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# A Review of Exoplanet Detection Processes using Artificial Intelligence and Neural Networks

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## ABSTRACT

Detecting exoplanets is a crucial research area because understanding exoplanets can help researchers discover new aspects of space and potentially lead to the development of new technologies that benefit humanity. There are several methods for detecting exoplanets, but achieving higher accuracy remains a significant challenge. The field of artificial intelligence (AI), particularly neural networks and convolutional neural networks (CNNs), plays a vital role in enhancing the accuracy of exoplanet detection. Various researchers have proposed and utilized numerous techniques employing artificial intelligence and neural network methods to detect exoplanets with improved precision. This paper presents a review of various exoplanet detection techniques using AI and neural networks, highlighting the approaches proposed and examined by different researchers (inclusion of the required tables and figures, accompanied by appropriate citations and references). By leveraging these advanced computational techniques, researchers can analyze vast astronomical datasets more efficiently and identify exoplanets with greater reliability. This integration of artificial intelligence and neural networks in exoplanet detection not only accelerates discoveries but also broadens our understanding of planetary systems beyond our solar system.

### General Terms

Exoplanet, detection, classify

### Keywords

Artificial Intelligence (AI), Neural Network (NN), Convolutional Neural Network (CNN), deep learning, machine learning, transit method, K2 data

## 1. INTRODUCTION

An exoplanet, also known as an extrasolar planet, is a planet that orbits a star outside our solar system. These planets exhibit a wide range of sizes, compositions, and orbital characteristics. Some exoplanets resemble Earth with rocky surfaces and the potential to harbor liquid water, while others are gas giants like Jupiter or ice giants similar to Neptune. Planet detection has emerged as a significant research focus in astrophysics [13, 14]. Detecting these planets is essential for several reasons. Studying these planets allows scientists to gain insights into the formation and evolution of planetary systems. By examining a diverse array of planetary systems, researchers can refine and test theories about planet formation and the dynamics of different types of planetary systems. Identifying exoplanets within the habitable zone—the region around a star where conditions might be suitable for liquid water—is particularly important for discovering environments that could support life. This, in turn, provides valuable information about the conditions necessary for life and the potential for its existence elsewhere in the universe. Additionally, finding Earth-like exoplanets helps us assess the uniqueness or prevalence of our own planet, offering clues about the factors that contribute to a planet's habitability. In summary, the detection of exoplanets is vital because it deepens our understanding of the universe, aids in the search for extraterrestrial life, drives technological and scientific advancements, and offers profound insights into our place in the cosmos.

Exoplanet detection employs various methods, each with unique strengths, to identify and analyze planets outside our solar system. The transit method, used by missions like Kepler and TESS, detects dimming of starlight as a planet passes in front, revealing its size and orbit. Radial velocity measures a star's wobble due to a planet's gravitational pull, providing mass information, with instruments like HARPS. Direct imaging captures actual images of exoplanets, suitable for large, distant planets, while gravitational microlensing uses a star's gravitational field to magnify background light, detecting distant, low-mass planets. Astrometry and timing variations offer precise measurements of stellar movements and event timings to infer planet presence, with missions like Gaia enhancing detection accuracy. To date, over 4,000 exoplanets have been identified using various techniques, including the radial velocity method [8, 15, 16], astrometry [8, 17, 18], direct imaging [8, 19, 20], and gravitational microlensing [8, 21, 22]. However, the majority of confirmed exoplanets have been discovered using the transit method [23, 24].

Artificial Intelligence (AI) refers to the simulation of human-like intelligence in machines, allowing them to perform tasks that traditionally require human cognition. Neural Networks are computational models inspired by the human brain, composed of interconnected nodes organized in layers, where each connection has a weighted strength. Convolutional Neural Networks (CNNs) are a specialized type of neural network designed for processing grid-like data such as images, employing convolutional layers to extract features effectively. Machine Learning (ML) involves developing algorithms that enable computers to learn and make predictions or decisions based on data patterns, rather than explicit programming. Deep Learning, a subset of Machine Learning, utilizes deep neural networks with multiple layers to automatically learn hierarchical representations of data, achieving remarkable performance in tasks like image and speech recognition. These technologies collectively revolutionize various fields by enhancing capabilities in tasks ranging from data analysis to complex decision-making processes.

Artificial Intelligence (AI), machine learning (ML), deep learning, neural networks, and convolutional neural networks (CNNs) significantly enhance exoplanet detection by automating and improving the analysis of vast astronomical datasets. Artificial intelligence and machine learning algorithms can efficiently sift through large volumes of data, identifying patterns and anomalies indicative of exoplanetary presence. Deep learning, particularly through neural networks, excels at recognizing complex and non-linear relationships in light curves, which are crucial for detecting the subtle dimming events caused by transiting exoplanets. CNNs, a specialized type of neural network, are particularly effective in processing and analyzing the intricate data patterns in light curves and images, improving the accuracy of exoplanet identification. These advanced computational techniques enable the extraction of relevant features from noisy data, significantly reducing false positives and enhancing detection reliability. Furthermore, they facilitate the study of exoplanetary atmospheres by analyzing transit spectroscopy data, revealing chemical compositions and potential habitability. Overall, the integration of AI, ML, deep learning, and neural networks in exoplanet detection accelerates discoveries and broadens our understanding of planetary systems beyond our solar system.

