Data Mining and Machine Learning 2 CA1: Asteroid Diameter Prediction Using Artificial Neural Network

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***Abstract*—We are a little element of a vast cosmos, about which we yet know very little. For the goal of research and development for the future, studying space is crucial. Our galaxy is the subject of a large amount of data. We may study many gray regions with the use of machine learning and artificial intelligence tools together with space exploration. We use an artificial neural network in this article to estimate the diameter of asteroids. Asteroids are cosmic objects that come in many different sizes and shapes. Some of them may be harmful if they collided with the earth. A tiny asteroid can nonetheless do significant damage if it collides with the planet due to its velocity. If a big asteroid strikes our planet, it might create a wave of dust that is powerful enough to wipe out all the flora and consequently all of humanity. Therefore, estimating the asteroid's diameter is important since doing so will allow us to calculate the potential harm the asteroid may do if it collides with the earth. NASA has enormous data available through its constant research in space. With this data they have identified a lot of asteroids depending on a variety of factors such as distance, rotation. We used artificial neural network technique, which provides us an accuracy of 83.5%. We can learn a lot more about our galaxy and surrounds by using a similar method.**

***Index Terms*—Artificial Neural network, Asteroid diameter prediction, Space research, NASA.**

I. Introduction

A. Background

We still don't know a lot of items and facts about our vast solar system. Since the creation of our solar system around 4.6 billion years ago, it has been undergoing constant change. Small, stony objects called asteroids orbit the sun. No two asteroids are identical since they originated in various places at various distances from the sun. Small fragments of asteroids make up meteors. On impact, tiny meteors frequently burn up in the Earth's atmosphere and do significant damage. It follows that asteroid will unavoidably cause further harm. There is application of ML and AI in almost all modern-day fields. This technology can hugely be beneficial to the vast space domain which still remains unexplored in majority.

B. Motivation

Earth was desert-like and arid when it was created. It's believed that comet and asteroid encounters brought water ice and other emission chemicals to the planets that enabled the emergence of life. Ironically, it may be because of collisions that could have killed mankind that we are still alive today. But if any such collisions happen in near future it can be of huge impact. Asteroids are in the millions and range in size from several kilometers to a few feet. Almost all asteroids have erratic shapes. The biggest known asteroid, Vesta, has a diameter of 460 km, although the majority are as tiny as pebbles. Asteroids are potentially deadly despite their size. Many have already collided with Earth, and more will do so in the future. That is one of the reasons why asteroids are studied by scientists, who are keen to understand more about their composition, orbits, and physical attributes. We want to be informed if an asteroid is heading in our direction. The asteroid belt, which is located between Mars and Jupiter, contains the majority of asteroids. They won't affect the planet in any way. Many of them, however, are outside of this main belt. They are categorized as near-Earth asteroids by NASA. It is crucial to research them and compile data on them. According to CNEOS, more than 2.5 million near-Earth asteroids have been found by astronomers as of October 2021. Just about 10,000 of them have diameters more than 500 feet. For an asteroid to create a major worldwide catastrophe, it must be around 250 miles broad. An asteroid like this impacting the planet once per 1000 years is extremely uncommon. Smaller asteroids, which are thought to reach Earth each 1,000 to 10,000 years, have the potential to obliterate cities and unleash catastrophic tsunamis.

C. Goals

Scientists have identified many asteroids as potentially dangerous. There still is time to act, say scientists, if it turns out that an asteroid will collide with Earth in 30 or 40 years. Exploding the thing or redirecting it are options, although technology would need to be created. But there are far more asteroids out there than have been discovered, and faster reaction times could be more dangerous. So, based on several criteria, we will try to forecast the diameter of an asteroid using machine learning and artificial intelligence techniques.

Classifying and researching them will be highly beneficial for safety and research reasons. The same techniques we are using for asteroid diameter detection ca further be used in other similar space related research

D. Research Question

Here is the research problem that we will attempting to answer for our project, based on the subject and after the literature review.

How accurately can model be made that determine asteroid's diameter using deep learning techniques?

