Neural Network Approaches for Applications and Challenges of Artificial Intelligence in Space Missions

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Abstract: Planet identification has traditionally been done by teams of astronomers and astrophysicists using techniques and instruments only available to persons with years of academic education and expertise. NASA's Exoplanet Exploration program has introduced contemporary satellites capable of collecting a large variety of data about celestial objects of interest to aid in their investigation. The availability of satellite data has made planet identification possible for anyone who can write and comprehend machine learning models. Several classification methods and datasets are used in this work to assign a likelihood that an observation is an exoplanet. More than 160 transiting exoplanets have been identified in the Wide Angle Search for Planets (WASP) data since the program's inception. In the past, probable transit-like events detected by the WASP pipeline were manually reviewed to minimize false alarms and blatant false positives. The purpose of this research is to evaluate the efficacy of machine learning as a quick, automated, and dependable method of executing the same duties on ground-based wide-field transit survey data without human interaction..

Keywords: Classification Algorithm, Exoplanets, WASP.

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INTRODUCTION

The mission to locate planets outside of our solar system, often known as exoplanets, has led to the discovery of many interesting new things. Identification of exoplanets has historically been a time-consuming job that has been reserved for highly educated and trained scientists who have access to sophisticated equipment that is often quite costly. When conducting their tedious search for exoplanets using photos obtained by terrestrial observatories and satellite-based telescopes like Hubble, these specialists relied on their education, intellect, dedication, and the team expertise they had gained over the course of their careers.

Techniques from the field of machine learning have been used by amateur astronomers in order to categorize interesting objects. One of the most significant examples of this may be seen in the research that

Shallue and Vanderberg conducted in 2011 (1) for their study. Two machine learning engineers working for Google, Shallue and Vanderberg, were responsible for training a neural network model to search through archival data in order to find planets by leveraging transit events that had been missed by previous researchers (1). In addition to this, the "Autovetter Project" developed a Navie Bayes Model to categorize items of interest based on transit data (1). The categorization of exoplanets is now, in effect, determined by the general public.

The labeled observations in the KCOI table serve as the basis for the generation of the test and train datasets. The KCOI data set includes more than eighty columns or characteristics, all of which were gathered and preaggregated from the Kepler data. The purpose of this data purification process is to structure the data in a way that is suitable for feature selection. After the most prominent and influential characteristics have been found, a support vector machine is trained, fitted, and then used to assign a probability that an observation from the KCOI table is an exoplanet. This process takes place after the most prominent and influential features have been identified.

Kepler, a space telescope that was developed by NASA and put into operation in 2009, is an example of a new generation of contemporary satellites designed to look for planets. It is the telescope that has been responsible for the finding of more extrasolar planets than any other [3]. As of October 2018, Kepler has discovered more than 9500 objects of interest, with more than 2000 of them confirmed exoplanets7. Kepler is particularly effective at locating planets the size of Earth, while previous telescopes were only able to locate bigger "gas giant" planets comparable to Jupiter [2]. Kepler uses known stars as its points of reference in its search for exoplanets in the habitable zone of their parent solar systems [3]. The Kepler spacecraft has been fine-tuned to precisely detect the brightness of stars [3]. A decrease in the brightness of a star may be an indication that one of its planets is moving in front of or behind it when it is seen via a telescope. A light curve obtained from the Kepler space telescope that displays a "U-shaped" dip; this dip suggests the presence of a transiting exoplanet

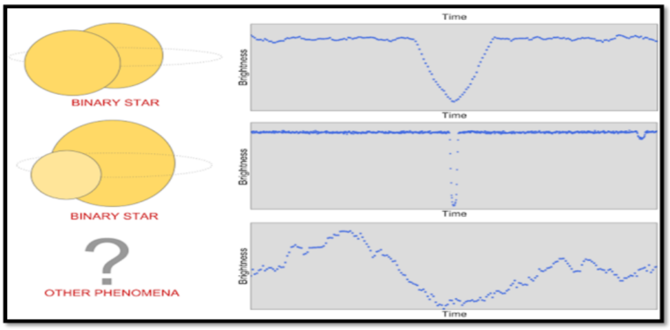


Fig -1: Transit shape

A dip in a star's brightness could indicate one of its planets is passing between the star and the observing telescope. The time it takes for the planet to pass between the start and observing telescope is the transit time and is usually measured in hours. The magnitude of the reduction in brightness and transit time can provide mathematical clues to the relative size and position of the planet relative to its star [2]. Though Kepler was technically a telescope, it is essentially a statistical mission (1). Kepler was purpose-built to collect data to support proven exoplanet identification techniques [2].

