hazardous Asteroids. Random Forest classifier performed the best in terms of overall performance. Accuracy alone is not a good representation of model performance. Probabilistic prediction methods tend to develop bias towards class with higher data points. Authors aim to extend the research to include overall analysis of asteroids.

In Paper [10], Quantum Machine Learning (QML) is used to classify Potentially Hazardous Asteroids (PHAs). QML approach employs Variational Quantum Circuits (VQC) and PegasosQSVC algorithms. Proposed method outperforms other classification algorithms with 98.11% accuracy. Aim is to detect whether an asteroid with specific parameters is hazardous or not. Existing machine-learning approaches for predicting asteroid hazards are resource-intensive. Quantum Machine Learning can improve the accuracy and precision of asteroid classification. The proposed QML-based method outperformed existing techniques with high accuracy. Image-based analysis can enhance the accuracy and efficiency of the proposed work. Integrating the QML-based methodology can aid in real-time detection and mitigation of asteroid risks. Future work includes clustering similar characteristic objects in 3D space using QML.

Paper [11] aims to classify Near-Earth Asteroids as potentially hazardous or non-hazardous. Deep neural networks used to learn patterns in asteroid orbital data. Automatic potentially hazardous asteroid detector can speed up asteroid characterization. PHAC hybrid classifier achieved 90% accuracy, 99% precision, and 80% recall. The hybrid model is cost-effective and can save computational resources. The model took 2.54 hours to train and can make predictions within 0.001597s.

Paper [12] uses machine learning algorithms to predict potentially hazardous asteroids. Different machine learning methods were applied to identify hazardous and non-hazardous asteroids. Random Forest tree algorithm provided the best optimal solution in terms of training time and accuracy. The dataset was split into test and train sets, with 938 data in the test set and 3749 data in the train set. Support Vector Machine algorithm with the kernel RBF was used to predict hazardous asteroids. The algorithm achieved an accuracy of over 90%. Word frequency was used as a predictor by the classifier. Random forest tree gives the best optimal solution in terms of training time and accuracy. The paper helps identify newly discovered near-earth asteroids and their hazards. Machine learning models are used to predict hazardous asteroids approaching Earth.

Paper [13] uses ChaosNet, an Artificial Neural Network, to predict the hazardousness of asteroids. Traditional classifiers like Support Vector Machine are used for comparison. The model is trained using a dataset from the National Aeronautics and Space Administration. ChaosNet is better at predicting the hazardousness of asteroids than other classifiers. Further research includes incorporating ChaosNet with classical classifiers like AdaBoost or kNN.

Paper [14] aims to understand relationship between asteroid classifications and observational properties. Machine learning algorithm applied to derived spectrophotometric data. Comparison made to current classification efforts through the Bus-DeMeo taxonomy. Space weathering theory extrapolated to asteroids. Applying machine learning to spectrophotometric data for asteroid classification. Comparison of results with current classification efforts using Bus-DeMeo taxonomy. Difficulty in asteroid surface characterization and taxonomic classification using remote sensing techniques.

In Paper [15] ,ML is used in asteroid dynamics to identify asteroid families and resonant arguments. Deep learning is a branch of ML based on artificial neural networks which is also extensively used. The paper conducts a review of available literature on ML in asteroid dynamics. ML is used in asteroid dynamics to identify asteroid families and resonant arguments.

Paper [16] predicts asteroid diameter using Multilayer Perceptron Regressor algorithm. Activation function used is tanh to squeeze values between -1 and 1. Backpropagation technique used for training and adjusting connecting weights. Dataset includes various types of asteroids and their physical properties. Performance evaluated using metrics such as Mean Absolute Error and R2-Score. Multilayer Perceptron algorithm performed best in predicting asteroid diameter. Dataset was cleaned by removing rows with missing values and irrelevant columns. R2-Score achieved through Multilayer Perceptron is 0.9665626238

In Paper [17], Legal regulations for space mining are being discussed based on the Outer Space Treaty. Moon is a potential source of natural resources, including Helium-3. US and Luxembourg have regulations for space mining. International space legislation lacks detailed provisions for resource exploitation. Space mining will be inevitable due to scarcity of resources. Space mining would breach the articles of the Outer Space Treaty. Taxation is an essential component of sovereign status. A specific legal regime for space mining should be elaborated through the United Nations.

The current methods for mining and exploring asteroids are hampered by insufficient data, especially when it comes to crucial characteristics like diameter, absolute magnitudes, and albedo values, which affect the precision of predictions. The suggested solution uses cutting-edge machine learning methods, such as Multilayer Perceptron (MLP) models and CatBoost regressors, to get around these restrictions and improve the accuracy of asteroid diameter forecasts. Through the addition of features such as "approx_diameter" and model refinement, the system gains increased stability and predictive power. In addition, it uses characteristics like the semi-major axis, eccentricity, inclination, and longitude of the ascending node to categorize asteroids into two groups according to their orbits: potentially hazardous asteroids (PHAs) and Near Earth Objects (NEOs). Overall, the proposed system offers a solution to the challenges posed by incomplete data and inaccurate estimations, enabling informed decisions in space resource exploration and mining efforts.

III. Proposed Methodology

Our Solar System is estimated to contain an asteroid population of nearly 1.3 million. And a considerable amount of those asteroids consists of extreme quantities of rare metals. For example, the asteroid 16 Psyche which is orbiting the Sun between Mars and Jupiter has huge quantities of gold, iron ,nickel valued around $10,000 quadrillion . But access to these abundant resources is difficult with current technology. Thus, evaluating asteroids precisely is crucial in order to identify the right asteroids to mine. But evaluating the feasibility and potential benefits of asteroid mining necessitates a multifaceted approach, and machine learning stands poised to play a pivotal role in this endeavor.