E. Plan of the paper

For the purpose of calculating asteroid diameter, several investigations have been conducted in the field of space science. To choose the most effective strategy, we thoroughly reviewed prior relevant work and the literature. For measuring the asteroid's diameter, we used an artificial neural network. For our project, we used the KDD technique. Data selection, preprocessing, data transformation, data mining, and ultimately data interpretation are significant elements of the technique.

II. Related Work

According to Paper [1], the basis of proactive congestion control is high-speed network traffic fore-cast.The fuzzy neural network (FNN) and multilayer perceptron are two alternative artificial neural network (ANN) architectures that we utilize in this study to forecast the value of MPEG and JPEG vid-eo, Ethernet, and Internet traffic data one step ahead (MLP). To improve prediction accuracy, the output of several ANN predictors is merged using a variety of combination strategies. Combination techniques and ANNs both use an adaptive updating approach. The results show that the ANN predic-tors outperform the autoregressive (AR) model and that the combination technique increases predic-tion accuracy. The use of neural networks to predict and manage nonlinear discrete systems is discussed in this arti-cle. The neural networks that are the subject of the discussion are discrete systems that could either be radial basis functions (RBF) or cerebellar model articulation controllers (CMAC). The stability char-acteristics are guaranteed, i.e., the errors between the expected values and the real values in predic-tion, or between the intended values and the actual values in control, are constrained. Examples are provided to further explain the theoretical findings, which are based on strict findings from the re-search [2]

The scientific report [3] describes One of the various methods for calculating Value-at-Risk (VaR), a tool for assessing risk, is the parametric technique. The parametric method was found to be ineffec-tive for particular market conditions, such as those involving crises or rapid changes in behavior, in the bibliographic study. The objective of this study is to investigate whether alternate computation techniques, such as the usage of neural networks, are more effective. In this study, the parametric approach for computing VaR as well as feedforward neural networks and recurrent networks with long short-term memory (LSTM) were assessed.

IBOVESPA, the B3 So Paulo Stock Exchange, served as the study's index. The results of the experiment showed that LSTM networks outperformed the exception rate generated by the complete model. When evaluating crisis situations or abrupt changes in behavior, LSTM and Feedforward networks per-formed less well at predicting VaR than the parametric approach. People who have merely had a passing familiarity with NASA's spacecraft, systems, and missions may assume that artificial intelligence has always played a significant role in what NASA achieves. Risk management is especially important when it comes to risky space missions since it requires a balance between creative thinking and meticulous engineering. New capabilities, whether AI-based or not, are only put into use when they are overwhelmingly helpful to a mission. The risks connected with learn-ing a new skill must be fully comprehended and quickly eliminated. Nevertheless, whether it is carried out by robotic spacecraft or astronauts, space exploration is not for the weak of heart or vision. In particular, the 1999-launched Remote Agent Experiment (RAX) and the 2003-deployed and still-running Autonomous Sciencecraft Experiment (ASE) on the Earth Observing One (EO-1) platform demonstrated the proper use of AI-based capabilities in prospective robotic missions. NASA outlines how these capabilities support the organization's reinvigorated focus on robotic and human explora-tion of the Moon, Mars, and beyond in a report [4].

An approach for training recurrent neural networks is suggested in this publication [5]. The recom-mended approach can explain many nonlinear systems with greater parsimony than higher order neu-ral networks based on Volterra series since it is based on the bilinear polynomial. The proposed bilin-ear recurrent neural network (BLRNN) is compared to multilayer perceptron neural networks for time series prediction problems (MLPNN). The BLRNN is more dependable and accurate in making predic-tions than the MLPNN, according to the study article.

Time series predictions have frequently employed neural networks.. In this study, we propose a novel approach for training neural networks to make long-term predictions.The authors' [6] strategy em-ploys traditional time series analysis based on the Box- Jenkins method to select the appropriate neu-ral network design, the inputs for the neural network, and the appropriate lead time for updating the neural network's correlation during training (1976). We demonstrate the effectiveness of our method in producing precise multistep forward forecasts on a few real-world problems as well as simulated time series data.

