Stage V : Final Report

Abstract

The main mission of the Kepler space telescope was collecting data that would contribute to the discovery of stars with planets orbiting them. This data can be converted into a lightcurve, which is a graph of the observed star's light intensity over time. The changes in the light intensity sometimes occur in patterns that give useful information about the star. One pattern is the transit signal which can be an evidence of the existence of a planet. These are large amounts of data that might be challenging for astronomers to analyze. On the other hand, Artificial Intelligence can help accelerate the data analysis process to detect extraterrestrial planets (Exoplanets). In this work, we built different machine learning (ML) algorithms that can detect exoplanets from the Kepler time series dataset. We trained Random Forest, Logistic Regression models, and Convolutional Neural Network (CNN) models on the dataset, these models have been evaluated using accuracy, sensitivity, precision metrics. The Random Forest, Logistic Regression and CNN respectively scored 99.08%, 99.08%, 99.12% accuracy, 99.08%, 99.08%, 100% precision, 100%, 100% recall for all of them. Hence, they might be the best performing ML models that can be useful for astronomy and astrophysics researchers and other experts working in the extra terrestrial planet searching field.

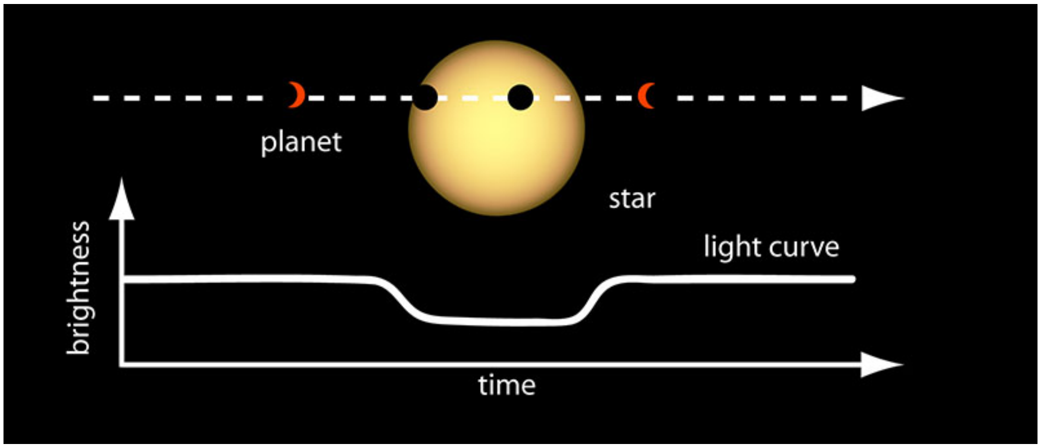
Introduction

Recently, discovering the exoplanets in the near galactic stars has been an active research topic in astronomy and machine learning fields, aiming to find earth-like habitable planets that could be the humans' next station within the next decades or centuries. For that reason, in 2009, NASA sent the Kepler space telescope to scan the sky looking for planetary systems other than ours. By 2015, Kepler had discovered evidence of other potentially habitable planets within the Milky Way galaxy. It was a rocky Earth-like planet that has been named 'Kepler-452b'. It is known to be the closest planet to Earth so far. There are many exoplanets discovered after that and have similar physical properties to the Earth. An enormous quantity of data is being transmitted from space missions and telescopes to earth, where astrophysicists and data scientists must analyze and investigate them. This process is complicated and time-consuming. Therefore there was a demand for automation of this process using data analysis tools and artificial intelligence solutions. (Pat Brennan, 2015).

A planetary system consists of one or more planets around a host star, which itself orbits in another orbit. Furthermore, planetary systems can be detected using a variety of techniques, including radial velocity, direct imaging, polarimetry, astrometry, transient photometry, gravitational microlensing, and transit time variation and other methods. Transient photometry is the most often employed technique for planet detection. It occurs when a planet passes in front of a star, resulting in a modest periodic drop in the star's light intensity, and is referred to as the transit signal. Once a transit signal is detected, we may use Kepler's third law of planetary motion to determine the planet's orbital size and the period required for the planet to orbit the star, in addition to the star's mass. As a result, the characteristic temperature of a planet may be determined using its orbital radius and the temperature of its star. With this in mind, the issue of whether the planet is habitable or not may be answered.