Recent findings [1, 2, 3, 4, 5, 7] indicate that convolutional neural networks (CNNs) offer an efficient, automated method for classifying exoplanet candidates. Utilizing a CNN can significantly decrease the time required by human reviewers and help identify promising candidates that might have been overlooked, especially in low signal-to-noise (S/N) environments where false positives are common.

This review paper examines several recent advanced exoplanet detection methods developed by other researchers using artificial intelligence (AI) and neural networks (NN). This study aims to aid researchers in comprehending the application of artificial intelligence and neural network in exoplanet detection. Additionally, it serves as a comprehensive guide for novice researchers, providing insights into the research techniques, data, and training methods employed in this field.

## 2. A CASE STUDY OF EXOPLANET DETECTION BY REDUCING ARTIFICIAL NEURAL NETWORK COMPLEXITY

Koning et al. (2019) [6] proposed and evaluated two methods utilizing a convolutional neural network (CNN) with a reduced number of parameters. They applied these methods to the time-varying data of stars to automatically classify and detect exoplanets. The results demonstrated satisfactory accuracy despite the parameter reduction in the CNN.

The dataset used here includes all observed stellar light patterns corresponding to Kepler Threshold Crossing Events (TCEs) within the Kepler Data Release 24 (DR24). These events are transit-like occurrences resembling potential exoplanet transits. The dataset encompasses 15,740 TCEs with four distinct training labels: Planet Candidate (PC), astrophysical false positive (AFP), non-transiting phenomena (NTP), and unknown (UNK). TCEs labeled as UNK, whose transit nature (exoplanetary or otherwise) is indeterminate, were excluded from their dataset. All stellar light patterns were sourced from the Mikulski Archive for Space Telescopes website and are formatted in Flexible Image Transport System (FITS) format.

They used two methods. First method is Decreased Depth Network (DDN) and second method is Decreasing Depth and Multi-Scale Network (DDMSN). Figure 1 has shown the overview of the network configuration per experiment for this research [6].

The first method involves reducing the depth of the original model. This results in a modified model known as the Decreased Depth Network (DDN), which reduces the number of convolutional and max pooling layer blocks from five to three for a broader perspective. Additionally, each block now consists of only one convolutional layer before a max pooling layer, down from two in the original configuration. This reduction applies to both the global and local perspectives. In this adjusted architecture, all convolutional layers employ a kernel size of 5. Each view begins with 16 feature maps generated through convolution, followed by max pooling with a stride of 2 in each layer. The global view uses a pooling window size of 5, while the local view employs a size of 7. Subsequently, the resulting feature maps from both views are concatenated and passed through two fully connected layers, reduced from four in the original design, each containing 128 neurons. The final prediction is produced using a sigmoid unit.

The second method combines a reduction in the number of layers in AstroNet with a simplified representation of the global view known as the Gaussian view, achieved through a Gaussian pyramid . This pyramid decomposes the high-resolution temporal signal of the light curve into multiple progressively lower-resolution versions, each corresponding to a level of the pyramid. In our experiments, a 5-level pyramid was used, and only the lowest-resolution level was utilized as input for the network.

Named Decreasing Depth and Multi-Scale Network (DDMSN), this approach also involves reducing the number of convolutional and max pooling layers, while keeping the configuration of fully connected layers unchanged. The Gaussian view serves as the exclusive input, undergoing two sequences of two convolutional layers followed by one max pooling layer, before passing through four fully connected layers of size 512 to make predictions. All convolutional layers use a kernel size of 5, starting with 16 initial feature maps, and employing a pooling window size of 7 with a stride of 2. The models were set up to train on eight training partitions and were validated during training on a separate validation partition using the train.py script. Training proceeded for 10,000 steps, where each step processed a batch of 64 samples.

In the DDN experiment, the results indicate that the accuracy decreased by only 0.6 percent compared to the original AstroNet configuration (95.62% versus 96.25%), when a dropout rate of 0.3 was applied. Concurrently, the training time was reduced by 60 percent. However, employing dropout does slightly increase the training time compared to our implementation without dropout, which reduces training time by 65 percent. The results from the DDMSN experiment demonstrate a substantial reduction in training time, reaching 85 percent compared to the baseline, and nearly three times faster than the DDN experiment setup when no dropout is utilized. Despite a slightly lower classification performance of 94.54 percent compared to DDN, this remains acceptable given the significant time savings during training. Introducing a dropout rate of 0.1 or 0.2 increases accuracy by 0.2 percent in this configuration. However, this improvement comes with an almost twofold increase in training time, which makes this addition less attractive compared to the DDN experiment.

| Experiment | View (length) | Blocks | Layers in block |
|---|---|---|---|
| Baseline | Global (2001) | 5 | 2 convolutional layers<br>1 max pooling layer |
| | Local (201) | 2 | 2 convolutional layers<br>1 max pooling layer |
| | Post-conv | 1 | 4 FC layers (size 512) |
| DDN | Global (2001) | 3 | 1 convolutional layer<br>1 max pooling layer |
| | Local (201) | 2 | 1 convolutional layer<br>1 max pooling layer |
| | Post-conv | 1 | 2 FC layers (size 128) |
| DDMSN | Global (251) | 2 | 2 convolutional layers<br>1 max pooling layer |
| | Post-conv | 1 | 4 FC layers (size 512) |

