Exoplanet Detection Using CNN

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ABSTRACT

Detection of exoplanets, which are planets orbiting stars other than our Sun, is very important in understanding planetary systems and their habitability. This research examines the applicability of Convolutional Neural Networks (CNNs) in the detection of exoplanets using light curve data obtained from space telescopes like Kepler and TESS. The main aim is to automate and improve the accuracy in the identification of exoplanetary transits in noisy datasets. A CNN-based model was developed and trained on a labeled dataset comprised of light curves, which were labeled with binary data that indicated the presence or absence of an exoplanet. The architecture was optimized for feature extraction from time-series data, capturing subtle variations in brightness indicative of planetary transits.

The proposed CNN achieved 98% accuracy, significantly outperforming traditional methods such as manual vetting and classical machine learning models. Results show that the model is indeed robust in distinguishing transit signals from stellar variability and instrumental noise. The analysis further indicated that the model generalizes well to unseen datasets, reducing false positives and negatives significantly.

This work concludes that CNNs are a powerful, scalable approach to exoplanet detection: faster and more reliable. Future work would be the extension of the model to multiple planet systems and the consideration of other astrophysical parameters for greater precision.

Keywords: Kepler, TESS , Planetary transits , Stellar variability , Habitability.

I .INTRODUCTION

Exoplanet detection, the discovery of planets orbiting stars beyond our solar system, has revolutionized our understanding of planetary systems and their diversity. These discoveries hold the promise of answering profound questions about the formation and evolution of planets, the uniqueness of our solar system, and the conditions that may support life elsewhere in the universe. Since the first confirmed observation of an exoplanet was detected in the 1990s, researchers have explored numerous techniques to identify the remote worlds. Among these were radial velocity measurements, direct imaging, and transit photometry, and transit photometry became one of the methods used the most and enjoyed much success. It involves monitoring the brightness of a star over time and detecting periodic dips caused by a planet passing in front of its host star, partially blocking its light. While effective, transit photometry presents significant challenges.

Planetary transit signals are often subtle and buried within noisy datasets, caused by factors such as stellar activity, instrumental noise, and environmental conditions. This challenge is complicated by the sheer volumes of data generated by modern space telescopes such as Kepler and TESS. These telescopes are tasked with continuously monitoring thousands of stars. For example, in the case of Kepler, its mission produced light curves for over 200,000 stars, many of which were described by complex patterns of variability and low signal-to-noise ratios. Such large datasets are impossible to inspect manually and prone to many errors, thus requiring automatic methods for the efficient detection of planetary transits with accuracy. Machine learning techniques have emerged as a powerful tool for addressing these challenges. The traditional machine learning algorithms like random forests and support vector machines have been used to classify light curves. However, most of these approaches rely on handcrafted features, requiring domain expertise and significant preprocessing. There is a growing need for more sophisticated, scalable solutions that can learn directly from raw data as the complexity and size of datasets grow. Convolutional Neural Networks (CNNs), which are deep learning models, have recently been thrust into prominence because of their phenomenal ability to identify patterns in high-dimensional data. From its roots in image recognition tasks, CNNs are nowadays being applied to a wide array of problem domains, one of them being astronomy.

The use of CNNs in exoplanet detection allows for the analysis of time-series light curve data, automatically extracting features signaling the presence of planetary transits. Unlike traditional methods, CNNs require minimal preprocessing and can learn complex relationships within the data, making them especially well-suited for noisy and large-scale datasets. This study investigates the application of CNNs to exoplanet detection using light curve data from space telescopes such as Kepler and TESS. The main goal is to develop an automated, robust, and accurate method for identifying exoplanetary transits while minimizing false positives and negatives. A CNN-based model is developed on labeled datasets of light curves and optimized in architecture in order to catch the minimal changes in brightness that confirm the existence of a planet.