1. Data Acquisition and Preprocessing

Our methodology, analyzes the asteroid dataset through data acquisition and preprocessing steps. We retrieve the dataset from the asteroid database provided by NASA and JPL. Subsequently, the data is imported into a Pandas DataFrame for further manipulation.Within the DataFrame, we perform necessary cleaning and transformations, including handling missing data and encoding categorical features. Descriptive statistics, missing value analysis, and visualizations aid in data exploration. Finally, the dataset is split into training and validation sets for subsequent model training and evaluation.The initial steps are undertaken to prepare the data for training the asteroid valuation prediction models. This process adheres to standard data preprocessing protocols, encompassing data acquisition, cleaning, exploration, and splitting for further analysis and model construction. In summary, the data acquisition and preprocessing steps align with standard procedures for preparing data for machine learning analysis. These steps encompass obtaining the data, cleaning and transforming it as necessary, and exploring the data to gain insights into its features and relationships.

2.Basic Physics of Asteroids

Asteroids' orbits are described by their semi-major axis (a), eccentricity (e), inclination (i), longitude of the ascending node (om), argument of perihelion (wp), and other parameters.The eccentricity (e) describes how elongated an asteroid's orbit is, with values ranging from 0 (a perfect circle) to 1 (a parabolic orbit).The inclination (i) describes the angle between the asteroid's orbital plane and the plane of the ecliptic, which is the plane of the Solar System. Asteroids are classified as Near Earth Objects (NEOs) if their perihelion distance (q) is less than 1.3 AU, and as Potentially Hazardous Asteroids (PHAs) if their orbits pass within 0.05 AU of Earth's orbit and their absolute magnitude (H) is 22.0 or brighter. Further Classifications based on their spectral features such as albedo values are useful to predict mineral compositions.This is performed using the equation (1).

$$a = (1 - D)\bar{\alpha}(\theta_i\ ) + D\bar{\alpha} \quad (1)$$

a =albedo

D=proportion of diffuse illumination

$\bar{\alpha}(\theta_i\ )$ =directional-hemispherical reflectance at that solar zenith angle

$\bar{\alpha}$=bi-hemispherical reflectance

The M – type asteroids consists of highest density of valuable metals.

M – type asteroid : 0.1 < albedo < 0.3

The surface temperature of asteroids is also linked to albedo as shown in equation (2).

$$T = \sqrt[4]{\frac{(1-A)L}{\eta\varepsilon\sigma 4\pi r^2}} \quad (2)$$

T- Temperature r- Radius

A-Albedo σ- Stefan-Boltzmann

L-Luminosity of star

η- distance between the asteroid and the star it orbits

We can also calculate the Perhellion of the asteroid using equation (3)

$$e = \sqrt{1 - \left(\frac{b}{a}\right)^2} \quad (3)$$

e- eccentricity

b- focal distance

a- semi-major axis

where T is the equilibrium surface temperature, A is the bolometric Bond albedo, L is the luminosity of the Sun, h is the “beaming parameter" describing rotational and thermal inertia properties, e is the emissivity of the asteroid in the infrared, and r is the asteroid's heliocentric distance. We also evaluate the interference required to alter the asteroids path using equation (4).

$$v_{a2} = \left(\frac{2v_{D1}}{1+\frac{m_a}{m_D}}\right) \quad (4)$$

v_{D1} – Velocity of Deflector

m_a – Mass of Asteroid

m_D – Mass of Deflector

v_{a2} - Velocity of Asteroid

3. Feature Engineering and Selection

Not all data points hold equal weight in the evaluation process. Feature engineering involves identifying the key features that significantly impact our objectives. Asteroid size, the presence of valuable metals, distance from Earth, and mining technology efficiency are a few examples. Since the JPL Open Asteroid Database consists of 32 columns for each asteroid, any machine learning implementation without Feature Selection is impossible. Feature selection techniques come to the rescue, employing methods like correlation analysis and feature importance scores to pinpoint the features that truly drive the evaluation. By focusing on these select few, we equip our machine learning models with the most relevant information, paving the way for accurate and meaningful results. Feature Selection makes the model both efficient and accurate. It also helps to avoid common machine learning obstacles such as overfitting and outlier datapoints. Feature Correlation analysis is also crucial to better understand the data, as machine learning is a great to finding relations between such complex and vast number of features.

4. Model Selection and Training

Our methodology utilizes various observable characteristics to predict asteroid diameters through machine learning models. We will explore different machine learning models and conclude which model provides best accuracy. Firstly, we explore the data and engineer relevant features for modelling. Next, we construct each model, and fine tune them by adjusting the parameters, activation functions etc to get maximum accuracy from each model. Model performance is assessed using mean squared error (MSE) and Adam optimization, with early stopping to prevent overfitting .Our methodology also includes a comprehensive dataset description, problem statement, and project motivation. We aim to estimate the value of asteroids based on observable characteristics, aiding in understanding potential study and exploration mission planning. Using data published by JPL's Solar System Dynamics (SSD) group, we create diameter prediction models. And by classifying the asteroids using another model we identify the composition. With size and composition predicted and using metal economies in current market we are able to approximate the value of the asteroids. Visualizations and statistical analysis uncover relationships between features and predicted diameters which can also help in obtaining other valuable information about the asteroids.

5. Evaluation and Interpretation

Our methodology, delves into the evaluation and interpretation of the asteroid analysis models. We primarily rely on two metrics to assess performance: mean squared error (MSE) and R2 score. MSE reflects the average squared difference between predicted and actual diameters, while R2 score indicates how well the model explains target variable variability. By comparing their performance based on these metrics, we identify the best-performing model.