Fig. 1. Overview of network configurations per experiment [6]

## 3. IDENTIFYING EXOPLANETS WITH DEEP LEARNING II: TWO NEW SUPER-EARTHS UNCOVERED BY A NEURAL NETWORK IN K2 DATA

Dattilio et al. (2019) [7] identified two new exoplanets by using deep learning. They adapted a neural network originally designed to identify exoplanets in the Kepler field to work with different K2 campaigns, which span various galactic environments. They developed a convolutional neural network, named AstroNet-K2, to determine whether a potential exoplanet signal is genuine or a false positive. AstroNet-K2 achieved a remarkable 98% accuracy on their test set for classifying exoplanets and false positives. It successfully identified and validated two previously unknown exoplanets. This method represents a significant step towards the automatic detection of new exoplanets in K2 data and understanding how exoplanet populations vary based on their galactic origins. Their work focuses on creating an automated system for identifying planet candidates in K2 data using deep learning, a modern machine learning technique. They expanded on the work of Shallue and Vanderburg (2018) [2], which distinguished planet candidates from false positives in Kepler data, to classify these signals in the K2 mission data. Building on Shallue and Vanderburg's (2018) [2] supervised convolutional neural network architecture, they made several key modifications to improve its performance with the qualitatively different K2 dataset.

Here, supervised learning was utilized by the neural network, meaning a labeled set of examples, called a training set, was provided for it to learn from. Advantage was taken of the work done by the team over the past four years as K2 data was released to the public. During that time, light curves were routinely produced, transits were searched for, and likely planet candidates were identified to support a wide variety of scientific objectives [25, 26].

The training set consists of three main parts: "Identifying Threshold Crossing Events," "Labeling Threshold Crossing Events," and "Preparing Input Representations."

Part 1, "Identifying Threshold Crossing Events," involves two key functions: producing light curves and conducting transit searches. The training set includes potential planet signals known as "Threshold Crossing Events" (TCEs), which are periodic signals indicating a decrease in star brightness detected by an algorithm searching for transiting exoplanets in a light curve. The first step in identifying TCEs is to generate searchable light curves. This is done by producing systematics-corrected light curves and selecting the best photometric apertures for each K2 target, followed by searching these targets for periodic dipping signals.

Part 2 involves triage and vetting. The transit search identified 51,711 TCEs, with the majority (31,575) manually categorized to create the labeled training set for the neural network. The objective was to classify TCEs into two categories: planet candidates and false positives. This labeling process involved two steps: a rapid triage to quickly review large numbers of TCEs, followed by detailed vetting of the subset most likely to be true transit signals. Triage was conducted on most TCEs detected by the transit search. Early in the K2 mission, every TCE identified by the transit search was examined closely. Following triage, signals classified as planet candidates underwent more detailed analysis using a variety of diagnostics. To ensure consistency in the training set, a set of rules was established to guide the determination of which signals were included as candidates in the final training set.

After identifying and labeling each TCE, they were processed into standardized input representations (Part 3 of the training set) to be used by the neural network. Here, the neural network architecture was based on the AstroNet model [2], which is implemented in TensorFlow, an open-source machine learning framework [27].

The initial approach involved training the original AstroNet architecture using the new K2 input data and training set labels. However, this initial training attempt did not converge. As a result, the neural network architecture and training parameters were optimized by using the Kepler data set and the Autovetter training labels from Shallue and Vanderburg (2018) [2].

The neural network's performance was assessed using various metrics. To reduce small variations between models, an averaged model was used for evaluation. This involved training ten separate models with identical parameters and averaging their final predictions for each TCE. All metrics in this section were calculated based on the test set.

In this research, using the averaged neural network model, researchers identified two new exoplanets in K2 data. Both exoplanets are categorized as super-Earths orbiting G-dwarf stars. The neural network efficiently sifted through a large collection of previously unclassified potential planet signals. It successfully flagged several signals that had been overlooked by the existing planet detection pipeline, identifying them as promising planet candidates. Follow-up observations confirmed EPIC 246151543 b and EPIC 246078672 b as genuine exoplanets. These newly discovered planets orbit closely around their host stars and fall in size between Earth and Neptune. This study made use of NASA's Astrophysics Data System and the NASA Exoplanet Archive, managed by the California Institute of Technology under contract with NASA's Exoplanet Exploration Program.

## 4. EXOPLANET DETECTION USING MACHINE LEARNING

Malik et al. (2022) [8] have introduced a novel machine learning approach for exoplanet detection using the transit method. By leveraging the time series analysis library TSFRESH to analyze light curves, they extracted 789 features from each curve, encompassing detailed information about their characteristics. These features were subsequently employed to train a gradient boosting classifier using the machine learning tool LIGHTGBM.

Here, a binary classifier was developed to categorize each time series photometry, known as a light curve, into either 'planet candidate' or 'non-candidate' classes. Classical machine learning techniques were employed in their approach. TSFRESH, a Python-based library for scalable hypothesis testing and feature extraction from time series data, was utilized. The methodology was inspired by feature engineering approaches commonly employed in time series prediction projects.

