# FORM 2

THE PATENTS ACT, 1970 (39 of 1970)

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5 The Patent Rules, 2003

# COMPLETE SPECIFICATION

(See section 10 and rule 13)

# 10 TITLE OF THE INVENTION

“Chandrayaan-3: Method of Detecting and Identifying Exoplanets in the Deep Space using Artificial Intelligence”

We, applicant(s)

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The following specification particularly describes the nature of the invention and the manner in which it is performed:

# FIELD OF INVENTION:

The proposed invention related to detecting and identifying exoplanets using Artificial Intelligence

# Background of the Invention:

Transiting exoplanets provides a great opportunity for researchers to detect planetary

5 atmospheres using spectroscopic characteristics during primary transit, which occurs when a

planet crosses in front of its parent star, the light that travels through the planet's atmosphere and shows the atomic and molecular species that are absorbing light displays these absorption properties. At this time, 3,513 exoplanets have been found (Please rephrase as 5514 discovered. Source NASA) , with the majority of them coming from space missions such as Kepler (Borucki et al. 2010), K2 (Howell et al. 2014), and CoRoT

10 (Auvergne et al. 2009), as well as from ground-based observatories such as HAT/HATnet

(Bakos et al. 2004), SuperWASP (Pollacco et al. 2006 The thresholds that restrict the ability to exist photometric surveys are going to be raised by future planet-hunting surveys like TESS, PLATO, and LSST so that they can sample brighter stars at quicker cadences and across the broader field of views (LSST Science Collaboration et al. 2009; Ricker et al. 2014; Rauer et al.

15 2014).

The first findings of Kepler's four-year investigation found that around 15 percent of solar-type stars contain a planet with a radius between one and two times that of Earth with an orbital period ranging from five to fifty days (Fressin et al., 2013; Petigura et al. 2013). Because the transit depth, which is 100 ppm for a solar-type star, hits the limit of existing photometric

20 surveys and is below the typical stellar variability, the discovery of such tiny planets, which

are about the size of Earth, is problematic. Stellar variability may be seen in about 25 percent

of the 133,030 main sequences of Kepler stars. Its magnitude can vary from 950 parts per million (the 5th percentile) to 22,700 parts per million (the 95th percentile), and its period can be anywhere from 0.2 to 70 days (McQuillan et al. 2014). In the future, the analysis of data will need to be sensitive to planets similar to Earth while also being resistant to variations in

5 star characteristics.

The most common methods for locating planets involve using a least-squares optimization, grid-search, or matched filter approach (Kov'acs et al. 2002; Jenkins et al. 2002; Carpano et al. 2003; Petigura et al. 2013). These methods aim to maximise the correlation between the data and a simple transit model. The objective of a least-squares optimization is to reduce the

10 amount of mean-squared error (MSE), which occurs when comparing data and a model.

Because the transit parameters cannot be determined in advance, a box function is used to develop a simplified model of the transit process.

When attempting to minimise the MSE, least-square optimizers are prone to discovering local minima, which may lead to erroneous transit detections unless the global solution can be

15 identified. Least-square optimizers are vulnerable to finding local minima. Constructively

binning the data may boost the signal-to-noise ratio when individual transit depths are below the scatter, which is the situation for Earth-like planets at the moment (SNR). Grid searches make use of binning by executing a brute-force assessment across various periods, epochs, and durations to search for transits using either a Least-squares technique (Kov'acs et al. 2002); or

20 matchedfilter. This evaluation is carried out in order to locate transits (Petigura et al., 2013).

Convolving the data with a custom-designed kernel or filter that emphasises the characteristics of the transit is what a matched filter technique does in order to try to improve the quality of the signal produced by a transit.

# Summary of the Present invention:

5 In this day and age of "big data," the human assessment of prospective exoplanet candidates is

a laborious process that is difficult to do with modest transit signals (e.g. Earth-sized planets).

Because of things like the activity of their stars, transits of exoplanets may take on a variety of forms. Therefore, a basic template is insufficient to capture the nuances of the details, particularly if the signal is buried behind the noise or if there are significant systematics at play.

10 In order to learn the photometric characteristics of a transiting exoplanet, we make use of an

artificial neural network. The deep learning technique of machine learning is able to analyse millions of light curves in only a few seconds.