We can check the accuracy of these models using the MSE and R^2 values using equation (5) and (6) respectively.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \tilde{y}_i)^2 \quad (5)$$

n – Number of rounds

y_i – Actual data

$\tilde{y}_i$ – Predicted data

$$R^2 = 1 - \frac{SS_{RES}}{SS_{TOT}} = \frac{\sum_i (y_i - \hat{y}_i)^2}{\Sigma_i (y_i - \overline{y_i})^2} \quad (6)$$

SST - Sum of Squares of Total

SSE - Sum of Squares of Errors

Furthermore, we leverage visualizations and statistical analysis of the asteroid data to uncover relationships between features and predicted diameters. We explore inclinations, eccentricities,

longitudes of ascending nodes, arguments of perihelion, perihelion distances, and absolute magnitudes in relation to predicted diameters. Scatterplots, boxplots, and kernel density plots visually represent these relationships. This analysis unlocks insights into the feature-diameter connections, aiding in interpreting model results and gaining a deeper understanding of the asteroid dataset. This analysis offers a comprehensive grasp of both model results and the asteroid dataset, proving valuable for researchers and practitioners in the field.

The Kepler's Law (Equation (7)) can be used to calculate orbital time periods.

$$T^2 = \frac{4\pi^2}{G(M_1+M_2)} a^3 \qquad (7)$$

G- Gravitational Constant

M_1, M_2 – Mass of objects

a- Distance between objects

T- Time period

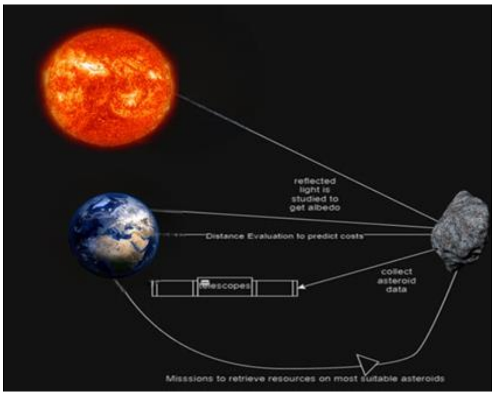

Figure 0: Asteroid data collection and mining

By harnessing the power of machine learning within this multifaceted approach, we unlock it from a distant dream into a tangible reality. As we embark on this exciting journey, let us remember that the true value lies not just in the resources extracted, but in the knowledge gained and the challenges overcome.

IV. Implementation and Results

The SBDB (JPL database) includes object identification, naming details, orbital data, and selected physical characteristics for known asteroids and comets in the solar system. Orbits are computed by JPL's Solar System Dynamics (SSD) group using precise dynamical and measurement models. These models incorporate the latest observational data from the Minor Planet Center (MPC), including radar astrometry where applicable. Sophisticated data weighting schemes and editing algorithms are utilized for accurate computations.

name	Description/object full name
a	semi-major axis (au)
e	eccentricity
i	inclination; angle with respect to x-y elluptic plane (deg)
om	longitude of the ascending node (deg)
w	argument of perihelion (deg)
q	perihelion distance (au)
ad	aphelion distance (au)
per_y	orbital period (years)
data_arc	number of days spanned by the data arc(d)
condition_code	orbit condition code
n_obs_used	number of observations used
H	absolute magnitude parameter
neo	Near-Earth Object flag (Y/N)
pha	Potentially Hazardous Asteroid flag (Y/N)
diameter	object diameter (from equivalent sphere) (km)
extent	object bi/tri-axial ellipsoid dimensions (km)
albedo	geometric albedo
rot_per	rotation period (h)
BV	color index B-V magnitude difference
UB	color index U-B magnitude difference

IR	color index I-R magnitude difference
spec_B	spectral taxonomic type (SMASSII)
spec_T	spectral taxonomic type (Tholen)
G	magnitude slope parameter (default is 0.15)
moid	Earth minimum orbit intersection distance (au)
class	asteroid orbit class (f.e. MBA, OMB)
n	mean motion (deg/d)
per	orbital period (d)
ma	mean anomaly (deg)

Table 1: features of the database

The features of the database are presented in table(1) .The dataset predominantly comprises numerical features with limited categorical data. However, certain features exhibit either negligible or substantial missing data, such as GM and BV, where approximately 99% of data is missing. Regrettably, the target column, diameter, suffers from 83.6% missing entries, rendering imputation impractical. Consequently, the dataset will undergo row removal for instances with NaN values in the diameter column. Subsequently, approximate diameter calculations utilizing available features will be employed for analysis.

(i)Diameter:

In the analysis, it has been observed that approximately 83.6% of entries in the dataset lack diameter information, necessitating their removal despite the consequential loss of data. Examination of the dataset reveals asteroid diameters ranging from 0.0025 to 939 units, with the majority falling within the 1 to 10 unit range. Notably, while certain asteroids exhibit considerable size, with diameters exceeding 800 km, the median diameter among asteroids in this dataset approximates 4 km. It is essential to recognize that larger asteroid diameters do not inherently imply greater Earth-threatening potential. The classification of an asteroid as potentially hazardous is contingent upon its status as a Near-Earth object (NEO). Larger asteroids, owing to their greater gravitational pull from the Sun, tend to maintain more stable orbits farther from Earth, thereby reducing their proximity and hazard potential. Furthermore, larger asteroids constitute a smaller proportion of the total asteroid population, diminishing their prevalence among NEOs. This nuanced understanding warrants further exploration, particularly concerning NEOs and Potentially Hazardous Asteroids (PHAs).Figure(1) presents the diameter data of the asteroid population.

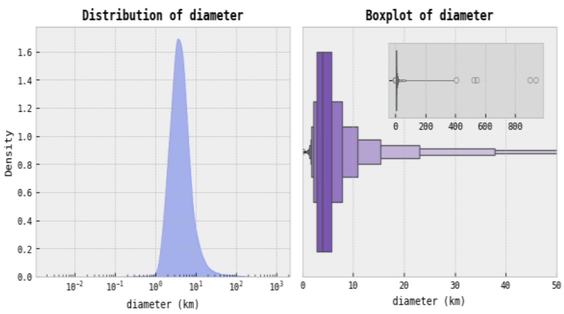

Figure 1: Distribution of diameter

(ii)class:

The following table(2) represents the classes of asteroids as defined by NASA PDS.