The performance of the proposed model is compared to traditional models. It considers the aspect of generalization to datasets not used in training along with its ability for large scale applications. This research demonstrates the effectiveness of CNNs in exoplanet detection and highlights their role in pushing forward our understanding of planetary systems and accelerating discoveries in potentially habitable worlds. Future extensions of this work will include adapting the model for identifying multi-planet systems, including additional astrophysical parameters to enhance precision and reliability in exoplanetary science.

II. METHODOLOGY

The detection of exoplanets combines sophisticated observational techniques with advanced methods of data analysis. As the detection of planets beyond our solar system is difficult, given that their planetary signals are very small in comparison to their host stars, there have been several methods of indirect and direct identification developed. This section discusses the fundamental methodologies of exoplanet detection, which includes an explanation of their principles and how they are applied in contemporary astronomy.

1.Indirect Methods

The indirect methods are based on observing the effects of an exoplanet on its host star rather than seeing the planet itself. They are effective in detecting planets at huge distances from Earth, particularly if they are too faint to be imaged directly.

(a) Transit Method

The transit method is one of the most popular techniques used to detect exoplanets. It generally monitors the light curves of the stars for periodic dips in brightness, which occur when the planet passes in front of its host star while being viewed from Earth. This transit causes a temporary decrease in the measured stellar brightness.

Data Acquisition: Transiting exoplanets are detected and measured through high-precision photometry in time series with instruments aboard the Kepler and soon with those aboard TESS.

Analysis: Based on depth and duration of a transit, size of planet, and orbital period; many transits yield discovery by verification of an exoplanet.

Advantages: This technique is particularly successful at identifying planets that are relatively near their stars, even smaller Earth-sized planets in habitable zones.

Limitation: The technique depends on a chance occurrence of the orbit of the planetary system: only systems for which the planet's orbit coincides with our line of sight yield observable transits.

(b) The radial velocity method

Or Doppler wobble method, measures the tiny shifts in a star's spectral lines caused by the gravitational tug of an orbiting planet. As the planet orbits, it induces a wobble in the star's motion, causing the star's light to shift slightly toward the red or blue end of the spectrum.

Data Acquisition: High resolution spectrographs like HARPS, or High Accuracy Radial Velocity Planet Searcher, detect these Doppler shifts.

Data Interpretation: The astronomers determine the mass, orbital distance, and eccentricity of the planet based on the amplitude and periodicity of the shifts.

Benefits: It is very sensitive to the massive planets that are close to their stars. It supports the transit method by offering mass measurements.

Advantages/Disadvantages: This technique is not as good for discovering smaller planets or those far from their host stars, because their gravitational pull is much weaker.

(c) Gravitational Microlensing

Gravitational microlensing exploits the phenomenon predicted by Einstein's General Theory of Relativity, wherein the gravitational field of a planet-star system bends light from a background star. When the lensing star crosses in front of a distant background star, the gravitational field magnifies the background star's light, and the presence of a planet introduces further distortions in the light curve.

Data Collection: Ground-based surveys, such as OGLE (Optical Gravitational Lensing Experiment), and space-based observatories monitor dense star fields for microlensing events.

Analysis: The specific distortions due to the planet are then used to estimate its mass and orbital distance.

Advantages: The method of microlensing can detect planets at large distances, even those in very wide orbits or free-floating planets without host stars.

Limitations: Microlensing events are rare and non-repeating, meaning that follow-up observations are impossible.

(d) Astrometry

Astrometry is the measurement of subtle changes in a star's position on the sky produced by the gravitational effect of an orbiting planet. In this case, the star changes position relative to background stars due to its motion from the gravitational effect of the planet.

Observations: Tools such as the space telescope Gaia make very high-precision measurements of a star's position over a long term.

Interpretation: An astronomer can infer both the mass and orbit of the planet by mapping out how the star moves.

Pros: Astrometry can see wide-orbit planets. It gives complementary data with radial velocity and transit techniques.