There are a number of limitations on how conventional ATM cells can be disposed of. Either they are rigid or they are challenging to implement. In this study [7], we proposed a novel cell discarding method based on time-delayed neural networks' traffic load prediction. Using the limited impulse response (FIR) filtration in multilayer neural networks, we decide which cells will be deleted when the network buffer is close to overflowing. With a total of 10 sources, the simulation generates cells based on the distinctive property of each source. The number of learning iterations and the standard-ized squared sum prediction error are metrics for the multilayer neural network. The goodput is used to evaluate how well the suggested cell discarding policy is performing. The simulation's findings im-ply that the suggested cell discarding procedure could deliver a high goodput score that is very near to the ideal.

An automatic suggestion has turned into a problem that is growing more and more important for many organizations in order to help users locate things that meet their interests and to help the sys-tem target the right consumers for products. Many scholars are interested in chart neural networks, which have evolved into powerful recommendation tools. The author [8] of this study suggests a sep-arate graph neural recommendation model (SGNR), which is based on graph neural networks and yields superior results. There is also a three-attention operator for feature fusion, which makes the feature accumulation better by employing a more logical and flexible propagation technique. The suggested strategies exceed the most modern recommendation algorithms in terms of prediction ac-curacy for quantitative evaluations and are also simpler to read and comprehend, according to exper-imental results on four public databases.

The use of GCNs to classify functional brain networks has gained appeal as a method for the early de-tection and prognosis of neurodegenerative diseases. This work by the author [9] thoroughly exam-ines the effectiveness of GCNs for the categorization of brain functional circuits of Alzheimer's data. We look at how various variables, including graph generation thresholds, graph sizes, data sizes, or subject numbers, affect the results. We find that the models' precision grows with larger graphs and when all topic visits are taken into account. Application of transfer learning has also improved catego-risation accuracy. Last but not least, execution times for asynchronous calculations using CUDA streams have decreased by as much as 60%.

Because of its popularity, Android has turned into one of the most important platforms for attackers to carry out their wicked schemes. Due to the sophistication of Android malware encryption and de-tection avoidance tactics, many traditional malware detection approaches that were once successful due to their limited representation capabilities are now inapplicable. This research [10] proposes a potent enhanced deep neural network dubbed to guard Android devices against dangerous applica-tions, inspired by deep learning's effectiveness in transfer learning. We propose an unique deep neu-ral network-based design from the perspective of an ensemble classifier, where the combined predic-tive outputs of all hidden layers lead to the final prediction. The first hidden layer efficiently extracts a feature description from the source data using a number of subnetworks. A loss function is created by adding together each base classifier linked to a specific hidden layer's prediction loss. The complexity and volume of astronomy data are rapidly increasing. Numerous data science studies are carried out to develop models and techniques to extract data or datasets and derive new infor-mation from them. Astronomers are adopting machine learning more and more as a result. Many ac-ademics have used machine learning techniques to research astronomy for a number of reasons. The researchers in [11] employed a number of strategies to use Deep Learning algorithms to judge how habitable an exoplanet might be. Deep learning was employed in their study to control the complexi-ty of the data. Understanding the challenges of using traditional supervised machine learning algo-rithms has been made easier by this research.

The impact of any asteroids that cross Earth's orbit or are about to do so is detected by the authors' [12] analysis of ATLAS (Asteroid Terrestrialimpact Last Alert System). The major shortcoming of this study so far is that it predicted falsely good outcomes. The author developed a model using deep neu-ral networks to distinguish between real movement and false positives.

Similar to other studies, scientists in [13] investigated natural catastrophes, such as an asteroid colli-sion, that may be entirely averted or at least greatly mitigated with prompt and accurate predictions. Their study suggests a strategy that uses deep neural networks to learn complex representations that are included in the distribution of accessible asteroids orbital data in order to characterize the popu-lation of near-Earth asteroids as potentially dangerous or non-hazardous. Researchers came to the conclusion that while neural network classifiers can recognize complex patterns in skewed datasets, deep learning can help us achieve the intended target.