	Name	Description	Details
MBA	Main-belt Asteroid	Objects orbiting between Mars and Jupiter in the main portion of the asteroid belt.	2.0 au < a < 3.2 au; q > 1.666 au
OMB	Outer Main-belt Asteroid	Objects orbiting between Mars and Jupiter in the outer reaches of the main asteroid belt.	3.2 au < a < 4.6 au
TJN	Jupiter Trojan	Objects trapped in Jupiter's L4/L5 in Lagrange points, share Jupiter's orbit around the sun.	4.6 au < a < 5.5 au, e < 0.3

IMB	Inner Main-belt Asteroid	Objects orbiting between Mars and Jupiter within the inner portion of the asteroid belt.	$a < 2.0$ au; $q > 1.666$ au
APO	Apollo	Near-Earth asteroids whose orbit crosses the orbit of Earth.	$a > 1.0$ au; $q < 1.017$ au
MCA	Mar-crossing Asteroid	Objects with an orbit that crosses the orbit of Mars.	1.3 au $< q <$ 1.666 au; $a < 3.2$ au
AMO	Amor	Near-Earth asteroids whose orbit approaches the orbit of Earth but does not cross it	$a > 1.0$ au; 1.017 au $< q <$ 1.3 au
ATE	Aten	Near-Earth asteroids whose orbit could bring it in close proximity to Earth.	$a < 1.0$ au; $ad > 0.983$ au
CEN	Centaur	Objects with an orbit between Jupiter and Neptune.	5.5 au $< a <$30.1 au
TNO	Trans-Neptunian Object	Objects with orbits outside Neptune.	$a > 30.1$ au
AST	Asteroid (other)	Asteroid orbit not matching any defined orbit class.	

Table 2: Classes of asteroids based on location

MBA	126390
OMB	7510
TJN	1874
IMB	588
APO	486
MCA	355
AMO	269
ATE	95
CEN	49
TNO	13
AST	7

Table 3: Asteroid population by classes

The class-wise count of asteroids is provided in table(3).The dataset analysis reveals that the majority, around 92%, of asteroids belong to the Main-belt Asteroids (MBAs) class, indicating a dominance of inner solar system objects. Notably, the dataset includes only a limited number of asteroids from the Outer Main-belt and a mere 13 asteroids orbiting beyond Neptune, which may challenge model generalization, particularly in predicting diameters accurately for Trans-Neptunian Objects (TNOs). TNOs, typically larger due to the conditions of the outer solar system, present complexities in prediction due to limited data. While ongoing research sheds light on TNO characteristics, the model's current focus remains on predicting MBA diameters. Moreover, potentially hazardous asteroids predominantly belong to Near-Earth Asteroids (NEAs) classes AMO, APO, and ATE, with diameters typically ranging from 0.1 km to 1 km, emphasizing the importance of accurate size prediction for Earth-crossing or close-proximity asteroids.

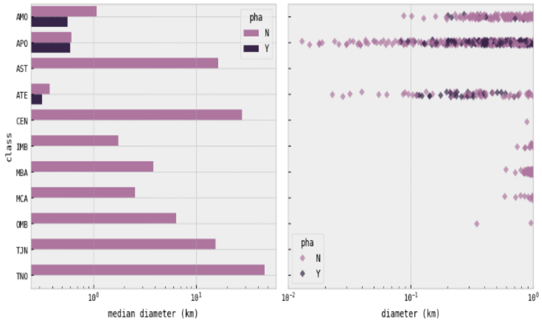

Figure 2:Class-wise diameter distribution

The analysis of figure(2) reveals a correlation between the distance of asteroids and their median diameter, indicating that asteroids classified as potentially hazardous (ATE, APO, and AMO) tend to have slightly smaller median diameters compared to non-threatening counterparts within these classes. While asteroids with diameters below 0.14 km generally fall outside the potentially hazardous range, exceptions exist where asteroids with diameters around 0.1 km challenge this threshold. Accurately measuring the diameter of potentially hazardous near-Earth asteroids proves challenging due to factors such as irregular shapes, rotation rates, and distances from Earth. Achieving precision often necessitates integrating data from diverse sources, including radar observations and brightness measurements, to derive more reliable estimates of asteroid sizes.

(iii) H(Absolute magnitude):

Absolute magnitude serves as a critical measure of an object's intrinsic brightness, differing between stars and asteroids. While it represents the apparent magnitude of stars if they were 10 parsecs away, for asteroids, it signifies the visual magnitude at 1 AU from both the Earth and the Sun, at a zero phase angle, denoted by H. With 747 missing absolute magnitudes, filling them with values using median, logistic regression, and k-nearest neighbours (KNN) imputation methods yielded consistent results, suggesting randomness in the missing values. This implies that any imputation method could be suitable. Given the importance of absolute magnitude in estimating an asteroid's size and composition, further analysis incorporating albedo could enhance our understanding of celestial bodies. The imputed absolute magnitude values can be compared in figure(4).

