

An Explainable CNN-Based Approach for Exoplanet Detection Using Light Curve Data

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I, Ayush Patidar hereby declare that the thesis titled "An Explainable CNN-Based Approach for Exoplanet Detection Using Light Curve Data" which is submitted by me to the Department of Information Technology, Delhi Technological University, Delhi in partial fulfillment of the requirement for the award of degree of Master of Technology, is original and has not been copied from any source without proper citation. This work has not previously formed the basis for the award of any Degree, Diploma, Associateship, Fellowship, or any other similar title or recognition.


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I hereby certify that the thesis titled "An Explainable CNN-Based Approach for Exoplanet Detection Using Light Curve Data" which is submitted by Ayush Patidar, Roll No. – 24/ISY/04, Department of Information Technology, Delhi Technological University, Delhi, in partial fulfillment of the requirement for the award of the degree of Master of Technology, is a record of the project work carried out by the student under my supervision. To the best of my knowledge, this work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere.

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Abstract

Exoplanet detection has become one of the most significant research areas in modern astronomy due to its importance in understanding planetary systems and the possibility of extraterrestrial life. Among various detection techniques, the transit method is widely used because it identifies periodic dips in stellar brightness caused by a planet passing in front of its host star. The NASA Kepler mission has generated a massive amount of light curve data, making manual analysis difficult and time-consuming.

Recent advancements in Artificial Intelligence and Deep Learning have enabled automated analysis of astronomical datasets. Convolutional Neural Networks (CNNs) have shown remarkable performance in extracting hidden patterns from light curve data and accurately classifying exoplanet signals. However, many deep learning models operate as black-box systems and fail to provide interpretability, which limits trust and understanding in scientific applications.

This thesis proposes an Explainable CNN-Based Approach for Exoplanet Detection using light curve data obtained from the NASA Kepler dataset. The proposed framework focuses on both accurate prediction and interpretability of model decisions. A comparative analysis between CNN and ResNet-based architectures is also performed to evaluate classification performance in terms of accuracy, precision, recall, F1-score, and confusion matrix. Furthermore, explainable AI techniques are incorporated to visualize important light curve regions responsible for predictions, thereby improving transparency and reliability.

Experimental results demonstrate that the proposed model achieves high detection accuracy while also providing meaningful interpretation of predictions. The integration of explainable deep learning techniques with astronomical data analysis can support future space missions and improve the reliability of automated exoplanet discovery systems.

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List of Symbols and Abbreviations

AI	Artificial Intelligence
ML	Machine Learning
DL	Deep Learning
CNN	Convolutional Neural Network
ResNet	Residual Neural Network
XAI	Explainable Artificial Intelligence
NASA	National Aeronautics and Space Administration
TESS	Transiting Exoplanet Survey Satellite
ROC	Receiver Operating Characteristic
AUC	Area Under Curve
TP	True Positive
TN	True Negative
FP	False Positive
FN	False Negative

CHAPTER 1 Introduction

1.1 Background

The discovery of planets orbiting other stars (exoplanets) is one of the greatest accomplishments of modern astronomy/astrophysics [15]. Over the past few decades, thousands of planetary candidates have been discovered with the help of advanced observational methods and space missions from the first discovery of an exoplanet [30]. Exoplanet studies are used to investigate the processes of planetary formation, stellar evolution, and life on planets around other stars.

One of the most popular techniques is the transit method, which has been used to detect exoplanets, and is also the method used by the TRAPPIST telescope that is currently studying the TRAPPIST-1 system. One of the techniques is the transit method, which is one of the most popular methods for detecting exoplanets and is the method employed by the TRAPPIST telescope that is now studying the TRAPPIST-1 system. This approach involves measuring a slight dimming of the brightness of a star by a planet transiting its face. These changes in brightness create patterns called light curves, which can be used to find out if there are planets orbiting other stars [28].

The NASA Kepler Space Telescope has greatly advanced the field of exoplanet science through its acquisition of a large set of light curve data from thousands of stars [15]. But manually analysing such large data sets is very time consuming and difficult to compute. The traditional methods are generally time-consuming and difficult to analyze, and are not always well suited to the vast quantities of astronomical data that are produced [9].

With the developments of Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) in recent years, increasingly efficient tools have come into existence to aid in automated exoplanet detection [17]. Deep learning models like Convolutional Neural Networks (CNNs) can learn and extract key attributes from light curve information automatically and classify it effectively [24]. CNN-based methods have been shown to be very successful in astronomy applications thanks to their ability of

discovering hidden patterns in large data sets .

Although deep learning models are often referred to as black-box models, they are difficult to interpret as their decision making process is not easy to understand [1]. For scientists, interpretability is imperative: They must know the answer to the question of why a model predicts the presence of an exoplanet. The use of Explainable Artificial Intelligence (XAI) techniques can increase transparency and trust in AI-based astronomical systems [26].

In this research, we propose an explainable framework based on CNN for exoplanet detection from the light curve data provided by NASA Kepler. The proposal also contains a comparison between CNN architecture and ResNet architecture to assess classification performance [20]. In addition, visualization and explainability methods are integrated to explain the prediction results and gain insights into the behavior of the model.

1.2 History of Exoplanet Discovery

It was long thought that planets could exist beyond the solar system, but they had not been directly confirmed until then because of the limitations of observational technology. With the aid of new astronomical instrumentation and computational methods, astronomers were able to detect planets around other stars successfully [2].

In 1995, Michel Mayor and Didier Queloz were able to use the radial velocity technique to detect the first confirmed planet around a Sun-like star, the planet rho Bootis B [15]. The discovery was of monumental importance, and began a new era of astronomical research as well as inspired scientists to look for planetary systems around other stars.

After this discovery, a few large-scale observational missions were launched for the purpose of exploring exoplanets. Kepler was one of the most successful planetary discovery and transit signal analysis missions of NASA [10]. Kepler kept staring at thousands of stars and created huge time-series data sets for detecting brightness changes due to planetary transits.

The use of Artificial Intelligence and Machine Learning helped to further boost the research of exoplanets by having astronomical data automatically processed [17]. Techniques of deep learning like Convolutional Neural Networks (CNNs) were able to detect the underlying patterns of the transit data in the Kepler light curve with great success [30].

The field of exoplanet exploration is still growing and new missions like TESS and the

James Webb Space Telescope have begun to contribute high-resolution astronomical observations [16]. The missions produce massive amounts of data that are to be analyzed and classified in real-time and efficiently, which needs computational models that are efficient.

The drive to find planets orbiting other stars is also fueled by the idea that Earth-like planets can be found that will be able to support life. Thus, the importance of developing intelligent and interpretable AI based systems is still a research direction in astronomy and space science [13].

1.3 Artificial Intelligence in Astronomy

Conventional astronomical methods, which have relied on manual observations and expert interpretation, are inefficient in dealing with the large number of data points collected by large-scale space missions like the present one [2].

The use of Deep Learning and Machine Learning methods is a powerful solution for analysing complex astronomical patterns. These methods can discover hidden relationships in data and classify data with almost no human involvement with high accuracy [3].

In the field of image processing and classification by time series, deep learning models like Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs) and Residual Networks (ResNet) have offered outstanding performance [24]. In astronomy, these models are used for detecting exoplanets, classifying galaxies, identifying supernova and analyzing stellar signals [7].

The NASA Kepler mission produced vast amounts of data and light curve information that is hard to analyze by hand. Automated identification of transit signals using AI-based systems greatly reduces the computational complexity [28]. Researchers have been able to use CNN based models to classify Kepler data, achieving an accuracy up to 95

Residual learning architectures like ResNet benefit from feature extraction ability and alleviate vanishing gradient problems of deep neural networks [20]. These architectures can capture more complex representations and can yield better classification accuracy for astronomical data.

Although deep learning systems have benefits, they tend to be black-box models and are not interpretable [1]. Explainable Artificial Intelligence (XAI) techniques are thus incorporated into AI systems to enhance the transparency and reliability of the predictions [26].

AI will be vital in future astronomical discoveries and will provide intelligent data analysis, automated observatories, and astronomical monitoring systems through real-time processing of data [18].

1.4 NASA Kepler Mission

NASA's Kepler Space Telescope was launched in 2009 to search for Earth-sized planets around other stars [15]. The Kepler mission monitored the brightness of over 150,000 stars continuously and recorded precise, detailed measurements to look for transits in order to detect planets.