Because of the discriminative nature of neural networks, it is only possible to give a qualitative evaluation of the candidate signal by expressing the chance of finding a transit within a subset

15 of the time series. This is how neural networks make their assessments. We come up with a

way of discovering periodic transits by using a phase folding approach, which produces a constraint when fitting for the orbital period. This method is used for planet signals that are less than the noise. Because neural networks are extremely generalizable, it is possible to assess data using a variety of sample rates simply by interpolating the data into a standard grid. This

is made possible by the flexibility of neural networks. We evaluate our deep nets using light curves from the Kepler mission, and we discover periodic transits that have a period that is comparable to the actual period without having to fit any models. In addition to this, we examine a number of other approaches. We investigate the sensitivity of our deep net in the

5 context of the next-generation planet survey by using the expected photometric accuracy of

TESS. Our goal is to find planets similar in size to Earth. When calculating the transit depth, we use the assumption that the star is of the G type and has the same radius as the sun. Our values impose a lower limit on the transit depth and, as a result, the detection accuracy; this is the case even though TESS will focus mostly on M dwarf stars. The CNN 1D algorithm can

10 reliably identify a single Earth-like transit in bright stars with a V value of 8 or above, but it

will need to bin the data in order to achieve a higher signal-to-noise ratio for fainter stars.

Our planet identification rates, which include the use of 1D convolutional networks and feature modifications like wavelets, are shown, and a considerable improvement using CNNs is found. The methods of machine learning give an artificially intelligent platform that, in comparison

15 to a person, is able to acquire nuanced characteristics from massive data sets in a more time

and effort-effective way.

The next generation of data processing automation will be more adaptable, capable of self- learning, and able to optimise itself with little to no supplemental human input. A qualitative pre-selection will be made, and then a quantitative characterisation of the exoplanet signal will

20 be performed when the computer has gained an understanding of what it is seeing. In the future,

we would want to investigate the possibility of making use of other deep learning approaches (such as long short-term memory or PReLU), with the goal of improving the detection system's resistance to background noise. In addition, there is ongoing research being done in the field of machine learning with the goal of optimising the network design and having it adapt to

5 particular issues. By eliminating systematics from the time series, the addition of a pre-

processing phase has the potential to significantly enhance the performance of the transit detection algorithm.

# Brief description of the invention:

Our deep neural networks are trained with simulated training data to learn how to

10 accurately forecast single planetary transits in noisy photometric data. The data that was

simulated is very comparable to what we would anticipate receiving from an actual planetary search survey. After the deep nets have been trained, we utilise the network to determine the probability of the presence of prospective planetary signals in data that it has not before seen.

In order to train our deep nets, we create a total of 31,1040 sets of data, including both

15 transit and non-transit data. The training data come from a discretely sampled nine-dimensional

hypergrid in our parameter space, and they are generated from that. The parameters set a maximum limit of four hours for the length of the transit, with a minimum of thirty minutes. This range covers 1./12 to 2./3 of the time domain. We made sure that our criteria included a

wide variety of potential systematic forms and transit sizes so that they would be an accurate representation of the data obtained from actual search surveys.

As a part of future enhancements to the training datasets, the data from the SHAPE module of Chandrayan-3 can also be added into the training coherent. The SHAPE module which is the only scientific payload on board Chandrayan-3, was released into the lunar orbit for its observational journey. The Payload designed with three main components including an optic module pointed towards Earth, Electrical components and an RF source. The SHAPE module is designed to analyze Earth from the point of view of a possible Exoplanet, studying the various atmospheric and spectrum properties of the planet. As a result of this procedure, we get to analyze how the data from an earth like exoplanet should behave like and this dataset can be used as an point of reference for further exploration and hunting projects.

This data can also be used to better train the neural networks and provide an even better sturdiness to the validation dataset. By using the value points of earth like exoplanets as reference the Weights of the neural network can be remodified according to the exploration scenarios, even before the spectrum and photometry data is entered into the neural network. This helps in improving the overall efficiency of the system as more accurate and reliable outputs can be expected as a result.

One of the main challenges incurred in exoplanet hunting is the fact that even though a considerable number of exoplanets have been identified so far, an significant number of possible exoplanet candidates have also been identified, which are yet to be classified as possible exoplanets or not. One of the main reasons behind this is the lack of possible data points to be used as refence to confirm the existence of such planetoidal bodies.

The SHAPE module will also analyze and capture the disc-integrated spectrum of earth, thereby analyzing the polarization signatures exhibited by earth from various vantage points within the lunar orbit. Analyzation of this variations can provide detailed insights regarding the atmospheric compositions of a planet, along with slight indications regarding how the terrestrial outlook of the planet appears to be. The analyzation of the polarization spectrums can also help us to identify the presence of clouds and other moisture locked entities in the upper and lower stratospheric regions of the planet.