The model underwent training and testing on three types of datasets. The initial stage included simulated data using K2 photometry as a baseline with additional injected transits. Subsequently, training was conducted on Kepler data, followed by TESS photometry. Each stage was subdivided into three parts: processing and labeling the training data, feature extraction from each light curve using TSFRESH, and model training.

The K2 Campaign 7 photometry was obtained from the Mikulski Archive for Space Telescopes (MAST) and calibrated following Vanderburg and Johnson (2014) [29]. Transit signals were randomly injected into half of the processed light curves. They utilized the publicly available dataset used in Shallue and Vanderburg's work (2018) [2]. For TESS data, publicly available data from Yu et al. (2019) [5] were employed in their model, AstroNet-Vetting.

Following the processing of the light curves, features were extracted in the subsequent step, encapsulating the characteristics of each light curve and serving as input for our classification model during both training and inference. The PYTHON framework TSFRESH (Christ et al. 2018) [28] was utilized to extract typical time series features, such as the count of values exceeding the mean and the coefficients from the one-dimensional discrete Fourier transform. For all datasets used, the light curves were resampled to an hourly frequency. These resampled time series were then directly employed with various time series analysis tools. TSFRESH's efficient feature extraction setting, which extracted approximately 790 generalized time series features that was applied.

The machine learning method employed in this study operates effectively with a global perspective of the light curve. Its training process is swift, suggesting it can be readily adapted to new data sources. The identical model setup and code are applicable to data from various sources like Kepler, K2, and TESS, requiring hyperparameter optimization just once. This approach automatically identifies the most significant features, facilitating a deeper understanding of the data and the underlying physical processes.

This approach was evaluated using K2 campaign 7 data with artificially injected transit signals, demonstrating competitiveness with the traditional box least-squares fitting method. It delivered results comparable to state-of-the-art deep learning models, yet with significantly higher computational efficiency and without requiring folded or secondary views of the light curves. For Kepler data, the method achieved an AUC of 0.948, indicating that 94.8% of true planet signals were ranked above non-planet signals. The recall rate was 0.96, meaning 96% of real planets were correctly classified. When applied to Transiting Exoplanet Survey Satellite data, the method classified light curves with an accuracy of 0.98 and identified planets with a recall of 0.82 and a precision of 0.63.

## 5. SEARCHING FOR EXOPLANETS USING ARTIFICIAL INTELLIGENCE

Pearson et al. (2018) [9] introduced a novel approach for identifying exoplanet candidates in extensive planetary search initiatives using a neural network. Their convolutional neural network excels at identifying Earth-like exoplanets in noisy time series data with improved accuracy. Their deep network analysis of Kepler light curves has validated the method, successfully detecting periodic transits that match the actual period without requiring any model fitting.

In this research, simulated training data were utilized to train the deep networks to predict single planetary transits in noisy photometric data. The simulated data closely resemble what is expected from an actual planetary search survey. After training the deep networks, they were employed to assess the probability of potential planetary signals in new, unseen data.

Here, a total of 311,040 transit and non-transit samples were generated to train the deep nets. The training data were computed from a discretely sampled nine-dimensional hypergrid in the parameter space used in this study. The parameters limited transit duration to a range between 30 minutes and 4 hours, covering 1/12 to 2/3 of the time domain. These parameters were chosen to mimic data from real search surveys by encompassing a variety of possible systematic shapes and transit sizes.

Each model was trained using 311,040 samples, processed in batches of 128 over 30 epochs to learn the transit features. The validation/ test dataset was not used for training any model. This validation set, comprising 933,120 samples, spans a wider range of noise compared to the training data.

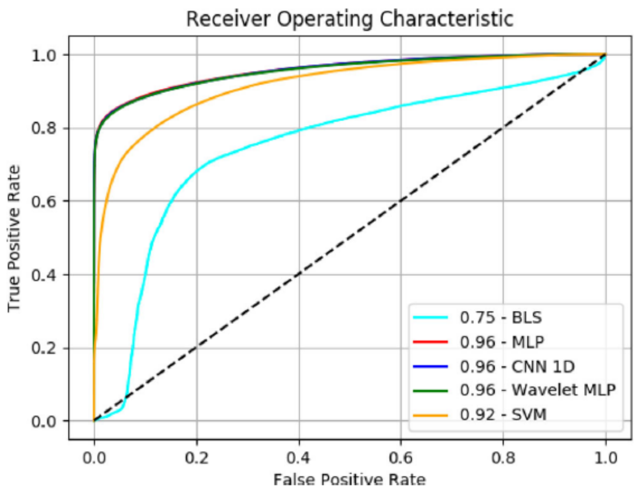


Fig. 2. The comparison of the classification of different transit detection algorithms have been done: a fully connected neural network (MLP), CNN, fully connected network with wavelet-transformed input (wavelet MLP), an SVM and a BLS. The ROC plot shows the cumulative distribution of true positives and false negatives as the discrimination threshold is varied. The discrimination threshold and the probability output from the deep nets are used to classify the input. BLS and SVM are non-probabilistic algorithms so an artificial score has been made up based on the accuracy of the transit depth and mid-transit time such that we can compare it to our other models. All of the test data has been used to calculate the ROC plot and report the area under each curve in the legend. A perfect classifier has an area of 1. [9]

An ROC plot has been employed to compare the results of each transit detection algorithm. This plot demonstrates the performance of a classifier, which outputs a probability indicating whether a sample belongs to a specific class. This probability is often rounded to indicate transit or non-transit detection (0 or 1). The ROC plot modifies the classification by adjusting the threshold at which the probabilities are rounded. The true positive rate (TPR), also known as the probability of detection, can be used to determine the false negative rate by calculating 1-TPR.