A basic astronomical conundrum that appears during observations using ultrahigh angular resolution interferometers was approached in a novel way by the authors of [14]. This tactic is based on the ap-plication of artificial neural network theory. A multiparameter model for a celestial object like Sgr A* has been suggested and calculated. Researchers have numerically created a variety of credible images for the neural network training of this model. Using a different set of photographs from the same model, the neural network's performance was assessed after it had been trained on these images. We have demonstrated that a neural network can classify and identify celestial objects almost as well as a human can.

This study on the real-time restoration of dim astronomical images through turbulence over a wide field of view was inspired by the authors' study of centroid prediction using ANN in [15]. The centroid of a research object was predicted using a simulation platform that was convolved through numerous perturbation fields and projected onto an image plane. To train an artificial neural network to esti-mate centroids over a spatial grid constructed on the image plane, centroids were chosen from a vari-ety of sources and target locations. With the help of a priori centroid data matching to specific grid points, it was established if the network could be trained to predict centroids across new target loca-tions. Their findings lay the groundwork for future modal tomography study and implementation.

Binary asteroid exploration is actually an important research emphasis in the domains of deep space research and space informatics due to its unique scientific significance in analyzing the structure and gravitational properties of asteroids, including the genesis and development of celestial objects. Re-mote photometric observations may provide a useful and efficient way to find binary asteroids by revealing the key characteristics that set them apart from other forms of asteroids, particularly unary asteroids. However, the problem of automated binary asteroid detection utilizing state-of-the-art ma-chine learning approaches remains unanswered when working with complex asteroid photometric data.
This research [16] suggests computing unary as well as binary asteroid systems using cellinoid and oblate spherical shape models, and producing the pertinent light curve brightness data with different asteroid physical properties, in order to overcome this issue. Following is the development of a benchmark set of binary and unary asteroid light curves. Then, a binary asteroid device is trained in a layered content of information by enlarging the response discrepancies seen between the light curve information of unary and binary asteroids, enabling highly accurate differentiation between the two common types of asteroids. This is done using the layered discriminative confined energy minimiza-tion (LDCEM) technique. In comparison to numerous common detection techniques, the experimental results on the simulated asteroid light curve data and the empirically observed asteroid light curve facts show that the suggested LDCEM strategy may offer promising binary asteroid identification performance.
The effects of an asteroid hitting Earth might be severe. The first approach in lowering this risk is to identify any asteroids that may be nearby Earth in advance. A convolutional neural network model that can categorize celestial pictures based on the presence of asteroids is presented in this article [17]. The model was developed using data from the Isaac Newton Telescope (INT), which is located near La Palma, Spain's Canary Islands. This project's goal is to create an automated system for aster-oid identification while reducing the false-negative rate to the absolute minimum. We show that when trained on individual pictures, the model's recall is 94%.
This study [18] offers a planning method for hopping trajectories based on in-depth reinforcement learning for successfully landing on a surface with less gravity. A hopping rover's dynamic analysis is first developed. Then, a hopping technique is proposed that takes attitude angle and angular velocity as parameters. The deep reinforcement learning method is utilized to quickly solve the control varia-bles for autonomous hopping trajectory planning. In accordance with the reward functions of either the approach or deceleration stages of the landing procedure, two agents are trained. Sliding mode control is used to resolve the control torque in order to achieve the desired attitude angle and angu-lar velocity provided by the agent outputs. Finally, a low-gravity landing mission validates the hopping path planning strategy. The results show that, under different initial conditions, the rover may ap-proach and stop at the target via clever hopping.
A novel sampling technique for subsurface asteroidal regolith under constrained time constraints is presented in this study [19]. In order to complete sampling processes within a few hours, it is neces-sary to use methods that can address any potential subsurface obstructions. Sampling is further complicated by significant uncertainty as a result of our ignorance of the properties of regolith. Machine learning-based and haptic feedback-based detection methods may be able to detect the presence of rocks that are smaller than the probe's length, enabling precise sampling in open areas. In addition, a corer shot mechanism that uses a particular shape-memory alloy to collect regolith in just under a minute has been developed because of the wide range in soil hardness and the constrained time available. Testing with shooting-corer ejection and subsurface obstacle detection demonstrated the effectiveness of this strategy.
The use of artificial intelligence to resolve real-time problems is growing daily as more data and com-puting power become available. It is now important to use AI-based tools and methods in space ex-ploration. Stoney asteroids that circle the sun frequently have a variety of harmful effects on people and other creatures on Earth. The effects of these impacts include, but are not limited to, wind burst, overpressure impact, heat conduction, cratering, seismic trembling, ejecta deposition, and tsunami. With the data on parameters and characteristics of asteroids currently available, machine learning can be used to resolve this problem and lessen the danger it poses. This study [20] provides a thor-ough analysis of the consequences of Potentially Harmful Asteroids (PHAs) and proposes a supervised learning method for identifying whether or not an asteroid has a particular set of features that make it potentially harmful. Different classification techniques based on the data are contrasted. In terms of effectiveness (99.99%) and mean F1-score (99.22%), Random Forest performed best.