A quasiperiodic systematic trend may be seen in the simulated data, much as signals that can be detected in the Kepler data (Aigrain et al., 2015). Given the values we chose for the

5 parameters PA and P, the simulated variability may be thought of as a sinusoid whose

frequency and amplitude both change over time. When PA and P are both equal to 1000 days, we construct a normal sinusoidal model that does not change in amplitude or frequency from its previous value. When PA is equal to one day, the amplitude of the sinusoidal function will increase by a factor of two in the space of only six hours. When PA is equal to -1 day, the

10 amplitude of the sinusoidal function will begin to decrease until it reaches zero. However,

despite the fact that having a negative period is physically impossible, we make use of it as a mathematical tool in order to get the form we want. When P=1 day, the oscillation period will increase by two times, and when P=-3 days, it will decrease by one-third.

An artificial neural network is a computer technique that models the biological manner in

15 which a brain solves issues. This may be done by simulating how neurons communicate with

one another. It makes use of a collection of brain units that are linked to a large number of other units and contains linkages and synapses that, depending on the activation state, may either be enforced or inhibited. Networks are built from layers of "neurons," which are more commonly known as Restricted Boltzmann Machines (RBM). Each neuron possesses a set of input

20 parameters, and each of those parameters is paired with a weight to indicate the relative

significance of one input parameter in comparison to another. The circles in the graph each represent one unit or neuron in the network, and the letter h denotes a transformation that the neuron applies to the input data in order to abstract the information for the layer that comes after it. A neuron also contains something called a bias, which may be thought of as a cutoff

5 value for the choice the neuron makes in the end, whether it be a yes/no decision or a

probability. One definition of a fully connected neural network is one in which the input for each neuron in a higher layer is the output from every neuron in the layer below it. Each of our deep neural networks has an implementation of a fully linked multi-layer perceptron.

One of the benefits of using a neural network is that it may be taught to recognize minor

10 characteristics that are already present in a huge data collection. This learning capability is

achieved by permitting the weights and biases to fluctuate in such a way as to minimize the difference (also known as the cross-entropy) between the output of the neural network and the expected or desired value derived from the training data. This is accomplished by allowing the weights and biases to vary in such a way as to minimize cross-entropy. Our classifier makes

15 use of the cross-entropy rather than the mean squared error because the cross-entropy more

accurately captures the mistake in a binary classifier (transit vs non-detection). We are interested in dividing the input data by a line (or plane), which will enable us to make predictions based on whether the data is above or below the surface that is being divided. This goes in accordance with the SHAPE referential dataset, that has been discussed above, by using these data points as validation parameters the weights or the biases of the network can be variated to seek for inputs that would be more aligned with the targeted readings. Supposing we have a model that can predict two classes, with the ground truth or accurate label

being y and the predicted probability being y', which is derived from the output of the neural network, let's say we have this model.

Other embodiments of the present disclosure will also become readily apparent to those skilled in the art from the following detailed description of the embodiments concerning the

5 accompanying figures, the intention not being limited to any particular embodiment or any

particular set of embodiments disclosed in any particular case.

While the present invention is described herein by example using embodiments and illustrative drawings, those skilled in the art will recognize that the invention is not limited to the images of drawing or drawings described and are not intended to represent the various scale

10 components. Further, some features that may form a part of the invention may not be illustrated

in specific figures for ease of illustration. Such omissions do not limit the embodiments outlined in any way. It should be understood that the drawings and detailed descriptions are not intended to limit the invention to the particular form disclosed. Still, on the contrary, the story is to cover all modifications, equivalents, and alternatives falling within the scope of the

15 present invention as defined by the appended claims. As used throughout

In this description, the word "may" is used in a permissive sense (i.e., meaning having the potential to) rather than the mandatory reason (i.e., meaning must).

Further, the words "a" or "an" mean "at least one," and the word "plurality" means "one or more" unless otherwise mentioned. Furthermore, the terminology and phraseology used herein

are solely for descriptive purposes and should not be construed as limiting in scope. Language such as "including," "comprising," "having," "containing," or "involving," and variations thereof, is intended to be broad and encompass the subject matter listed after that, equivalents, and additional subject matter not recited, and is not intended to exclude other additives,

5 components, integers or steps. Likewise, the term "comprising" is considered synonymous with

the words "including" or "containing" for applicable legal purposes. Any discussion of documents, materials, devices, articles, and the like are included in the specification solely to provide a context for the present invention. It is not suggested or represented that any or all of these matters form part of the prior art base or were common general knowledge in the field

10 relevant to the present invention.

In this disclosure, whenever a composition or an element or a group of elements is preceded with the transitional phrase "comprising," it is understood that we also contemplate the same design, component or group of elements with transitional words "consisting of," "consisting," "selected from the group of consisting of, "including," or "is" preceding the recitation of the

15 composition, element or group of elements and vice versa.

The present invention is described from various embodiments concerning the accompanying drawings, wherein reference numerals used in the accompanying drawing correspond to the like elements throughout the description. However, this invention may be embodied in many different forms and should not be construed as limited to the embodiment set forth herein.