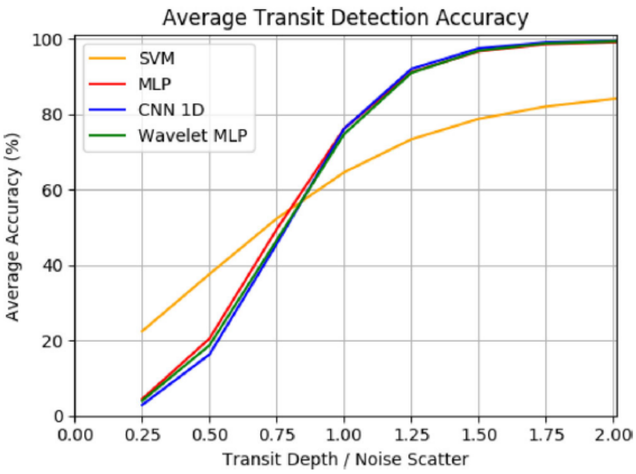


Fig. 3. The sensitivity of the deep nets to data beyond the range trained on this research was evaluated by generating 77,760 light curves for each noise value. The findings indicated that the transit depth size does not affect accuracy; rather, the accuracy of each detection algorithm is determined by the ratio of transit depth to noise. This plot allows for estimating the number of light curves needed to reliably detect a planet below the noise level by binning the data together. [9]

The sensitivity of their algorithms was examined to understand the detection limits and robustness in discovering new planets. The test dataset was utilized to assess accuracy under different levels of noise. Figure 3 illustrates the accuracy of their deep learning algorithms on data with varying noise amplitudes.

Exoplanet transits exhibit diverse shapes, making simple templates insufficient to capture the nuanced details, particularly when signals are below the noise level or strong systematics are present. In this study, researchers employed an artificial neural network to learn the photometric characteristics of transiting exoplanets. Deep machine learning can process millions of light curves in seconds. The discriminative nature of neural networks allows for a qualitative assessment of candidate signals, indicating the likelihood of finding a transit within a subset of the time series. For planet signals that are smaller than the noise, they devised a method to detect periodic transits using a phase folding technique, which provides constraints when fitting for the orbital period. They validated their deep networks on Kepler mission light curves, detecting periodic transits consistent with the true period without model fitting. Additionally, they tested various methods to improve planet detection rates, including 1D convolutional networks and feature transformations like wavelets, and found significant improvements with CNNs. Machine learning techniques offer an intelligent platform capable of learning subtle features from large datasets more efficiently than humans. Their study also suggests that machine learning will enhance the characterization of exoplanets in future analyses of large astronomical datasets.

## 6. CLASSIFYING EXOPLANET CANDIDATES WITH CONVOLUTIONAL NEURAL NETWORKS: APPLICATION TO THE NEXT GENERATION TRANSIT SURVEY

Chaushev et al. (2019) [10] introduced the first use of a Convolutional Neural Network (CNN) for analyzing data from the Next Generation Transit Survey (NGTS) [30], demonstrating its effectiveness in classifying exoplanet candidates detected by ORION, an implementation of the box least squares (BLS) detection algorithm [31].

For training the network, they compared the performance using both real data with injected planetary transits and entirely simulated data, examining how these different data compositions impacted the network's effectiveness. They have also shown a strong correlation between the CNN's rankings and the classifications from their extensive database produced by expert human reviewers. Additionally, they expanded on previous research by examining the optimal size and composition of the training data set for the neural network. Through the use of transit injections, they discovered that the number of human-labeled light curves needed for training could be reduced without compromising the quality of the results.

In this work, both fully simulated data and injections of simulated transits into real data were considered when training the CNN. Additionally, the effect of varying the composition of the non-planet class data set was examined. This was achieved by including injections of artificial false positives, such as eclipsing binaries, as well as true planet and false positive signals that were deliberately phase-folded on an incorrect period. To create the planet class for the network's training, validation, and test data sets, a sample of light curves was initially selected by filtering out those containing ORION candidates. This process minimized the likelihood of real transits or false positive signals remaining in the data, which could potentially confuse the network with the injected signals. The ELLC package [32] was utilized to perform the transit injections.

A set of 100,000 pure noise light curves, modeled on the observational properties of the NGTS survey, was generated. The time sampling of each light curve was determined by first defining a corresponding pseudo-field. For each field, the baseline length of night was selected from a uniform distribution ranging from 7 to 9 hours. The duration of darkness at Cerro Paranal, between astronomical dusk and dawn throughout the year, was modeled using a sinusoid function, with a random phase chosen to correspond to the epoch when observations began. Starting with a rising field visible for 30 minutes at the end of the first night, which rose 4 minutes earlier each successive night, the nights were stepped through to construct a time series, with the maximum length of night set by the chosen baseline.