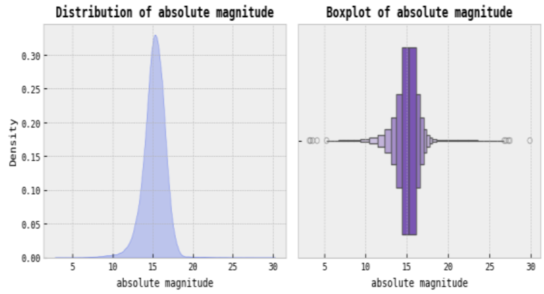

Figure 3: Distribution of absolute magnitude

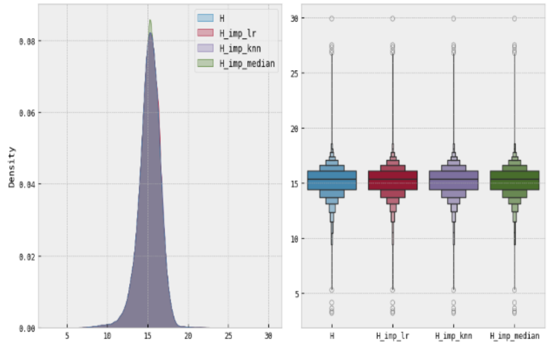

Figure 4: Imputed absolute magnitude values

(iv)albedo:

Albedo, as applied to asteroids, denotes the measure of a celestial body's reflectivity, specifically the fraction of solar radiation it reflects. This metric, typically ranging from 0 to 1, signifies the extent to which an asteroid reflects incoming radiation, with 0 indicating complete absorption and 1 denoting full reflection. Higher albedo values correspond to brighter appearances in telescopic observations, indicative of a more reflective surface, whereas lower values suggest darker surfaces with greater absorption. Notably, albedo, in conjunction with absolute magnitude, facilitates the estimation of asteroid sizes. For instance, while the Moon exhibits a notably low albedo of 0.07, Venus boasts a significantly higher albedo of 0.60.

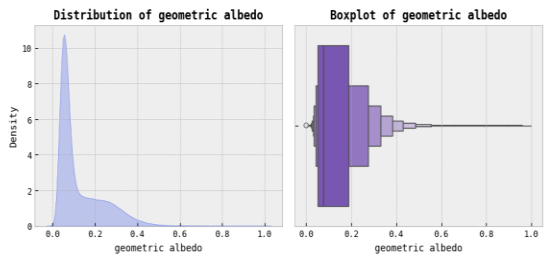

Figure 5: Distribution of geometric albedo

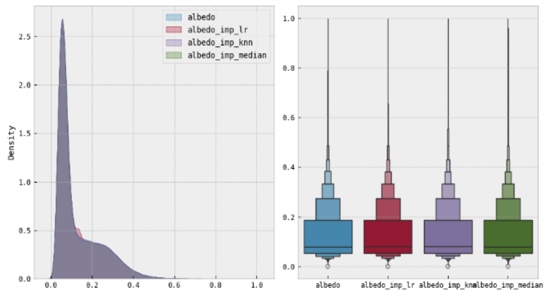

Figure 6: Imputed geometric albedo values

In the study of asteroid classes, distinct trends emerge regarding absolute magnitudes (H), diameter, and albedo. Main Belt Asteroids (MBAs) typically exhibit a uniform distribution around H=13, with smaller asteroids tending to have higher absolute magnitudes and larger ones lower. Albedo plays a crucial role, with higher albedo objects showing lower absolute magnitudes. Inner Main Belt Asteroids (IMBs) often boast higher albedos due to their silicate rock composition and space weathering. Outer Main Belt Asteroids (OMBs) and Middle Main Belt Asteroids (MCAs) generally possess low albedos, correlating lower H values with larger size. Near-Earth Asteroids (NEAs) demonstrate higher albedos for brighter and larger bodies but remain lower than 0.6, unlike MBAs. Trans-Neptunian Objects (TNOs) exhibit a wide range of absolute magnitudes, with brighter TNOs usually larger but not necessarily less absorptive. Similarly, Centaurs (CENs) follow the trend of brighter ones being larger, albeit not consistently showing increased albedo. Overall, these findings from figure(7) shed light on the interplay between absolute magnitude, diameter, and albedo across various asteroid classes, informing our understanding of their physical characteristics and origins.

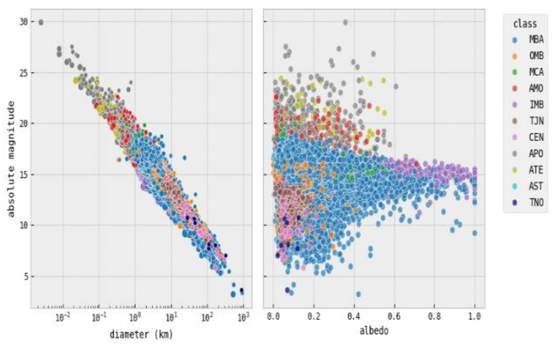

Figure 7: Diameter absolute magnitude relation

In general, the relationship between absolute magnitude and semi-major axis can vary depending on the class of asteroid. There is a negative correlation between absolute magnitude and semi-major axis, meaning that asteroids with smaller semi-major axes tend to have higher absolute magnitudes.

(v)moid(Minimum Orbit Intersection Distance):

MOID, an acronym for Minimum Orbit Intersection Distance, serves as a crucial metric for evaluating the potential close approach between celestial bodies, typically asteroids and planets. It represents the minimum distance between the orbit of an asteroid and that of a planet, notably Earth, at their intersection point. This parameter is instrumental in assessing the likelihood of collisions between asteroids and planets. A smaller MOID suggests a higher probability of collision between the asteroid and the planet in question. Often, MOID is complemented by other factors such as relative velocities to accurately gauge the collision risk. This measure holds significant importance in astronomical research and collision risk assessment endeavors.

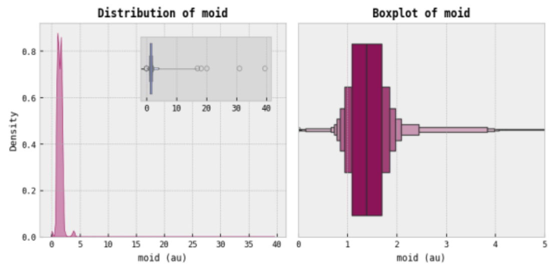

Figure 8:Distribution of moid

The figure(8) suggest that the most common minimum orbit intersection distance between the asteroid and Earth is around 1.5 au.