There are two types of transit; the first one is FACE-ON which considered the best transit and the second one is EDGE-ON which used with -radial velocity "The transit led to the monitoring of 530,000 stars in the Cygnus constellation and it has confirmed the existence of more than 2,600 exoplanets in 2018."

Light curves are graphs that plot the brightness of an object over time Figure(1). They are an extremely useful instrument for studying objects whose brightness fluctuates over time, such as novae, supernovae, and variable stars. LightKurve is an easy-to-use tool for analyzing and visualizing time series data regarding the brightness of planets, stars, and galaxies. Originally developed to support astrophysicists using NASA's Kepler and TESS observatories, this package may also be used by amateur astronomers to examine light curves.



Figure(1). The transit of a planet causes a noticeable and gradual decrease in the flux of a star for a period of time (NASA Ames, 2021).

Related works

(Thompson, 2015) performed a k-nearest-neighbors machine learning model that yielded to 99% accuracy using Kepler mission data and (Kyle A. Pearson, 2019) trained a random forest machine learning model for the first time to classify the kepler mission dataset scoring 98.94 accuracy and 5.85% overall error rate. Both of the researches helped us to identify the testing methods that were used in this new research in a developed phase.

(Sean D. McCauliff, 2015)Sectors 1-3 of Kepler data set has been studied to search for transit timing variations (TTVs). Several artificial intelligence techniques, such as Convolutional Neural Network (CNN), with multi-input and multi-output systems have been conducted to quickly detect new planets by vetting non-transit signals before characterizing light-curve time series. In order to achieve other effective outputs and find other planets, an enhanced machine learning method is going to apply and study new sets of data.

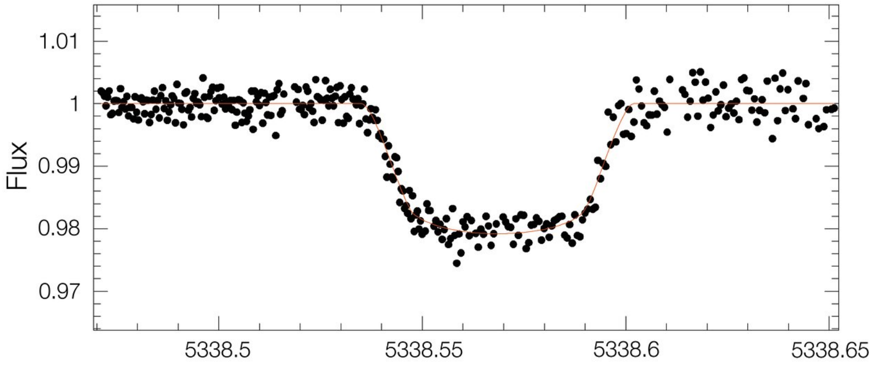
(Li-Chin Yeh1, 2020) The research aims to explore exoplanets moving around the lighted stars through photometric light curves that are analyzed from the BRITE satellites group by using Machine Learning algorithms and methods. We constructed several Convolutional Neural Network (CNN) models to find transit candidates based on different transit periods of time, which were trained by using synthetic transit signals combined with BRITE light curves until they were above 99.7% percentage of accuracy. The researcher used this method because it is very efficient and effective regarding the small number of selected transits that are possible to appear in the result. For instance the Machine Learning system had chosen only 2 systems "HD37465 and HD186882', which reached higher priority during the future observations processes. The result is valuable regarding focusing on 2 systems that would. (Abhishek Malik, 2020) Suggested using astrophysics approaches to improve the performance of the machine learning algorithms and tested them on a simulated dataset, yielding better results when compared to box least squares fitting. Training the Binary Classification models and Decision Tree on Kepler dataset resulted in 94.8% accuracy and 96% recall.