The mission employed the transit photometry approach of identifying transiting exoplanets by periodic drops in the brightness of a host star, as the planet moves across it [10]. The variations are depicted as "light curves," and give critical information about planetary characteristics.

Kepler yielded one of the largest astronomical data sets ever available for the study of exoplanets. The data set has time-series flux measurements which are very well suited for machine learning and deep learning applications [14].

CNN and deep neural network architectures have been successfully applied to a Kepler light curve to uncover hidden transit patterns from the data [30]. The automated analysis of Kepler data will greatly improve the speed of data discovery and decrease the amount of manual work for astronomical data.

The success of the Kepler mission also encouraged other space exploration missions to continue to produce the vast astronomical data sets that are continued by TESS and Gaia, among others [16]. Such datasets demand smart AI-driven models to analyze and comprehend efficiently.

Kepler has made a significant contribution to the discovery of thousands of confirmed exoplanets, and to the scientific understanding of planetary systems, stellar evolution and habitable environments outside the Solar system [9].

The transit method of planet discovery. Transit method of exoplanet discovery.

One of the most popular and effective methods of discovery for planets around other stars is the transit method. The approach is to look for periodic dimming of a star as the planet moves in front of it as seen by the observer [10].

As an exoplanet passes in front of its parent star it obscures a small amount of the star's light. This transient dimming results in a reduction of the light intensity measured. A light curve can be used to show the changes of brightness that are recorded over time. The depth, duration and frequency of the transit signal give clues to the character of

the exoplanet, such as its size, orbital period, and distance from the host star. Brighter dips on the planet are seen for larger planets and weaker dips for smaller planets.

The transit method has proven to be very successful because it has enabled astronomers to watch thousands of stars at once. A technique has been applied to space missions to identify large numbers of planetary candidates with success, such as TESS and Kepler. The transit method also has a number of difficulties, however. It's hard to see a planetary transit signal in stellar noise, observational error, or fluctuations in brightness. The manual analysis of these light curves is very time-consuming and requires a lot of computation.

The use of Machine Learning and Deep Learning techniques offers efficient solutions to automated transit signal classification. CNN-based architectures have the potential of learning hidden patterns automatically from light curve data and accurately classify planetary transit events [28].

The transit method yields large-scale time-series data that are very applicable to AI-related analysis. Deep learning models can detect subtle brightness changes that can not be easily detected by traditional analysis methods.

The transit method is the key basis of the research on analysing the Kepler light curve data and designing an interpretable DL system for automated planet detection.

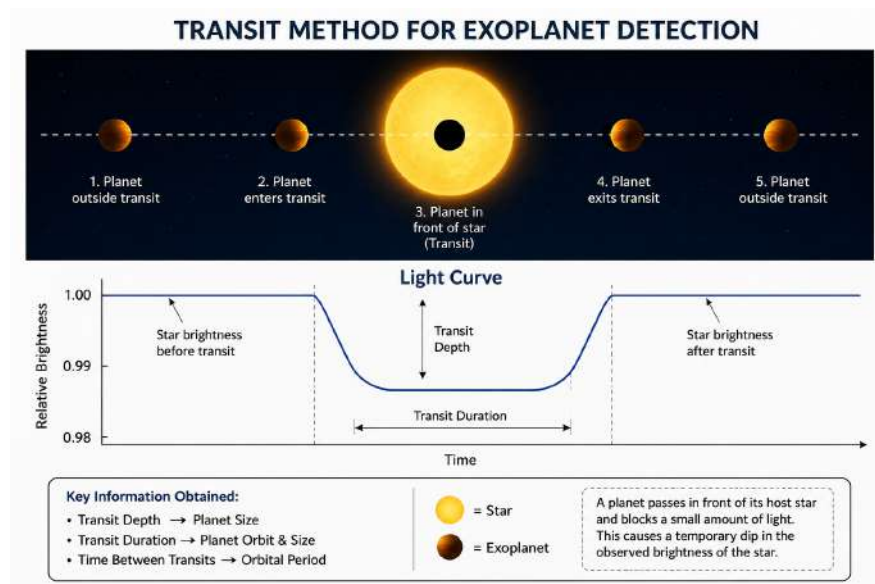


Figure 1.1: The illustration of Exoplanet Transit Method.

Table 1.1: Major Exoplanet Detection Methods.

Method	Working Principle	Advantages	Limitations
Transit Method	Detects brightness dips	High accuracy and scalability	Sensitive to noise
Radial Velocity	Measures stellar motion	Accurate mass estimation	Requires precise instruments
Direct Imaging	Captures planet images	Visual confirmation	Sensitive to distance planets
Microlensing	Uses gravitational lensing	Ideal for remote systems	Rare observational events
Astrometry	Observes the movement of stars very well	Optional for orbit analysis	High measurement complexity

1.5 Challenges in Exoplanet Detection

While there are great advances in the detection of planets outside the solar system in recent years, there are still some limitations in analyzing and classifying astronomical data. Many space missions produced an increasing amount of observational data making the computational and analytical challenge difficult for the researchers to face [2].

The detection of exoplanets is one of the most important challenges in the search for planets is the stellar noise and irregular variations in the light curve. The variations can be a result of stellar activity, instrumental errors, or environmental disturbances, which can make it challenging to detect signals of planetary transits as false positives [14].

Imbalance of astronomical datasets is another important challenge. Most observational data sets contain much more actual planetary transit signal than non-exoplanet signals. This imbalance has impact on classification performance and can be a cause of biased prediction by machine learning models [28].

Manual feature engineering, which is time consuming and knowledge intensive, is also needed for traditional machine learning methods. As the size of the light curve data set becomes larger, manually extracting meaningful patterns from these data becomes inefficient [3].

Deep learning models like CNNs offer automatic feature extraction capabilities, but tend to be black-box systems with little interpretability [1]. For scientific applications, transparency and reliability are crucial as scientists require to know the logic behind the model's predictions.

Another significant hurdles in astronomical analysis using deep learning is also computational complexity. Optimization methods and computational power are needed to train deep neural networks on large scale Kepler datasets [17]. Failing to converge or overfitting might also be a problem with deeper architectures.

Explainable Artificial Intelligence (XAI) techniques are used to enhance interpretability and transparency, although the integration of efficient explainability methods in deep learning systems is still a hot topic of research [13].

As the amount of data from future astronomical missions will continue to grow, scalable, interpretable, and efficient AI-based exoplanet detection frameworks will become even more important.

Table 1.2: Main Challenges in Exoplanet Detection

Challenge	Description	Impact on Detection
Stellar Noise	Periodic changes in luminosity of stars	Makes false positive predictions
Data Imbalance	Very few samples from exoplanet observations, compared to non-exoplanet signals	Reduces classification accuracy
Large Dataset Size	Kepler's large observational data sets	High computational complexity
Manual Feature Engineering	handcrafted features uses Traditional ML	Time intensive and less scalable
Black-Box Nature of DL Models	Deep Learning predictions are hard to explain	Lacks the ability to share trust and transparency
Overfitting	Model is trained with training data	Poor generalization performance
Computational Cost	High-performance hardware is required by these deep architectures	Increases processing time
False Transit Signals	Transit events	Incorrect classification results

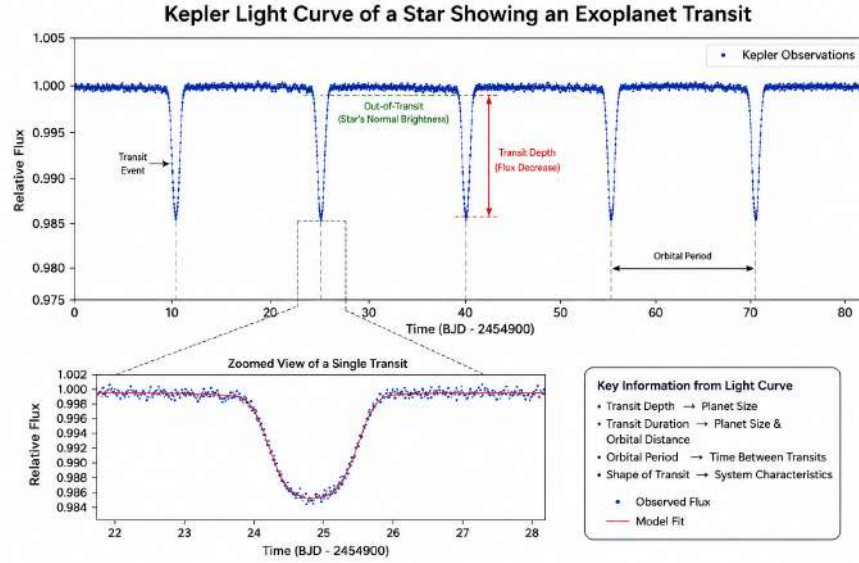


Figure 1.2: Kepler Light Curve of a Star Showing an Exoplanet Transit

1.6 Problem Statement

The current approaches to exoplanet detections based on the traditional methods of manual analysis are time-consuming and are not well suited to the volume of light curve data produced by the contemporary astronomical missions of the type used by [10]. While deep learning models have been shown to achieve high prediction accuracy, many of the current methods are not interpretable and transparent [13]. Hence, an efficient and interpretable deep learning framework is required that can accurately detect exoplanets, and provide meaningful interpretation of model predictions as well.