III. Methodology

This research article uses extensive data that was acquired from repositories authorized by NASA. Knowledge Decisions in Databases, or KDD Methodologies, is the term used to describe the process of extracting or mining, and finding meaningful and interpretable patterns from acquired massive data and will be implemented in this research work.

The primary goal of the KDD approach is to present methods that analyze the data while developing models, taking relevant premises and requirements into consideration, in order to help release the information or patterns and evaluate the outcome of the prediction done by the model built.

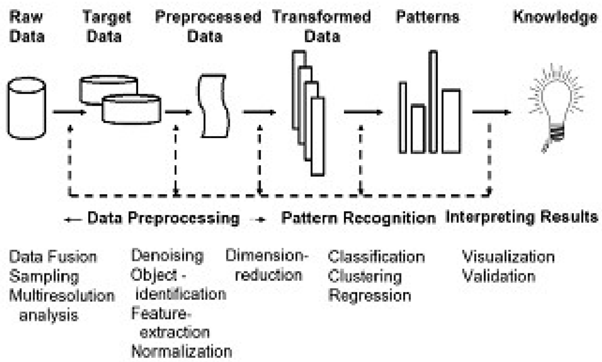

Fig. 1. KDD Methodology

As shown in Figure 1, below are the steps have been followed in this research work:

1) Selecting a dataset from the right source. Custom tables of orbital and/or physical properties for noteworthy asteroids and/or comets from our small-body database were available in NASAauthorizedsed repositories. The necessary data columns or variables were gathered and downloaded using various combinations. Data types like Asteroid's Object Kind, Orbit Class, Orbit Constraints, and Output Selection Controls fall under these categories.
2) Tensorflow Python libraries were used to import the downloaded data into a dataframe.
3) To extract pertinent information from the produced dataframe, exploratory data analysis was performed.
4) Following EDA, data purification, management, and transformation occurred. This technique includes the elimination or replacement of null values, the elimination of duplicate columns and the elimination of unnecessary columns.
5) Data in cleaned format was separated into training and testing sets for the construction of ANN which is Artificial Neural Network Model
6) Results and conclusions were made using the Evaluation metric.

Implementation of Artificial Neural Network:

A neural system is created to mimic neurons that are interconnected as shown by a certain type of system engineering. The neural system seeks to alter the contributions to meaningful yields. An Artificial Neural Network (ANN), which is more frequently not referred to as a brain system, is based on the structure or perhaps useful components of a natural neural system. For acknowledgment, clarification, expectation, and diagnosis, ANN is used.

1) Feature Extraction: In pattern identification and exploratory data analysis, feature extraction and multivariate data projection are crucial concerns. The "complex dimensionality" can be avoided, classifier generalization is improved, and pattern classification processing needs are decreased by feature extraction.

