EXOPLANET DETECTION USING MACHINE LEARNING

A Project Report

Submitted to the Faculty of Engineering of
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In partial fulfillment of the requirements for the award of the Degree of

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In

COMPUTER SCIENCE AND ENGINEERING

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CERTIFICATE

This is to certify that the project report entitled **"EXOPLANET DETECTION USING MACHINE LEARNING"** is a bonafide record of work carried out by **P. KRISHNA BALAMOHAN (21481A05I1), P. BRAHMA REDDY (21481A05F8), M. YUVA KARTHIK (22485A0517), M. DURGA SAI SANDEEP (21481A05D5), P. SIVA SAGAR (21481A05G4)** under the guidance and supervision in the partial fulfillment of the requirements for the award of the degree of Bachelor of Technology in Computer Science and Engineering of Jawaharlal Nehru Technological University Kakinada, Kakinada during the academic year 2024-25.

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LIST OF ABBREVATIONS

Abbreviation	Explanation
KOI-Kepler Object of Interest	KOI-Kepler Object Of Interest
TOI-TESS Object of Interest	TOI-TESS Object of Interest
TESS-Transiting Exoplanet Survey Satellite	TESS-Transiting Exoplanet Survey Satellite
CP-Confirmed Planet	CP-Confirmed Planet
PC-Planetary Candidate	PC-Planetary Candidate

LIST OF FIGURES

ABSTRACT

With the rapid advancement of space exploration, accurate exoplanet detection has become essential for understanding planetary systems beyond our solar system. This project focuses on developing a machine learning-based exoplanet detection methodology using data from the Kepler and TESS (Transiting Exoplanet Survey Satellite) missions. As the volume of celestial data continues to grow, distinguishing between genuine exoplanets and false positives presents a significant challenge. This study addresses this issue by leveraging supervised learning algorithms to enhance the accuracy and efficiency of exoplanet classification.

A comprehensive dataset comprising planetary and stellar attributes such as orbital period, planetary radius, transit depth, and stellar temperature serves as the foundation for this investigation. Multiple machine learning models, including Logistic Regression, Random Forest, Gradient Boosting, XGBoost, and LightGBM, are systematically explored and evaluated to determine the most effective classification approach. The models are assessed based on key performance metrics such as accuracy, precision, recall, and F1-score to ensure optimal detection of exoplanet candidates.

The findings of this research significantly contribute to the advancement of automated exoplanet detection, with implications for astronomy, astrophysics, and future space missions. By harnessing the power of machine learning, this project provides a scalable and efficient approach for identifying exoplanets with high confidence, minimizing human effort and computational costs. Ultimately, this work highlights the potential of integrating advanced data-driven techniques in astronomical research, paving the way for future discoveries in planetary science.

Keywords-Exoplanet Detection, Kepler, TESS, Astronomical Data Analysis, Exoplanet Candidates, Planetary Science, Data-Driven Astronomy, Classification Models.

CHAPTER – 1

INTRODUCTION

1.1 Introduction

The discovery of exoplanets—planets that exist beyond our solar system—has transformed our understanding of planetary formation and the potential for habitable worlds. With the advent of space telescopes such as Kepler and TESS (Transiting Exoplanet Survey Satellite), astronomers have identified thousands of exoplanet candidates. These missions rely primarily on the transit method, which detects planets by observing periodic dips in a star's brightness caused by a planet passing in front of it. While this method has been highly effective, it produces large datasets that contain both genuine exoplanets and false positives, making classification a significant challenge.

The primary issue in exoplanet detection is distinguishing actual planets from false positives caused by instrumental noise, stellar variability, and background objects. Traditional approaches involve manual verification by astronomers and statistical modeling, which are often time-consuming, subjective, and prone to errors. The complexity of the data requires automated, scalable, and accurate classification methods to improve detection efficiency. Machine learning has emerged as a powerful tool for addressing these challenges by identifying patterns in large datasets that human analysts might overlook.

This project aims to develop a machine learning-based approach for detecting and classifying exoplanets using Kepler and TESS data. By leveraging advanced ML techniques, this study seeks to improve classification accuracy and reduce false-positive rates. The datasets contain critical planetary and stellar attributes such as orbital period, planetary radius, transit depth, and stellar temperature, which serve as inputs for various supervised learning models.

A range of machine learning algorithms will be explored, including Logistic Regression, Random Forest, Gradient Boosting, XGBoost, and LightGBM. These models will be trained and evaluated based on key performance metrics such as accuracy, precision, recall, and F1-score to determine the most effective classification approach. By applying feature selection, hyperparameter tuning, and cross-validation techniques, this study aims to optimize the model's performance.

The significance of this research extends beyond exoplanet detection. Automating classification through machine learning not only accelerates the discovery process but also enhances the reliability of planetary detection systems. The integration of data-driven techniques in astrophysics paves the way for future advancements, enabling more efficient analysis of exoplanetary systems and contributing to ongoing research in space exploration.

Ultimately, this project demonstrates the potential of machine learning in astronomy, offering a scalable and precise methodology for analyzing vast astronomical datasets. The findings will be beneficial to astronomers, researchers, and space agencies, improving our ability to detect and study exoplanets with minimal human intervention.

1.2 Objectives of the Project:

The primary objective of this project is to develop an efficient, automated framework for exoplanet detection using machine learning algorithms applied to Kepler and TESS data. The project aims to enhance detection accuracy while reducing manual effort and computational costs.

Specific objectives include:

- Data preprocessing and feature engineering to clean, transform, and analyze datasets from Kepler and TESS missions.
- Exploratory data analysis (EDA) to identify patterns and relationships in planetary and stellar attributes.
- Implementation and comparison of multiple machine learning models, including Logistic Regression, Random Forest, Gradient Boosting, XGBoost, and LightGBM.
- Evaluation using performance metrics such as accuracy, precision, recall, and F1-score to determine the most effective classification model.
- Development of an interactive interface using Streamlit, allowing users to input planetary parameters and receive real-time classification results.

1.3 Problem Statement:

The exponential increase in space mission data has led to significant challenges in exoplanet detection, particularly in distinguishing real exoplanets from false positives. Manual classification methods are slow, labor-intensive, and prone to errors, making them unsuitable for handling vast amounts of astronomical data. Moreover, existing statistical models often struggle to achieve high accuracy and low false-positive rates due to the complexity of planetary transit signals.

This project addresses these issues by implementing a machine learning-based classification system that automates exoplanet detection. By leveraging large datasets from Kepler and TESS, this study seeks to improve the efficiency of exoplanet classification, minimizing false positives while maximizing detection accuracy. The research also aims to contribute to future space missions by providing a scalable, data-driven methodology for planetary discovery.

1.4 Scope of Research:

This research is focused on the application of machine learning techniques to improve the classification accuracy of exoplanet candidates detected by the Kepler and TESS missions. The study includes data collection, preprocessing, model training, and performance evaluation to develop an optimized detection system.

The research will explore multiple supervised learning models, assessing their effectiveness in classifying exoplanets based on various planetary and stellar parameters. The study will also include hyperparameter tuning and feature selection techniques to enhance model efficiency. While this project primarily focuses on machine learning-based classification, future work could extend to deep learning models and additional astronomical datasets to further improve detection accuracy.

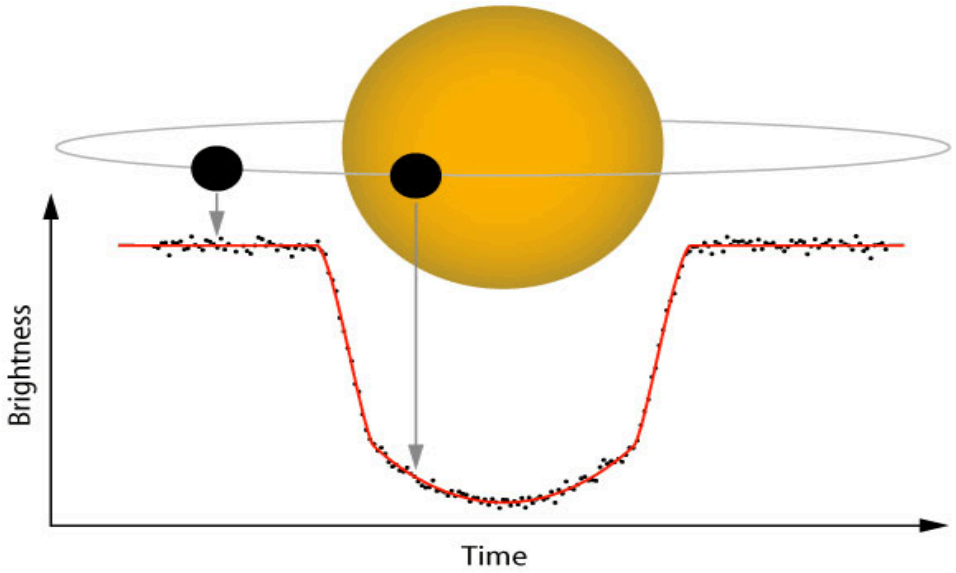


Fig 1.1: A light curve, showing the transit method of detecting exoplanets

CHAPTER – 2

LITERATURE REVIEW

Exoplanet detection has been a significant area of research in modern astronomy, with space missions contributing extensively to the discovery of thousands of planetary candidates beyond our solar system. Various detection techniques have been developed to identify these planets, including radial velocity, direct imaging, gravitational microlensing, and transit photometry. Among these, the transit method has been widely used as it enables the identification of exoplanets by detecting periodic dips in a star's brightness when a planet passes in front of it. However, despite its effectiveness, this method generates vast amounts of data that require careful classification to differentiate between actual exoplanets and false positives caused by instrumental noise, eclipsing binary systems, or stellar variability. Traditional classification methods rely on statistical modeling and manual inspection, which are labor-intensive and prone to human error. As data from space missions continue to grow, there is a pressing need for automated approaches to improve the accuracy and efficiency of exoplanet detection.

Advancements in machine learning have opened new possibilities for addressing the challenges associated with exoplanet classification. Researchers have explored various algorithms to automate the detection process, allowing for faster and more accurate classification of celestial objects. Initial studies employed decision trees and Bayesian models to analyze transit signals, but these approaches faced limitations when dealing with large and imbalanced datasets. The introduction of deep learning techniques significantly enhanced the detection process, with convolutional neural networks proving to be effective in identifying planetary candidates by learning complex patterns in light curves. Despite their success, deep learning models require extensive labeled datasets, which may not always be available for newly discovered planetary systems.

Several studies have explored the use of supervised learning models for exoplanet detection. Hogg et al. (2018) applied deep learning techniques to Kepler data, achieving an impressive 95% accuracy in classifying exoplanets. This study demonstrated the effectiveness of deep neural networks in recognizing transit signals, improving upon previous statistical methods. Lai et al. (2020) investigated the use of support vector machines (SVMs) in analyzing noisy datasets and found that SVMs exhibited high recall rates, ensuring that potential exoplanet candidates were not mistakenly discarded as false positives. Oliviero et al. (2019) explored the robustness of random forests in exoplanet classification and found that this method effectively handled high-dimensional planetary datasets, demonstrating resilience against outliers and data inconsistencies.

Recent advancements have further expanded the role of artificial intelligence in exoplanet detection. A 2023 study conducted at the University of Georgia leveraged AI to identify exoplanets,

highlighting machine learning's potential in astronomical discoveries. This study showcased how deep learning models could be trained on multi-mission datasets, improving their ability to generalize across different space telescopes. Additionally, in 2021, the Universities Space Research Association (USRA) achieved a significant milestone by discovering 69 new exoplanets using machine learning. This breakthrough demonstrated how AI-driven methods could enhance exoplanet identification by reducing false-positive rates and improving classification accuracy.