For input representation, The method of Shallue an Vanderburg (2018) [2] was adopted and expanded to include local views of any secondary transits in addition to the primary event.

Firstly, global view input representations of the entire light-curve flux series were generated. The light curves were phase folded based on their orbital periods, disregarding the transit epoch, to allow the transit event to be centered at any phase value. This adjustment aimed to enhance the network's resilience to uncertainties in ephemerides for ORION candidates and showed improved performance during initial tests. Subsequently, the light curves were divided into uniformly spaced bins. The views of the light curves were normalized so that the maximum depth was set to 1 and the median (baseline) value to 0. The global views of the centroid series were generated similarly to the flux views, with the exception that performed normalization by maximum depth was omitted. Instead, following Ansdell et al. (2018) [1], normalization was performed using the standard deviation of the centroid series scaled by that of the flux series, calculated from out-of-transit regions across the entire dataset. Local views of the flux and centroid series were created similarly to the global views, but rather than using the entire light curves, they focused on windows encompassing phase 0 and 0.5, spanning three times the average transit duration of confirmed ex-

oplanet populations (3.23 hours). The events were randomly offset from the window center, up to a maximum of 2/3 of the center-to-edge span. Additionally, the orbital period was provided as an auxiliary scalar input to investigate whether the network could utilize it to filter out spurious signals caused by the observation window function of the NGTS survey.
Secondly, the normalization of the maximum depth of the flux series views is enabled to enhance the network's ability to interpret the data. However, in this process, information concerning the actual transit depth is lost. To retain this information, the maximum depth normalization factor is introduced as an auxiliary input.
Finally, the inclusion of the stellar host radius enables differentiation between genuine exoplanetary transits and those resembling exoplanets.
Figure 4 illustrates the CNN architecture employed in this study, adapted from ASTRONET (Shallue and Vanderburg, 2018) [2].
A neural network was trained using 100,000 fully simulated NGTS light curves, evaluating its performance across four key metrics. The first metric, AUC (Area under the ROC curve), quantifies the probability that a randomly selected planet receives a higher score than a randomly selected false positive. Accuracy, the second metric, measures the proportion of correct classifications made by the network. Precision, the third metric, denotes the ratio of correctly classified planets to all candidates classified as planets. Lastly, Recall, the fourth metric, signifies the fraction of actual planets identified by the network.
On unseen test data, the network achieved impressive metrics: an AUC score of 98.82%, accuracy of 95.31%, precision of 99.18%, and recall of 91.34%. These results highlight the network's robust performance on simulated data, suggesting its capability to effectively execute the classification task.
The NGTS dataset utilized in this study comprises 91 fields, over 890,000 light curves, and detects transit events in more than 58,500 targets. Each target is processed by ORION, which identifies up to 5 distinct detections at various periods and epochs, corresponding to the top 5 peaks in the BLS periodogram. Each peak represents a candidate classified using PlaNET. For comprehensive evaluation, candidates with periods exceeding 15.0 days were included in the performance assessment, despite their exclusion from the training data.
This research work focused on examining how variations in the training dataset affect performance. Previous studies have typically used confirmed planets, as well as promising and rejected candidates identified through the vetting process, in their training datasets. Here, artificial planetary transit injections and false positive signals are also employed by the researchers. For the non-planetary class, various combinations of four false positive categories are considered: candidates identified as false positives through vetting (OFP), injections of stellar binary eclipses (EB), light curves lacking strong periodic transit signals (NP), and signals from transits and eclipsing binaries folded at incorrect periods (WP).
The findings of this study indicate that models trained using all four categories of false positives within the non-planetary class perform nearly as effectively as models trained exclusively on candidates identified as false positives through vetting. They achieve AUC values of approximately 76.5% and 77.9%, respectively, based on vetting labels. This suggests that future efforts could potentially expand training datasets by reducing reliance on vetted candidate labels. The preferred model, NP/EB/OFP/WF, demonstrates an AUC of (76.5 ± 0.4)%, accuracy of (74.6 ± 1.1)%, precision of (0.98 ± 0.02)%, and recall of (63.0 ± 2.0)% on vetting labels.