2) Data Cleaning and Transformation: The massive dataset that was obtained from NASA's archives contained a number of null values, errors, and undesirable data types. Cleaning the data, as described in the KDD Methodology, comes first before creating the neural network model. Using Python's Panda libraries, we eliminated null values. After deleting them, we changed NaN values to the feature's Mean values because the standard deviation was so small. To rapidly and simply train the model on the dataset, the "diameter" variable has been converted to "float" data types. Lastly, the independent variables "albedo" and "H" have been eliminated because they had no appreciable impact on the development of our data.
The treated data is then split into 80 percent train data and 20 percent of train data.
For Feature Scaling, Another scaling method is standardization, which centers the numbers around the mean and uses a unit standard deviation. As a result, the attribute's mean becomes zero, and the distribution that results has a unit standard deviation. This has been applied to training data before building model.

IV. Design Architecture and Specification

The model specification and architecture will be covered in this section. The section is organized into three sections: the suggested architecture, the key architectural elements, and the compilation techniques used to create the model.

A. Architecture to Design Model

Artificial neurons are a group of interconnected units or nodes that serve as the foundation of an ANN and are meant to approximate the function of biological brain neurons. Each link has the ability to communicate with other neurons, much like the synapses in a human brain. An artificial neuron can communicate with nearby neurons after processing signals that are sent to it. Each neuron's output is calculated by some non-linear function of the total of its inputs, and the "signal" at each link is a real integer. Edges are what link things together. As learning progresses, the weight of neurons and edges often changes. Weight affects whether a connection's signal is stronger or weaker.Neurons may have a threshold that must be crossed for a signal to be conveyed, according to one theory. Neurons are frequently grouped into layers. Different layers may subject their inputs to various modifications. Signals may pass through the layers more than once as they move from the first layer, the input layer, to the last layer, the output layer.

The three layers of architecture are depicted in the above figure. The data is imported using the data frame. Data cleansing and data transformation have been used in the pre-processing processes. When a model is being trained, a

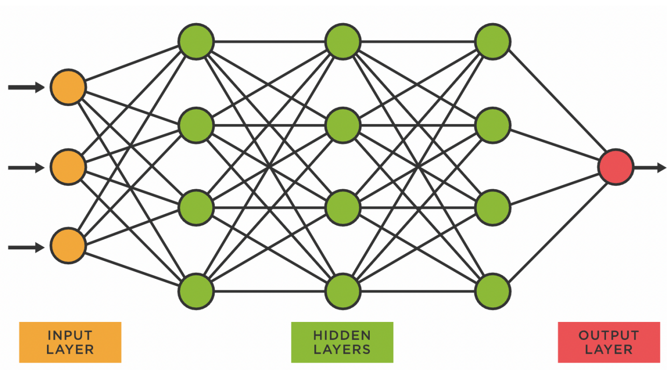

Fig. 2. ANN Architecture Diagram

runtime procedure known as model compilation is used Keras API and TensorFlow.

B. Model Compilation Parameters

Without the compilation process, a model cannot be made. Once compilation is complete, training can begin. An optimizer and metrics are used in the compilation of a model. These studies employ the metrics and optimizers are listed below:

Metrics: Accuracy

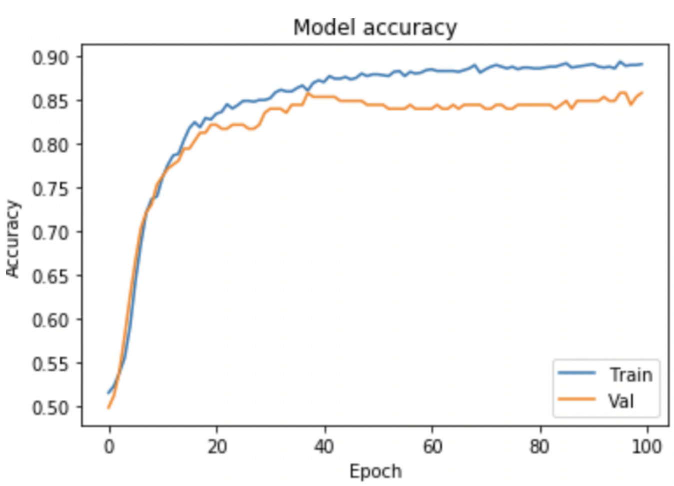

Fig. 3. Accuracy Metrics

Optimizer: Adaptive Moment Estimation (ADAM)

