APPLIED RESEARCH METHOD PROPOSAL

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Research and select a problem domain (10)	writing Abstract & Conclusion (10)	Develop a literature review (10)	Research Obj(10)	Formulate a Research Plan (20)	Provide and appropriate Bibliography/References (10)	Appropriately formatted using the agreed format (10)	Total (80)

Exoplanet Detection by Transit Method Using Convolutional Neural Network

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Abstract: The detection of exoplanets has become increasingly important as researchers continue to search for potentially habitable planets outside our solar system. The transit method is a widely used technique for exoplanet detection, relying on the observation of periodic dimming in a star's light as an orbiting planet passes in front of it. This proposal investigates the application of convolutional neural networks (CNNs) to enhance the transit method's accuracy and efficiency in detecting exoplanets. We will conduct a thorough literature review to understand the current state of research in the field and develop a research plan that includes data collection, preprocessing, model development, and evaluation. The outcome of this research will contribute to the development of more accurate and efficient techniques for exoplanet detection using the transit method.

Index Terms: Exoplanets, Kepler Telescope, Convolutional Neural Networks, NASA, TESS

1. Literature Review

Exoplanet detection has gained significant interest in recent years due to the potential for discovering habitable planets beyond our solar system. One of the widely used techniques for exoplanet detection is the transit method, which observes the periodic dimming of a star's light as an orbiting planet passes in front of it. In this literature review, we examine the latest research on applying convolutional neural networks (CNNs) to improve the transit method's accuracy and efficiency in detecting exoplanets. We discuss the state of the art in transit detection methods, the advantages of using CNNs, and the challenges that remain in this field.

The transit method has been instrumental in detecting numerous exoplanets since its first successful application in 1999 (Charbonneau et al., 2000) [1]. The Kepler Space Telescope, launched in 2009, has significantly contributed to the discovery of thousands of exoplanets using the transit method (Borucki et al., 2010) [2]. In recent years, the Transiting Exoplanet Survey Satellite (TESS) has continued these efforts (Ricker et al., 2015) [3]. However, the transit method has faced challenges in detecting smaller planets and differentiating true exoplanets from false positives due to various factors, such as stellar activity or instrumental noise (Coughlin et al., 2014) [4].

Machine learning techniques have been applied to improve the accuracy and efficiency of exoplanet detection using the transit method. These techniques include support vector machines (SVM) (Armstrong et al., 2017) [5], random forests (RF) (McCauliff et al., 2015) [6], and deep learning algorithms such as neural networks (NN) (Shallue & Vanderburg, 2018) [7]. Research has shown that machine-learning models can achieve high accuracy in detecting exoplanets while reducing false positives (Ansdell et al., 2018) [8].

Convolutional neural networks (CNNs) have been widely used in various applications, including image classification (Krizhevsky et al., 2012) [9] and natural language processing (LeCun et al., 2015) [10]. In recent years, researchers have started to apply CNNs to exoplanet detection using the transit method.

Pearson et al. (2018) [11] first demonstrated the use of a CNN for detecting exoplanets in light curves, achieving an accuracy of over 96%.

Since then, several studies have further explored the use of CNNs for exoplanet detection. Osborn et al. (2020) [12] proposed a CNN-based approach for detecting exoplanets in TESS data, achieving an accuracy of over 98%. This approach can handle noisy data and variations in the transit signal (Osborn et al., 2020) [12]. Additionally, Cobb et al. (2019) [13] developed a deep learning framework, named ExoMiner, to identify exoplanets in the Kepler dataset, which utilizes both CNNs and recurrent neural networks (RNNs).

CNNs offer several advantages over traditional machine-learning techniques for exoplanet detection. Firstly, CNNs can automatically learn complex features from the input data, eliminating the need for manual feature engineering (LeCun et al., 2015) [10]. This feature-learning capability enables CNNs to adapt to various types of transit signals and improve detection accuracy.

Secondly, CNNs are inherently robust to noise, making them well-suited for handling noisy light curve data (Osborn et al., 2020) [12]. This robustness to noise allows CNNs to reduce false positives and provide more reliable exoplanet detections.

Thirdly, CNNs can efficiently process large volumes of data, which is crucial for analyzing vast datasets from space telescopes like Kepler and TESS (Schmidhuber, 2015) [14]. This efficiency enables researchers to analyze more data and potentially detect more exoplanets.