Limitations: The positional changes are incredibly small and require high-precision instruments, making this method challenging.

2. Direct Imaging

Unlike indirect methods, direct imaging aims to capture the actual light emitted or reflected by the exoplanet. This technique is challenging because planets are much dimmer than their host stars, and the starlight can overwhelm the faint planetary signal.

Data Collection: Advanced imaging techniques, such as Very Large Telescope (VLT) and James Webb Space Telescope (JWST), are used in observatories with coronagraphs and star shades to block the starlight and reveal the planetary signal.

Analysis: By analyzing the captured light, astronomers can determine the planet's atmospheric composition, temperature, and potential habitability.

Pros: Direct imaging offers extensive information about the physical and chemical properties of exoplanets. It is specially helpful in studying massive planets at large orbits.

Cons: The method is applicable only to those planets located far from their parent stars. It is unsuitable for detecting small or Earth-like planets close to their host stars.

Each method has its strengths and weaknesses, and the applicability depends on the type of planetary system under observation. For example, the transit and radial velocity methods are highly effective in detecting close-in planets, whereas microlensing and direct imaging are good for the identification of planets that are further away from their stars. Usually, a combination of these methods is used to confirm the existence of exoplanets and to extract detailed information about their properties.

Transit photometry using the Convolutional Neural Networks was adopted as a focus for this study. Based on this, a study focusing on improving accuracy, scalability, and efficiency when detecting exoplanets from large, noisy datasets using deep learning together with transit method's strengths may help identify exoplanets from vast and noisy data sets in future studies, complementing possibly other approaches like radial velocity and direct imaging methods.