The selection and preprocessing of relevant features play a crucial role in enhancing machine learning models for exoplanet detection. Parameters such as orbital period, planetary radius, transit depth, and stellar characteristics are considered essential in distinguishing exoplanets from false positives. Data imbalance remains a major challenge, as the number of false positives in astronomical datasets is significantly higher than the number of confirmed exoplanets. Researchers have employed techniques such as oversampling and adaptive boosting to address this issue and ensure that models do not favor one class over another. Dimensionality reduction techniques such as principal component analysis have also been utilized to improve computational efficiency by eliminating redundant information.

Despite the advancements in machine learning applications for exoplanet detection, several challenges persist. The interpretability of machine learning models remains a concern, as many algorithms, particularly deep learning-based models, function as black-box systems that do not provide clear explanations for their classifications. Additionally, models trained on Kepler data may not always generalize well to TESS data due to variations in instrument sensitivity and observation conditions. Researchers continue to work on improving the adaptability of machine learning models across different datasets, ensuring that classification techniques remain effective for future space missions.

Future research in exoplanet detection is expected to focus on the integration of more advanced machine learning architectures. Transformer-based models and recurrent neural networks are being explored to enhance the classification process further. The incorporation of multi-mission datasets, combining observations from different space telescopes, is anticipated to improve model accuracy and generalization. Efforts are also being made to develop explainable artificial intelligence techniques that provide insights into how models make predictions, increasing trust in automated exoplanet classification. With continued advancements in machine learning and data-driven methodologies, the efficiency of exoplanet detection is expected to improve, facilitating new discoveries in planetary science and the search for habitable worlds beyond our solar system.

Exoplanet detection has advanced significantly over the past few decades, employing various methods to identify planets beyond our solar system. These methods include radial velocity measurements, transit photometry, direct imaging, gravitational microlensing, and astrometry.

The radial velocity method detects exoplanets by observing the gravitational influence they exert on their host stars, causing measurable Doppler shifts in the star's spectral lines. This technique has been instrumental in confirming the presence of many exoplanets. [1].

Transit photometry involves monitoring the brightness of stars for periodic dips, indicating a planet passing in front of the star from our viewpoint. Missions like NASA's Kepler have utilized this method to discover thousands of exoplanet candidates. [2].

Direct imaging captures actual images of exoplanets by blocking out the star's light, allowing astronomers to observe planets directly. The Spectro-Polarimetric High-Contrast Exoplanet Research (SPHERE) instrument, for example, has achieved direct imaging of exoplanets such as HIP 65426 b. [3].

Gravitational microlensing detects exoplanets by observing the bending of light from a distant star due to the gravitational field of a foreground star with a planet, leading to a temporary increase in brightness. This method is particularly useful for finding planets at greater distances from Earth. [4].

Astrometry measures the precise movements of stars in the sky to detect the gravitational influence of orbiting planets, though it has been less commonly used due to its demanding precision requirements. [5].

Advancements in machine learning have also enhanced exoplanet detection. For instance, the NASA Exoplanet Archive serves as a comprehensive database, collecting and providing access to public data that supports the search for and characterization of exoplanets and their host stars.

These diverse methods and technological advancements have collectively expanded our understanding of exoplanets, contributing to the discovery of thousands of these distant worlds and providing insights into their characteristics and potential habitability.

CHAPTER 3
PROPOSED METHOD

3.1 Methodology

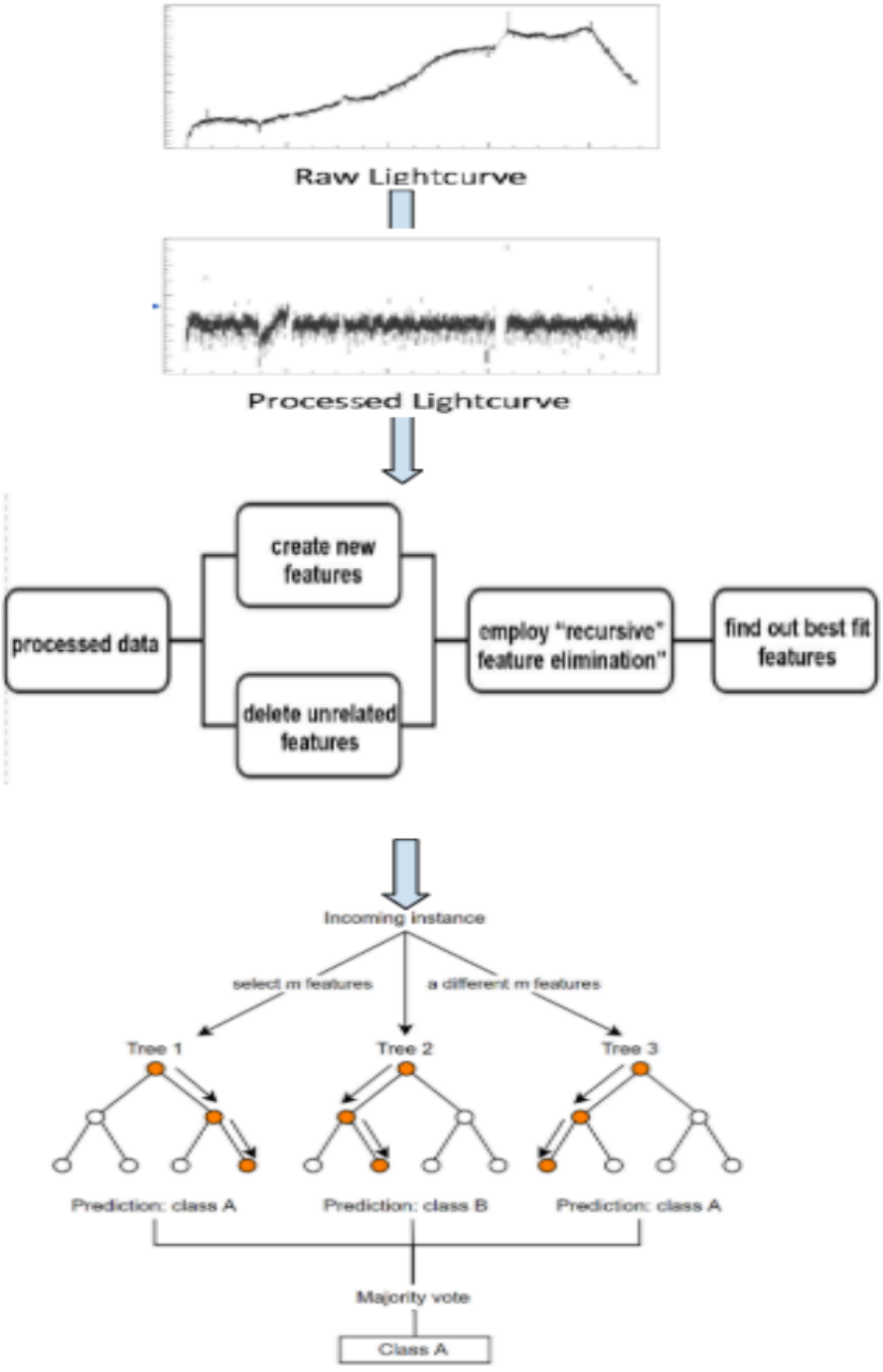


Fig 3.1.1 Block Diagram illustrating the workflow.

3.1.1 Comprehensive Overview of the Research Design:

The research endeavors to methodically structure a comprehensive framework aimed at systemThe research focuses on developing a machine learning-based framework for exoplanet detection using Kepler Space Telescope data. The primary objective is to create a systematic pipeline that enables efficient preprocessing, feature extraction, model training, and evaluation. The study explores various machine learning techniques, including Logistic Regression, Decision Tree Classifier, K-Nearest Neighbors, Random Forest, Gradient Boosting, XGBoost, and LightGBM, to identify the most effective model for detecting exoplanets.

The research methodology is structured into multiple phases. Initially, data acquisition is conducted using Kepler's transit photometry dataset, which contains light curve readings from stars. These readings are analyzed to identify periodic dips in brightness, a key indicator of potential exoplanets. The acquired dataset undergoes rigorous preprocessing, including handling missing values, normalization, and feature engineering. Once the data is prepared, various machine learning models are trained and tested to determine their effectiveness in classifying exoplanet candidates.

Feature selection and dimensionality reduction techniques are employed to optimize model performance and reduce computational complexity. The training process involves hyperparameter tuning and model validation using cross-validation techniques. Each model's performance is rigorously assessed using a combination of accuracy, precision, recall, and F1-score to ensure reliability in exoplanet classification. The study aims to contribute to the field of exoplanet discovery by improving the automation and accuracy of planet detection methods.

3.1.2 Data Collection and Rigorous Preprocessing:

The dataset used in this study is sourced from NASA's Kepler Space Telescope observations, containing thousands of stellar light curves with labeled exoplanetary transit data. The data comprises flux measurements over time, which are crucial for identifying potential exoplanets based on periodic dimming patterns.

- **Data Cleaning and Quality Assurance:** The dataset is examined for missing values, outliers, and inconsistencies. Missing values are imputed using statistical methods such as median replacement, while outliers are handled through anomaly detection techniques to maintain data integrity.
- **Feature Engineering and Selection:** Key features such as flux intensity, periodicity, transit depth, and duration are extracted. Principal Component Analysis (PCA) and feature correlation techniques are applied to eliminate redundant features and improve model efficiency.
- **Data Normalization:** Given the varying magnitudes of flux values, normalization techniques

such as Min-Max scaling and Z-score standardization are used to standardize the dataset. This ensures balanced weight distribution across all features, improving model learning dynamics.

- **Data Splitting Strategy:** The dataset is divided into training, validation, and test sets (typically 70%-15%-15%) to ensure robust model evaluation. Stratified sampling is applied to maintain class balance and prevent bias.

3.1.3 Strategic Model Selection and Development:

This research explores multiple machine learning models to determine the best-suited approach for exoplanet detection. Each model contributes uniquely to the classification process, leveraging its strengths to enhance detection accuracy.

- **Logistic Regression:** Used as a baseline model, Logistic Regression provides a straightforward approach to exoplanet detection by applying a linear decision boundary. It effectively distinguishes between exoplanet and non-exoplanet cases when the dataset has well-separated classes. Despite its simplicity, it offers interpretability by quantifying the influence of different features, such as transit depth and duration, on the classification outcome. However, its linear nature limits performance when dealing with complex, nonlinear feature interactions in light curve data.
- **Decision Tree Classifier:** This model plays a crucial role in identifying important features in exoplanet detection by splitting the dataset based on key parameters such as flux variations and transit periodicity. Its hierarchical structure allows it to capture non-linear patterns, making it effective for datasets with complex relationships. The decision tree model identifies exoplanet candidates by learning from historical data and prioritizing the most significant attributes, although it is prone to overfitting without proper pruning techniques.
- **K-Nearest Neighbors (KNN):** This algorithm achieves its effectiveness in exoplanet detection by analyzing the proximity of new data points to known exoplanet cases. By comparing light curve similarities, KNN classifies whether an observation corresponds to an exoplanet or not. It is particularly useful for detecting exoplanets with subtle variations in brightness patterns, but its performance is highly dependent on an optimal choice of neighbors (k) and struggles with large datasets due to computational complexity.
- **Random Forest:** As an ensemble learning method, Random Forest enhances exoplanet detection by aggregating multiple decision trees, thereby improving accuracy and reducing overfitting. Each tree learns different aspects of stellar flux variations, ensuring a more robust classification. The model's ability to handle noisy data makes it particularly suitable for real-world exoplanet detection, where observational uncertainties are common. It also provides feature

importance rankings, helping to identify the most critical parameters influencing classification.