Overall, this research is to enhance the transit method's accuracy and efficiency in exoplanet detection by utilizing convolutional neural networks to overcome its limitations and challenges. The findings of this research are expected to contribute to the advancement of exoplanet detection techniques, which can lead to a better understanding of the universe and the potential for discovering habitable planets beyond our solar system. Furthermore, the proposed methodology can be extended and adapted to other fields of research that involve pattern recognition and classification tasks.

2. State of Art

2.1 Research Question

How can convolutional neural networks be effectively applied to enhance the accuracy and efficiency of exoplanet detection using the transit method?

2.2 Research Objective

The research objective is to develop a novel approach using convolutional neural networks to address the challenges and limitations of the transit method for exoplanet detection. By overcoming these challenges, this research aims to contribute to the development of more accurate and efficient techniques for detecting exoplanets and enhancing our understanding of planetary systems beyond our solar system.

2.3 Research Problem

Several exoplanets have been discovered using the transit technique. However, the method's effectiveness is limited by factors such as noise, stellar activity, and the detection of smaller planets.

This research aims to address these limitations by developing a novel approach using convolutional neural networks to improve the accuracy and efficiency of exoplanet detection.

Light curve data obtained from telescopes, such as Kepler and TESS, are often affected by noise and stellar activity, which can lead to false positives or missed detections. This noise can arise from various sources, including instrumental noise, background stars, or the intrinsic variability of the host star. CNNs have shown potential in handling noisy data, making them a promising solution for improving the transit method's effectiveness (Osborn et al., 2020).

Detecting smaller exoplanets, particularly Earth-sized planets, is challenging due to their relatively weak transit signals. Smaller planets produce shallower transit signals that are often difficult to distinguish from noise or stellar activity. Developing a CNN-based approach that can effectively detect these weaker signals and differentiate them from noise and other sources of variability is crucial for improving the transit method's performance in detecting smaller exoplanets.

The transit method is prone to false positives due to various factors, such as eclipsing binary stars, background eclipsing binaries, or star spots. These false positives can significantly impact the accuracy of exoplanet detection. CNNs have demonstrated their ability to reduce false positives in various applications (Pearson et al., 2018), making them a promising solution to address this challenge in exoplanet detection using the transit method.

Large volumes of data are generated by space telescopes, such as Kepler and TESS, and require efficient processing to detect exoplanets accurately. Traditional machine learning techniques may struggle to handle such vast datasets, limiting their effectiveness in exoplanet detection. CNNs, however, have demonstrated their ability to efficiently process large datasets, making them a suitable solution for analyzing the extensive data generated by space telescopes and improving the transit method's overall efficiency.

3. Methodology and Research Timeline

The research plan and methodology for this study will involve a systematic approach to applying convolutional neural networks (CNNs) to enhance the transit method's accuracy and efficiency in detecting exoplanets. The following steps outline the detailed research plan and methodology:

3.1 Data Collection and Preprocessing

The first step in this research will be to collect light curve data from space telescopes, such as Kepler and TESS, which provide a wealth of information about exoplanetary transits and other astronomical phenomena. These datasets will be carefully curated to ensure a diverse and representative sample of exoplanet transit signals and various other phenomena, such as eclipsing binaries and star spots. It is essential to include data with different signal-to-noise ratios and transit depths to ensure that the CNN model can generalize well to real-world scenarios.

Once the data is collected, preprocessing will be carried out to clean and prepare the data for model training. This preprocessing will involve several steps, including detrending to remove systematic trends in the light curve data due to instrumental or observational effects, normalization to scale the light curve data to a standard range to ensure consistency across different datasets, and windowing to segment the light curve data into smaller, fixed-size windows for efficient training and evaluation of the CNN model. Additional data augmentation techniques, such as flipping, rotation, or adding Gaussian noise, may also be employed to further enhance the model's generalization capabilities and robustness to noise.

3.2 Model Development

After preprocessing the data, the next step will be to develop a CNN model tailored for exoplanet detection using the transit method. The model architecture will be designed based on a thorough literature review and consideration of the unique characteristics of exoplanetary transit data. This architecture may consist of several layers, including convolutional layers for feature extraction, pooling layers for dimensionality reduction, and fully connected layers for classification. Activation functions, such as ReLU, will be employed to introduce nonlinearity into the model, and techniques like batch normalization and dropout may be used to improve model training and prevent overfitting.

The choice of model hyperparameters, such as the number of layers, filter sizes, and learning rates, will be guided by the literature review and preliminary experimentation. A suitable loss function, such as binary cross-entropy, will be used to train the model based on the ground truth labels of the dataset. Additionally, an appropriate optimization algorithm, such as stochastic gradient descent (SGD) or Adam, will be employed to update the model weights during training.