1.7 Research Objectives

The main aims of this study are:

To build a CNN-based deep learning model to detect exoplanets from Kepler light curve data. in order to perform pre-processing and normalization of astronomical time-series data to the model training To compare the performance of CNN and ResNet architectures for binary classification of exoplanet and non-exoplanet signals. To assess the performance of the model based on accuracy, precision, recall, F1 score and confusion matrix. To incorporate Explainable Artificial Intelligence (XAI) methods to increase the interpretability and transparency. To show light curve patterns that give rise to predicting exoplanets.

1.8 Scope

This research is a study on detection methods for exoplanets using light curve data from NASA's Kepler mission with deep learning methods. This study focuses on binary classification of planetary and non-planetary signals using architecture (CNN and ResNet). An explanation method is embedded to enhance the transparency and prediction explanation. The proposed framework can be adopted for future astronomical surveys and automated space explorers.

1.9 Research Contributions

The Principal findings of this research work are summarised as follows:

Design of an interpretable framework based on CNN for exoplanet identification.

- Comparison of CNN vs ResNet architecture.
- Support for interpretability of AI models.
- Better visualization and prediction patterns of light curve.
- Automated exoplanet discovery: efficient analysis of astronomical time-series data.

The structure of the thesis is as follows:

- The introduction along with problem statement, objectives and scope of the research work is given in Chapter 1.
- The literature review and previous research on exoplanet detection and deep learning techniques are discussed in Chapter 2.
- The description of the dataset, preprocessing techniques and proposed methodology is described in chapter 3.
- Experimental results, performance evaluation and comparative analysis are presented in Chapter 4.
- The thesis ends in Chapter 5 with some future research directions.

CHAPTER 2 Literature Review

2.1 Introduction

The detection of planets orbiting other stars is a field of active research in astronomy, and has seen a rapid increase in astronomical data from recent space missions, including Kepler and TESS [15]. In the past, the discovery of exoplanets was a manual process that involved a lot of observation and analysis, which was time-consuming and costly. In response to these drawbacks, Artificial Intelligence (AI), Machine Learning (ML) and Deep Learning (DL) methods are becoming more and more popular to analyze light curve data in an automatic way [2].

Deep learning methods, in particular Convolutional Neural Networks (CNNs), have shown to be very effective for uncovering meaningful patterns in large astronomical datasets [17]. Many of the current deep learning systems, however, are black-box systems and are not interpretable. Thus, the use of Explainable Artificial Intelligence (XAI) techniques is gaining relevance to improve the comprehension and trust in model decisions for automated astronomical systems [13].

This chapter reviews the literature on the various studies related to exoplanet detection, machine learning techniques and deep learning architectures, and explainability techniques applied in astronomical applications.

2.2 Exoplanet Detection with a Traditional Methods

There are a number of traditional techniques used to identify exoplanets. These methods involve a direct imaging, radial velocity, gravitational microlensing, and the transit method [15].

One of the most common techniques is the transit method, which uses this information to detect periodic decreases in the brightness of a star which are caused by a planet transiting the star [10]. This approach yields light curve data which can be used to search for exoplanets. Astronomical data is very large in size, and, while effective,

manual analysis of light curves is increasingly difficult.

The RV technique is used to determine changes in the velocity of a star due to gravitational interaction with an orbiting planet [14]. Though correct, it is an expensive process that necessitates highly precise instruments and a large amount of analysis of observations.

2.3 Exoplanet Detection with a Machine Learning Approach

In recent years, several machine learning methods have been introduced to perform exoplanet detection automation. Some of the earliest methods were based on Support Vector Machines (SVM), Random Forest, Decision Trees, and Logistic Regression classifiers to classify planetary candidates [3].

McCauliff et al. have created automated classification methods for Kepler planetary transit candidates based on machine learning methods [14]. They showed that the use of ML techniques could effectively reduce the manual work in the process of astronomical data analysis.

Pearson et al. developed an AI-based system for the detection of exoplanets to enhance the classification accuracy, which relies on machine learning techniques (MLT) [28]. Likewise, probabilistic machine learning methods for the detection and rejection of false positives in exoplanet searches were used by Armstrong et al.[30].

While machine learning methods enhanced automation, most of the traditional machine learning models necessitate the manual extraction of features, and many of them are not able to identify complex patterns in light curve data.

Now, let's examine some traditional machine learning techniques. Now let's look at some classic machine learning methods.

Prior to the advent of the deep learning methods, there was a wide usage of traditional machine learning algorithms in the exoplanet detection research and astronomical data analysis. These techniques focused mainly on the handcrafted features and statistical learning to detect planetary transit signals from light curve data [3].

In the early days of astronomical classification systems, some of the most popular machine learning approaches were Support Vector Machines (SVM), Decision Trees, Random Forests, Logistic Regression, and K-Nearest Neighbours (KNN) [4]. These methods gave efficient classification performance with small/medium size data sets.

Astronomical applications especially embraced the Random Forest algorithms due to their robustness and the capability of dealing with noisy observational data [8]. The

use of ensemble learning methods helped to increase the stability of predictions and decreased classification variability for planetary candidate detection.

In an effort to automate the Kepler classification system, McCauliff et al. developed an automated classification system that utilizes machine learning techniques [14]. They found that machine learning algorithms could substantially alleviate the manual workload of astronomical observations and candidate verification.

Pearson et al. created an Artificial Intelligence (AI) based exoplanet detection system that was able to detect the hidden transit patterns within the light curve data [28]. The benefits of automated classification methods for enhancing the efficiency of exoplanet discovery were their focus.

Manual feature engineering is used in traditional machine learning techniques, in which domain experts are tasked to identify meaningful statistical and signal-based features from light curve datasets [2]. This is very time-consuming and can only be scaled to a small extent for large astronomical datasets from missions like NASA Kepler.

Different dimensionality reduction algorithms were also investigated as a way to reduce the computational complexity and increase the effectiveness of classification, including Principal Component Analysis (PCA) [27]. These methods were useful to eliminate the redundant feature and enhance the generalization ability of models.

Traditional machine learning methods had moderate success, but were often found to be unable to deal with extremely complex and noisy timeseries data. They were unable to discern subtle nonlinear relationships that might have been found in the astronomical data they studied because they could not perform handcrafted features. They could not perform handcrafted features and thus were unable to detect subtle nonlinear patterns that might have been learned from the astronomical data they studied [19].

These limitations of the traditional machine learning methods led to the use of deep learning methods which have the ability to learn features automatically and in a hierarchical manner [25].

Table 2.1: Comparison of traditional machine learning algorithms:

Algorithm	Advantages	Limitations	Application in Astronomy
Support Vector Machine (SVM)	For small datasets	Needs manual feature extraction	Transit signal classification
Random Forest	Robust against noise	High memory usage	Planet candidate detection
Decision Tree	Simple and interpretable	Overfitting problems	Stellar classification
Logistic Regression	Fast and computationally efficient	Limited nonlinear learning	Binary astronomical classification
K-Nearest Neighbors (KNN)	Easy implementation	Is sensitive to size of the data set	Pattern similarity analysis
Naive Bayes	Probabilistic classification	Assumes feature independence	Preliminary astronomical prediction
Principal Component Analysis (PCA)	Dimensionality reduction	Information loss possibility	In this course, feature extraction from light curves is discussed.