LITERATURE SURVEY

Exoplanet transit surveys such as the Convection Rotation and Planetary Transits (CoRoT; Auvergne et al. 2009), Hungarian-made Automated Telescope Network (HATnet; Hartman et al. 2004), HATSouth (Bakos et al. 2013), the Qatar Exoplanet Survey (QES; Alsubai et al. 2013), the Wide- angle Search for Planets (WASP; Pollacco et al. 2006), the Kilodegree Extremely Little Telescope (KELT; Pepper et al. 2007), and Kepler (Borucki et al. 2010) have been extremely prolific in detecting exoplanets, with over 2,900 confirmed transit detections as of August 9, 20181 . The majority of these surveys employ a system where catalogue-driven photometric extraction is performed on calibrated CCD images to obtain an array of light curves.

Following decorrelation of common patterns of systematic error (eg Tamuz et al. (2005)), an algorithm such as the BoxLeast Squares method (Kov´acs et al. 2002) is applied to all of the lightcurves. Objects that have signals above a certain threshold are then identified as potential planet candidates. Before a target can be flagged for follow-up observations, the phase-folded light curve is generally inspected by eye to verify that a genuine transit is present. As these surveys contain thousands of objects, the manual component quickly becomes a bottleneck that can slow down the identification of targets. Additionally, even with training it is difficult to establish consistency in the validation process across different observers. It is therefore desirable to design a system that can consistently identify large numbers of targets more quickly and accurately than the current method. Several different techniques have been used to try to automate the process of planet detection.

A common method is to apply thresholds to a variety of different data properties such as signal-to-noise ratio, stellar magnitude, number of observed transits, or measures of confidence of the signal, with items exceeding the given threshold being flagged for additional study (For WASP- specific examples, see Gaidos et al. (2014) and Christian et al. (2006)). Applying these criteria can be a fast and efficient way to find specific types of planets quickly, but they are not ideal for finding subtle signals that cover a wide range of system architectures. Machine learning has quickly been adopted as an effective and fast tool for many different learning tasks, from sound recognition to medicine (See, e.g., Lecun et al. (2015) for a review). Recently, several groups have begun to use machine learning for the task of finding patterns in astronomical data, from identifying red giant stars in asteroseismic data (Hon et al. 2017) to using photometric data to identify quasars (Carrasco et al. 2015), pulsars (Zhu et al. 2014), variable stars (Pashchenko et al. 2018; Masci et al. 2014; Naul et al. 2017; Dubath et al. 2011; Rimoldini et al. 2012), and supernovae (du Buisson et al. 2015). For exoplanet detection in particular, Navie Bayes Classifiers (McCauliff et al. 2015; Mislis et al. 2016), Artificial Neural Networks (Kipping & Lam 2017).

Convolutional Neural Networks (Shallue & Vanderburg 2018), and Self-Organizing Maps (Armstrong et al. 2017) have been used on Kepler archival data. Convolutional Neural Networks were trained on simulated Kepler data by Pearson et al. (2018). While Kepler provides an excellent data source for machine learning (regular observations, no atmospheric scatter, excellent precision, large sample size), similar techniques can also be applied to ground-based surveys, and in fact machine learning techniques have recently been incorporated by the MEarth project (Dittmann et al. 2017) and NGTS (Armstrong et al. 2018). The work of highly skilled astrophysicists or other researchers can be redirected towards more specialized exoplanet research. Light curves vary greatly, even at a large scale. Planets closer to the sun like Venus, are too hot to support life as we know it; while planets further out like Mars and beyond thought are too cold. Using a combination of transit time and other measurements collected by Kepler.

PROPOSED SYSTEM 3.1.Dataset:

Our main focus in this project is to analyze the features extracted from Dataset .which are required by windows loader. This contains various elements like size of code, size of data, overlay number. With help of this one can understand how a program is going to execute.

Training Set:

- 5087 rows or observations.
- 3198 columns or features.
- Column 1 is the label vector. Columns 2–3198 are the flux values over time.
- 37 confirmed exoplanet-stars and 5050 non-exoplanet-stars.

Dev Set:

- 570 rows or observations.
- 3198 columns or features.
- Column 1 is the label vector. Columns 2–3198 are the flux values over time.
- 5 confirmed exoplanet-stars and 565 non-exoplanet-stars.

Classification Algorithm:

For predicting exoplnets existence we aim at using three classifiers. By using different classification algorithm we can get different results.