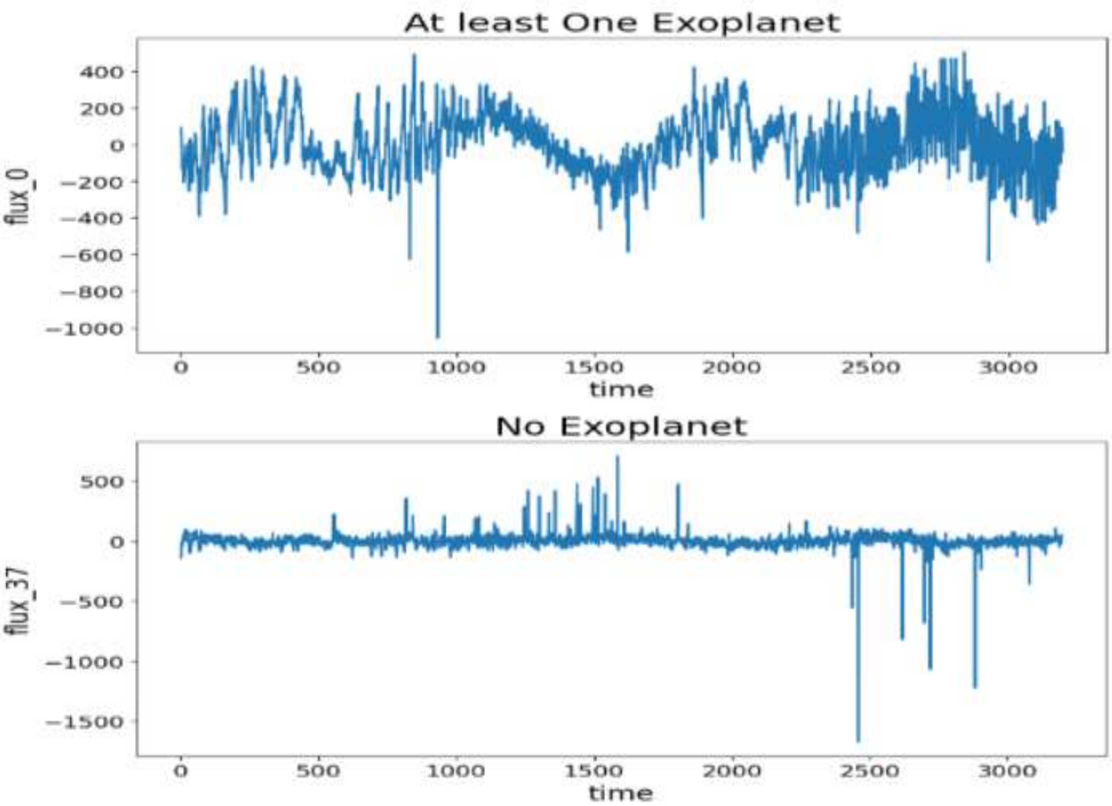
III .MODELING AND ANALYSIS

We look into several Machine Learning models to accurately predict the existence or non-existence of exoplanets based on the flux variation of the stars. The Machine Learning model is tuned with GridSearch Method. Furthermore, we are suggesting a CNN model to predict it precisely. We have implemented this CNN model with TensorFlow and Keras to utilize their deep learning abilities.

CNN Architecture The architecture of CNN involves a combination of multiple convolutional layers, batch normalization, max pooling, dropout regularization, and dense layers. The model is trained with the training set and evaluated with the test set to get its performance in exoplanet detection.

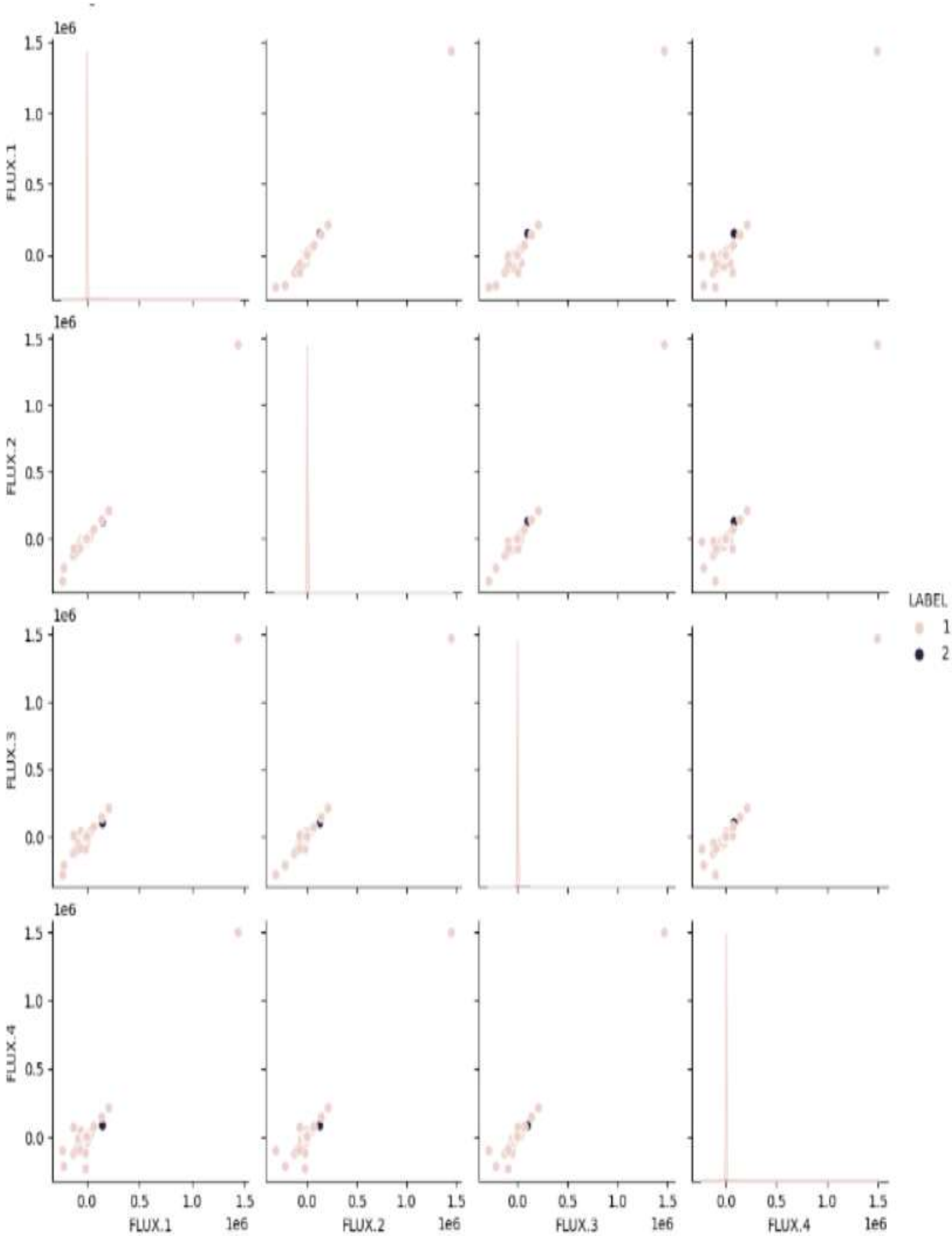
```
Layer (type)                         Output Shape          Param #
=================================================================
reshape_7 (Reshape)                  (None, 3197, 1)       0

normalization_7 (Normalizat          (None, 3197, 1)       3
ion)

conv1d_14 (Conv1D)                   (None, 3196, 11)      33

batch_normalization_14 (Bat          (None, 3196, 11)      44
chNormalization)

conv1d_15 (Conv1D)                   (None, 3195, 7)       161

batch_normalization_15 (Bat          (None, 3195, 7)       28
chNormalization)

max_pooling1d_7 (MaxPooling          (None, 1597, 7)       0
1D)

dropout_21 (Dropout)                 (None, 1597, 7)       0

flatten_7 (Flatten)                  (None, 11179)         0

dense_28 (Dense)                     (None, 50)            559000

dropout_22 (Dropout)                 (None, 50)            0

dense_29 (Dense)                     (None, 30)            1530

dropout_23 (Dropout)                 (None, 30)            0

dense_30 (Dense)                     (None, 12)            372

dense_31 (Dense)                     (None, 1)             13

=================================================================
Total params: 561,184
Trainable params: 561,145
Non-trainable params: 39
```