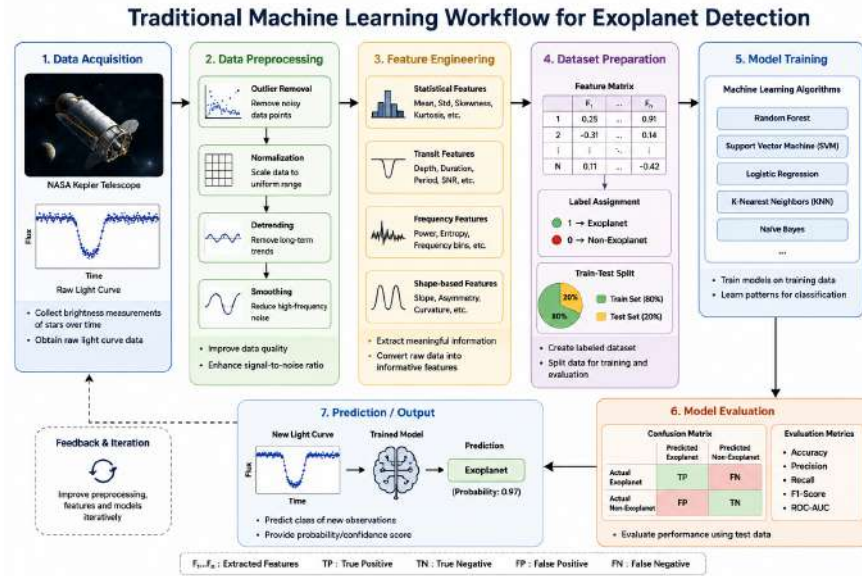


Figure 2.1: Here's the traditional workflow of machine learning for exoplanet detection.

2.4 Exoplanet Detection using Deep Learning

Deep learning has greatly enhanced the accuracy of automated exoplanet detection tools, allowing for the intelligent extraction of features and efficient analysis of astronomical data. In contrast to conventional machine learning approaches, deep learning models learn hierarchical representations from raw data without human effort in creating features [17].

One of the most popular deep learning architectures used for detection of exoplanets is the Convolutional Neural Network (CNN). A CNN model can be used automatically to detect unexpected transit features, including dimness and brightness changes, in the light curves obtained from the Kepler space telescope [24].

The most influential CNN-based exoplanet detection system proposed with NASA Kepler data is by Shallue and Vanderburg. They were able to classify at high accuracy with the help of their deep learning framework and proved the effectiveness of automated transit signal analysis.

Dattilo et al. also enhanced deep learning models to detect more planetary candidates in astronomical data [5]. Their findings showed how neural networks can find the hidden signals of planets orbiting other stars that would not have been detected by conventional methods.

The researchers also looked into Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks to study astronomical data that is sequential in nature, like [21]. These architectures are especially well suited for time-series analysis as they can incorporate temporal dependencies that may exist in the light curve.

To assist with gradient flow and obtain deeper representation learning, Residual Networks (ResNet) were introduced in [20]. The ResNet architectures were built to overcome the vanishing gradient problem that deep neural networks often faced and for better classification.

Transformer models are also becoming an important tool in deep learning for astronomical science, and have been proposed for a variety of other tasks [6]. These models utilize attention mechanisms to selectively focus on relevant features in time-series data and enhance learning efficiency.

Compared to the traditional machine learning approaches, deep learning models offer several benefits such as automatic feature extraction, higher classification accuracy, scalability and handling of large volume data effectively [25]. However, these models can be difficult to interpret, and are often extremely complex.

By combining Explainable Artificial Intelligence (XAI) with deep learning systems,

the predictions' transparency and interpretability can be enhanced [13]. Visualization techniques like Grad-CAM and SHAP help researchers explain the mechanisms that deep learning models use to recognize patterns of planetary transits.

The development of deep learning exoplanet detection systems is still ongoing and will have a significant contribution to the upcoming astronomical missions and intelligent space exploration systems.

Table 1: A comparison of Deep Learning Architectures used for Exoplanet Detection.

Architecture	Advantages	Limitations	Application
CNN	A high accuracy and automatic feature extraction are achieved.	Limited temporal dependency learning	Light curve classification
RNN	Captures sequential dependencies	Vanishing gradient problems	Time-series analysis
LSTM	Avoiding the "long-term dependency" problem by learning in an efficient way.	High computational complexity	Sequential transit prediction
ResNet	Improved deep feature learning	Complex architecture	Advanced astronomical classification
Transformer	Deep learning and scalability	Needs vast training sets	Large-scale astronomical analysis
Autoencoder	Efficient anomaly detection	Limited interpretability	Noise reduction and feature learning
Hybrid Models	Uses various learning approaches and	High training complexity	Multi-modal astronomical analysis

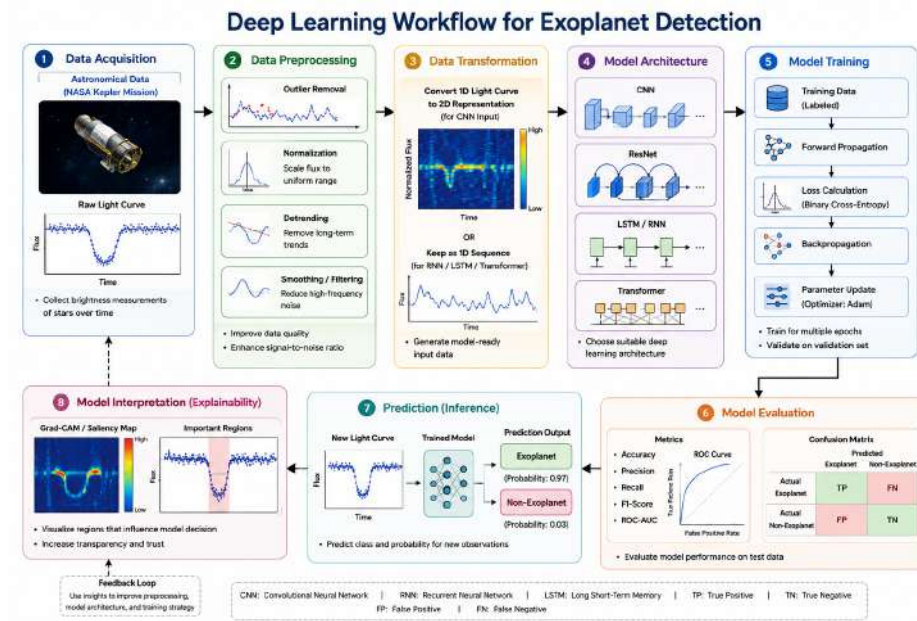


Figure 2.2: ExoPLANet Detection Deep Learning Workflow

2.5 CNN-Based Exoplanet Detection

Exoplanet detection tasks have been successfully tackled using deep learning approaches, including Convolutional Neural Networks (CNNs) [24]. CNNs learn hierarchical features from the input data automatically, and do not require the manual process of feature engineering.

One of the most influential CNN-based exoplanet detection systems developed by Shallue and Vanderburg from NASA Kepler data. is considered. The exoplanet detection accuracy of their deep learning model exceeded the stellar brightness pattern, resulting in high detection accuracy.

Dattilo et al. followed up on this finding by developing new neural network architectures to find other exoplanet candidates, [5]. They showed the effectiveness of deep learning for large-scale astronomical surveys.

Yu and others created automated models based on deep neural networks for time-series light curve analysis and enhancing classification accuracy [11]. Osborn et al. proposed the classification of rapid methods for exoplanet candidates that both lowered the computational cost and retained a high accuracy [9].

CNN-based systems, although performing well, tend to have poor interpretability as their prediction mechanism is hard to interpret.

2.6 Deep Learning Models based on ResNet

To solve the problem of degradation in deep neural networks, Residual Networks (ResNet) have been introduced [20]. ResNet architectures have skip connections to enable residual mapping learning, enhance training efficiency and classification accuracy.

In image recognition as well as time series analysis applications, ResNet has been very successful. ResNet architectures have been becoming more popular in astronomical research for their use in analysing complex light curve patterns, and to enhance the accuracy of the classification of exoplanets.