Naive Bayes (Nb) Classifier:

Naive Bayes algorithm is a supervised learning algorithm, which is based on Bayes theorem and used for solving classification problems.It is mainly used in text classification that includes a high-dimensional training dataset.Naïve Bayes Classifier is one of the simple and most effective Classification algorithms which helps in building the fast machine learning models that can make quick predictions.

Formula :-$P(A/B)=(P(B/A)P(A))/P(B)$
Where,
P(A|B) is Posterior probability: Probability of hypothesis A on the observed event B.
P(B|A) is Likelihood probability: Probability of the evidence given that the probability of a hypothesis is true.
P(A) is Prior Probability: Probability of hypothesis before observing the evidence.
P(B) is Marginal Probability: Probability of Evidence.

Support Vector Machine (Svm):

Support vector machines exist in different forms, linear and non-linear. A support vector machine is a supervised classifier. What is usual in this context, two different datasets are involved with SVM, training and a test set. In the ideal situation the classes are linearly separable. In such situation a line can be found, which splits the two classes perfectly. However not only one line splits the dataset perfectly, but a whole bunch of lines do. From these lines the best is selected as the "separating line".

3.2.2. Artificial Neural Network:

Neural Network is built by stacking together multiple neurons in layers to produce a final output. First layer is the input layer and the last is the output layer. All the layers in between is called hidden layers. Each neuron has an activation function. Some of the popular Activation functions are Sigmoid, ReLU, tanh etc. The parameters of the network are the weights and biases of each layer. The goal of the neural network is to learn the network parameters such that the predicted outcome is the same as the ground truth.

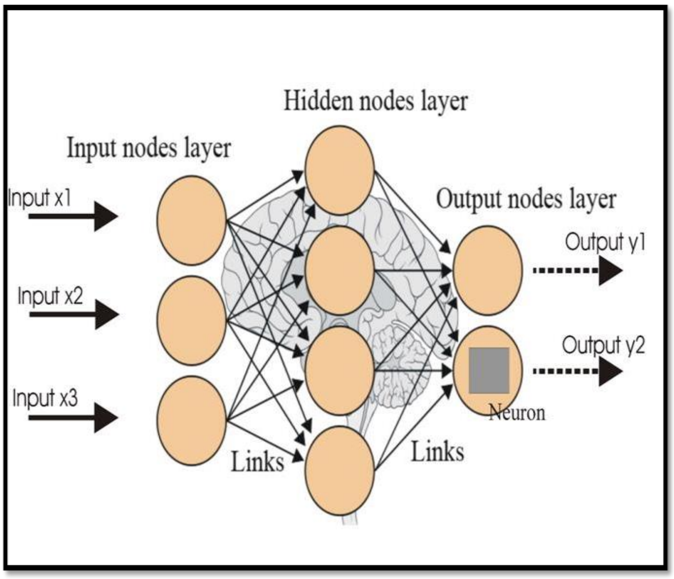
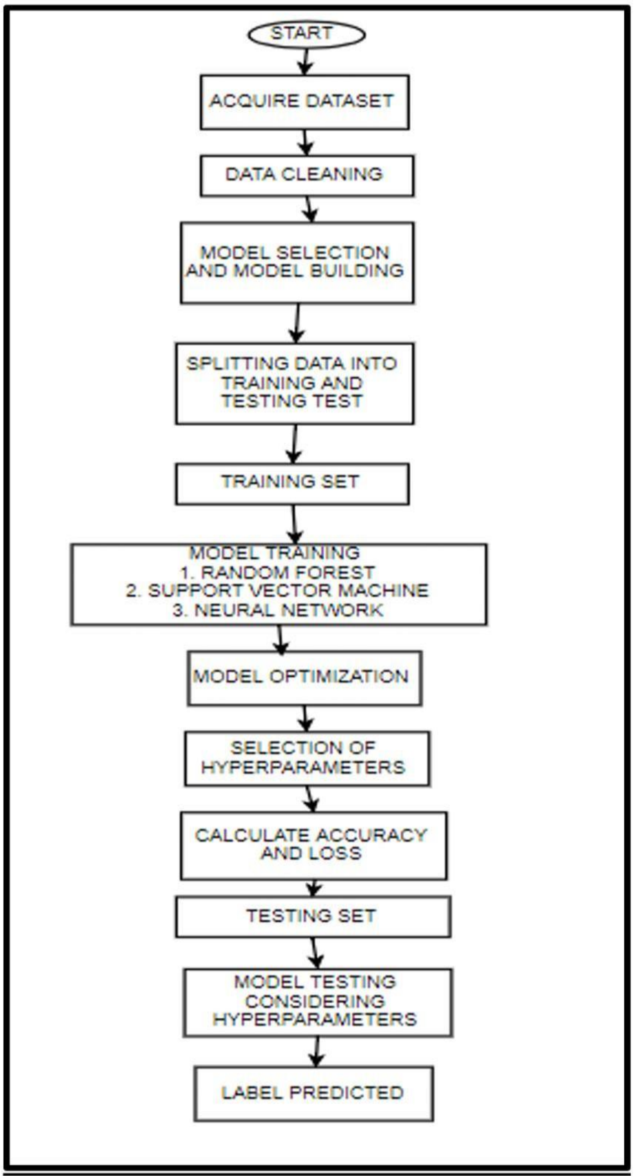


