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Searching Exoplanets using Artificial Intelligence

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ABSTRACT

The rapid advancements in artificial intelligence have catalyzed progress across a myriad of disciplines, notably in the realm of space technology. AI has proven instrumental in devising sophisticated missions aimed at addressing critical issues, such as the removal of space debris from Earth's orbit. Furthermore, it has unlocked the potential to explore the possibility of extraterrestrial life beyond our solar system. In recent times, AI has demonstrated remarkable capabilities, empowering scientists to tackle intricate challenges that were previously beyond the reach of conventional computing methods. Throughout history, humanity has gazed at the cosmos with a deep-rooted conviction that numerous inhabited worlds exist beyond our own. Present-day estimates suggest that there could be billions of planets in our galaxy, potentially surpassing the count of stars. Consequently, a fundamental inquiry arises: Whether other planets in the universe support life, and if it is conceivable to anticipate which exoplanets might harbor the conditions for life to thrive. As AI continues to mature, its potential for unraveling the mysteries of the universe and enhancing our understanding of space becomes ever more promising, promising to reshape humanity's exploration of the cosmos in profound ways.

KEYWORDS: Exoplanets, Astronomy, Habitable plants, Space exploration.

1. INTRODUCTION

Exoplanets, the extraterrestrial worlds situated beyond our solar system, gracefully orbit stars other than our Sun. These celestial bodies serve as captivating subjects of scientific investigation, offering profound insights into the rich diversity of planetary systems that extend far beyond our own cosmic neighborhood..In the modern era, the quest for new exoplanets, particularly those within the habitable zone, has become a matter of paramount importance for scientists and astronomers[12]. The majority of these discoveries have been concentrated within a relatively restricted region of our home galaxy, the Milky Way. Presently, Over 4,900 exoplanets, celestial bodies orbiting stars beyond our solar system, have been definitively confirmed within our galaxy. However, it is highly probable that their actual count reaches into the trillions, employing a diverse array of sophisticated techniques for detection. These techniques encompass planetary transits, radial velocities, gravitational microlensing, and direct imaging, all harnessed through the use of cutting-edge space and ground-based telescopes. Noteworthy contributions in this realm include the revolutionary NASA Kepler space telescope and the Transiting Exoplanet Survey Satellite (TESS), which continue to provide invaluable data to expand our understanding of exoplanetary systems[13]. The most optimal algorithm for planet detection should possess speed, noise resilience, and the ability to comprehend intricate nonlinear systems. Exoplanets possess variety of sizes and shapes. Gas giants encompass planets ranging from the size of Saturn or Jupiter, the largest celestial bodies in our solar system, to those of much grander proportions.Within this classification, a plethora of distinctions remains concealed. Notably, Hot Jupiters were among the initial planetary variants discovered. These gas giants orbit their stars in such close proximity that their temperatures surge to thousands of degrees in Fahrenheit or Celsius scales.Neptune planets share similarities in size with Neptune or Uranus from our solar system. While their internal compositions might vary, they all possess outer atmospheres dominated by hydrogen and helium, enshrouding rocky cores. Additionally, a category known as mini-Neptunes has surfaced - planets smaller than Neptune yet larger than Earth, a classification alien to our own solar system. Super-Earths are primarily terrestrial planets, potentially possessing atmospheres or not. Their mass surpasses that of Earth but falls short of Neptune's. Terrestrial planets are akin to Earth in size or smaller, comprised of materials like rock, silicate, water, or carbon. Extensive inquiry is required to ascertain whether some host atmospheres, oceans, or other hints of habitability. In recent decades, the scientific community's fascination with exoplanets, planets located beyond our solar system, has evolved into a thriving and transformative domain of research within astronomy. With advancements in observational technologies and space missions, our ability to peer into the vast cosmic expanse has unveiled a plethora of distant worlds, each holding the potential to expand our understanding of planetary systems and the conditions necessary for life. Central to this burgeoning field is the integration of artificial intelligence (AI), a technological force that has the capacity to revolutionize the way we search for and comprehend exoplanets.The traditional methods of exoplanet detection, while successful, have their limitations, particularly in managing the exponentially increasing volume of data generated by modern astronomical instruments. This is where AI, with its capacity to rapidly process and analyze vast datasets, comes into play. The amalgamation of AI techniques with exoplanet research brings forth the promise of streamlined analysis, rapid identification of potential candidates, and the optimization of resources.