A ResNet architecture can learn deeper representations and avoid the vanishing gradient problem as compared to traditional CNN architectures. Hence, it is crucial to compare the CNN model with the ResNet model to find the most efficient way for the detection of exoplanets.

2.7 Explainable Artificial Intelligence

Explainable Artificial Intelligence (XAI) is concerned with making machine learning models more transparent and interpretable [18]. For scientific applications like astronomy, knowing the predictions of a model is crucial in order to raise trust and confidence.

Ribeiro et al. proposed LIME for explaining the predictions of a black-box classifiers [29]. Lundberg and Lee suggested game-theoretic methods to interpret machine learning outputs in the form of SHAP values [26].

Selvaraju et al. have introduced Grad-CAM visualization techniques that emphasize significant areas that contribute to the deep learning predictions of the model [12].

Explainability techniques can be used in exoplanet detection to reveal the parts of the light curve data that are most important for predictions in the model. This enhances the scientific understanding and minimizes dependence on black-box models.

Table 2.2: Difference between Explainable AI Techniques

Technique	Working Principle	Advantages	Limitations
LIME	Local surrogate model explanation	Model-agnostic and interpretable	Limited global understanding
SHAP	Game-theoretic feature importance	Consistent feature attribution	High computational cost
Grad-CAM	Gradient-based visualization	A helpful CNN interpretation	Limited for non-image models
Saliency Maps	Highlights important input regions	Simple visualization technique	Sensitive to noise
Attention Mechanism	Focuses on important sequence regions	Improves interpretability	Complex implementation
Feature Importance Analysis	Measures variable contribution	Easy interpretation	Lack of deep understanding of features.
Rule-Based Explanation	Uses human-readable rules	High transparency	Hard for deep networks to learn,

Table 2.3: Comparative Analysis of the Existing Research Work

S.No.	Author(s)	Existing Work	Limitations	Future Work
1	Shallue and Vanderburg (2018)	Exoplanet detection with Kepler data, based on CNN.	Lack of explainability	AI techniques that can be understood by humans
2	Dattilo et al. (2019)	Better deep learning structure for exoplanet classification.	The complexity of the calculation is high	Optimization of the efficiency of the model
3	Pearson et al. (2018)	Using AI to automate the search for planets beyond the Solar System.	Limited transparency in predictions	integration with Explainable deep learning
4	Yu et al. (2019)	Deep neural network for light curve analysis	Overfitting issues	Robust regularization techniques
5	Osborn et al. (2020)	Rapid classification of exoplanet candidates	Limited visualization support	Advanced visualization approaches
6	Armstrong et al. (2018)	Machine learning for transit signal classification	control. False positive predictions	Better features extraction techniques
7	McCauliff et al. (2015)	Automated Kepler candidate classification	Manual feature engineering was needed for	Deep learning-based automation
8	Ansdell et al. (2018)	Synthetic domain knowledge integration	Limited generalization	Transfer learning approaches
9	Naul et al. (2018)	Time-series classification using deep learning	Large training time	Lightweight neural architectures
10	Charnock and Moss (2017)	The study of deep recurrent neural networks for astronomy	Interpretability challenges	Explainable recurrent networks
11	Baron (2019)	Machine learning applications in astronomy	Scalability issues	Big data optimization
12	Ball and Brunner (2010)	Data mining of astronomical data.	Limited automation	Advanced AI integration
13	Fluke and Jacobs (2020)	Survey of ML methods in astronomy	A lack of a common framework	Hybrid AI architectures
14	Mislis et al. (2016)	Transit detection using ML methods	Low classification accuracy	Deep learning enhancement
15	Krizhevsky et al. (2012)	Deep CNN architectures	High computational cost	Efficient CNN optimization
16	He et al. (2016)	Residual learning (ResNet)	Complex architecture	Lightweight residual models
17	Ribeiro et al. (2016)	LIME explainability framework	Local explanation limitation	Global interpretation models

2.8 Research Gap

Previous studies have shown that deep learning has high accuracy of exoplanet detection. But there are a number of caveats:

Most current systems are black box systems and are not interpretable.

There are relatively few studies that compare CNN and ResNet architectures in exoplanet detection research. Current methods primarily have accuracy as the main concern and neglect transparency and explainability.

There is not a thorough exploration of visualization of light curve regions responsible for predictions. AI models need to be more efficient and easily understood for handling large-scale astronomical datasets.

2.9 Chapter Summary

This chapter provided a review of the literature on exoplanet detection methods, machine learning techniques, deep learning architectures, and explainable approaches to AI. As per the literature survey, CNN and ResNet models are found to be suitable for automated planet detection of exoplanets. But, interpretability is a considerable issue in current systems. Hence this study aims to produce a framework that can be explained by CNN for analytical improvement of prediction accuracy and transparency of exoplanet detection systems.

CHAPTER 3 Proposed Methodology

3.1 Introduction

In this chapter, the dataset for exoplanet detection is introduced, exoplanet data preprocessing approaches are explained, proposed deep learning architectures are presented, and methods of explainability approaches are explained. The overall methodology is centered on the creation of an interpretable CNN based system to detect exoplanets accurately, from light curve data acquired by the NASA Kepler mission.

3.2 Dataset Description

The data for this study comes from the NASA Kepler Space Telescope mission, which has been observing the brightness of thousands of stars for a long time to search for possible exoplanets [15]. The Kepler data consists of time-series data showing how the brightness of the stars changes with time.

For each sample in the dataset, the observation is a star and there are flux values measured at various timestamps. A dip in brightness on a regular basis suggests that an exoplanet transit may have occurred.

The data is split into 2 classes:

- Exoplanet Signals
- Non-Exoplanet Signals

With reliable results, an extensive number of observations, and labeled transit observations, the Kepler dataset is widely used in astronomical research [30].

Table 3.1: Description of NASA Kepler Dataset

Dataset Parameter	Description
Dataset Source	NASA Kepler Space Telescope
Data Type	Time-Series Light Curve Data
Classification Type	Binary Classification
Classes	Exoplanet and Non-Exoplanet
Input Feature	Flux Intensity Values
Application	Automated Exoplanet Detection
Nature of Data	Sequential Astronomical Observations

3.3 Data Preprocessing

Astronomical data is often noisy, sparse, and has irregular patterns. So, deep learning models require pre-processing before training.

The following pre-processing is done:

3.3.1 Handling Missing Values

The dataset is consistently maintained by removing/replacing missing data in the light curve using interpolation methods.

3.3.2 Normalization

These of course are normalized light curve values, to stabilize training and minimize variations in the size of the data.

3.3.3 Reshaping of Data

The data is restructured to be suitable for CNN and ResNet model input.

3.3.4 Train-Test Split

The data set is split into training and testing sets to test the model's performance.

3.4 Proposed CNN Architecture

Convolutional Neural Networks (CNNs) are strong deep learning architectures that are commonly applied to image processing, pattern recognition problems, and classification problems involving time series data [24]. This research, we propose a CNN-based framework to automatically detect the exoplanets from the data of NASA Kepler light curve.

CNN learns the hierarchical feature representations from raw input data automatically without any manual feature engineering. This ability makes CNN architectures very useful in the astronomical field to detect unobserved transit patterns and brightness fluctuations in the data [17].

The proposed CNN model is composed of multiple layers that extract important features from the light curve observations. The architecture consists of convolutional layers, activation layers, pooling layers, flatten layers, and fully connected dense layers for the binary classification.