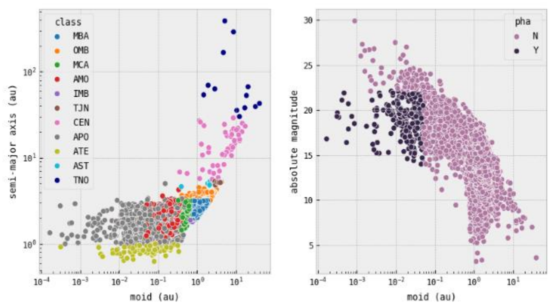

Figure 9: moid semi-major axis relation

NEAs are more likely to have smaller MOIDs due to their proximity to Earth and their orbits that intersect Earth's orbit.MBAs generally have larger MOIDs because they have more circular orbits and are located farther from Earth.Only NEAs whose moid < 0.05 and whose H <= 22.0 may usually be considered PHAs. The figure(9) tells that asteroids in our dataset are entirely in accord with the statement.

(vi)ma(Mean anomaly):

Mean anomaly is an orbital parameter that specifies the angle between the current position of an asteroid and its position at a hypothetical time when it was at its perihelion, assuming a perfectly circular orbit. It is a measure of the asteroid's progress along its orbit, and increases uniformly with time.

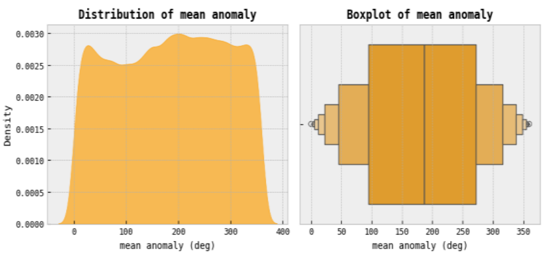

Figure 10: Distribution of mean anomaly

It is noted from Figure(10) that Mean anomaly spans all values, with the median of 187 deg.

Correalation:

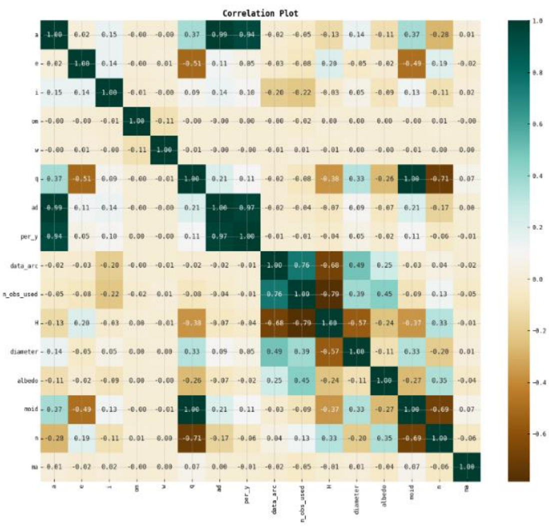

Figure 11: Correaltion between features

From analysis of figure(11), it has come to our attention that numerous highly correlated features exist within the dataset. Specifically, some notable correlations include:

1. Semi-major axis a and aphelion distance ad

2. Semi-major axis a and orbital period per_y

3. Perihelion distance q and mean motion n .

4. Aphelion distance ad and orbital period per_y , among others.

This observation underscores the interconnectedness and interdependency among certain orbital parameters within the studied celestial systems. Such correlations are pivotal considerations in our analysis and hold significance for the broader understanding of orbital dynamics and system characteristics.

Feature Engineering and Data Preprocessing:

In our analysis of asteroid data, we have diligently curated a subset of 20 relevant features from an initial pool of 31, eliminating those with extensive missing data or negligible predictive value. While the majority of these features are numerical and require minimal manipulation, several key attributes such as condition_code, neo, pha, and class are categorical in nature. Notably, condition_code, although numerical, carries nuanced implications beyond its numerical representation. To enhance the predictive capability of our model, we intend to derive a novel feature that promises to augment the accuracy of asteroid diameter predictions. This forthcoming feature, which warrants significant attention, shall be generated through meticulous computations leveraging existing data columns. Its integration into our analysis holds substantial promise for refining the precision of asteroid diameter forecasts.

Approximate Asteroid Diameter Feature

In the context of asteroid diameter estimation, we utilized an equation to compute approximate diameters based on absolute magnitude and geometric albedo. We observed a strong linear relationship between the computed diameters and the actual diameters of asteroids, demonstrating the potential for accurate diameter estimation. To assess the impact of excluding this feature, we employed one-hot encoding for categorical features and prepared data splits for training, testing, and validation. With 30% of the data allocated for testing, 58% for training, and 12% for validation, we standardized numerical features using StandardScaler(), ensuring consistency across sets. This rigorous approach facilitates model training and evaluation, crucial for achieving high predictive performance in asteroid diameter estimation.

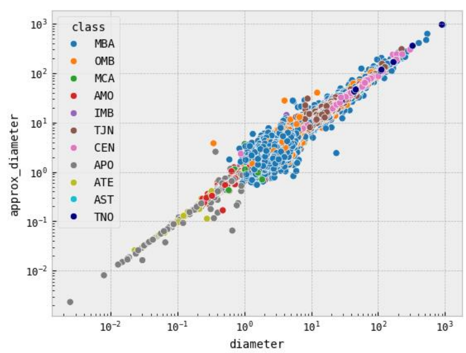

Figure 12: Diameter prediction accuracy

Building and Fine-Tuning the Models:

This section centers on the construction and fine-tuning of three models: MLP neural network, CatBoost, and Light GBM, with the objective of identifying the optimal model for predicting asteroid diameter. The focus is on a rigorous exploration and optimization process to facilitate a comparative analysis of their performance. The ultimate goal is to make an informed decision based on empirical results, discerning which model exhibits the most favorable outcomes for our specific predictive task.