In this context, machine learning algorithms, including deep neural networks and convolutional neural networks, stand as the linchpin of innovation. These algorithms exhibit remarkable capabilities in pattern recognition, enabling them to sift through the intricate light curves – variations in a star's brightness over time – and discern subtle transit signals that betray the presence of orbiting planets[14]. By efficiently sifting through immense datasets and distinguishing authentic signals from noise, AI-driven algorithms hold the potential to unearth exoplanetary candidates that might otherwise go unnoticed. This survey paper is all about how we're using artificial intelligence (AI) to discover planets beyond our solar system. With the help of AI, we're making our search for these distant worlds faster and smarter. We'll explore how AI algorithms, like deep neural networks and convolutional neural networks, can look at the patterns in starlight to find clues about planets orbiting those stars. By teaming up AI with astronomy, we're able to sort through lots of data quickly and find potential planets that we might have missed before[1]. This paper aims to show how AI is changing the game in finding and understanding exoplanets, helping us learn more about the variety of planets out there in the universe.

2. LITERATURE SURVEY

The realm of exoplanet exploration, which focuses on planets orbiting distant stars, has embarked on a groundbreaking journey due to the fusion of Artificial Intelligence (AI) with conventional detection techniques. Methods such as radial velocity and transit, which were pivotal in the initial discovery of exoplanets, now benefit immensely from AI's computational prowess. Furthermore, direct imaging, enabling the capture of entire planetary systems in their full splendor, represents a significant achievement in the field of exoplanetary science. However, the most exhilarating and revolutionary strides have emerged from the domain of deep learning, notably embodied by Convolutional Neural Networks (CNNs). These AI-driven innovations have unlocked new dimensions in exoplanet research, reshaping the way we detect and understand these distant worlds.The most profound breakthroughs have emerged from the domain of deep learning, where Convolutional Neural Networks (CNNs) stand as the ultimate frontier.

The available literature brims with compelling evidence regarding AI's transformative influence on exoplanetary research. As we delve further into this domain, the ever-expanding volume of astronomical data collected by observatories like Kepler and TESS presents an imposing challenge. AI algorithms, including the formidable CNNs, have risen to prominence as the driving force behind the automation and optimization of exoplanet detection processes, leading to a substantial reduction in false positives and a remarkable expansion of the catalog of confirmed exoplanets. Beyond their detection capabilities, AI tools empower the intricate characterization of these enigmatic celestial bodies, offering profound insights into their atmospheric compositions, physical properties, and potential habitability. This comprehensive survey of the literature serves as a testament to the shifting paradigm within exoplanetary science, reaffirming the pivotal role of deep learning, particularly CNNs, in the relentless quest to unveil the mysteries concealed within distant worlds. Guided by AI, the exploration of exoplanets enters a thrilling phase, holding the promise of unveiling a diverse array of potentially habitable celestial neighbors nestled within the vast expanse of our cosmic surroundings.This comprehensive literature review serves as a testament to the paradigm shift within exoplanetary science, reinforcing the central role of deep learning, particularly CNNs, in our unyielding quest to unravel the mysteries concealed within distant worlds. Guided by AI, the exploration of exoplanets embarks on an exhilarating journey, poised to reveal a diverse array of potentially habitable celestial neighbors nestled within the vast tapestry of our cosmic domain.