3.4.1 System Workflow

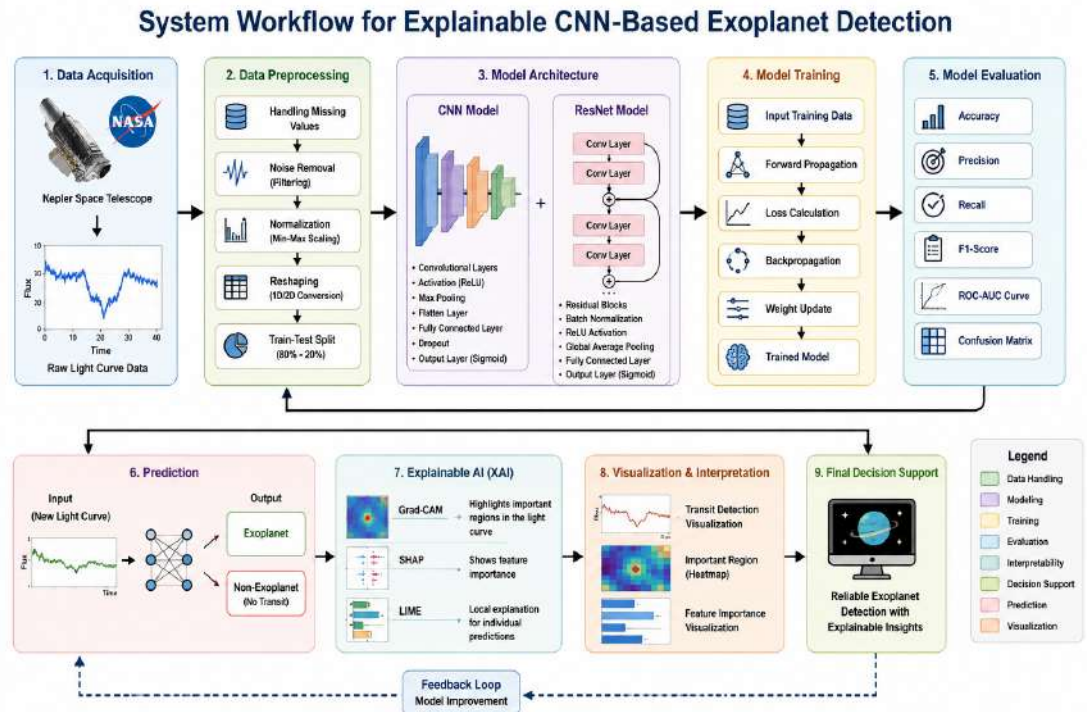


Figure 3.1: System Workflow for Exoplanet Detection Using Deep Learning

3.4.2 Convolutional Layer

The convolutional layer is used for learning local patterns and significant features from the input light curve data. Filters are applied to the input sequence to extract meaningful characteristics of the transit.

A mathematical representation of the convolution operation is:
where:

- X is the input data.
- K is a convolution kernel
- $(X * K)$ is the output of the convolution.

3.4.3 Activation Function

To add the non-linearity to the neural network, a Rectified Linear Unit (ReLU) activation function is employed. During training, ReLU yields more efficient learning and faster convergence of the learning process [25].

The ReLU function is given by:

3.4.4 Max Pooling Layer

Max pooling layer is used to decrease the dimensionality and complexity, by finding the max value from local feature regions. Pooling also decreases over fitting and enhances the ability of the feature generalization.

3.4.5 Flatten Layer

The flatten layer reduces the multidimensional feature maps to a one dimensional vector which can be fed into fully connected dense layers.

Fully Connected Dense Layer (FCD)

Dense layers provide the high level reasoning and classification using features extracted. The last output layer has a sigmoid activation function, for binary classification.

The sigmoid activation function is given by:

Table 3.2: CNN Architecture Configuration (Proposed)

Layer	Operation	Purpose
Input Layer	Reads light curve information	Input representation
Convolution Layer	Feature extraction using filters	Detect transit patterns
ReLU Activation	Applies nonlinearity	Improve learning capability
Max Pooling Layer	Dimensionality reduction	Reduce computational cost
Flatten Layer	Combines a map to vectors.	For dense layers:
Dense Layer	Fully connected learning	High-level classification
Output Layer	Sigmoid activation	Binary prediction

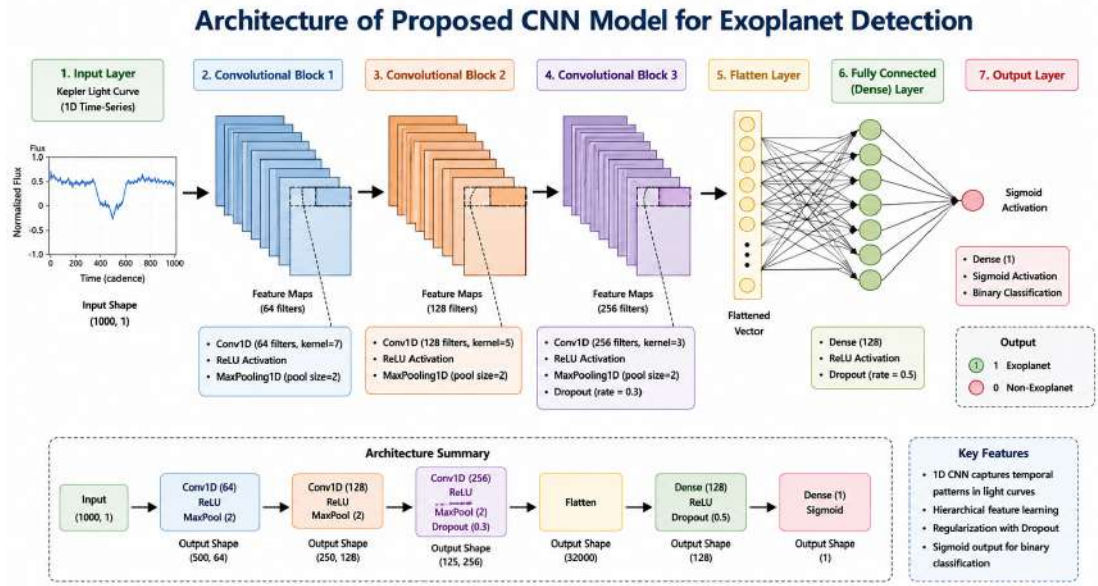


Figure 3.2: Architecture of Proposed CNN Model

3.5 ResNet-Based Architecture

Residual Networks (ResNet) are deep learning networks with special features to address the vanishing gradient problem of very deep networks [20]. ResNet adds shortcut or skip connections to allow for easy flow of gradients and better deep feature learning. A ResNet based architecture is implemented in this research for comparison with the proposed CNN model. The ResNet model can be used for extracting complex transit

patterns in NASA Kepler light curve data, and enhance its performance of classifications for exoplanet detection tasks.

The key benefit of ResNet architectures is the opportunity to train deeper networks with minimal accuracy loss. The addition of residual connections aids in the preservation of important information in both forward and backward propagation.

3.5.1 Residual Block

Residual block is the basic component of ResNet architecture. The network learns residual functions that make the optimization easier, rather than the direct mappings.

The residual learning function is represented as:

where:

- $H(x)$ is the End Product Output
- $F(x)$ is a learned residual mapping
- x is the identity mapping of the input valueThe function x represents input identity mapping.

Residual learning is a technique that enhances propagation of gradients and allows deeper representation learning.

3.5.2 Batch Normalization

For deep neural networks, batch normalization is employed to improve the stability of training and speed up the convergence of the network [22]. It helps to normalize intermediate activations and mitigate internal covariate shift while training.

The normalization process is represented in the following:

where:

μ is the mean The variance is denoted by σ^2 A small number ϵ for stability.

3.5.3 Global Average Pooling

Dimensionality reduction and generalization performance improvement adopted through Global Average Pooling (GAP). GAP is used instead of fully connected layers and helps to avoid overfitting in deep networks.

3.5.4 Output Layer

The last output layer is activated by sigmoid function for binary classification of exoplanet and non-exoplanet signals.