Machine Learning Models

(i)MLP:

This study employs a Multilayer Perceptron (MLP) model for regression tasks, utilizing a sequential architecture comprising an input layer of shape (41,), two hidden layers (with 50 and 10 neurons, respectively), each employing Rectified Linear Unit (ReLU) activation functions, and an output layer predicting scalar values, specifically diameters.This adopt Mean Squared Error (MSE) loss and Adam optimization for model training over 50 epochs, implementing early stopping after 10 epochs to mitigate overfitting. Despite initial fluctuations, the model's validation loss diminishes steadily, indicating improved generalization. This framework underscores the effectiveness of MLP models in capturing intricate relationships between input features and target variables, thus warranting further investigation and application in regression tasks.

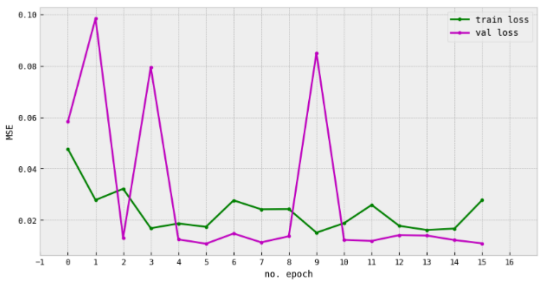

Figure 13: MSE value through 15 epochs

Figure (14) implies that the Multilayer Perceptron (MLP) model exhibits promising performance metrics, achieving a low mean squared error (MSE) of 1.020 and a high R-squared (R2) value of 0.983 in predicting asteroid diameters. While the MSE signifies generally accurate predictions, it's essential to contextualize its significance relative to asteroid sizes. Although a deviation of 1 km may seem negligible for larger asteroids around 100 km in diameter, it becomes more substantial for smaller asteroids ranging from 1 to 10 km. Consequently, the model's predictions necessitate a nuanced assessment to align with the practical implications of accuracy in asteroid diameter estimation. Moreover, the high R2 value indicates a strong correlation between input features and target variables, underscoring the model's ability to capture underlying patterns effectively.

The constructed MLP model, featuring sequential architecture with two hidden layers employing ReLU activation functions, demonstrates potential for capturing complex relationships between input features and asteroid diameters. Utilizing MSE loss and Adam optimization, the model is trained for 50 epochs with early stopping mechanisms to mitigate overfitting. Despite initial fluctuations in validation loss, the model's performance stabilizes, yielding minimized losses over successive epochs. These findings underscore the MLP model's capacity to generate accurate predictions and capture a significant portion of the variance in asteroid diameter data, highlighting its potential utility in asteroid research and exploration endeavors.

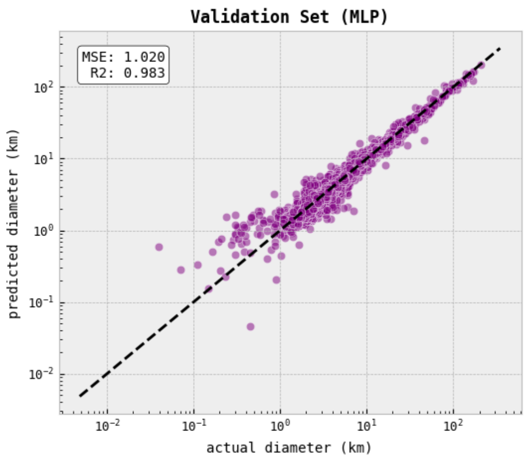

Figure 14: MLP trained with approx_diameter feature diameter prediction

MLP trained on dataset without approx_diameter feature:

The MLP model, with consistent hyperparameters and complexity, demonstrates superior performance on a reduced dataset, exhibiting low mean squared error (MSE) and high R2 scores on the validation sets. Despite occasional fluctuations in validation loss, the overall trend remains satisfactory, indicating robust predictive capabilities. Both models, with and without the "approx_diameter" feature, yield competitive results, albeit the former shows slightly better metrics. The inclusion of "approx_diameter" enhances predictive accuracy, as evidenced by lower MSE and higher R2 scores. Given the modest computational overhead and theoretical significance, retaining the "approx_diameter" feature is prudent, offering potential incremental gains in predictive accuracy for future models. In the context of interpreting MSE for asteroid diameters, choosing the model incorporating "approx_diameter" ensures more reliable predictions, facilitating more precise estimations of asteroid sizes with increased confidence.

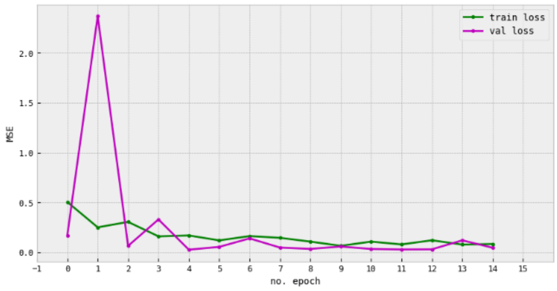

Figure 15: MSE value through 15 epochs

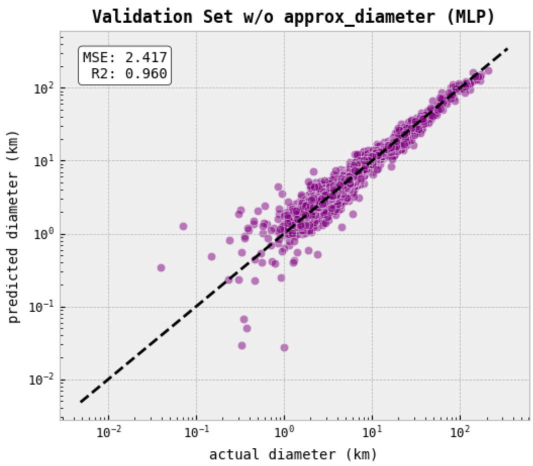

Figure 16: MLP trained without approx_diameter feature diameter prediction

Comparing figures (14) and (16) it is noted that the initial model outperforms the second model, showcasing its effectiveness in predicting asteroid diameters. With a Mean Squared Error (MSE) of 2.417, indicating an average deviation of roughly 1.4 km from actual diameters, and an R2 score of 0.960, signifying significant variance capture, the chosen model demonstrates reliability and accuracy in its predictions. These findings underscore the model's precision, essential for comprehending the characteristics of celestial objects like asteroids.