Table I. Literature Survey			
Sr. No.	**Title**	**Methodology**	**Conclusion**
1	Searching for Exoplanets Using Artificial Intelligence. [1]	This work presents convolutional neural networkthat exhibits a superior ability to identify Earth- like exoplanets.	This introduces a novel approach for exoplanet detection, employing neural networks, a cutting-edge form of machine learning, in lieu of traditional transit detection algorithms..
2	The Transit Method for Exoplanet Detection.[2]	To detect planets with the transit method, we continuously monitor star brightness, looking for periodic "dips" in light flux. These dips indicate a planet has passed in front of the star from our perspective.	The transit method, which relies on measuring lightobstruction from a star, is prone to numerous false positives because not all apparent transiting objects are actually planets in transit.
3	A convolutional neural network (CNN) based ensemble model for exoplanet detection.[3]	By leveraging Artificial Intelligence techniques, including advanced Machine Learning algorithms, we can potentially differentiate whether the orbiting object is an exoplanet or not.	Indeed,Convolutional Neural Networks (CNNs) are renowned for their robustness and capacity to handle a higher number of parameters compared to traditional feedforward neural networks.
4	Direct Imaging of Exoplanets.[4]	In this work,Direct planet imaging denotes the endeavor to identify and examine exoplanets by directly observing the light they emit or reflect.	By examining a series of these visual records, we can infer the orbital trajectory of a planet. Additionally, by analyzing the photometricdata, color profiles, and spectral information spanning the visible and infrared spectra, we can deduce various attributes of the planet.
5	Habitability of Exoplanets using Deep Learning. [5]	This paper suggests a deep learning framework designed to search for potentially habitable exoplanets, taking into account factors such as planetary gravity, eccentricity, mass, radius, and other pertinent characteristics.	The approach is assessed using actual light curves from Kepler's catalog and showcases superior performance compared to other contemporary methods. The primary contribution of this study lies in the enhancement of a detection model, whichinvolves generating synthetic light curves with transits based on estimated parameters.
6	Identifying Exoplanet Candidates with Machine Learning	This study's objective is to pinpoint potential exoplanets from a collection of celestial and space-orbiting objects observed during the K2 mission.	It involves utilizing machine learning and deep learning algorithms. Our findings indicate that recursive feature elimination, followed by the fully connected model, emerged as the most effective strategy.

3. METHODOLOGY

Having examined various sources and reviewing the literature, it's evident that exoplanet detection primarily relies on three predominant techniques. In this segment, we will delve into a comprehensive exploration of these methodologies.

a. RADIAL VELOCITY METHOD

Concerning these indirect techniques, one of the most widely embraced and efficient approaches is the Radial Velocity Method, often referred to as Doppler Spectroscopy. This approach hinges on the scrutiny of stellar spectra for indications of a distinct "wobble" pattern, where the star exhibits alternating movements toward and away from Earth. These motions arise due to the gravitational influence exerted by planets[8].

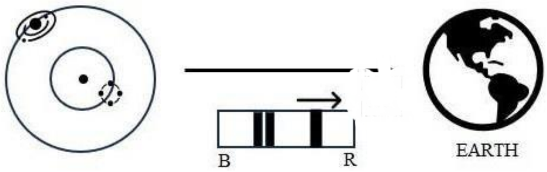

Fig.1. As the star recedes from Earth, its light waves shift towards the red end of the spectrum

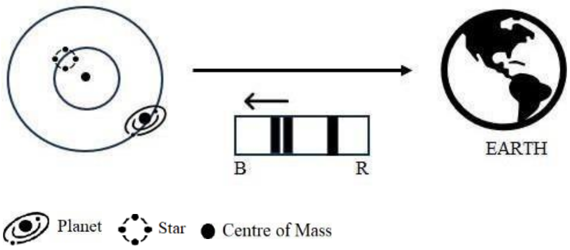

Fig. 2. With the star approaching Earth, its light waves shift towards the blue end of the spectrum

The crux of the Radial Velocity Method lies not in direct planetary observation, but rather in monitoring stellar activity for changing signs of displacement. They use a special tool called a spectrometer to measure how the star's light shifts due to the Doppler Effect, altering the position of the star's light on the spectrum – denoted as redshift or blueshift. Such shifts serve as indicators that the star is in motion, either retreating from Earth (redshift) or drawing closer (blueshift)[10]. These variations offer insights into the star's velocity, enabling astronomers to infer the presence of a planet or even a planetary system. Despite the substantially smaller mass of a star's center of mass compared to a planet, contemporary spectrometers can still discern the velocity at which a star revolves around this center. The radial velocity method was employed in the initial detection of exoplanets and continues to be a significant contributor to the exploration and characterization of exoplanetary systems.