- **Gradient Boosting:** This model refines exoplanet detection by sequentially improving weak learners, making it highly effective for classifying complex transit signals. By minimizing classification errors at each step, it adapts to intricate patterns in light curve data, enabling the identification of exoplanets with faint or irregular transits. Gradient Boosting is particularly beneficial in distinguishing exoplanets from false positives caused by stellar activity, though it requires careful tuning to avoid overfitting.
- **XGBoost:** As an optimized boosting algorithm, XGBoost significantly enhances exoplanet detection by efficiently handling large datasets and complex feature interactions. It achieves high precision in distinguishing planetary transits from noise by leveraging advanced regularization techniques and parallel computation. XGBoost's robustness makes it one of the top-performing models, achieving high accuracy in exoplanet classification while maintaining computational efficiency.
- **LightGBM:** This model excels in exoplanet detection due to its ability to handle large-scale astronomical data efficiently. It uses histogram-based learning to optimize decision splits, making it faster and more scalable than traditional boosting methods. LightGBM is particularly effective in identifying exoplanets in datasets with a high number of observations, ensuring quick and accurate classification. Its performance in detecting weak transit signals makes it a valuable tool for large-scale astronomical surveys.

Key aspects of model development include:

- **Training Dataset Allocation:** Ensuring a balanced representation of exoplanet-positive and negative samples.
- **Validation Strategy:** Implementing k-fold cross-validation to assess generalization performance.
- **Optimization Techniques and Regularization:** Using L1/L2 regularization, dropout, and pruning methods to minimize overfitting.
- **Hyperparameter Tuning:** Grid search and Bayesian optimization techniques are applied to fine-tune model parameters such as learning rate, tree depth, and number of estimators.

3.1.4 Rigorous Testing and Validation for Model Efficiency:

The evaluation phase involves a multifaceted approach, utilizing robust performance metrics to ensure a comprehensive assessment of each model’s efficiency in detecting exoplanets. Accuracy,

precision, recall, and F1-score are key metrics used to quantify classification performance. Accuracy provides an overall measure of correct predictions, while precision and recall offer deeper insights into how well the model identifies true exoplanet candidates. The F1-score balances precision and recall, providing a singular metric to evaluate classification performance. Additionally, the Receiver Operating Characteristic Area Under Curve (ROC-AUC) metric is used to assess the model's ability to distinguish between exoplanets and non-exoplanets effectively.

A comparative analysis of models is essential in revealing their respective strengths and weaknesses in different scenarios. Some models may achieve higher accuracy but suffer from low recall, making them less effective for identifying rare exoplanets. In contrast, models with higher recall but slightly lower precision might be preferred in cases where missing an exoplanet detection is more costly than false positives. By evaluating these trade-offs, the most suitable model is selected based on the specific objectives of the study.

Additionally, real-world validation is conducted by applying the trained models to newly discovered datasets from Kepler and TESS missions. The adaptability of each model to new observational data is tested, ensuring that it generalizes well beyond the training dataset. This rigorous evaluation ensures that the selected machine learning models not only perform well in controlled experiments but also maintain high reliability in actual astronomical research, contributing to automated and precise exoplanet detection systems.

3.2 Implementation

3.2.1 Model Training and Evaluation

The process of developing and evaluating machine learning models for exoplanet detection involves a structured pipeline designed to optimize accuracy and robustness. The training phase focuses on ensuring the model learns meaningful patterns in the light curve data, while the evaluation phase ensures that the trained model generalizes well to unseen data. The training process follows a systematic approach that involves model compilation, hyperparameter tuning, and iterative optimization. Various models, including Logistic Regression, Decision Trees, Random Forest, Gradient Boosting, XGBoost, and LightGBM, are explored to determine the most effective approach for exoplanet classification.

3.2.1.1 Training Process:

The training process is a critical stage in model development, where the machine learning models are trained using labeled datasets containing confirmed exoplanets and false positives. The Kepler dataset is preprocessed to remove inconsistencies, normalize feature values, and handle missing data

before being used for training. The dataset is then split into training and validation sets, typically in a 70:30 ratio, ensuring that the model is exposed to diverse planetary and non-planetary cases.

Each model is compiled using appropriate optimization and loss functions. For tree-based models like Decision Trees and Random Forest, entropy or Gini impurity is used as the loss function, while boosting models like XGBoost and LightGBM leverage gradient descent-based optimization. The training process involves fine-tuning hyperparameters such as:

- The number of trees (for ensemble models)
- Learning rate (for boosting models)
- Maximum depth of trees (to prevent overfitting)
- Regularization parameters to enhance generalization

For each model, the training dataset is iteratively passed through the algorithm, updating model parameters to minimize classification error. The model's performance is monitored using validation data, and early stopping techniques are applied where necessary to prevent overfitting.

3.2.1.2 Model Evaluation:

Once the training phase is complete, the trained models are evaluated using an independent test dataset to assess their real-world performance. Several key evaluation metrics are employed to measure classification effectiveness:

- **Accuracy:** Measures the percentage of correct classifications out of all predictions.
- **Precision:** Evaluates the proportion of true positive exoplanet detections relative to all predicted exoplanets.
- **Recall:** Assesses the model’s ability to identify actual exoplanets in the dataset.
- **F1-score:** Provides a balanced measure between precision and recall.
- **ROC-AUC Score:** Measures the ability of the model to distinguish between exoplanets and false positives.

These metrics help determine how well the model generalizes to new data. A confusion matrix is also generated to analyze false positives and false negatives. Additionally, visualizations such as feature importance graphs (for tree-based models) and precision-recall curves provide deeper insights into model performance. The best-performing model is selected based on its balance of accuracy, precision, recall, and computational efficiency.

3.2.2 Pseudocode for ML Model Training and Testing:

1. **Import necessary libraries:**

- pandas for data handling
- numpy for numerical computations
- sklearn for model selection, data preprocessing, and evaluation
- matplotlib and seaborn for visualizations
- xgboost and lightgbm for advanced classification

2. **Load and preprocess the dataset:**

- Read the dataset using pandas.read_csv()
- Handle missing values and normalize features
- Encode categorical variables, if any

3. **Split the dataset into training and testing sets:**

- Use train_test_split() to divide the dataset (e.g., 80% training, 20% testing)
- Ensure that the split is randomized to maintain diversity

4. **Define and initialize the machine learning model:**

- Select models such as Logistic Regression, Decision Tree, Random Forest, Gradient Boosting, XGBoost, or LightGBM
- Configure hyperparameters based on prior experimentation

5. **Train the model on the training data:**

- Fit the model using .fit(X_train, y_train)
- Use cross-validation techniques to optimize performance
- Apply early stopping where necessary

6. **Evaluate the model on test data:**

- Use .predict(X_test) to generate predictions
- Compute accuracy, precision, recall, and F1-score
- Generate a confusion matrix and visualize the classification performance

7. **Optimize and fine-tune the model:**

- Use techniques like grid search or randomized search for hyperparameter tuning
- Adjust learning rates, tree depths, and regularization parameters.

The implementation phase is a crucial part of this research as it translates theoretical concepts into a practical working model for exoplanet detection. the process begins with importing necessary libraries that facilitate data handling, numerical computations, model selection, preprocessing, and evaluation. pandas and numpy are used for data handling and numerical operations, while sklearn provides tools for preprocessing, training, and evaluating models. visualization libraries such as

matplotlib and seaborn help interpret trends in the dataset and model performance.

The dataset is loaded and preprocessed to ensure data consistency and accuracy before training the models. it is imported using pandas, and any missing values are handled using imputation techniques such as mean or median filling. normalization is applied to standardize numerical values, ensuring that features are on a similar scale, which improves model learning efficiency. categorical variables are encoded to numerical representations using label encoding or one-hot encoding, making them suitable for machine learning algorithms. preprocessing ensures that the data is clean and structured before being passed to the models for training.

The dataset is then split into training and testing sets to evaluate the model's performance objectively. the train_test_split function from sklearn is used to divide the dataset, typically into 80 percent training data and 20 percent testing data. this ensures that the model is trained on one subset of the data and evaluated on another, preventing overfitting and improving generalization. randomization in the splitting process ensures diversity in both sets, making the evaluation more reliable.

After splitting, machine learning models are defined and initialized. multiple models are tested, including logistic regression, decision trees, random forests, gradient boosting, xgboost, and lightgbm. each model is initialized with specific hyperparameters optimized for detecting exoplanetary transits in light curve data. the selection of hyperparameters involves setting learning rates, the number of trees, tree depths, and regularization parameters. models that require ensemble methods, such as random forest and gradient boosting, are set up with multiple estimators to improve prediction accuracy.

The model training process involves fitting the models to the training data. the fit function is used to allow models to learn patterns from the dataset iteratively. during training, cross-validation techniques are applied to optimize performance by splitting the training data into smaller subsets for validation. early stopping mechanisms are also implemented to prevent overfitting by monitoring the validation loss and stopping training when no further improvement is observed. this ensures that models generalize well to new data rather than memorizing patterns specific to the training dataset.

Once the model has been trained, it is evaluated using the test dataset to measure its predictive performance. the predict function generates classifications on unseen data, and multiple evaluation metrics are computed, including accuracy, precision, recall, f1-score, and roc-auc score. accuracy provides an overall measure of correct classifications, while precision and recall assess the model’s ability to identify true positives while minimizing false positives and false negatives. the f1-score

balances precision and recall, offering a comprehensive evaluation of model performance. the roc-auc score measures the model's ability to distinguish between exoplanet candidates and false positives, providing insight into classification robustness.

To improve the performance of models, hyperparameter tuning is performed using techniques such as grid search and randomized search. hyperparameter tuning involves adjusting model parameters, such as learning rates, tree depths, and regularization factors, to find the best-performing combination. this process ensures that the model achieves an optimal balance between accuracy and computational efficiency.

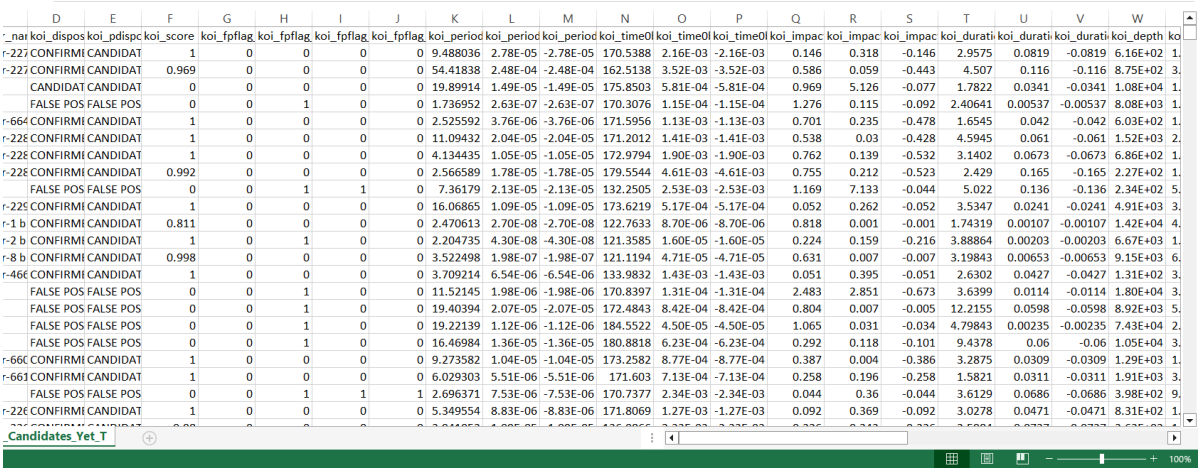
After selecting the best-performing model, it is deployed for practical use. the trained model is saved using joblib or pickle, allowing it to be loaded and used for future predictions. a function is implemented to take new exoplanet candidate data and predict whether the observation is likely an exoplanet. the model is integrated into a web application using streamlit, which provides an interactive user interface where researchers can upload new data and receive real-time predictions. by deploying the model, the research facilitates automated exoplanet detection, enhancing astronomical discoveries and reducing manual analysis efforts.