(Priyadarshini, 2021) Compared the performance of Decision Trees, Support Vector Machines, Logistic Regression, Random Forest Classifier, Multilayer Perceptron (MLP) ,Convolutional Neural Network(CNN) and Ensemble-CNN Model that have been trained on Kepler time series and K2 datasets, concluded that the Ensemble-CNN is the best performing model in exoplanet detection scoring 99.64% accuracy.

These research papers helped us a lot in our topic. The machine learning approaches that were used for detecting exoplanets aided us to select best performing models, more improved approaches to preprocess the dataset. AI made the processes of predicting and analyzing way easier than before by reducing time, cost, and efforts. Regarding these studies we realized that this is one of most important topics in the Astronomy field and will add a huge value to this science by discovering new things in the field that contribute to the development of science and facilitate life for living organisms. Our main purpose is to explore new things about this wonderful planet.

Dataset

The Kepler mission sent us various information about the observed objects (stars) to search for Earth-sized planets around distant stars and designed to survey our region of the Milky Way galaxy. Each star has been observed over a period of time, mostly 8 hours. For this period of time, the luminosity or the flux of the star is the amount of energy emitted every unit of time. It changes due to several reasons, one reason can be the transit of a planet causing a decrease in the flux in a drop shaped pattern. See Figure (2).



Figure(2).The transit of a planet causes a gradual drop in the light intensity of the host star within a period of time (ESO, 2021).

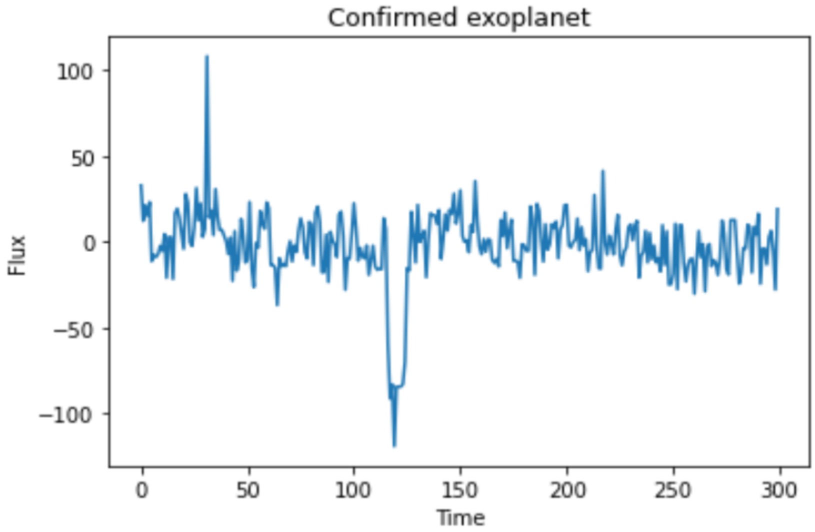
Our dataset has been retrieved from kepler mission archives, labelled and organized into a time series table, see Table(1). Column number 0 represents the predicted value or the label (1 , 2) not confirmed, confirmed planet respectively. While the remaining columns (1- 3197) represent the light intensity or the flux of the star observed in a period of time. Each row contains the brightness and the label of a certain object of interest (star) collected by Kepler.

Table(1). First 5 examples of Kepler time series in the training dataset where the y is the label, x are the flux from 1 to 3197.