b. DIRECT IMAGING METHOD

As the name implies, Direct Imaging involves taking pictures of exoplanets directly. This is achievable by seeking out the light coming from a planet's atmosphere in the form of infrared wavelengths. The rationale behind this choice is that, in the realm of infrared wavelengths, a star's brightness tends to be only around 1 million times greater than that of a planet reflecting light. This is in stark contrast to the situation in visible wavelengths, where the difference can often be as much as a billion times. Direct Imaging is particularly suitable for planets that have orbits far from their stars, preventing them from being overshadowed by the star's brightness. This approach also shines when dealing with planetary systems that are aligned in a way that makes them look like they're facing us from Earth. This complements the radial velocity method, which works best for planetary systems that appear sideways to Earth and for planets that are situated very close to their host stars[4].

c. THE TRANSIT METHOD

Planets might reveal their presence when they move across a star and cause a temporary reduction in its brightness. This event, when a planet moves between a star and our vantage point on Earth, is termed a "transit".

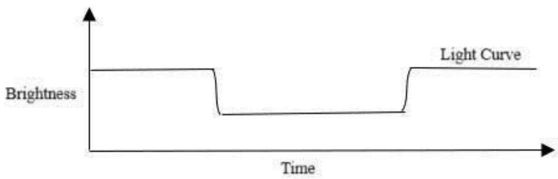

Fig. 3. Transit Light Curve

If this decrease in brightness happens consistently at predictable intervals and lasts for a consistent, repeated duration, it strongly indicates the existence of another, less luminous object orbiting that star. While some of these objects might be faint, small stars (resulting in a pair known as an "eclipsing binary"), the majority of such cases involve planets[2].

3.3.1 Light curve

The alterations in light observed during a transit yield astronomers a treasure trove of valuable insights into both the transiting planet and its host star. It's exclusively through exoplanets that showcase transits that astronomers have managed to derive direct assessments of both the planet's mass and its dimensions. Equipped with these pivotal parameters, astronomers can set critical constraints on models that unravel the intrinsic characteristics of the exoplanet, such as its average density and the gravitational forces acting on its surface. On the light curves of stars, conventional transit studies are performed by applying periodogram-like methods. The two that model the transits using the theoretical Mandel and Agol shape are transit least squares (TLS) and box least squares (BLS), which model the transits as squared boxes. They can all very precisely measure transit-like signals in the light curves and estimate a number of planetary system properties, such as the planet's radius in relation to the host star's radius, orbital period, etc. However, their processing cost was significant, and to understand the presence of transit-like signals in the light curves, all the data were required to be double-checked.

The light curves also show long-term trends brought on by processes related to stellar variability, such as stellar rotation or pulsations. The apparent magnitude of the star, also known as magnitude, is a measurement of the brightness of a star seen from Earth. Poisson noise, which is dependent on sensor accuracy, is also present in the light curves. Particularly, the noise is less in stars that are brighter. All of these factors make it difficult to predict the presence of transit-like signals in light curves through visual inspection, which makes it more efficient to use periodogram-like methods to only study the light curves that have these signals. Artificial intelligence (AI) solutions are now being proposed as a remedy for this problem.

3.3.2 Artificial intelligence (AI)

Artificial intelligence (AI) refers to a computer program with the capability to perform tasks automatically. As an illustration, when examining the presence of planets in orbit around stars, we can furnish observed light-curve data of stars to an AI program. Following its analysis, the AI program will provide a determination regarding the existence of planets around specific stars. Depending on the AI program's structure, besides confirming the presence of planets, it might also generate additional parameters like orbital periods in its output.

3.3.3 Machine Learning

It would be advantageous if a computer program could autonomously learn how to code itself. Within the realm of artificial intelligence, machine learning is an algorithmic approach wherein computer programs strive to learn and adapt autonomously to enhance analysis accuracy and deliver accurate outcomes. Typically, these programs are trained using data to recognize patterns and relationships between input and output. Certain machine-learning methods, such as k-Nearest Neighbors (kNN), essentially store and recall training data for subsequent analysis. In this scenario, "learning" equates to data memorization, categorizing these techniques as non-parametric algorithms. In contrast, most machine-learning techniques avoid memorizing training data, instead iteratively adjusting parameter values during the learning process. This approach is classified as a parametric algorithm. A prime example of a parametric algorithm is logistic regression, a straightforward machine-learning technique frequently utilized for data classification purposes[6].