To summarize, this model applies a sequence of convolutional, pooling, normalization, dropout, and dense layers for the processing of input data in order to extract the desired features. The flattened output is then fed into a sequence of dense layers to progressively reduce the dimensionality and introduce non-linearities. The final layer produces a binary classification prediction using the sigmoid activation function. We use Adam optimizer for optimization purposes.



Also, we utilize Early Stopping. That's when it ceases the training of our model once there is no enhancement in improvement. Moreover, Exponential Decay refines even more deep-learning model training.

Inside that repository's Exoplanet Detection notebook are where the required hyperparameters regarding how to train the model might be located.



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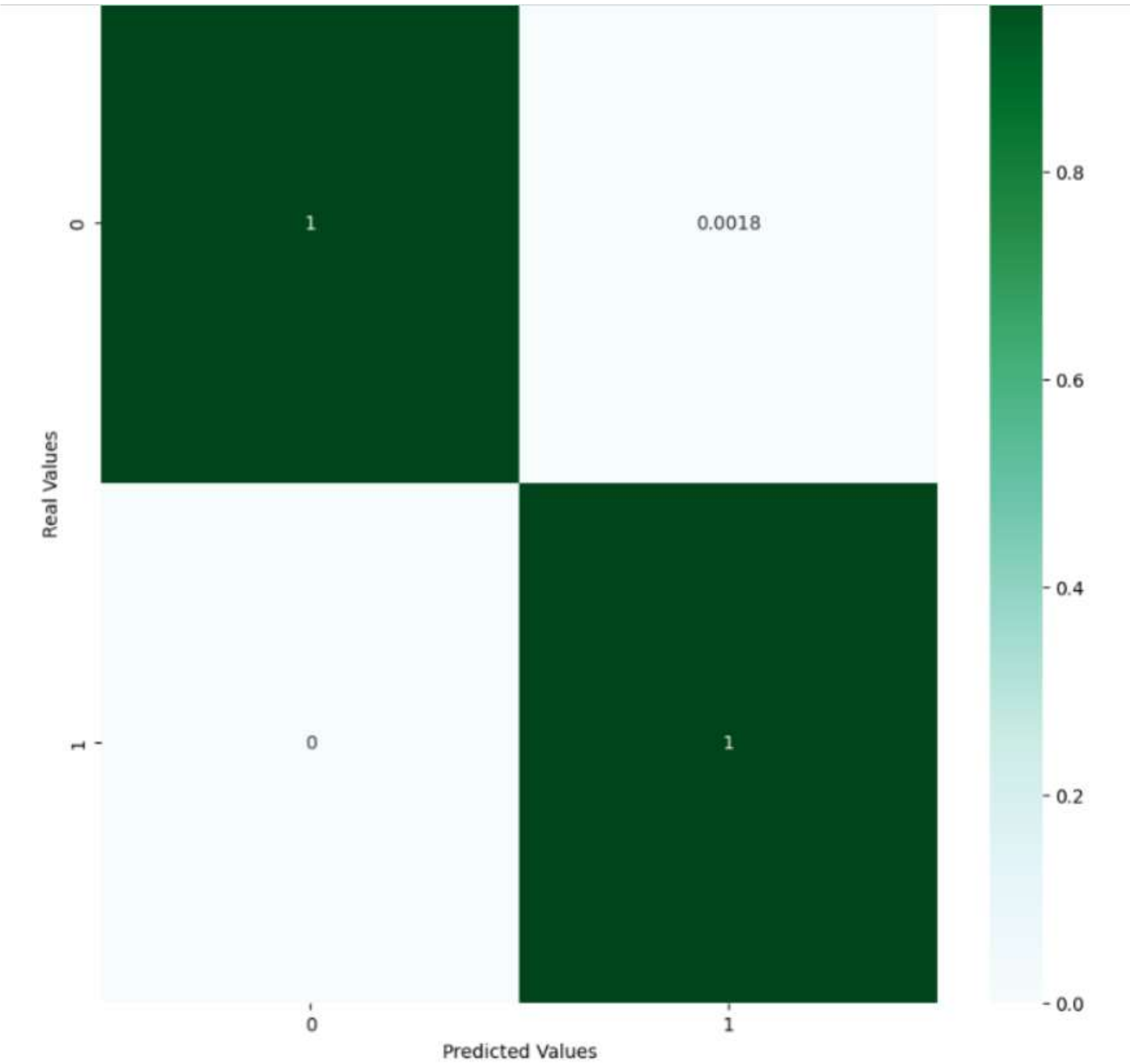
IV .RESULTS AND DISCUSSION

Proposed CNN Model:

The proposed CNN model performed excellently, with 99.82% precision, 100% recall and 99.91% accuracy on the test set after multiple iterations and fine-tuning. Although such high accuracy is rare in real-world scenarios, it shows that the model can learn well and capture the underlying patterns in exoplanet detection. The best-performing model has been saved and can be accessed in the GitHub repository.



Machine Learning Models:

Traditional machine learning models did not perform as well as the CNN model in the exoplanet detection task. These may have failed to capture the complex relations and patterns in the data, which led to suboptimal performance compared with the CNN model. But they are still useful as benchmarks for performance evaluation purposes.