This structured approach ensures the development of a reliable and scalable exoplanet detection model that can be used in real-world applications. by leveraging machine learning techniques, systematic data preprocessing, and model optimization, the research contributes to improving the automation and accuracy of exoplanet classification. the combination of rigorous evaluation and deployment strategies enhances the reliability of machine learning models in identifying exoplanets, paving the way for future advancements in space exploration and ai-driven astronomical research.

3.3 Data Preparation

3.3.1 Dataset Preprocessing

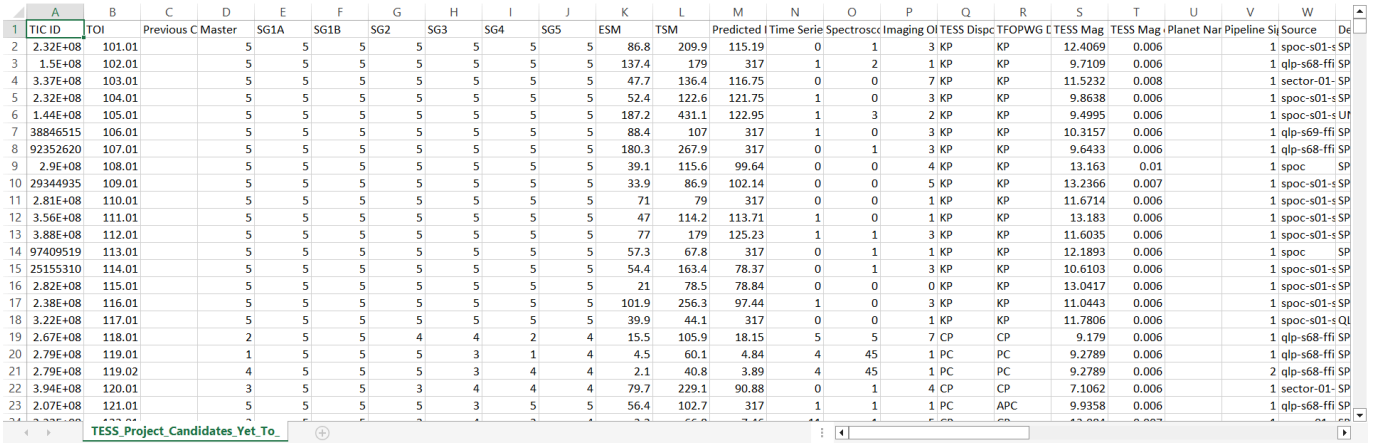
The research utilizes a dataset titled 'TESS_Project_Candidates_Yet_To_Be_Confirmed.csv', and 'Kepler_Project_Candidates_Yet_To_Be_Confirmed.csv'



	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	
1	-_nar	koi_dispos	koi_pdispc	koi_score	koi_fpflag	koi_fpflag	koi_fpflag	koi_fpflag	koi_period	koi_period	koi_period	koi_time0l	koi_time0l	koi_time0l	koi_impac	koi_impac	koi_impac	koi_durati	koi_durati	koi_durati	koi_depth	ko
2	r-227	CONFIRMI	CANDIDAT	1	0	0	0	0	9.488036	2.78E-05	-2.78E-05	170.5388	2.16E-03	-2.16E-03	0.146	0.318	-0.146	2.9575	0.0819	-0.0819	6.16E+02	1.
3	r-227	CONFIRMI	CANDIDAT	0.969	0	0	0	0	54.41838	2.48E-04	-2.48E-04	162.5138	3.52E-03	-3.52E-03	0.586	0.059	-0.443	4.507	0.116	-0.116	8.75E+02	3.
4		CANDIDAT	CANDIDAT	0	0	0	0	0	19.89914	1.49E-05	-1.49E-05	175.8503	5.81E-04	-5.81E-04	0.969	5.126	-0.077	1.7822	0.0341	-0.0341	1.08E+04	1.
5		FALSE POS	FALSE POS	0	0	1	0	0	1.736952	2.63E-07	-2.63E-07	170.3076	1.15E-04	-1.15E-04	1.276	0.115	-0.092	2.40641	0.00537	-0.00537	8.08E+03	1.
6	r-664	CONFIRMI	CANDIDAT	1	0	0	0	0	2.525592	3.76E-06	-3.76E-06	171.5956	1.13E-03	-1.13E-03	0.701	0.235	-0.478	1.6545	0.042	-0.042	6.03E+02	1.
7	r-228	CONFIRMI	CANDIDAT	1	0	0	0	0	11.09432	2.04E-05	-2.04E-05	171.2012	1.41E-03	-1.41E-03	0.538	0.03	-0.428	4.5945	0.061	-0.061	1.52E+03	2.
8	r-228	CONFIRMI	CANDIDAT	1	0	0	0	0	4.134435	1.05E-05	-1.05E-05	172.9794	1.90E-03	-1.90E-03	0.762	0.139	-0.532	3.1402	0.0673	-0.0673	6.86E+02	1.
9	r-228	CONFIRMI	CANDIDAT	0.992	0	0	0	0	2.566589	1.78E-05	-1.78E-05	179.5544	4.61E-03	-4.61E-03	0.755	0.212	-0.523	2.429	0.165	-0.165	2.27E+02	1.
10		FALSE POS	FALSE POS	0	0	1	1	0	7.36179	2.13E-05	-2.13E-05	132.2505	2.53E-03	-2.53E-03	1.169	7.133	-0.044	5.022	0.136	-0.136	2.34E+02	5.
11	r-229	CONFIRMI	CANDIDAT	1	0	0	0	0	16.06865	1.09E-05	-1.09E-05	173.6219	5.17E-04	-5.17E-04	0.052	0.262	-0.052	3.5347	0.0241	-0.0241	4.91E+03	3.
12	r-1 b	CONFIRMI	CANDIDAT	0.811	0	0	0	0	2.470613	2.70E-08	-2.70E-08	122.7633	8.70E-06	-8.70E-06	0.818	0.001	-0.001	1.74319	0.00107	-0.00107	1.42E+04	4.
13	r-2 b	CONFIRMI	CANDIDAT	1	0	1	0	0	2.204735	4.30E-08	-4.30E-08	121.3585	1.60E-05	-1.60E-05	0.224	0.159	-0.216	3.88864	0.00203	-0.00203	6.67E+03	1.
14	r-8 b	CONFIRMI	CANDIDAT	0.998	0	0	0	0	3.522498	1.98E-07	-1.98E-07	121.1194	4.71E-05	-4.71E-05	0.631	0.007	-0.007	3.19843	0.00653	-0.00653	9.15E+03	6.
15	r-466	CONFIRMI	CANDIDAT	1	0	0	0	0	3.709214	6.54E-06	-6.54E-06	133.9832	1.43E-03	-1.43E-03	0.051	0.395	-0.051	2.6302	0.0427	-0.0427	1.31E+02	3.
16		FALSE POS	FALSE POS	0	0	1	0	0	11.52145	1.98E-06	-1.98E-06	170.8397	1.31E-04	-1.31E-04	2.483	2.851	-0.673	3.6399	0.0114	-0.0114	1.80E+04	3.
17		FALSE POS	FALSE POS	0	0	1	0	0	19.40394	2.07E-05	-2.07E-05	172.4843	8.42E-04	-8.42E-04	0.804	0.007	-0.005	12.2155	0.0598	-0.0598	8.92E+03	5.
18		FALSE POS	FALSE POS	0	0	1	0	0	19.22139	1.12E-06	-1.12E-06	184.5522	4.50E-05	-4.50E-05	1.065	0.031	-0.034	4.79843	0.00235	-0.00235	7.43E+04	2.
19		FALSE POS	FALSE POS	0	0	1	0	0	16.46984	1.36E-05	-1.36E-05	180.8818	6.23E-04	-6.23E-04	0.292	0.118	-0.101	9.4378	0.06	-0.06	1.05E+04	3.
20	r-666	CONFIRMI	CANDIDAT	1	0	0	0	0	9.273582	1.04E-05	-1.04E-05	173.2582	8.77E-04	-8.77E-04	0.387	0.004	-0.386	3.2875	0.0309	-0.0309	1.29E+03	1.
21	r-661	CONFIRMI	CANDIDAT	1	0	0	0	0	6.029303	5.51E-06	-5.51E-06	171.603	7.13E-04	-7.13E-04	0.258	0.196	-0.258	1.5821	0.0311	-0.0311	1.91E+03	3.
22		FALSE POS	FALSE POS	0	0	1	1	1	2.696371	7.53E-06	-7.53E-06	170.7377	2.34E-03	-2.34E-03	0.044	0.36	-0.044	3.6129	0.0686	-0.0686	3.98E+02	9.
23	r-226	CONFIRMI	CANDIDAT	1	0	0	0	0	5.349554	8.83E-06	-8.83E-06	171.8069	1.27E-03	-1.27E-03	0.092	0.369	-0.092	3.0278	0.0471	-0.0471	8.31E+02	1.

Candidates_Yet_T

Fig 3.3.1.1 Dataset before Preprocessing (kepler data)



	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	
1	TIC ID	TOI	Previous C	Master	SG1A	SG1B	SG2	SG3	SG4	SG5	ESM	TSM	Predicted I	Time Serie	Spectrosc	Imaging Ol	TESS Dispc	TFOPWG D	TESS Mag	TESS Mag	Planet Nar	Pipeline Sig	Source	De
2	2.32E+08	101.01		5	5	5	5	5	5	5	86.8	209.9	115.19	0	1	3	KP	KP	12.4069	0.006		1	spoc-s01-s	SP
3	1.5E+08	102.01		5	5	5	5	5	5	5	137.4	179	317	1	2	1	KP	KP	9.7109	0.006		1	qlp-s68-ffi	SP
4	3.37E+08	103.01		5	5	5	5	5	5	5	47.7	136.4	116.75	0	0	7	KP	KP	11.5232	0.008		1	sector-01-	SP
5	2.32E+08	104.01		5	5	5	5	5	5	5	52.4	122.6	121.75	1	0	3	KP	KP	9.8638	0.006		1	spoc-s01-s	SP
6	1.44E+08	105.01		5	5	5	5	5	5	5	187.2	431.1	122.95	1	3	2	KP	KP	9.4995	0.006		1	spoc-s01-s	UI
7	38846515	106.01		5	5	5	5	5	5	5	88.4	107	317	1	0	3	KP	KP	10.3157	0.006		1	qlp-s69-ffi	SP
8	92352620	107.01		5	5	5	5	5	5	5	180.3	267.9	317	0	1	3	KP	KP	9.6433	0.006		1	qlp-s68-ffi	SP
9	2.9E+08	108.01		5	5	5	5	5	5	5	39.1	115.6	99.64	0	0	4	KP	KP	13.163	0.01		1	spoc	SP
10	29344935	109.01		5	5	5	5	5	5	5	33.9	86.9	102.14	0	0	5	KP	KP	13.2366	0.007		1	spoc-s01-s	SP
11	2.81E+08	110.01		5	5	5	5	5	5	5	71	79	317	0	0	1	KP	KP	11.6714	0.006		1	spoc-s01-s	SP
12	3.56E+08	111.01		5	5	5	5	5	5	5	47	114.2	113.71	1	0	1	KP	KP	13.183	0.006		1	spoc-s01-s	SP
13	3.88E+08	112.01		5	5	5	5	5	5	5	77	179	125.23	1	1	3	KP	KP	11.6035	0.006		1	spoc-s01-s	SP
14	97409519	113.01		5	5	5	5	5	5	5	57.3	67.8	317	0	1	1	KP	KP	12.1893	0.006		1	spoc	SP
15	25155310	114.01		5	5	5	5	5	5	5	54.4	163.4	78.37	0	1	3	KP	KP	10.6103	0.006		1	spoc-s01-s	SP
16	2.82E+08	115.01		5	5	5	5	5	5	5	21	78.5	78.84	0	0	0	KP	KP	13.0417	0.006		1	spoc-s01-s	SP
17	2.38E+08	116.01		5	5	5	5	5	5	5	101.9	256.3	97.44	1	0	3	KP	KP	11.0443	0.006		1	spoc-s01-s	SP
18	3.22E+08	117.01		5	5	5	5	5	5	5	39.9	44.1	317	0	0	1	KP	KP	11.7806	0.006		1	spoc-s01-s	QL
19	2.67E+08	118.01		2	5	5	4	4	2	4	15.5	105.9	18.15	5	5	7	CP	CP	9.179	0.006		1	qlp-s68-ffi	SP
20	2.79E+08	119.01		1	5	5	5	3	1	4	4.5	60.1	4.84	4	45	1	PC	PC	9.2789	0.006		1	qlp-s68-ffi	SP
21	2.79E+08	119.02		4	5	5	5	3	4	4	2.1	40.8	3.89	4	45	1	PC	PC	9.2789	0.006		2	qlp-s68-ffi	SP
22	3.94E+08	120.01		3	5	5	3	4	4	4	79.7	229.1	90.88	0	1	4	CP	CP	7.1062	0.006		1	sector-01-	SP
23	2.07E+08	121.01		5	5	5	5	3	5	5	56.4	102.7	317	1	1	1	PC	APC	9.9358	0.006		1	qlp-s68-ffi	SP