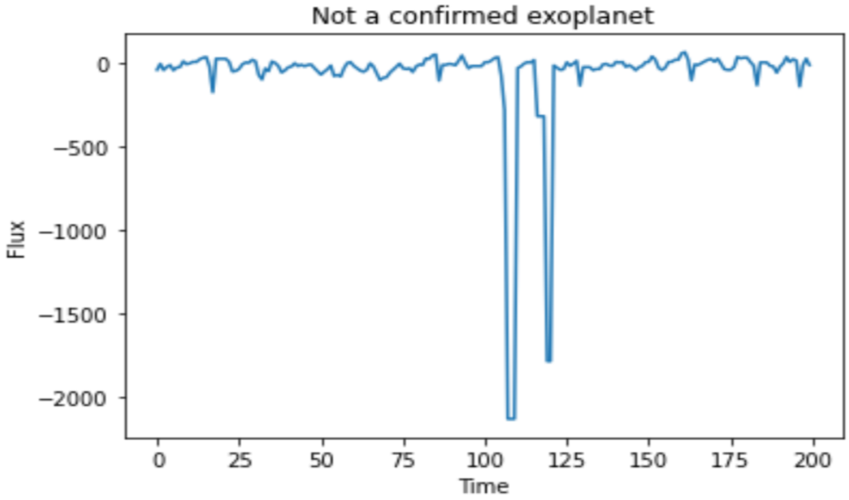
LABEL	FLUX.1	FLUX.2	FLUX.3	FLUX.4	…	FLUX.3193	FLUX.3194	FLUX.3195	FLUX.3196	FLUX.3197
2	93.85	83.81	20.1	-26.98	…	92.54	39.32	61.42	5.08	-39.54
2	-38.88	-33.83	-58.54	-40.09	…	0.76	-11.7	6.46	16	19.93
2	532.64	535.92	513.73	496.92	…	5.06	-11.8	-28.91	-70.02	-96.67
2	326.52	347.39	302.35	298.13	…	-12.67	-8.77	-17.31	-17.35	13.98

2	-1107.21	-1112.59	-1118.95	-1095.1	…	-438.54	-399.71	-384.65	-411.79	-510.54

The selected features for the training are 1-3197 columns (the light intensity). The label or the prediction value is the 0 column. For each instance in this time series dataset, we can create a light curve graph (figure(3), figure(4)).



Figure(3). a time series plotting of an object illustrates the transit signal as a sign of a confirmed planet before the data preprocessing (containing noise and outliers).



Figure(4). A time series plotting of an object illustrates a different type of a flux change that is not similar to a transit signal, hence is not a confirmed planet (containing noise and outliers).

Methods

The Kepler time series dataset has been preprocessed using methods similar to astrophysics data analysis. Then Random Forest, Logistic Regression and CNN models training has been performed on the dataset. Evaluation using accuracy, recall and precision metrics has been done. These models have been selected based on the previous work done on Kepler data.Then comparison to find the best performing algorithm to detect transit shaped signals has been performed.

Light Curve data preprocessing

We split data to training set and test set, but as seen in table (1), the data needed to be filtered and preprocessed in multiple ways, as it contains false positives, instrumental noise and outliers that makes it difficult to detect a transit-like signal.

We dropped the null rows and columns, and reshaped value, then performed scaling and transforming ,then selected 3197 features ,

The LightKurve library helps the astrophysicist to analyze Kepler and TESS time series data, by removing outliers, scattering, flattening, and folding the data. However, this tool uses a retrieved dataset from NASA archives. For this reason, we tried to create functions similar to the LightKurve library to preprocess our own dataset, these functions include: Fourier Transformation, Reducing Upper Outliers, Smoothing Filters, Normalization, Standardization.

We applied these functions by creating a class then creating an object containing the dataset before feeding the dataset to our machine learning models.

Training the models

I. Logistic Regression model:

Logistic regression is one of the most common machine learning algorithms used for binary classification. It predicts the probability of occurrence of a binary outcome using a logit function. It is a special case of linear regression as it predicts the probabilities of outcome using log function. In this case, the activation function (sigmoid) has been used to convert the outcome into categorical values.

Logistic Regression model training:

After the preprocessing stage, we built and trained several Logistic Regression models that iterated 6000 times, using Sklearn and Pandas libraries.then we performed regularisation using GridSearchCV with penalty=12.

In the first training the scoring accuracy was 75.5%. After that we edited some of the preprocessing methods, accuracy increased to 77%. Finally, after using the light curve preprocessing class methods that imitates the astrophysics approaches the model scored 99% accuracy.