The Sigmoid activation function is given by:

Table 3.3: ResNet Architecture Configuration

Layer	Operation	Purpose
Input Layer	Accepts light curves data	Input representation
Convolution Layer	Feature extraction	Detect local patterns
Residual Block	Skip connection learning	Boost accuracy of deep learning algorithms
Batch Normalization	Activation normalization	Stable and quicker training
ReLU Activation	Nonlinear transformation	Improve learning capability
Global Average Pooling	Dimensionality reduction	Reduce overfitting
Dense Layer	High-level reasoning	Classification learning
Output Layer	Sigmoid activation	Binary classification

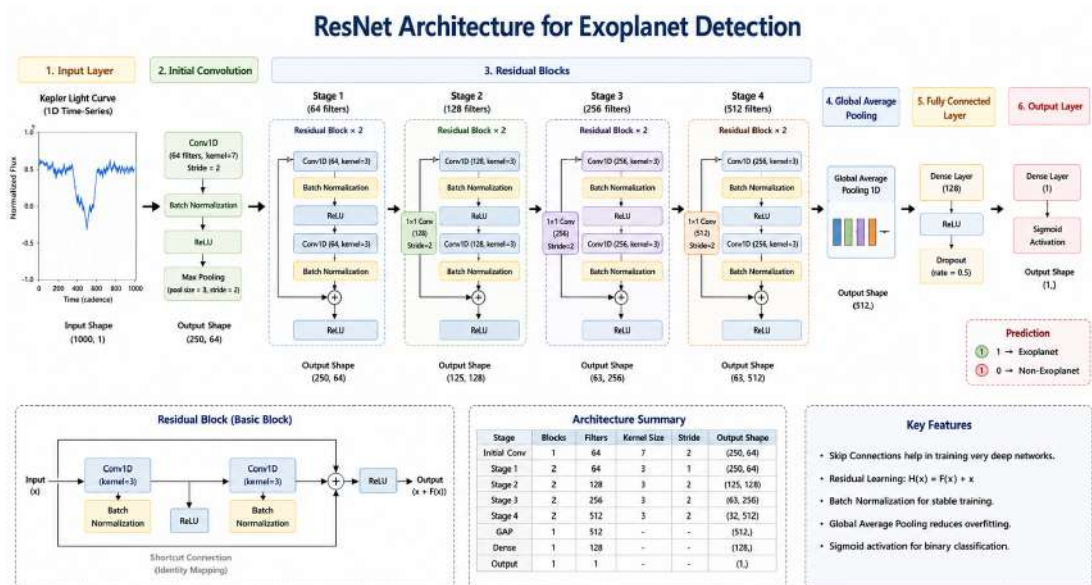


Figure 3.3: The architecture of ResNet for Exoplanet Detection is shown

3.6 Model Training

For the CNN model, we use labeled Kepler light curve data, while for ResNet, we use unlabeled Kepler light curve data. The analysis is done in binary classification to determine whether a signal is an exoplanet or a non-exoplanet event.

The following combinations of models are trained:

Sketch your problem and then use Adam Optimizer to resolve it. Loss Function: Binary Cross Entropy

- Metrics for evaluating the performance of a classification system: Accuracy, Precision, Recall, and F1-score

Repeat: Use multiple iterations to get convergence of the model.

Batch Size: Fixed size training batches.

It is chosen due to the efficiency of the optimizer Adam [23].

3.7 Experimental Setup

The experimental setup aimed to test the performance of the proposed CNN and ResNet models in detecting exoplanets from the NASA Kepler light curve dataset.

The implementation has been done in the deep learning frameworks such as TensorFlow and Keras in Python. Experiments were conducted on a computational system with adequate resources for training and evaluation of deep learning.

The dataset was split into training and test sets to get an unbiased assessment of the performance. The Adam optimiser and binary cross entropy loss function were used for training the models. In order to obtain stable convergence and better classification accuracy, multiple epochs and batch sizes were implemented.

Experimental configurations used were:

Optimizer: Adam Optimizer The following loss function is used, known as Binary Cross-Entropy: The activation functions used were ReLU and Sigmoid.

- Epochs: 50
- Batch Size: 32
- Evaluation Metrics: Accuracy: How often the predicted class matches the actual class $(TP+TN / (TP+TN+TN+FP))$

To prevent overfitting and to enhance generalisation performance, dropout layers and normalisation techniques were added.

3.7.1 Accuracy

Accuracy: Overall percentage of samples correctly classified.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (3.1)$$

where:

The number of true positive cases (TP).

- TN: True Negative
- FP: False Positive
- FN: False Negative

The higher the value of accuracy, the better the proposed model is in the overall classification.

3.7.2 Precision

Precision is the percentage of the positive observations that are correctly predicted divided by the total number of positive samples predicted.

$$\text{Precision} = \frac{TP}{TP + FP} \quad (3.2)$$

Improved precision results in fewer false positive predictions and more trustworthy proposed exoplanet detection framework.

3.7.3 Recall

Recall is the ability of the model to correctly recognize true positive samples.

$$\text{Recall} = \frac{TP}{TP + FN} \quad (3.3)$$

This is because there will be less drop in the recall, and thus more exoplanet transit signals will be detected.

3.7.4 F1-Score

F1-score is the combined metric of precision and recall, and is very useful for imbalanced astronomical datasets.

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (3.4)$$

The F1 score is higher the more balanced the precision and recall of the classed are.

3.7.5 ROC-AUC Curve

Receiver Operating Characteristic (ROC) curve is a plot that compares the True Positive Rate (TPR) with the False Positive Rate (FPR) at various classification thresholds. The true positive rate (TPR) is defined as:

$$\text{TPR} = \frac{TP}{TP + FN} \quad (3.5)$$

The False Positive Rate is defined as:

$$\text{FPR} = \frac{FP}{FP + TN} \quad (3.6)$$

Area Under Curve (AUC) is the overall classification ability of the model. The higher the ROC-AUC the better the ability to discriminate between the exoplanet and non-exoplanet class.

3.7.6 Confusion Matrix

Confusion matrix gives a detailed representation of the classification results and prediction errors produced by the model.

The confusion matrix has four major components:

- True Positive (TP)
- True Negative (TN)
- False Positive (FP)
- False Negative (FN)

The confusion matrix analysis can be used to assess the robustness, reliability and prediction ability of the proposed deep learning framework.

Table 3.4: Performance Evaluation Metrics

Metric	Purpose
Accuracy	Measures accuracy of prediction overall
Precision	Makes accurate positive predictions
Recall	Correctly identifies real positive samples
F1-Score	Finds the trade-off between precision and recall performance
ROC-AUC	Measures classifies discrimination ability
Confusion Matrix	Evaluates the results of predictions and classification mistakes

Overall ability of the model to classify an object as an exoplanet or non-exoplanet is calculated by Area Under Curve (AUC). The larger the ROC-AUC value, the better the classification will be.

3.7.7 Confusion Matrix

Confusion matrix is a comprehensive way of showing prediction results and misclassifications produced by the model. It assists to analyse well distinguished and mis-distinguished observations.

The confusion matrix can be broken down into four important components:

True Positive (TP)

- False Negative (FN)
- False Positive (FP)

(item 6) False Negative (FN)

Evaluation of the robustness and reliability of the proposed framework is carried out using confusion matrix analysis.

Table 3.5: Performance Evaluation Metrics

Metric	Purpose
Accuracy	Predicts overall correctness of the measure.
Precision	Measures reliability of positive predictions
Recall	Measures ability to identify actual positive samples.
F1-Score	Evaluates and balances precision and recall performance
ROC-AUC	Measures classification discrimination capability.
Confusion Matrix	Interprets the results of prediction and classification errors

3.8 Chapter Summary

In this chapter, we have discussed the dataset, preprocessing techniques, CNN and ResNet architecture, methods of explainability and evaluation metrics used in this research. The proposed methodology will concentrate on building an efficient and interpretable deep learning framework to achieve automatic exoplanet detection using light curve data from the Kepler mission.

CHAPTER 4 Results and Discussion

4.1 Introduction

In this chapter, the experimental results from the proposed CNN and ResNet-based models employed for exoplanet detection from the light curve data from NASA-Kepler mission are presented. Various classification metrics like accuracy, precision, recall, confusion matrix analysis and F1-score are used to evaluate the performance of the models. The model efficiency and generalization capability are also analyzed by comparing CNN with ResNET architecture.

4.2 Model Performance

The Kepler light curve dataset has been preprocessed and used to train and test the CNN and ResNet models. The classification results for both the models showed good classification accuracy in identifying exoplanet or non-exoplanet signals.

The CNN model has an accuracy of around 95.7%, and the ResNet model has an accuracy of 99%. The outcomes show that deep learning models are extremely promising for exoplanet detection tasks using automatic methods.

The reason for the superior performance of the ResNet model is primarily attributable to the incorporation of residual connections that enhances the extraction capability of features and that aid in the better flow of the gradient in deeper models.

4.3 Performance Comparison

Table 4.1 shows the comparison of CNN and ResNet models.

The results demonstrate that the classification accuracy of both the architectures was high. The ResNet model, on the other hand, yielded slightly better results because of its deeper feature representation and residual learning ability.

Table 4.1: Performance comparison of CNN and ResNet Models.