(ii)CatBoost:

Baseline Model:

The performance evaluation of CatBoost models, both with and without the 'approx_diameter' feature, indicates that the baseline model, excluding the mentioned feature, slightly outperforms the one including it. However, the discrepancy in performance is negligible when compared to the baseline CatBoost model trained on the complete dataset. This suggests that the 'approx_diameter' feature may not significantly enhance the predictive capability of the model within this context. Moreover, the baseline CatBoost models exhibit comparable performance to the MLP model trained on the entire validation set, indicating their ability to effectively capture underlying data patterns. Therefore, it is reasonable to consider the baseline CatBoost model without the 'approx_diameter' feature as a dependable choice for asteroid diameter prediction. Nonetheless, further fine-tuning of the models is warranted to ensure optimal performance.

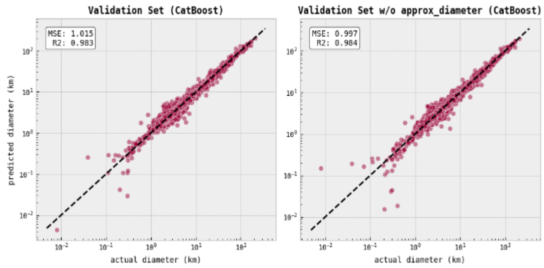

Figure 17: Baseline Catboost diameter prediction

Fine-tune models:

The fine-tuned CatBoost regressors demonstrate superior performance on validation sets compared to MLP models and baseline CatBoost models, with marginal differences between datasets containing and excluding the approx_diameter feature. As noted from figure (18), the model without approx_diameter achieves lower MSE (0.894) and slightly higher R2 (0.985), indicating it captures pertinent data patterns without this feature. This underscores the significance of feature selection and model fine-tuning for optimal performance. The ease of parameter optimization and stability of the reduced dataset model imply its suitability for consistent and accurate predictions. Furthermore, its alignment with the diagonal line suggests better accuracy and linear relationship capture, contrasting with outlier predictions in the other model. These findings favor the second model for its stability, MSE scores, and alignment with practical implications, endorsing its adoption for more reliable diameter predictions in research contexts.

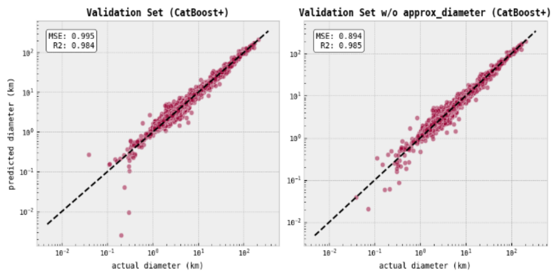

Figure 18: Finetuned Catboost diameter prediction

The selected model performs well on the test set, achieving an MSE of 2.128, indicating an average deviation of approximately 1.5 km from actual asteroid diameters, and an R2 score of 0.975, capturing a substantial portion of the target variable's variance. Despite not surpassing the MLP on the test set, the chosen model exhibited superior performance on the validation set, possibly due to differences in data distribution or characteristics. The MLP's strengths may have contributed to its better performance on the test set. Nonetheless, the chosen model provides reliable predictions for asteroid diameters, showcasing effectiveness alongside the MLP, each with distinct advantages.

Evaluation of asteroid:

There are multiple crucial procedures involved in determining the value of asteroids. The asteroid's diameter is estimated using the data. This is an important parameter for the computations that follow. The formula for the volume of a sphere is used to calculate the asteroid's volume based on its diameter. After that, the asteroid's kind is ascertained using measurable features, like its albedo, which sheds light on its reflectivity. M-type asteroids are identified with special attention because of their potential wealth in valuable metals. The asteroid's composition is next examined, usually by means of spectroscopic examination, in order to determine whether or not metals are present and in what quantity.

By utilizing this composition data in conjunction with the established type classification, the asteroid's estimated value is determined. Integrating market dynamics is the last stage after determining the asteroid's composition and kind. To assess the asteroid's worth, current market values for metals like gold, silver, platinum, and titanium are utilized. This calculation takes into account the asteroid's composition and volumetric parameters, integrating weighted averages of metal prices according to their relative abundance within the asteroid. Through the integration of scientific research and economic concepts, this procedure provides a thorough evaluation of the asteroid's economic feasibility, facilitating well-informed choices for the use of space resources and exploration activities.

V. Conclusion

This research concludes by presenting a systematic methodology for calculating the value of asteroids according to their type classification and composition. Our approach provides a systematic framework for evaluating the economic potential of asteroids by combining scientific study with economic concepts. This helps to make educated decisions about space resource exploitation projects. By measuring the diameter of asteroids, categorizing them, examining their composition, and calculating their market-value, our methodology offers a thorough understanding of the financial feasibility of mining operations on asteroids.

The results of this study highlight how asteroid mining has the power to fundamentally alter how humans will interact with space in the future. We can open up new avenues for technological advancement, space exploration, and sustainable development by making use of asteroids' plentiful resources. However, in order to overcome the technological, financial, and moral obstacles, players from all sectors of society—including governments, business, and the international community—must work together to realize this goal. In order to improve and validate the suggested methodology going ahead, more study and development will be required, taking into account developments in data analysis methods and market dynamics. Additionally, promoting ethical and responsible asteroid mining techniques would need concerted efforts to create precise legal frameworks and international collaboration channels. In the end, as we explore farther into space and use its limitless resources for the good of humanity, the goal of asteroid mining offers the possibility of a better future for future generations.

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