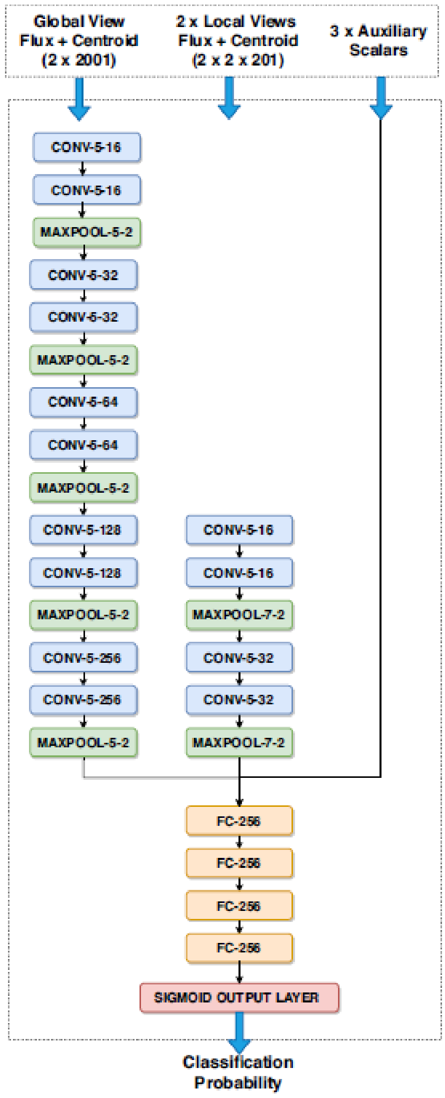


Fig. 4. Architecture of the best CNN model used in the research of Chaushev et al. (2019) [10]. The network inputs undergo sequential blocks of convolutional and max pooling layers. Global views, local views, and auxiliary scalars are stacked and processed through adjacent columns. The outputs from these columns are integrated before passing through fully connected layers. Convolutional layers are labeled as Conv-kernel size-number of feature maps, max pooling layers as MAXPOOL-window length-stride length, and fully connected layers as FC-number of units. The final output from the sigmoid layer represents the predicted probability of each light curve containing a transiting exoplanet. [10]

## 7. CONCLUSION

The modern world increasingly relies on Artificial Intelligence (AI) and Neural Network (NN) applications, facilitating efficient problem-solving with enhanced speed and performance. The detection of exoplanets also benefits from these technologies, reducing workload and time. This review paper introduces efficient methods for exoplanet detection using artificial intelligence and neural network techniques. It provides readers with valuable insights and

research guidelines, aiding in understanding current methodologies and fostering the development of new approaches for exoplanet detection through artificial intelligence and neural networks.
This review paper demonstrates that the use of AI and neural network methods can effectively detect exoplanets and provide accurate information about them. Conducting research in artificial intelligence, neural networks, machine learning, and deep learning requires significant study, effort, and dedication. Similarly, exoplanet research is a complex task. Therefore, successfully implementing exoplanet detection through artificial intelligence, neural networks, deep learning, machine learning, and related fields necessitates considerable effort and time.
New researchers in this field may need to study various research papers to grasp the intricate details of the research process. This review paper aims to assist researchers by providing insights into effective neural network design, training, input representation, tools, software, programming languages, data, and evaluation processes. By leveraging this information, researchers can develop more efficient methods for identifying exoplanets.

## 8. REFERENCES


[1] Ansdell, M., Ioannou, Y., Osborn, H. P., Sasdelli, M., Smith, J. C., Caldwell, D., ... Angerhausen, D. (2018). Scientific domain knowledge improves exoplanet transit classification with deep learning. The Astrophysical journal letters, 869(1), L7.

[2] Shallue, C. J., Vanderburg, A. (2018). Identifying exoplanets with deep learning: A five-planet resonant chain around kepler-80 and an eighth planet around kepler-90. The Astronomical Journal, 155(2), 94.

[3] Osborn, H. P., Ansdell, M., Ioannou, Y., Sasdelli, M., Angerhausen, D., Caldwell, D., ... Smith, J. C. (2020). Rapid classification of TESS planet candidates with convolutional neural networks. Astronomy Astrophysics, 633, A53.

[4] Schanche, N., Cameron, A. C., Hébrard, G., Nielsen, L., Triaud, A. H. M. J., Almenara, J. M., ... Wheatley, P. J. (2019). Machine-learning approaches to exoplanet transit detection and candidate validation in wide-field ground-based surveys. Monthly Notices of the Royal Astronomical Society, 483(4), 5534-5547.

[5] Yu, L., Vanderburg, A., Huang, C., Shallue, C. J., Crossfield, I. J., Gaudi, B. S., ... Quinn, S. N. (2019). Identifying exoplanets with deep learning. III. Automated triage and vetting of TESS candidates. The Astronomical Journal, 158(1), 25.

[6] Koning, S., Greeven, C., Postma, E. (2019). Reducing artificial neural network complexity: A case study on exoplanet detection. arXiv preprint arXiv:1902.10385.

[7] Dattilo, A., Vanderburg, A., Shallue, C. J., Mayo, A. W., Berlind, P., Bieryla, A., ... Yu, L. (2019). Identifying exoplanets with deep learning. ii. two new super-earths uncovered by a neural network in k2 data. The Astronomical Journal, 157(5), 169.

[8] Malik, A., Moster, B. P., Obermeier, C. (2022). Exoplanet detection using machine learning. Monthly Notices of the Royal Astronomical Society, 513(4), 5505-5516.

[9] Pearson, K. A., Palafox, L., Griffith, C. A. (2018). Searching for exoplanets using artificial intelligence. Monthly Notices of the Royal Astronomical Society, 474(1), 478-491.

[10] Chaushev, A., Raynard, L., Goad, M. R., Eigmüller, P., Armstrong, D. J., Briegal, J. T., ... Vines, J. I. (2019). Classifying exoplanet candidates with convolutional neural networks: application to the Next Generation Transit Survey. Monthly Notices of the Royal Astronomical Society, 488(4), 5232-5250.

[11] Petigura, E. A., Marcy, G. W., Howard, A. W. (2013). A plateau in the planet population below twice the size of Earth. The Astrophysical Journal, 770(1), 69.

[12] Kovács, G., Zucker, S., Mazeh, T. (2002). A box-fitting algorithm in the search for periodic transits. Astronomy Astrophysics, 391(1), 369-377.