The classifiers used:**1 . LightGBM** : The fine-tuned model used:

```
LGBMClassifier(learning_rate=1, max_depth=6, random_state=42)
```

Classification Report:

```
Classification Report is:

              precision    recall  f1-score   support

           0       0.99      1.00      1.00       565
           1       0.00      0.00      0.00         5

    accuracy                           0.99       570
   macro avg       0.50      0.50      0.50       570
weighted avg       0.98      0.99      0.99       570
```

2 .Random Forest

The fine-tuned model used:

```
RandomForestClassifier(max_depth=4, n_estimators=200, random_state=42)
```

Classification Report:

```
Classification Report is:

              precision    recall  f1-score   support

           0       0.99      0.99      0.99       565
           1       0.00      0.00      0.00         5

    accuracy                           0.98       570
   macro avg       0.50      0.50      0.50       570
weighted avg       0.98      0.98      0.98       570
```

3 .K Nearest Neighbors

The fine-tuned model used:

```
KNeighborsClassifier(n_neighbors=3, p=1)
```

Classification Report:

```
Classification Report is:

              precision    recall  f1-score   support

           0       0.99      1.00      1.00       565
           1       0.00      0.00      0.00         5

    accuracy                           0.99       570
   macro avg       0.50      0.50      0.50       570
weighted avg       0.98      0.99      0.99       570
```

Best Performing Machine Learning Model - Logistic Regression:

Among the tested machine learning models, Logistic Regression emerged as the top performer. It exhibited comparatively better accuracy and predictive capabilities compared to other models. Logistic Regression offers a reliable and interpretable approach for predicting the target variable. Its performance highlights the significance of considering simpler models alongside more complex techniques in certain scenarios.

The fine-tuned model used:

```
LogisticRegression(C=0.0001, random_state=42)
```

Classification Report:

Classification Report is:

	precision	recall	f1-score	support
0	0.99	0.55	0.71	565
1	0.01	0.60	0.02	5
accuracy			0.55	570
macro avg	0.50	0.58	0.37	570
weighted avg	0.99	0.55	0.70	570

V.CONCLUSION

Overall, the present project has demonstrated tremendous promise of machine learning, and CNNs in particular, in exoplanet detection and prediction. The application of CNNs to light curves data from space telescopes, including Kepler and TESS, shows the power of deep learning in automating exoplanetary transit detection. By processing large datasets with complex, noisy signals, CNNs were able to extract subtle patterns that are indicative of planetary transits, achieving a high level of accuracy in classification tasks. This approach significantly reduces the reliance on traditional methods such as manual vetting, which can be both time-consuming and prone to human error. The performance of the CNN model in distinguishing true planetary signals from stellar variability and instrumental noise also argues for the deep learning approach toward large-scale exoplanet surveys. It is also worth stressing that the proper choice of algorithms should relate to the problem at hand. CNNs are perfect for processing time-series data while capturing hierarchical features that other machine learning models may miss. However, the analysis also pointed out areas for improvement, such as optimizing model architectures and reducing false positives and negatives, which remain a challenge in noisy datasets. Further, the ability to generalize the model to unseen data further reflects its robustness, but it also highlights the need for continuous refinement to enhance prediction accuracy and reliability.

While the present model has yielded promising results, there is ample room for improvement in terms of refining the architecture, adding more astrophysical parameters, and expansion to multi-planet systems. Future work may be in combining CNNs with other machine learning techniques or hybrid models to achieve even higher performance and better adaptability across different types of exoplanetary systems. More specifically, further advances in improving the model to be better robust with respect to complex and sparse data can lead to precise exoplanet detection, especially about smaller, Earth-like planets or more distantly orbiting ones. The present work constitutes an important groundwork for future work regarding exoplanet research. These insights from applying machine learning techniques to this problem will guide further efforts in the development of more accurate, efficient, and scalable models for exoplanet detection. Ultimately, it will lead to a greater understanding of the universe and provide new avenues for identifying habitable planets beyond our solar system, eventually perhaps finding a new world that can sustain life.

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