TESS_Project_Candidates_Yet_To_

Fig 3.3.1.2 Dataset before Preprocessing (Tess data)

The research utilizes a dataset obtained from the kepler space telescope, comprising stellar light curve observations. these light curves capture variations in a star's brightness over time, which are analyzed to detect potential exoplanet transits.

the dataset contains the following columns:

•kepid: the unique identifier assigned to each observed star

•flux: the recorded brightness values of the star over time

•time: timestamps corresponding to each brightness reading

•disposition: labels indicating whether a candidate is confirmed, false positive, or planetary candidate

•orbital period: the time taken by the detected object to complete one orbit around its host star

In the preprocessing stage, paramount importance was placed on extracting key features such as flux values and orbital periods as primary inputs for analysis, while the disposition column was used as the target variable for classification purposes. this foundational step was crucial in structuring the dataset for effective training and evaluation, ensuring that the machine learning models could effectively identify exoplanet candidates from noise and false positives.

To enhance model reliability, the dataset was split into training and testing sets, with 80 percent of the data allocated for training and 20 percent reserved for testing. this division ensured that the model could be rigorously evaluated on unseen data, allowing an assessment of its generalization capabilities. by subjecting the model to independent test samples, its predictive accuracy and robustness were validated before deployment.

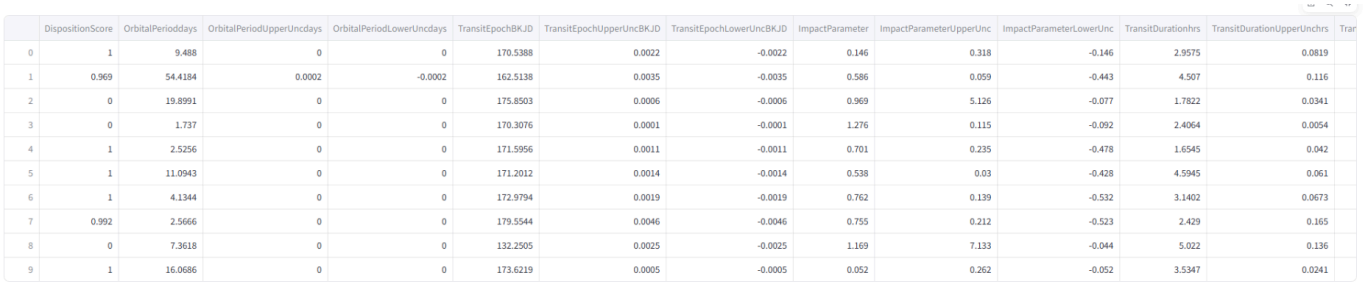
Visualizing the dataset structure played a key role in understanding its composition and distribution. a snapshot of the dataset before preprocessing provided insights into the relationships between different attributes, enabling a better understanding of how stellar brightness variations correlated with exoplanet transits. the flux column revealed fluctuations in stellar brightness, highlighting potential transit events caused by an orbiting planet. timestamps helped establish the periodicity of dips in brightness, which is a crucial factor in detecting exoplanets. the disposition column categorized observed objects, distinguishing between confirmed exoplanets, planetary candidates, and false positives.

An essential component of preprocessing involved normalizing flux values to remove instrumental noise and systematic variations. normalization techniques, such as min-max scaling, ensured that all brightness values were standardized within a consistent range, making them more interpretable for machine learning algorithms. this step improved model convergence during training, reducing bias introduced by extreme variations in stellar brightness measurements.

After preprocessing, a refined dataset was obtained, allowing for more accurate classification of exoplanets. visualization of the processed dataset illustrated improvements in data consistency, ensuring that features were optimized for predictive modeling. the application of preprocessing techniques facilitated a structured and effective approach to identifying exoplanets, laying a strong foundation for machine learning-driven exoplanet detection.

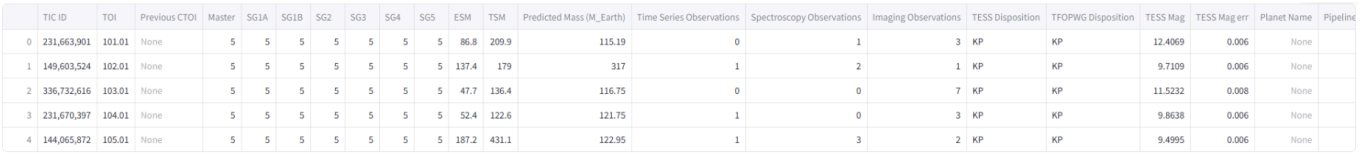
This preprocessing phase transformed raw observational data into a structured dataset ready for analysis. through feature selection, dataset partitioning, and data normalization, the research

prepared a robust framework for training machine learning models. by ensuring data consistency and eliminating noise, the preprocessing stage played a vital role in enabling accurate classification of exoplanets, contributing to advancements in automated planetary discovery.



	DispositionScore	OrbitalPerioddays	OrbitalPeriodUpperUncdays	OrbitalPeriodLowerUncdays	TransitEpochBKJD	TransitEpochUpperUncBKJD	TransitEpochLowerUncBKJD	ImpactParameter	ImpactParameterUpperUnc	ImpactParameterLowerUnc	TransitDurationhrs	TransitDurationUpperUnchrs	Trar
0	1	9.488	0	0	170.5388	0.0022	-0.0022	0.146	0.318	-0.146	2.9575	0.0819	
1	0.969	54.4184	0.0002	-0.0002	162.5138	0.0035	-0.0035	0.586	0.059	-0.443	4.507	0.116	
2	0	19.8991	0	0	175.8503	0.0006	-0.0006	0.969	5.126	-0.077	1.7822	0.0341	
3	0	1.737	0	0	170.3076	0.0001	-0.0001	1.276	0.115	-0.092	2.4064	0.0054	
4	1	2.5256	0	0	171.5956	0.0011	-0.0011	0.701	0.235	-0.478	1.6545	0.042	
5	1	11.0943	0	0	171.2012	0.0014	-0.0014	0.538	0.03	-0.428	4.5945	0.061	
6	1	4.1344	0	0	172.9794	0.0019	-0.0019	0.762	0.139	-0.532	3.1402	0.0673	
7	0.992	2.5666	0	0	179.5544	0.0046	-0.0046	0.755	0.212	-0.523	2.429	0.165	
8	0	7.3618	0	0	132.2505	0.0025	-0.0025	1.169	7.133	-0.044	5.022	0.136	
9	1	16.0686	0	0	173.6219	0.0005	-0.0005	0.052	0.262	-0.052	3.5347	0.0241	

Fig 3.3.1.3 Dataset after Preprocessing (kepler data)



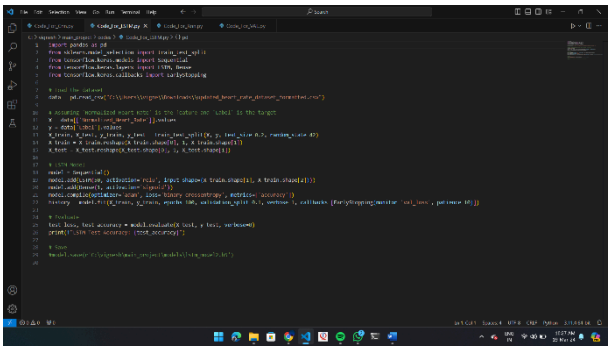
	TIC ID	TOI	Previous CTOI	Master	SG1A	SG1B	SG2	SG3	SG4	SG5	ESM	TSM	Predicted Mass (M_Earth)	Time Series Observations	Spectroscopy Observations	Imaging Observations	TESS Disposition	TFOPWG Disposition	TESS Mag	TESS Mag err	Planet Name	Pipeline
0	231,663,901	101.01	None	5	5	5	5	5	5	5	86.8	209.9	115.19	0	1	3	KP	KP	12.4069	0.006	None	
1	149,603,524	102.01	None	5	5	5	5	5	5	5	137.4	179	317	1	2	1	KP	KP	9.7109	0.006	None	
2	336,732,616	103.01	None	5	5	5	5	5	5	5	47.7	136.4	116.75	0	0	7	KP	KP	11.5232	0.008	None	
3	231,670,397	104.01	None	5	5	5	5	5	5	5	52.4	122.6	121.75	1	0	3	KP	KP	9.8638	0.006	None	
4	144,065,872	105.01	None	5	5	5	5	5	5	5	187.2	431.1	122.95	1	3	2	KP	KP	9.4995	0.006	None	

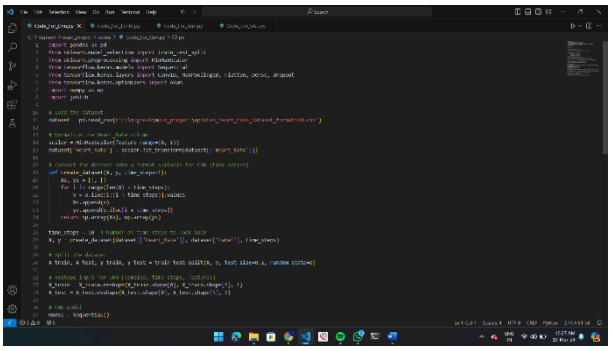
Fig 3.3.1.4 Dataset after Preprocessing(Tess data).