[13] Wolszczan, A., Frail, D. A. (1992). A planetary system around the millisecond pulsar PSR1257+ 12. Nature, 355(6356), 145-147.

[14] Mayor, M., Queloz, D. (1995). A Jupiter-mass companion to a solar-type star. nature, 378(6555), 355-359.

[15] Campbell, B., Walker, G. A., Yang, S. (1988). A search for substellar companions to solar-type stars. Astrophysical Journal, Part 1 (ISSN 0004-637X), vol. 331, Aug. 15, 1988, p. 902-921. Research supported by the National Research Council of Canada, Canada Employment and Immigration Commission, and NSERC., 331, 902-921.

[16] Latham, D. W., Mazeh, T., Stefanik, R. P., Mayor, M., Burki, G. (1989). The unseen companion of HD114762: a probable brown dwarf. Nature, 339(6219), 38-40.

[17] Benedict, G. F., McArthur, B. E., Forveille, T., Delfosse, X., Nelan, E., Butler, R. P., ... Mayor, M. (2002). A mass for the extrasolar planet Gliese 876b determined from Hubble space telescope fine guidance sensor 3 astrometry and high-precision radial velocities. The Astrophysical Journal, 581(2), L115.

[18] Muterspaugh, M. W., Lane, B. F., Kulkarni, S. R., Konacki, M., Burke, B. F., Colavita, M. M., ... Williamson, M. (2010). The phases differential astrometry data archive. V. Candidate substellar companions to binary systems. The Astronomical Journal, 140(6), 1657.

[19] Chauvin, G., Lagrange, A. M., Dumas, C., Zuckerman, B., Mouillet, D., Song, I., ... Lowrance, P. (2004). A giant planet candidate near a young brown dwarf-direct vlt/naco observations using ir wavefront sensing. Astronomy Astrophysics, 425(2), L29-L32.

[20] Thalmann, C., Carson, J., Janson, M., Goto, M., McElwain, M., Egner, S., ... Tamura, M. (2009). Discovery of the coldest imaged companion of a sun-like star. The Astrophysical Journal, 707(2), L123.

[21] Mao, S., Paczynski, B. (1991). Gravitational microlensing by double stars and planetary systems. Astrophysical Journal, Part 2-Letters (ISSN 0004-637X), vol. 374, June 20, 1991, p. L37-L40., 374, L37-L40.

[22] Beaulieu, J. P., Bennett, D. P., Fouqué, P., Williams, A., Dominik, M., Jørgensen, U. G., ... Yoshioka, T. (2006). Discovery of a cool planet of 5.5 Earth masses through gravitational microlensing. Nature, 439(7075), 437-440.

[23] Charbonneau, D., Brown, T. M., Latham, D. W., Mayor, M. (1999). Detection of planetary transits across a sun-like star. The Astrophysical Journal, 529(1), L45.

[24] Naef, D., Latham, D. W., Mayor, M., Mazeh, T., Beuzit, J. L., Drukier, G. A., ... Zucker, S. (2001). HD 80606 b, a planet on an extremely elongated orbit. Astronomy Astrophysics, 375(2), L27-L30.

[25] Mayo, A. W., Vanderburg, A., Latham, D. W., Bieryla, A., Morton, T. D., Buchhave, L. A., ... Winters, J. G. (2018). 275

candidates and 149 validated planets orbiting bright stars in K2 campaigns 0–10. The Astronomical Journal, 155(3), 136.

[26] Rodriguez, J. E., Becker, J. C., Eastman, J. D., Hadden, S., Vanderburg, A., Khain, T., ... Terentev, I. (2018). A compact multi-planet system with a significantly misaligned ultra short period planet. The Astronomical Journal, 156(5), 245.

[27] Abadi, M., Barham, P., Chen, J., Chen, Z., Davis, A., Dean, J., ... Zheng, X. (2016). TensorFlow: a system for Large-Scale machine learning. In 12th USENIX symposium on operating systems design and implementation (OSDI 16) (pp. 265-283).

[28] Christ, M., Braun, N., Neuffer, J., Kempa-Liehr, A. W. (2018). Time series feature extraction on basis of scalable hypothesis tests (tsfresh–a python package). Neurocomputing, 307, 72-77.

[29] Vanderburg, A., Johnson, J. A. (2014). A technique for extracting highly precise photometry for the two-wheeled Kepler mission. Publications of the Astronomical Society of the Pacific, 126(944), 948-958.

[30] Wheatley, P. J., West, R. G., Goad, M. R., Jenkins, J. S., Pollacco, D. L., Queloz, D., ... Titz-Weider, R. (2018). The next generation transit survey (NGTS). Monthly Notices of the Royal Astronomical Society, 475(4), 4476-4493.

[31] Collier Cameron, A., Pollacco, D., Street, R. A., Lister, T. A., West, R. G., Wilson, D. M., ... Wheatley, P. J. (2006). A fast hybrid algorithm for exoplanetary transit searches. Monthly Notices of the Royal Astronomical Society, 373(2), 799-810.

[32] Maxted, P. F. L. (2016). ellc: A fast, flexible light curve model for detached eclipsing binary stars and transiting exoplanets. Astronomy Astrophysics, 591, A111.