Model	Accuracy	Observation
CNN	95.7%	Efficient and fast classification
ResNet	99%	Improved feature learning ability

4.4 Training Analysis

Both CNN and ResNet models had a constant training accuracy curve and validation accuracy curve. The results showed that there were no significant fluctuations in both models when they converged, which suggested that they had been effectively preprocessed and optimised.

The CNN architecture showed a fast convergence rate and reduced computational cost, which is beneficial for real-time classification applications. The ResNet architecture, on the other hand, had a much deeper network structure which took up relatively more computational resources.

The accuracy of the validation remained close to the training accuracy during training process, which indicated that the overfitting were well suppressed by normalization and drop-out techniques.

4.5 Confusion Matrix Analysis

The detailed classification performance of the proposed CNN model was evaluated by using the confusion matrix. The matrix had high true positive and true negative rates, showing that these signals were accurately predicted as exoplanet or non-exoplanet signals.

The number of misclassified samples in the testing process was very few, thus the robustness and reliability of the proposed framework were justified. The confusion matrix also indicates the ability of deep learning models to detect small changes in brightness of light curve data.

The results from the experiments show that the proposed models are able to separate planetary transit patterns from non-planetary patterns.

The following section compares the CNN model with ResNet model. The next section compares CNN model with ResNet model.

An evaluation of the effectiveness for exoplanet detection was carried out for CNN and ResNet architectures.

The following observations were obtained:

- CNN provided efficient and computationally faster classification.

ResNet had a slightly higher accuracy and better generalization capability.

The design of the architecture for CNN was simpler, and the computational resources were also lower.

The performance gain due to ResNet was not that significant, as the dataset was preprocessed and not very noisy.

The results here indicate that even simpler CNN architectures can work very well for structured astronomical data.

4.6 Explainability Analysis

Improved the transparency and interpretability of deep learning predictions by including explainability techniques. Patterns in the light curve were visualised to identify important brightness dips for classification of exoplanets.

By using the explainable AI framework, it was possible to understand the CNN and ResNet models' prediction making processes. For better trust and reliability in the proposed system, the highlighted regions in the light curve were related to planetary transit events.

The incorporation of explainability techniques was effective in decreasing the black-box essence of deep learning models and improving scientific interpretability.

4.7 Discussion

The experimental results show that deep learning methods are very effective in detecting planets around other stars (exoplanets) from light curve data. CNN and ResNet were found to be very good in terms of classification accuracy and prediction ability. The ResNet model performed slightly better but only a marginal improvement over the existing CNN model. This indicates that very complex architectures are not always needed for preprocessed and structured data sets. Efficient performance with less computational cost can be achieved with simpler CNN model.

The study also highlights the importance of explainable AI in scientific applications. Traditional deep learning systems are frequently "black-box" models, which can lack interpretability and trust. The proposed explainability framework provided increased transparency through visualizing the important regions of the light curve data that are responsible for the prediction.

Moreover, the outcomes suggest that the proposed technique can be useful for future astronomical missions and automatic exoplanet discovery systems that involve reduction of reliance on manual work and enhance the reliability of exoplanet detection.

4.8 Chapter Summary

The experimental results and discussion on the proposed explainable CNN-based exoplanet detection framework were presented in this chapter. Highly accurate classification accuracy was obtained for both CNN and ResNet models on the NASA Kepler light curve data. The ResNet model showed a marginal improvement in feature learning capability and CNN model showed efficient and fast performance in terms of computation. Explainability techniques enhanced transparency and interpretation of the model predictions, making the proposed system appropriate for use in astronomical applications in real-world scenarios.

CHAPTER 5 Conclusion and Future Scope

5.1 Conclusion

The purpose of this research is to introduce an Explainable CNN Based Approach for Exoplanet Detection from NASA Kepler light curves. The research was concentrated on the use of deep learning methods, such as Convolutional Neural Networks (CNNs) and ResNet architectures, for automatic classification of exoplanet and non-exoplanet signals.

The experimental results showed that the CNN model and ResNet model obtained a high classification accuracy, effectively extracted the light curve patterns of planetary transit and achieved planetary transit data classification. CNN model achieved efficient and computationally faster performance and ResNet achieved slightly better generalization capability with residual learning and deeper feature extraction.

The incorporation of Explainable Artificial Intelligence (XAI) techniques for enhancing transparency and interpretability of model predictions was one of the key contributions of this research. The patterns of the light curves were then visualized to better understand the interpretation of the brightness dips found by the models as planetary transit events. This made the use of deep learning systems far less black box and made it more reliable in scientific applications.

The comparative analysis also showed that the performance of highly complex architectures is not significantly better for preprocessed and structured datasets. Effective and reliable classification performance with lower computational cost can be achieved by simpler CNN architectures. CNN architectures can be reduced that still perform effective and reliable classification with low computational cost.

In conclusion, this proposed framework illustrates the potential of deep learning and explainable AI in offering an efficient, interpretable, and scalable approach to automated exoplanet detection. The study opens new lines of research in astronomy with

the advent of artificial intelligence-driven astronomy and it will benefit future astronomical missions that demand intelligent analysis of very large observational datasets.

5.2 Future Scope

The proposed approach was successful in the results; however, there are some improvements and extensions for future research work.

For more complex astronomical data, advanced deep learning architectures like Transformers and Hybrid Neural Networks can be used.

Advanced Explainable AI (XAI) tools can be incorporated to enhance the interpretability of the model and gain a better understanding of the model's predictions. Future research may include enhancing the robustness in noisy and imbalanced data from real-world astronomical data.

Techniques for data augmentation can also be added to promote model generalization and mitigate overfitting. Optimized lightweight deep learning models can be used to create real-time exoplanet detection systems.

The framework can be expanded to other astronomical data, e.g., from TESS and Gaia missions. Fusion with cloud computing and distributed Deep learning techniques may enable the scaling of processing of very large astronomical data sets.

Spectral-Light Curve detection fusion methods can further enhance detection accuracy. In addition, the computational complexity can be further reduced while preserving the high prediction performance as future work.

The potential of the future space of this research points to the expanding possibilities of AI and EAI in Astronomical Data Analysis and Space Exploration systems.

5.3 Social Impact

AI and deep learning is revolutionizing scientific research and space exploration. The proposed framework for detection of exoplanets is a solution with a tremendous social and scientific impact, as it enhances the automated analysis of astronomical information with transparency and interpretability.

5.4 Scientific Impact

The proposed research can help advance astronomical science by enhancing the capabilities of exoplanet detection systems. Automated processing of the vast amount

of light curves that are available in a large photometric archive shortens the reliance on manual viewing and speeds up science discovery related to planetary systems and space exploration.

The inclusion of explainable AI techniques also helps build the trust of deep learning models, which would facilitate scientists to better understand and validate prediction results.

5.5 Educational Impact

The research is interdisciplinary in nature and brings together concepts from Astronomy, AI, ML and DL. The proposed framework could be implemented in academic research, student projects, and educational demonstrations in the field of scientific applications that utilize AI.

The research also invites the students and researchers to delve into the present technology to resolve the actual scientific issues.

5.6 Technological Impact

The proposed framework provides an example of how AI technologies can be applied to process large-scale time-series data. The findings of the research can be used for making intelligent astronomical systems, automatic observatories and space monitoring applications.

The incorporation of explainable AI also aids in the creation of trustworthy and transparent AI systems within the scientific field.

5.7 Societal Impact

Exoplanet research opens up new vistas of the universe and the prospect of alien life. Automated and interpretable exoplanet detection systems can aid in the future space missions and inspire scientific curiosity among society.

Moreover, the study underscores the broader implications of AI in addressing complex scientific problems and promoting technological advancement.

5.8 Environmental Impact

The proposed framework is basically software, and does not involve direct environmental pollution. The automated computational analysis helps to decrease the repetition of manual observations and optimize the use of resources that are used in astronomical research.

Further, efficient AI models can also be used to save computational energy compared to the very complex deep learning architectures.

5.9 Chapter Summary

In this chapter, the conclusion, future scope, and social impact of the proposed exoplanet detection framework using CNN and explainability was presented. The study showed that deep learning and explainable AI could be very effective for automated astronomical data analysis. Exoplanet detection systems can be enhanced in the future to make them more interpretable, scalable and applicable to real time planet detection, and to positively affect scientific research and development.

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