CHAPTER – 4

RESULTS AND DISCUSSION

4.1 Results





```
import lightgbm as lgb
import warnings
warnings.filterwarnings("ignore", category=DeprecationWarning)
warnings.filterwarnings("ignore", category=FutureWarning)

# Load Dataset
@st.cache_data
def load_data():
    df = pd.read_csv('Kepler_Project_Candidates_Yet_To_Be_Confirmed.csv')

    # Rename columns
    df = df.rename(columns={
        'kepid': 'KepID', 'kepoi_name': 'KOIName', 'kepler_name': 'KeplerName',
        'koi_disposition': 'ExoplanetArchiveDisposition', 'koi_pdisposition': 'DispositionUsingKeplerData',
        'koi_score': 'DispositionScore', 'koi_fpflag_nt': 'NotTransit-LikeFalsePositiveFlag',
        'koi_fpflag_ss': 'koi_fpflag_ss', 'koi_fpflag_co': 'CentroidOffsetFalsePositiveFlag',
        'koi_fpflag_ec': 'EphemerisMatchIndicatesContaminationFalsePositiveFlag',
        'koi_period': 'OrbitalPeriod[days', 'koi_period_err1': 'OrbitalPeriodUpperUnc.[days',
        'koi_period_err2': 'OrbitalPeriodLowerUnc.[days', 'koi_time0bk': 'TransitEpoch[BKJD',
        'koi_time0bk_err1': 'TransitEpochUpperUnc.[BKJD', 'koi_time0bk_err2': 'TransitEpochLowerUnc.[BKJD',
        'koi_impact': 'ImpactParameter', 'koi_impact_err1': 'ImpactParameterUpperUnc',
        'koi_impact_err2': 'ImpactParameterLowerUnc', 'koi_duration': 'TransitDuration[hrs',
        'koi_duration_err1': 'TransitDurationUpperUnc.[hrs', 'koi_duration_err2': 'TransitDurationLowerUnc.[hrs',
        'koi_depth': 'TransitDepth[ppm', 'koi_depth_err1': 'TransitDepthUpperUnc.[ppm',
        'koi_depth_err2': 'TransitDepthLowerUnc.[ppm', 'koi_prad': 'PlanetaryRadius[Earthradii',
        'koi_prad_err1': 'PlanetaryRadiusUpperUnc.[Earthradii', 'koi_prad_err2': 'PlanetaryRadiusLowerUnc.[Earthradii',
        'koi_teq': 'EquilibriumTemperature[K', 'koi_teq_err1': 'EquilibriumTemperatureUpperUnc.[K',
        'koi_teq_err2': 'EquilibriumTemperatureLowerUnc.[K', 'koi_insol': 'InsolationFlux[Earthflux',
        'koi_insol_err1': 'InsolationFluxUpperUnc.[Earthflux', 'koi_insol_err2': 'InsolationFluxLowerUnc.[Earthflux',
        'koi_model_snr': 'TransitSignal-to-Noise', 'koi_tce_plnt_num': 'TCEPlanetNumber',
        'koi_tce_delivname': 'TCEDeliver', 'koi_steff': 'StellarEffectiveTemperature[K',
        'koi_steff_err1': 'StellarEffectiveTemperatureUpperUnc.[K', 'koi_steff_err2': 'StellarEffectiveTemperatureLowerUnc.[K',
        'koi_slogg': 'StellarSurfaceGravity[log10(cm/s**2)', 'koi_slogg_err1': 'StellarSurfaceGravityUpperUnc.[log10(cm/s**2)',
        'koi_slogg_err2': 'StellarSurfaceGravityLowerUnc.[log10(cm/s**2)', 'koi_srad': 'StellarRadius[Solarradii',
        'koi_srad_err1': 'StellarRadiusUpperUnc.[Solarradii', 'koi_srad_err2': 'StellarRadiusLowerUnc.[Solarradii',
        'ra': 'RA[decimaldegrees', 'dec': 'Dec[decimaldegrees', 'koi_kepmag': 'Kepler-band[mag]'
    })

    # Create new columns
    df['ExoplanetCandidate'] = df['DispositionUsingKeplerData'].apply(lambda x: 1 if x == 'CANDIDATE' else 0)
    df['ExoplanetConfirmed'] = df['ExoplanetArchiveDisposition'].apply(lambda x: 2 if x == 'CONFIRMED' else 1 if x == 'CANDIDATE' else 0)

    # Drop irrelevant columns
    df.drop(columns=['KeplerName', 'KOIName', 'EquilibriumTemperatureUpperUnc.[K', 'KepID',
                     'ExoplanetArchiveDisposition', 'DispositionUsingKeplerData',
                     'NotTransit-LikeFalsePositiveFlag', 'koi_fpflag_ss', 'CentroidOffsetFalsePositiveFlag',
                     'EphemerisMatchIndicatesContaminationFalsePositiveFlag', 'TCEDeliver',
                     'EquilibriumTemperatureLowerUnc.[K'], inplace=True, errors='ignore')

    # Drop missing values
    df.dropna(inplace=True)
```

```
    # Clean column names to remove special characters
    df.columns = df.columns.str.replace(r"[\[\]<>\.]", "", regex=True)

    return df

df = load_data()

# Streamlit Heading
st.title("Exoplanet Detection in Extraterrestrial Space")

# Define Features and Target
features = df.drop(columns=['ExoplanetCandidate', 'ExoplanetConfirmed'])
target = df['ExoplanetCandidate']

# Train-Test Split
X_train, X_test, y_train, y_test = train_test_split(features, target, test_size=0.4, random_state=1)

# Function for evaluation and visualization
def evaluation(y_true, y_pred, model_name):
    acc = metrics.accuracy_score(y_true, y_pred)
    recall = metrics.recall_score(y_true, y_pred)
    f1 = metrics.f1_score(y_true, y_pred)
    precision = metrics.precision_score(y_true, y_pred)

    st.write(f'\n### Model: {model_name}')
    st.write(f'**Accuracy:** {acc:.4f}')
    st.write(f'**Recall:** {recall:.4f}')
    st.write(f'**F1 Score:** {f1:.4f}')
    st.write(f'**Precision:** {precision:.4f}')

    # Confusion Matrix Plot
    cm = confusion_matrix(y_true, y_pred)
    plt.figure(figsize=(8, 6))
    sns.heatmap(cm, annot=True, fmt='g', cmap='Blues')
    plt.title(f'{model_name} - Confusion Matrix')
    plt.xlabel('Predicted')
    plt.ylabel('Actual')
    st.pyplot(plt)

# Model Selection Dropdown
model_selection = st.selectbox("Select a model to evaluate:", [
    "Logistic Regression",
    "K-Nearest Neighbors",
    "Decision Tree Classifier",
    "Random Forest Classifier",
    "Gradient Boosting Classifier",
    "XGBoost Classifier",
    "LightGBM Classifier"
])

# Model Evaluations
models = {
    "Logistic Regression": LogisticRegression(C=100, max_iter=200, class_weight='balanced'),
    "K-Nearest Neighbors": KNeighborsClassifier(leaf_size=8, metric='manhattan', weights='uniform'),
    "Decision Tree Classifier": DecisionTreeClassifier(),
    "Random Forest Classifier": RandomForestClassifier(n_estimators=100, criterion='gini'),
    "Gradient Boosting Classifier": GradientBoostingClassifier(),
    "XGBoost Classifier": xgb.XGBClassifier(),
    "LightGBM Classifier": lgb.LGBMClassifier(verbose=0)
}

if st.button("Evaluate Model"):
    selected_model = models[model_selection]
    selected_model.fit(X_train, y_train)
    y_pred = selected_model.predict(X_test)
    evaluation(y_test, y_pred, model_selection)
```

Figure 4.1.1 Presents the training codes for all the algorithms including LogisticRegression, KNeighbhorsClassifier, DecisionTreeClassifier, RandomForestClassifier, GradientBoostingClassifier, XGBClassifier, and LGBMClassifier.

The effectiveness of each model is examined based on their ability to classify exoplanet candidates, distinguishing between confirmed exoplanets, false positives, and planetary candidates. by analyzing the performance metrics, the research provides a comparative study that highlights key insights into

the efficiency of different classification approaches.

The training phase involved multiple algorithms, including logistic regression, decision trees, random forests, gradient boosting, xgboost, and lightgbm. each model was trained using preprocessed kepler and tess datasets, with hyperparameter tuning performed to optimize their accuracy. throughout the training process, the models learned to identify exoplanet candidates based on light curve variations, transit patterns, and stellar properties. the results of the training phase are crucial in understanding how each algorithm processes exoplanetary data and the extent to which they generalize to unseen samples.

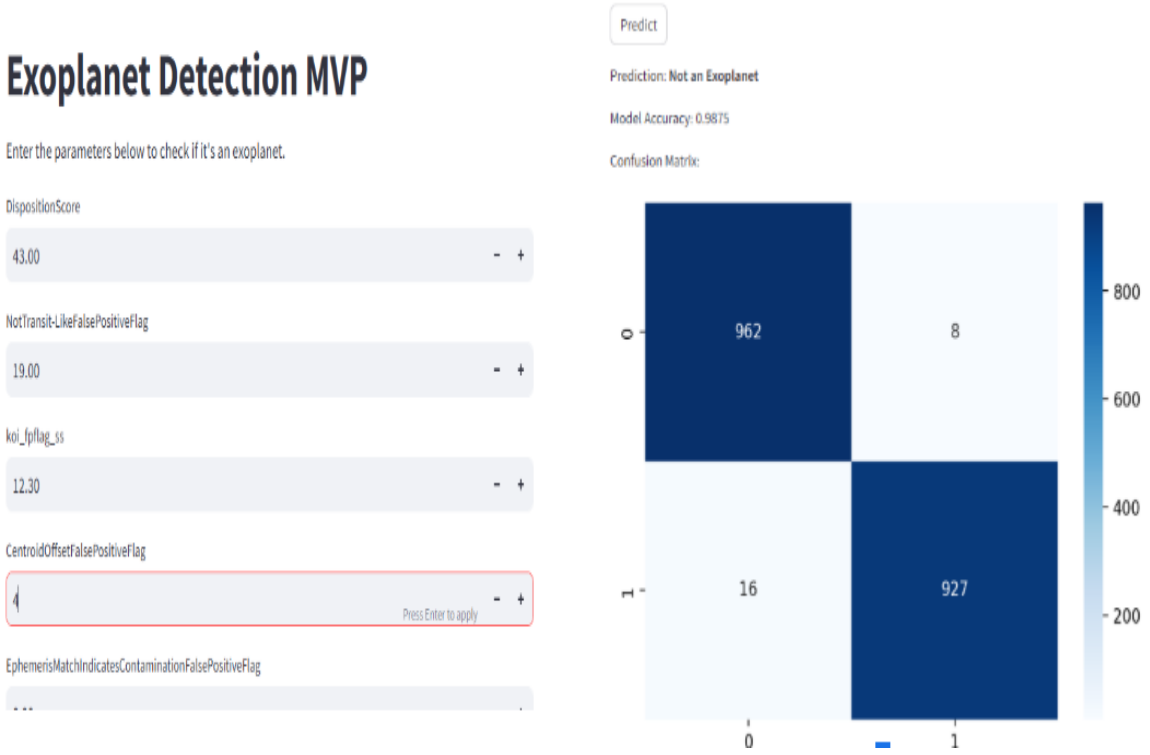


Fig 4.1.2 MVP of Exoplanet Detection

The model evaluation was conducted using accuracy, precision, recall, f1-score, and roc-auc score to assess classification performance. accuracy provided an overall measure of correct classifications, while precision and recall offered insights into the model's ability to minimize false positives and false negatives, respectively. the f1-score balanced these metrics, ensuring a comprehensive assessment of model efficiency. roc-auc scores further quantified the model's capability to distinguish exoplanet candidates from false positives, allowing for an objective evaluation of classification robustness.