II. Random Forest Model:

Random Forest is a robust machine learning algorithm that can be used for a variety of tasks including regression and classification. It is an ensemble method, meaning that a random forest model is made up of a large number of small decision trees, called estimators, which each produce their own predictions. The random forest model combines the predictions of the estimators to produce a more accurate prediction.

Random Forest model training:

The stages of building this model:

1- Choosing random samples from the dataset.

2- Building multiple decision trees for all samples then get a prediction result from each decision tree.

3- Taking the result from each decision tree.

4- Choosing a predicted result depending on the most repetition result as the final prediction.

We implemented several random forest models using sklearn, pandas, numpy libraries, the result was scoring 100% accuracy which is an overfit, then we used the lightcurve data preprocessing class to remove any noise and outliers, the resulting accuracy went down to 99.8%.

III.Convolutional Neural Network Model:

The architecture of this type of artificial neural network follows a similar pattern to multilayer perceptrons.This type of NN is specifically designed to process pixelfiles, and since the data coming from Kepler are originally a series of pixel files converted into a lightcurve, it can to be used in exoplanet detection.

Training the convolutional neural network model:

Before feeding the preprocessed dataset to the model, we had to scale and reshape it. Using Keras, TensorFlow, Sklearn and many other libraries, we build a convolutional neural network model. These libraries helped us flattening and max pooling the input then used ReLU and Sigmoid as the activation function, with 11 sized kernel. Editing some of the Lightcurve preprocessing class methods helped improve the accuracy from 99.08% to 99.12%.

Results and evaluation

The confusion matrix is helpful in evaluating the performance of a predictive model on unseen. it can be calculated in several steps:

1. Use part of the data (test dataset) as an expected outcome value (y_training_set).

2. Make a prediction for each row test dataset.

3. Compare the predicted result and true results.

These numbers are organized in a matrix. Rows refer to predicted class, columns refer to actual class.

Evaluation Metrics

After training the dataset, we used the testing set to evaluate the performance of our model. We used Accuracy, Precision, and Recall. The resulting metrics were significantly well performing.

Accuracy:

Accuracy defines how many times the machine learning model correctly classified the data, we calculate it using the formula:

$$\frac{TP + TN}{TP + TN + FP + FN}$$

Where TP means True Positive, TN True Negative, FP False Positive, FN False Negative.

The CNN model scored **99.12%** accuracy.
The Logistic Regression model scored **99.08%** accuracy.
The Random Forest model scored **99.08%** accuracy.

Precision:

Precision defines the ratio of the true values and the predicted values, we calculate it using the formula:

$$\frac{TP}{TP + FP}$$

Where TP means True Positive, TN True Negative, FP False Positive.

The CNN model received **100%** precision.
The Logistic Regression model received **99.08%** precision.

The Random Forest model received **99.08%** precision

Recall:

Recall or Sensitivity is the ratio of the actual positive values and the predicted values, we calculate it using the formula:

$$\frac{TP}{TP + FN}$$

Where TP means True Positive, TN True Negative, FN False Negative.

The CNN model scored **100%** sensitivity.
The Logistic Regression model scored **100%** sensitivity.

The Random Forest model scored **100%** sensitivity.

Conclusion

As the search for Earth-like possibly habitable planets outside our solar system continues to grow, newer space missions to discover the sky emerge, creating huge amounts of raw data, increasing the demand to automate the data analyzation process. Using Artificial Intelligence could be the possible solution for this problem. After reviewing several papers that used machine learning methods to detect exoplanets, we obtained an insight of best performing models to analyze the Kepler mission dataset. In this work, we used astrophysics approaches to preprocess the data, then built Logistic Regression, Random Forest and CNN models, trained them on Kepler time series dataset. As a result, the performances of each were significantly upstanding. Logistic regression model scored 99% accuracy, Random Forest scored 99% accuracy and CNN reached 99.1% accuracy. Those promising results can indicate that continued testing and prediction can lead to discovering new unexpected extra terrestrial planets that could possibly be our next destination.

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