20 Instead, the image is provided so that this disclosure will be thorough and complete and fully

convey the invention's scope to those skilled in the art. The following detailed description provides numeric values and ranges for various implementations described. These values and ranges are treated as examples only and are not intended to limit the claims' scope. Also, several materials are identified as suitable for various facets of the implementations. These materials

5 are to be treated as exemplary and are not intended to limit the invention's scope.

A more particular description will be rendered by referencing specific embodiments illustrated in the appended drawings to clarify various aspects of some example embodiments of the present invention. It is appreciated that these drawings depict only illustrated embodiments of the story and are therefore not considered limiting its scope. The invention will be described

10 and explained with additional specificity and detail through the accompanying drawings.

So that the advantages of the present invention will be readily understood, a detailed description of the story is discussed below in conjunction with the appended drawings, which should not be considered to limit the scope of the invention to the accompanying drawings.

Further, another user interface can also be used with the relevant modification to provide the

15 results above with the same modules, its principal, and protocols for the present invention.

It is to be understood that the above description is intended to be illustrative and not restrictive. For example, the above-discussed embodiments may be used in combination. Many other embodiments will be apparent to those of skill in the art upon reviewing the above description.

The benefits and advantages which the present invention may provide have been described above about specific embodiments. These benefits and advantages and any elements or limitations that may cause them to occur or become more pronounced are not construed as critical, required, or essential features of any or all of the embodiments.

5 While the present invention has been described concerning particular embodiments, it should

be understood that the images are illustrative and that the invention's scope is not limited to these embodiments. Many modifications, additions, and improvements to the embodiments above are possible. It is contemplated that these variations, changes, additions, and improvements fall within the invention's scope.

10

**We Claim:**

1. The photometric readings that are derived from a light curve are associated with one another at different points in time. In order to derive local features from time-ordered input data, we may make use of convolutions, abbreviated as conv. One way to think

5 of the generation of new input data by convolutional neural networks (CNN 1D) is as

the application of a particular filter on the data before it is fed into the network. The filter can be designed with the reference points derived from the SHAPE module, as this would enable the system to detect photometric variations in the spectrum with respect to the ones seen in earth like exoplanets. The weights of each filter are optimized in a way that is analogous to how a fully linked layer would be tuned. It is possible to rapidly expand the number of trainable parameters a model has by using fully connected layers, in which each and every input information is assigned a specific weight for each neuron. Convolutional neural networks (CNNs) are capable of computing local attributes of the data via the use of down sampling and convolutions when the data are correlated to one another.

1. The average pooling layer acts in a manner similar to that of binning observational observations in time. We also tried picking the largest value within bins of 3, which we

15 called the max pooling layer, but we found that it provided less accurate results than an

average layer. In the past, methods for detecting planets have made use of convolutions by way of a matched filter approach; however, the filters have been hand-designed, and only one is used. Our CNN 1D is comprised of four filters, each of which has six weights that are tuned based on the training data.

1. The substantial number of weights used in any deep net has the potential to produce a non-convex loss function, in which case there would be several local minimums. Therefore, because there are many possible initializations for the random weight, the accuracy of the validation might vary greatly. We find that the accuracies of our deep

5 learning algorithms vary on the order of 0.1 percent, which suggests that the SGD solver

that we utilize is reliable.

# ABSTRACT

Chandrayaan-3: Method of Detecting and Identifying Exoplanets in the Deep Space using Artificial Intelligence

Over a million stars have been tracked over the course of the last decade in an effort to find transiting planets. The manual interpretation of prospective exoplanet candidates is time-

5 consuming, prone to human mistakes, and the outcomes of this process are difficult to measure.

In this article, we offer a novel way of finding exoplanet candidates in big planetary search initiatives that utilises a neural network, in contrast to the methods that are currently being used. Neural networks, which are often referred to as "deep learning" or "deep nets," are intended to provide a computer with perception of a particular issue by teaching the computer

10 to detect patterns. Deep neural networks, in contrast to earlier methods of transit identification,

are taught to distinguish individual planet properties rather than depending on hand-coded criteria that humans consider to be the most representative. The convolutional neural network that we have developed is superior to the least-squares technique when it comes to the accuracy with which it can identify Earth-like exoplanets in noisy time-series data. With addition to referral points gathered using the data collected from the SHAPE module improves the understanding the system has about earth like exoplanets thereby making the network more adaptive to discovering such planetoidal bodies. Deep neural networks

15 are extremely generalizable, which enables data to be assessed after interpolation from a variety

of time series without negatively impacting the performance of the network. We do not need to fit any models in order to find periodic transits since our deep net analysis of Kepler light curves has shown that our results are in agreement with the actual period.