Fig -2: Multilayer Artificial Neural Network

Flowchart:



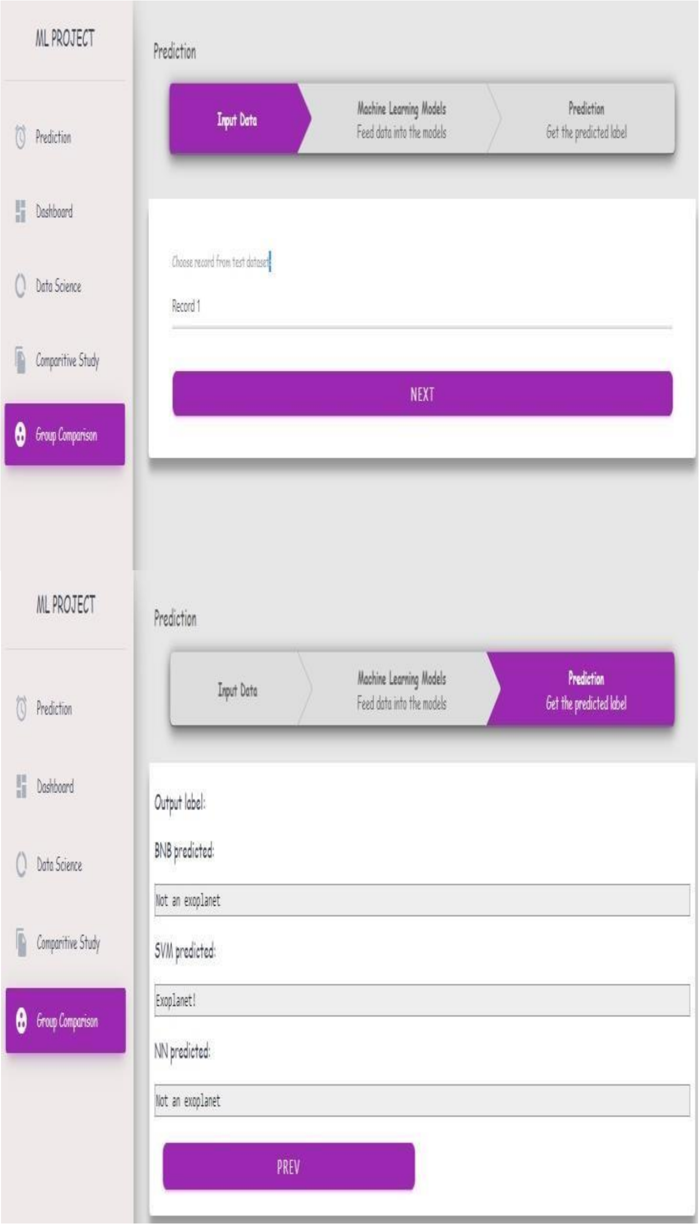
RESULT & CONCLUSION

Using multiple machine learning models is an effective framework that can be modified and applied to a variety of different large-scale surveys in order to reduce the total time spent in the target identification and ranking stage of exoplanet discovery. Combining the results from additional machine learning methods could further improve the predictions. An additional advantage of this approach is that the algorithms can be quickly re-trained as new information, such as new known classifications from completed follow-up observations, become available.

It has proven to be very effective in producing new candidates for future follow-up and eventual planet status. The large size of the WASP archive makes it undesirable for human observers to manually look at each one to determine whether it is a good candidate for further study. The machine-learning framework we have created provides a tool for the observer wanting to re-examine the full set of data holdings in any WASP field, enabling fast re- classification of all targets showing transit-like behavior and identification of new targets of interest.

Website Snapshots

After entering user ID and password.



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