Another method for calculating adaptive learning rates for each parameter is adaptive moment estimation (ADAM). Adam stores an exponentially decaying average of past gradients v, comparable to momentum, in addition to keeping an exponentially decaying average of past squared gradients s, like Adadelta and RMSprop. Adam behaves like a heavy ball with friction as opposed to momentum, which can be visualized as a ball rolling down a slope, and favours flat minima in the error surface.

$$v_t = \beta_1 v_{t-1} + (1 - \beta_1) g_t$$

$$s_t = \beta_2 s_{t-1} + (1 - \beta_2) g_t^2$$

Fig. 4. Initial ADAM Formula

The authors of Adam note that because v and s are initialized as vectors of zeroes, they are skewed toward zero, especially during the first few time steps and when the decay rates are slow. The first and second moment estimations are computed with certain biases taken into account:

$$v'_t = \frac{v_t}{1 - \beta_1^t}$$

$$s'_t = \frac{s_t}{1 - \beta_2^t}$$

Fig. 5. Initial ADAM Formula 1

Since the final update procedure really uses the same formula as adaptive gradient descent but with v in place of the gradient in the nominator, it should be evident that Adam builds on the principles of its forebears and develops into a better version.

$$g'_t = \frac{lr * v'_t}{\sqrt{s'_t} + \epsilon}$$

$$\theta_t = \theta_{t-1} - g'_t$$

Fig. 6. Final ADAM Formula

where the gradient of the two parameters a, b, used to minimize the loss of y—f(x) is determined.

$$f(x) = ax + b$$
$$(y - f(x))^2 = (y - (ax + b))^2$$
$$\frac{dy}{da} = -2x(y - (ax + b))$$
$$\frac{dy}{db} = -2(y - (ax + b))$$

Fig. 7. Implementation ADAM Formula

where the gradient of the parameters a, b, which we use to try to minimize the loss of y—f(x) is determined, is used.

Loss: Categorical cross-entropy

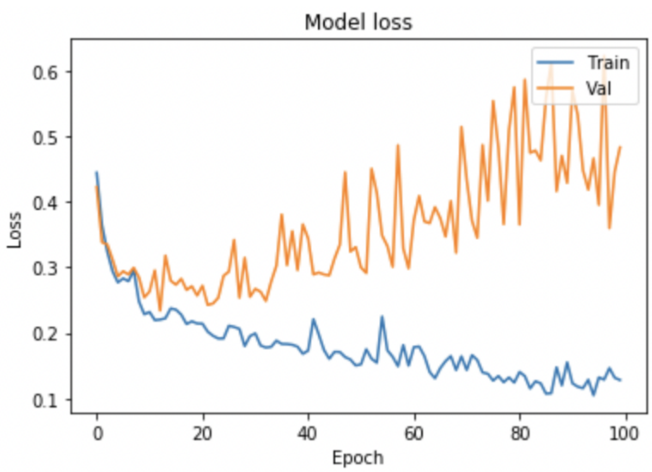

Fig. 8. Categorical cross-entropy

Multi-class classification tasks use the loss function categorical crossentropy. In these tasks, the model must determine which one an example belongs to as there are many alternative categories.

C. Architecture Main Components

According to the study, an artificial neural network system must have three layers.

First Layer: The input layer is where data enters the system.
Hidden Layer: Where information is processed is in the hidden layer.
Output Layer: In the output layer, the system makes decisions about how to proceed in light of the data.

Multiple layers, some of which are hidden, will be included in more complicated artificial neural networks.

Similar to artificial neurons, the neural network operates through a group of nodes or linked units. The neuron networks in the brain of an animal is roughly modeled by these nodes. An artificial neuron functions just like a biological neuron would: it receives a signals of a stimulation, processes it, and sends the signal to other neurons it is linked to.