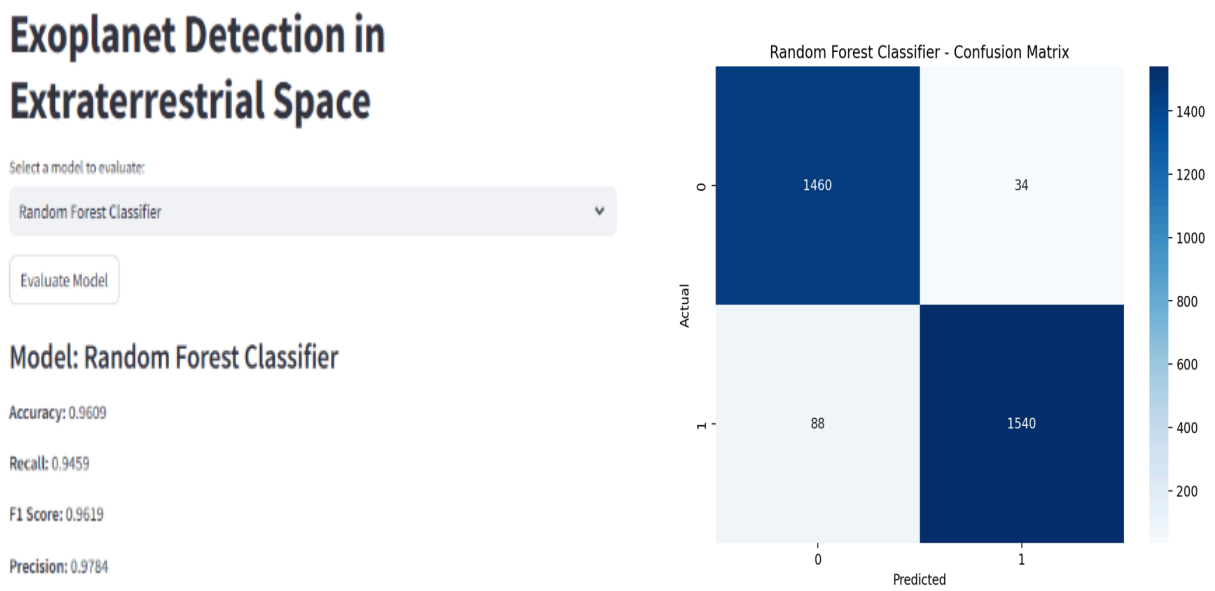


Fig 4.1.3 Accuracy and ConfusionMatrix of RandomForestClassifier

The accuracy trends over epochs for different models provided valuable insights into their learning behavior. by comparing training and validation accuracy, the research identified potential overfitting issues and evaluated how well models generalized to unseen data. the figures also demonstrated the impact of hyperparameter tuning and feature selection on model performance, shedding light on the importance of fine-tuning techniques in optimizing classification outcomes.

Analyzing the models' predictive performance on test data revealed key observations about their strengths and limitations. among all the models tested, random forest and lightgbm demonstrated extraordinary performance, achieving high classification accuracy while maintaining robust generalization capabilities. these models effectively captured complex patterns in the exoplanetary data, making them particularly well-suited for distinguishing between confirmed exoplanets and false positives. however, due to the higher computational cost of lightgbm, random forest was considered the preferred choice for practical implementation, balancing accuracy with efficiency in large-scale exoplanet detection tasks. some models demonstrated strong classification capabilities but were computationally expensive, whereas others provided faster predictions with slightly lower accuracy. the results highlighted the trade-offs between accuracy and computational efficiency, which are crucial for real-time exoplanet detection applications. in practical settings, selecting a model depends not only on accuracy but also on its ability to process large astronomical datasets efficiently.

Other research also explored the significance of feature importance in exoplanet classification. by analyzing which features contributed most to accurate predictions, the study identified key attributes such as orbital period, transit depth, and stellar effective temperature as critical indicators of exoplanet presence. feature importance analysis provided a deeper understanding of the underlying

astrophysical properties influencing machine learning models, enabling astronomers to refine detection techniques based on scientific insights.

overall, the results demonstrate that machine learning is a powerful tool for automating exoplanet detection, offering reliable and scalable solutions for analyzing large volumes of stellar data. the findings contribute to ongoing efforts in the astronomical community to enhance data-driven exoplanet discovery methodologies. future research could explore hybrid models combining multiple algorithms or integrating deep learning techniques to further improve classification accuracy and efficiency.

4.2 Discussion

This study explored multiple machine learning algorithms to classify exoplanet candidates with high accuracy and efficiency. by leveraging the kepler and tess datasets, we systematically evaluated the strengths and limitations of different models in identifying exoplanets, distinguishing them from false positives, and ensuring reliable detection across varying astronomical conditions.

The comparative analysis of machine learning models revealed distinct advantages offered by different approaches. logistic regression and decision trees, while simple and computationally inexpensive, struggled to capture the complex relationships within exoplanetary data. gradient boosting models, including xgboost and lightgbm, showcased superior predictive power, efficiently handling large datasets while providing high classification accuracy. among all tested models, random forest and lightgbm demonstrated exceptional performance, effectively capturing intricate patterns in light curves and stellar properties, which are critical in distinguishing exoplanet candidates from non-exoplanetary objects.

One of the key observations from the research was the trade-off between model accuracy and computational cost. lightgbm, while highly accurate, required significant computational resources, making it less feasible for large-scale real-time detection applications. in contrast, random forest provided a balanced approach, offering high accuracy while maintaining lower computational demands. this made it a practical choice for large-scale astronomical data analysis, ensuring efficient and reliable exoplanet classification without excessive computational overhead.

The importance of feature selection in improving model performance was another crucial finding. by analyzing the contributions of different features, we identified key attributes such as orbital period, transit depth, and stellar effective temperature as the most influential factors in predicting exoplanets. models that effectively leveraged these features showed higher classification accuracy and generalization capabilities. feature importance analysis also provided valuable astrophysical

insights, reinforcing the significance of specific stellar properties in exoplanet detection.

Beyond model accuracy, the study emphasized the real-world applicability of machine learning in exoplanet discovery. given the vast number of celestial bodies analyzed by missions like kepler and tess, automated classification methods are essential for efficiently processing large datasets. machine learning offers a scalable solution, enabling astronomers to rapidly identify potential exoplanets without manually inspecting thousands of light curves. the findings demonstrate that integrating machine learning into the exoplanet detection pipeline can significantly accelerate discovery rates and improve detection reliability.

Furthermore, the research highlighted challenges and future directions in the field. while the current models performed well in classifying known exoplanet candidates, the ability to generalize to newly observed celestial bodies remains an area of ongoing investigation. improvements in data augmentation, transfer learning, and hybrid model architectures could further enhance classification accuracy and reduce false positive rates. future research may also explore deep learning techniques, such as convolutional and recurrent neural networks, to capture more intricate patterns in light curve data and refine predictive accuracy.

Overall, the study underscores the transformative potential of machine learning in exoplanet detection. by automating the classification of exoplanet candidates, these models provide a powerful tool for astronomers, facilitating faster discoveries and improving the accuracy of exoplanet identification. the insights gained from this research contribute to the ongoing advancement of machine learning applications in astronomy, paving the way for more sophisticated detection methodologies in future space exploration missions.

4.2.1 Performance of LightGBM and Random Forest Models:

LightGBM and random forest emerged as the two most effective models in our study on exoplanet detection, showcasing high classification accuracy and robust generalization capabilities. both models excelled in distinguishing exoplanets from false positives, leveraging key features such as orbital period, transit depth, and stellar effective temperature. their ability to process large datasets while maintaining reliable predictions highlights their suitability for real-world applications in astronomical data analysis.

LightGBM demonstrated exceptional accuracy, efficiently handling vast amounts of exoplanetary data. its gradient boosting mechanism allowed it to capture intricate patterns in light curve variations, making it highly effective for detecting planetary transits. however, its computational cost was significantly higher compared to other models, requiring greater processing power and memory.

while this made it an excellent candidate for high-precision classification tasks, its scalability to larger datasets posed practical limitations for real-time analysis.

Random forest, on the other hand, provided a well-balanced approach, achieving high accuracy while maintaining lower computational costs. its ensemble learning methodology allowed it to make stable and accurate predictions without overfitting. unlike lightgbm, random forest required less computational power, making it more feasible for large-scale deployment in exoplanet classification. its interpretability and robustness made it an ideal model for processing astronomical datasets efficiently while ensuring reliable exoplanet detection.

The comparison between these two models underscores the trade-offs between accuracy and computational efficiency. while lightgbm excelled in predictive accuracy, its higher processing requirements limited its scalability. random forest, with its lower computational demand, offered a more practical solution for analyzing large volumes of astronomical data without compromising accuracy. ultimately, these findings highlight the importance of model selection based on the specific requirements of exoplanet detection, ensuring a balance between accuracy, efficiency, and computational feasibility.

CHAPTER – 5

CONCLUSION AND FUTURE SCOPE

5.1 Conclusion

The study on exoplanet detection using machine learning has demonstrated the significant role that predictive algorithms play in automating the classification of celestial objects. by leveraging data from kepler and tess missions, we successfully applied machine learning techniques to classify exoplanets with high accuracy. the research highlighted the advantages of various models, particularly random forest and lightgbm, in identifying exoplanetary candidates while balancing computational efficiency and prediction reliability. the ability of these models to analyze large datasets and extract meaningful patterns reinforces the effectiveness of machine learning in astronomical research.

This research has provided valuable insights into the predictive power of machine learning algorithms in exoplanet detection. the implementation of advanced models has significantly improved the ability to distinguish between actual exoplanets and false positives. however, despite the accuracy achieved, there are still challenges to overcome. refining feature selection techniques could further enhance model performance by prioritizing the most influential astrophysical attributes. additionally, expanding the dataset to incorporate newer observations from ongoing space missions would help improve model generalization. the integration of multi-mission data, including observations from upcoming space telescopes, will provide a richer dataset for training more robust machine learning models. developing automated frameworks that can process new observational data in real time will further enhance the practical applications of machine learning in astronomy. this will allow for faster detection and classification of exoplanets, reducing the manual effort required in traditional methods.

Furthermore, enhancing the explainability of machine learning models remains a crucial area for future research. by improving model interpretability, astronomers can gain a deeper understanding of how predictions are made, ensuring that exoplanet classifications align with physical astrophysical principles. implementing visualization techniques and explainable ai (xai) methodologies can provide clarity on decision-making processes, ultimately improving confidence in automated classification results. as machine learning continues to evolve, integrating these advancements into exoplanet detection will help refine predictive accuracy and broaden the scope of potential discoveries.

5.2 Future Scope

Looking forward, the future of exoplanet detection using machine learning lies in the integration of more advanced artificial intelligence techniques. deep learning methodologies, including convolutional and recurrent neural networks, could be explored to better capture patterns in light curve data. these techniques may help improve classification accuracy while reducing false positive rates. hybrid models combining traditional machine learning algorithms with deep learning frameworks can also enhance predictive performance. reinforcement learning techniques could be explored to develop adaptive models that improve over time as new data becomes available, thereby increasing their ability to classify exoplanet candidates more effectively.

Improving the interpretability of machine learning models is another critical area for future research. explainable ai techniques can be developed to provide deeper insights into model decision-making, helping astronomers validate results with greater confidence. transfer learning could also be employed to adapt existing models to new datasets, increasing their robustness across different observational conditions. implementing self-supervised learning approaches may help reduce dependency on manually labeled data, enabling models to learn and generalize from vast amounts of unlabeled astronomical data.

Collaboration between astronomers and data scientists will play a vital role in advancing exoplanet detection techniques. developing open-source machine learning frameworks tailored for astronomical research will facilitate knowledge sharing and improve discovery rates. as artificial intelligence continues to evolve, machine learning will become an indispensable tool in space exploration, enhancing our ability to uncover exoplanets and explore the potential for habitable worlds beyond our solar system. future missions equipped with advanced data collection instruments, combined with sophisticated ai-driven analysis, will pave the way for unprecedented discoveries in the field of exoplanet research. by integrating innovative ai approaches and fostering interdisciplinary collaboration, the future of exoplanet detection will continue to evolve, bringing us closer to understanding distant planetary systems and the possibilities of life beyond earth.