For example, if we want to classify light curves into two classes, with or without planet transits, the logistic regression is a linear equation as:

$$h(x)=\sum_{i=1}^{n} x(i)w(i) + b = x(1)w(1) + x(2)w(2)+\ldots+x(n)w(n) + b$$

where the input data x(i) is the light-curve flux, w(i) and b are parameters, and n is the number of input data. Thus, there are n + 1 parameters in this logistic regression model. The output of this model depends on h(x) as

$$y = \begin{cases} 0 \text{ when } h(x) < 0; \\ 1 \text{ when } h(x) \geq 0; \end{cases}$$

where y is the classification result that could be 0 (no transit) or 1 (with transit).

3.3.4 Deep learning

In contemporary times, deep learning stands out as a dominant category within machine-learning algorithms, revered for its exceptional potency. A distinguishing characteristic of deep learning is its capacity to autonomously extract meaningful features from data. Central to this approach is the artificial neural network (ANN), an architectural framework that mirrors the human brain's functionality. ANNs are comprised of numerous computation units known as neurons. Diverse ANN designs exist, with one of the simplest being the multilayer perceptron (MLP), characterized by its fully connected layers. These layers encompass an input layer, hidden layers, and an output layer. Each layer houses a designated number of neurons. These neurons receive[7].The depicted structure in Fig. 4. represents the layout of an artificial neural network. Within this network, every individual neuron undertakes a nonlinear operation on the input data, extracting essential information to pass on to subsequent layers. The outcome of each neuron undergoes adjustment through the utilization of our chosen activation function. This modified output then serves as the input for the subsequent layer. Ultimately, the network employs a sigmoid function as its final activation mechanism, generating a probability ranging from 0 to 1[11]. This probability indicates the potential presence or absence of a planetary signature.

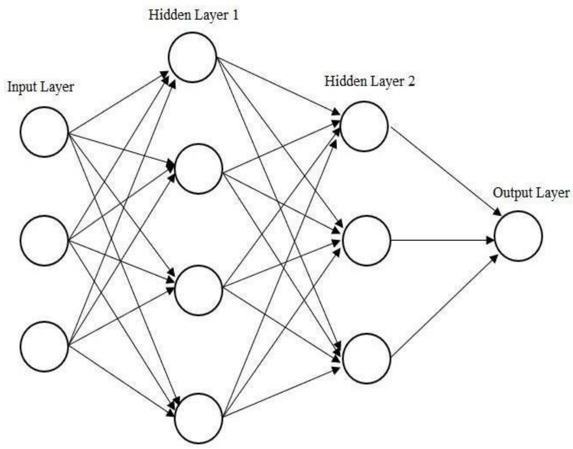

Fig.4. Structure of Artificial Neural Network

3.3.5 Neural Networks

A neural network is a technique used in artificial intelligence that tells computers how to process information in a way that is similar to the way the human brain does. In a layered design evocative of the human brain, linked nodes or neurons are used in this type of deep learning. This results in a flexible architecture that allows computers to learn from their mistakes and improve gradually. A standard Neural Network comprises of three layer types:

1. Input Layer: This is where we provide input to the model. The number of neurons in this layer corresponds to the total features in our data (for instance, pixels in an image).

2. Hidden Layer: The input from the Input layer is directed to the hidden layer. The model can include multiple hidden layers, contingent on the model's design and data size. Each hidden layer may encompass varying neuron counts, generally exceeding the feature count. The outcome of each layer is computed by performing matrix multiplication between the previous layer's output and the learnable weights of that layer. Subsequently, learnable biases are added, followed by an activation function. This process introduces nonlinearity to the network.

3. Output Layer: A logistic function like sigmoid or softmax is used to process the data from the hidden layer. This function converts each class' output into a probability score for that class.