V. Evaluation and Results

Consideration was given to thirty thousand asteroids' feature records. Adaptive Movement Estimation ADAM algorithm is used to adapt to the learning rate of each input component in order to minimize the gradient's moving average and update each input variable for accuracy. The degree of accuracy of this model may be judged by its ability to predict the diameter of an asteroid.

Fig. 9. Co-relation Matrix

The graphic above Figure 9 depicts the association between several asteroids dataset aspects to illustrate their interrelationship.

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The R^2 score achieved is : 83.5 %
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Fig. 10. R value for accuracy

The Sequential model permits the construction of deep neural networks through successively stacking layers. Since we are currently constructing logistic regression model, the input and output nodes will be directly linked, with no hidden layers. 83.5% R-Squared score is determined from Figure 10.

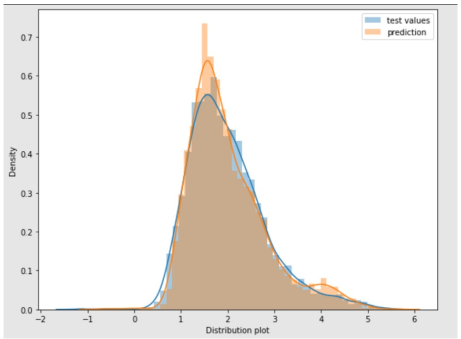

Fig. 11. Distribution Plot

Using the distribution plot, the density of test values and projected values together with a trend line are presented in Fig.11 . As the density of the predictions attempts to match that of test values, the specified model is able to identify with more precision, as seen by the figure.

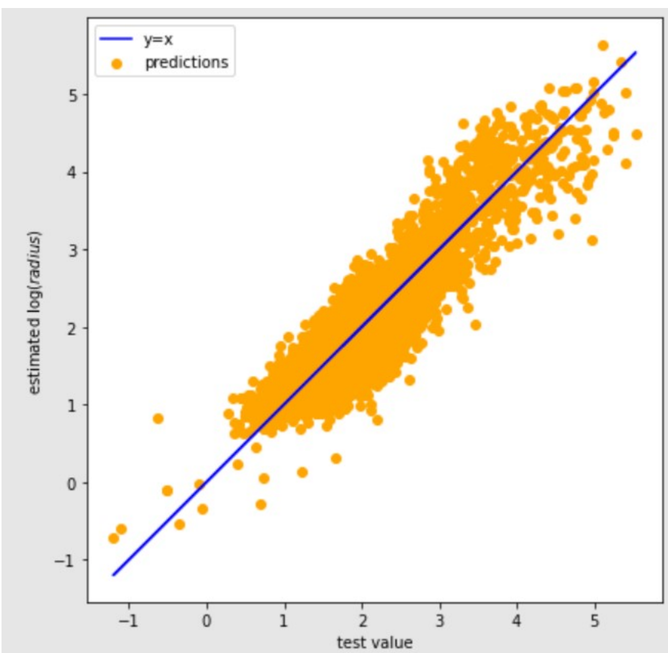

Fig. 12. Predicted Radius Accuracy Plot

In Figure 12 , projected logarithmic radius values are compared to test values, and the findings indicate that the proposed model performs well.

VI. Conclusions and Future Work

Predicting an Asteroid's radius constitutes one of the most difficult tasks in the aeronautics sector. This study prescribes a model for effectively determining the size of an asteroid. Using inner layers of a fully convolutional network, a novel approach is devised. The prescribed approach enhances the precision and dependability of radius detection by overcoming obstacles posed by distorted data.

Deep learning lowers the computational burden of training negative data, preserves the ratio of negative to positive samples, and improves the performance of the classifier. According to Asteroid testing information, the proposed method yields the most recent results.

We are currently supposing that the asteroid is progressing in a straight line. In the future, we will be able to improve the pipeline for forecasting velocity since we are presuming that the asteroid could be traveling in a straight line. Because of these changes, the distance calculation may need to be changed, which will affect the estimate of the total danger.

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