3.3 Model Training and Evaluation

With the CNN model developed, the next step will be to train and evaluate the model using the collected dataset. The dataset will be split into training, validation, and test sets, with the training set used to update the model weights, the validation set for model selection and hyperparameter tuning, and the test set for evaluating the model's final performance. Model training will involve iteratively updating the model weights based on the loss function and optimization algorithm until a predetermined stopping criterion, such as a maximum number of epochs or a minimum validation loss, is met.

The model's performance will be assessed using various evaluation metrics, such as accuracy, precision, recall, F1 score, and area under the receiver operating characteristic (ROC) curve. These metrics will help to quantify the model's ability to detect exoplanets accurately and efficiently, as well as its robustness to noise and false positives.

3.4 Ethical Considerations

Research on exoplanet detection using data from NASA's public Kepler data archives involves the analysis of publicly available data collected from the Kepler Space Telescope, which is primarily focused on discovering Earth-like planets orbiting other stars. This is to be ensured that the data used in the research is accurate and of high quality is crucial for obtaining reliable results. Researchers should be aware of any biases, inaccuracies, or limitations in the Kepler data and address these issues in their methodology and analysis.

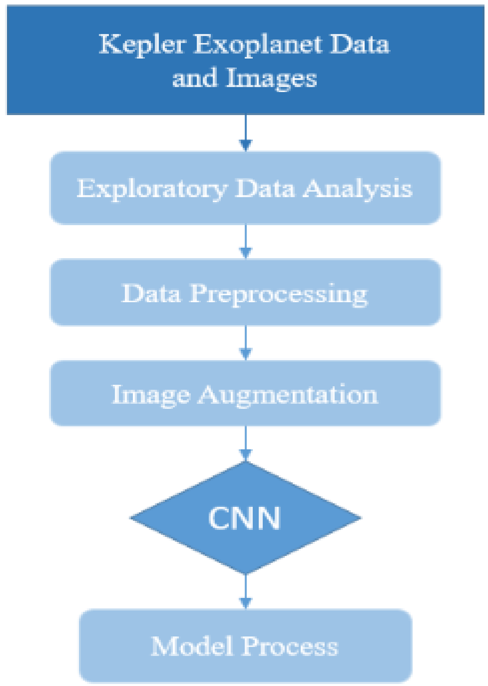

Figure 1: Interpretable DL Models Block Diagram

3.5 Research Timeline

The proposed study endeavor will last three months, beginning on June 23 and finishing by August 23. The project timetable is separated into various phases, as shown in the workflow timeline graphic below.

Table 1: Workflow Timeline

	June		July		August	
Exploratory Data Analysis						
Data Preprocessing						
Image Augmentation						
Feature Analysis						
Create CNN Model						
Dissemination						

4. Expected Outcome

Finally, the results of the model training and evaluation will be analyzed to understand the CNN model's effectiveness in enhancing the transit method's accuracy and efficiency in detecting exoplanets. This analysis will involve a detailed examination of the model's performance across various evaluation metrics, as well as a comparison with existing methods and techniques for exoplanet detection. Moreover, the results will be discussed in the context of the research problem, highlighting the CNN model's strengths and limitations in addressing the challenges faced by the transit method.

In addition to analyzing the results, insights gained from the research will be used to identify areas for further improvement or exploration. This may include refining the model architecture, incorporating additional features or data sources, or exploring alternative machine-learning techniques. Furthermore, potential applications of the developed approach to other astronomical problems, such as variable star classification or galaxy morphology, may be considered.

The outcome of this research is expected to contribute to the development of more accurate and efficient techniques for exoplanet detection using the transit method. By addressing the challenges and limitations of the transit method through the application of convolutional neural networks, this study aims to enhance our understanding of planetary systems beyond our solar system and ultimately aid in the search for potentially habitable exoplanets.

5. Conclusion

In conclusion, the proposed research plan and methodology involve a systematic approach to applying convolutional neural networks to improve the accuracy and efficiency of exoplanet detection using the transit method. Through data collection and preprocessing, model development, training and evaluation, and result analysis, this study aims to address the challenges faced by the transit method and contribute to the development of more effective techniques for detecting exoplanets in the vast datasets generated by space telescopes such as Kepler and TESS.

This literature review examined the latest research on using convolutional neural networks for exoplanet detection via the transit method. CNNs have shown promise in improving the accuracy and efficiency of exoplanet detection, but challenges such as data availability, interpretability, and model complexity remain. Future research should focus on addressing these challenges and developing novel methods to further enhance the capabilities of CNN-based models in exoplanet detection.

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