The best tool for detecting exoplanets is a neural network that has been trained to identify planets using simulated data. A computational method for simulating the biological way a brain solves issues by connecting groups of neural units is called deep learning with a neural network. The layers of "neurons" that make up deep nets each have a varied weight to show how important one input parameter is in comparison to another. A neural network is created to make judgments based on input parameters that address issues like the depth and form of a light curve, noise, and systematic error, such as star spots, such as whether or not an observation identifies a planet.

3.3.6 The convolutional neural network

A Convolutional Neural Network (CNN) is a kind of Deep Learning approach that can recognize differences between features and objects in an image and assign importance (adjustable weights and biases) to them. A structured feed-forward neural network variation known as a convolutional neural network (CNN) automatically develops feature engineering skills by optimizing filters (sometimes referred to as kernels). The convolutional neural network (CNN) serves as an alternative to the multilayer perceptron (MLP). Unlike the plain MLP, which treats individual data points as separate features and disregards their spatial arrangement, the CNN is designed to consider the intrinsic spatial structure.[9] Tasks requiring time series data or image processing benefit greatly from this feature. Both fully connected layers and convolutional layers are used in the CNN architecture.

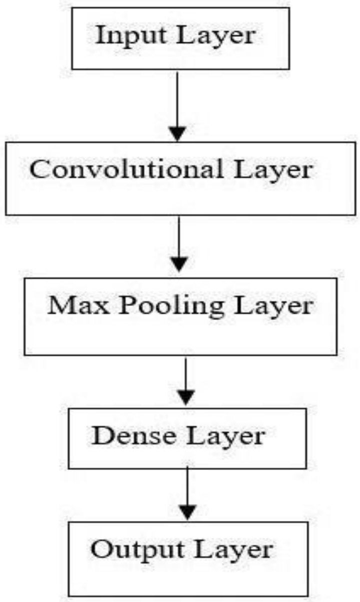

Fig. 5. CNN Architecture

Each convolutional layer in the CNN has the capacity to manage numerous channels, both for input and output.

Every convolutional neural network (CNN) component has a specific role within its receptive field. A CNN consists of several distinct types of layers, each serving a unique purpose.

The Convolutional layer's function is to create a feature map, predicting class probabilities for each feature by using a filter that scans the entire image. A pooling layer reduces the data volume created by the convolutional layer for each feature while retaining the most critical information. The fully connected input layer works to smooth the outputs from preceding layers into a single vector, suitable for the subsequent layer's input. The fully connected layer applies weights to the input derived from feature analysis and aims to predict an accurate label.

Finally, the fully connected output layer generates the ultimate probabilities, determining the image's class. Within these channels, there exist sequences of continuous data points that preserve spatial relationships. This unique feature makes CNNs exceptionally well-suited for applications that require processing time series data or conducting detailed image analysis[3]. The photometric measurements obtained from a light curve exhibit temporal correlations, linking them across time. To capture informative patterns from this ordered input data, convolutional operations can be employed. These operations can be conceptualized as generating novel input data by convolving with specific filters. The weights embedded within each filter undergo optimization akin to what's seen in fully connected layers. However, the application of fully connected layers, where each input feature necessitates an individual weight per neuron, can rapidly escalate the number of learnable parameters within a model. CNNs address this by utilizing convolutions and down sampling techniques to compute localized data characteristics, particularly when interdependencies exist between the data points.

4. CONCLUSION

In conclusion, the use of artificial intelligence (AI) in exoplanet exploration has proven to be a game-changing project for astronomy. A new era of efficiency, precision, and exploration has begun with the fusion of AI approaches with the search for exoplanets. Researchers have harnessed the ability of pattern recognition and data analysis to detect prospective exoplanets with remarkably high accuracy using machine learning techniques like deep neural networks and convolutional neural networks.

The use of AI in exoplanet research has solved a number of persistent issues, such as the requirement for quick processing of large datasets and rigorous inspection of light curves for transit signals. Astronomers have expanded their knowledge of exoplanets by more accurately identifying, confirming, and characterizing them thanks to AI's automation and improvement of these procedures. Within the comprehensive survey encompassing the examination of three distinct techniques, it became evident that the convolutional neural network (CNN) emerged as the most efficacious approach. The combination of CNN's strong pattern recognition skills with the well-known transit method creates a powerful synergy that has the potential to revolutionize astronomy

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