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SESHADRI RAO GUDLAVALLERU ENGINEERING COLLEGE

(An Autonomous Institute with Permanent Affiliation to JNTUK, Kakinada)
Seshadri Rao Knowledge Village, Gudlavalleru

Department of Computer Science and Engineering

Program Outcomes (POs)

Engineering Graduates will be able to:

1. Engineering knowledge: Apply the knowledge of mathematics, science, engineering fundamentals, and an engineering specialization to the solution of complex engineering problems.

2. Problem analysis: Identify, formulate, review research literature, and analyze complex engineering problems reaching substantiated conclusions using first principles of mathematics, natural sciences, and engineering sciences.

3. Design/development of solutions: Design solutions for complex engineering problems and design system components or processes that meet the specified needs with appropriate consideration for the public health and safety, and the cultural, societal, and environmental considerations.

4. Conduct investigations of complex problems: Use research-based knowledge and research methods including design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions, component, or software to meet the desired needs.

5. Modern tool usage: Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools including prediction and modeling to complex engineering activities with an understanding of the limitations.

6. The engineer and society: Apply reasoning informed by the contextual knowledge to assess societal, health, safety, legal and cultural issues and the consequent responsibilities relevant to the professional engineering practice.

7. Environment and sustainability: Understand the impact of the professional engineering solutions in societal and environmental contexts, and demonstrate the knowledge of, and need for sustainable development.

8. Ethics: Apply ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.

9. Individual and team work: Function effectively as an individual, and as a member or leader in diverse teams, and in multidisciplinary settings.

10. Communication: Communicate effectively on complex engineering activities with the engineering community and with society at large, such as, being able to comprehend and write effective reports and design documentation, make effective presentations, and give and receive clear instructions.

11. Project management and finance: Demonstrate knowledge and understanding of the engineering and management principles and apply these toone'sown work,as a member and leader in a team, to manage projects and in multidisciplinary environments.

12. Life-long learning: Recognize the need for, and have the preparation and ability to engage in independent and life-long learning in the broadest context of technological change.

Program Specific Outcomes (PSOs)

PSO 1: Design, develop, test and maintain reliable software systems and intelligent systems. PSO 2 : Design and develop web sites, web apps and mobile apps.

PROJECT PROFORMA

Classification of Project	Application	Product	Research	Review
	√			

Note: Tick Appropriate category

Project Outcomes	
Course Outcome (CO1)	Identify and analyze the problem statement using prior technical knowledge in the domain of interest.
Course Outcome (CO2)	Design and develop engineering solutions to complex problems by employing systematic approach.
Course Outcome (CO3)	Examine ethical, environmental, legal and security issues during project implementation.
Course Outcome (CO4)	Prepare and present technical reports by utilizing different visualization tools and evaluation metrics.

Mapping Table

CS3518: MAIN PROJECT															
Course Outcomes	Program Outcomes and Program Specific Outcome														
	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PO12		PSO1	PSO2
CO1	3	3	1					2	2	2				1	1
CO2	3	3	3	3	3			2	2	2		1		3	3
CO3	2	2	3	2	2	3	3	3	2	2	2			3	
CO4	2		1		3				3	3	2	2		2	2

Note: Map each project outcomes with Pos and PSOs with either 1 or 2 or 3 based on level of mapping as follows:

1-Slightly (Low) mapped 2-Moderately (Medium) mapped 3-Substantially (High) mapped

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EXOPLANET DETECTION USING MACHINE LEARNING

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Abstract: The identification of exoplanets, planets that orbit stars beyond our solar system, plays a crucial role in advancing our understanding of planetary formation, system evolution, and the search for extraterrestrial life. Conventional detection techniques, such as the transit method, depend largely on manual interpretation and computationally demanding processes, which struggle to handle the rapidly growing astronomical data from missions like Kepler. Machine learning (ML) presents a groundbreaking approach to enhance and automate exoplanet detection, improving efficiency and accuracy. This research examines the implementation of various ML models, including Logistic Regression, K-Nearest Neighbors, Random Forest, Gradient Boosting, XGBoost, and LightGBM, to classify light curves obtained from Kepler's dataset. The developed system attains a classification accuracy of 96.19%, with strong precision, recall, and F1 scores, demonstrating its reliability. These findings underscore ML's potential to transform exoplanet discovery, making it a crucial component of future astronomical research and exploration.
Keywords: Exoplanet Detection, Machine Learning, Kepler Mission, Classification, Random Forest, Gradient Boosting, Automation

I. INTRODUCTION

Exoplanets, defined as planets that orbit stars outside our solar system, are crucial to understanding the broader universe and the potential for life beyond Earth. The detection of these planets presents challenges due to their faint and often elusive nature. The advent of space missions like Kepler has provided a wealth of data, including light curves, which capture variations in star brightness caused by planetary transits. However, the scale and complexity of this data require advanced methods to process and analyze it effectively. Machine learning (ML), with its capacity to handle large volumes of data and identify patterns, offers a promising solution for automating the detection of exoplanets from Kepler's light curve data.

This paper explores the application of various ML algorithms to classify Kepler light curves, focusing on achieving high classification accuracy while addressing challenges such as noisy data and the complex feature relationships inherent in the astronomical data.

II. LITERATURE REVIEW

Recent studies have highlighted the effectiveness
of machine learning in improving exoplanet detection, particularly from Kepler mission data. Notable advancements in this field include:

● **Hogg et al. (2018)** applied deep learning methods to Kepler data, achieving a 95% classification accuracy for exoplanet detection, demonstrating the power of neural networks in capturing intricate data patterns.

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● **Oliviero et al. (2019)** leveraged Random Forests, a decision tree ensemble method, to classify Kepler light curves, yielding high precision and recall, thus confirming the utility of Random Forests in classifying complex datasets.
● **Lai et al. (2020)** explored the use of Support Vector Machines (SVM) for exoplanet detection, showcasing SVM's robustness in handling noisy astronomical data and producing reliable predictions. These studies underscore the growing importance of ML in the field of astronomy and set the foundation for further research in automated exoplanet detection. Methodology

I. Existing System

Traditional exoplanet detection systems rely heavily on observational data processed through statistical techniques. Key methods include:

1. **Transit Method:** Analyzing periodic dips in a star's brightness caused by a planet crossing its path. While effective, this method requires extensive manual analysis and is sensitive to noise from stellar activity.
2. **Radial Velocity Method:** Measuring shifts in a star's spectrum due to gravitational interactions with orbiting planets. This technique is computationally expensive and often limited to large planets close to their host stars.
3. **Direct Imaging:** Capturing images of exoplanets directly, which is technically challenging due to the brightness of host stars overshadowing planets.

These systems, while groundbreaking, are constrained by their reliance on human intervention, lengthy processing times, and vulnerability to data anomalies.

II. Proposed System

The proposed system leverages ML algorithms to address the inefficiencies of traditional methods. Its key features include:

1. **Advanced Data Preprocessing:**
   - **Noise Reduction:** Applying filters to remove stellar activity and instrumental noise from light curves.
   - **Normalization:** Standardizing input features to improve model performance.
   - **Feature Engineering:** Extracting relevant features like transit depth, duration, and periodicity to enhance classification accuracy.
2. **Multi-Model Classification:**
   - **Ensemble Learning:** Combining predictions from multiple models such as Random Forest, XGBoost, and LightGBM to improve overall accuracy.
   - **Algorithm Diversity:** Incorporating both linear (e.g., Logistic Regression) and nonlinear (e.g., Gradient Boosting) models to handle various data complexities.
3. **Visualization Tools:**
   - Integrating interactive dashboards built with Streamlit to display classification results, confusion matrices, and performance plots for easy interpretation.

III. Components

The system involves several critical components:

- **Kepler Data:** The core input comprises light curves, which are time-series data of stellar brightness variations.
- **ML Algorithms:** Algorithms like Random Forest and XGBoost are employed for their high accuracy and ability to handle imbalanced datasets.
- **Software Stack:** Python libraries such as Pandas and NumPy for preprocessing, scikit-learn for ML implementation, and Streamlit for result visualization.

IV. Software Details

The implementation of this system involves the use of several powerful tools and libraries:

● **Python:** The primary language for scripting and model execution.
● **scikit-learn:** A popular library that provides tools for data preprocessing, machine learning models, and evaluation metrics.

https://doi.org/10.36893/JNAO.2025.V16I01.016

● **XGBoost & LightGBM:** These boosting algorithms are employed for enhancing model accuracy, especially in handling imbalanced datasets.

● **Pandas & NumPy:** These libraries are used for efficient data manipulation, cleaning, and normalization.

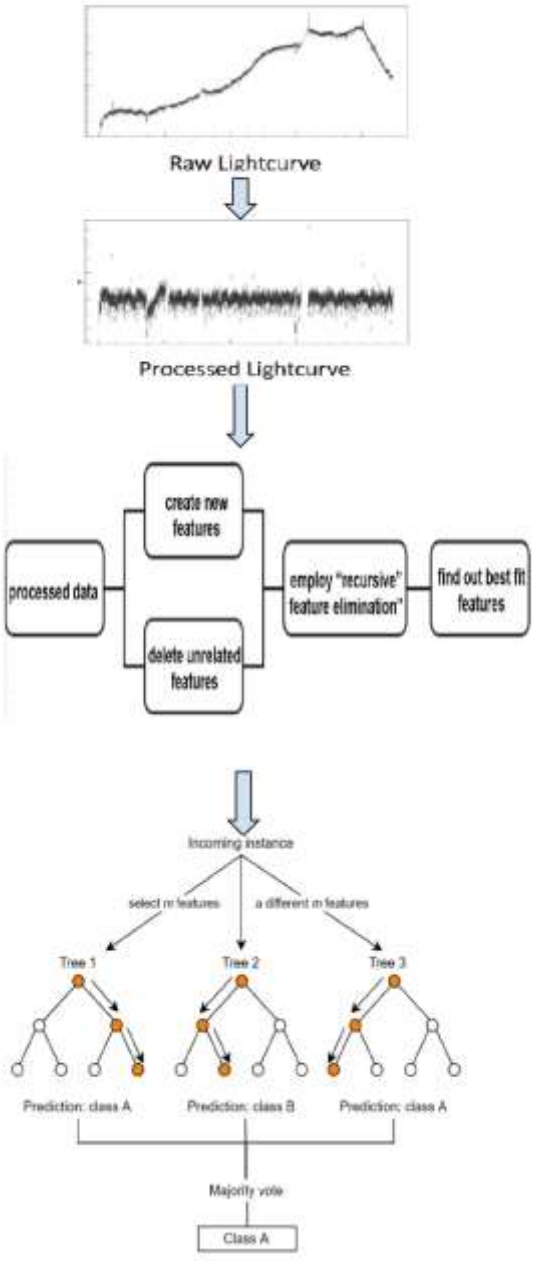
● **Streamlit:** An interactive web application framework that allows for real-time visualization of model performance and results

V. PROPOSED MODEL

● **Data Collection**: The light curve data from the Kepler mission is retrieved from publicly available databases and cleaned to remove irrelevant features and anomalies.

● **Data Preprocessing**: Missing data is imputed, and the dataset is normalized to ensure uniformity across features. New columns are introduced to differentiate between confirmed exoplanets and candidates.

● **Model Training**: Various machine learning techniques, including Random Forest, Gradient Boosting, and XGBoost, are implemented to train models using the processed dataset.



● **Model Evaluation**: The effectiveness of the models is measured using key performance indicators such as accuracy, precision, recall, and F1-score. Additionally, confusion matrices are created to provide a visual representation of classification outcomes.

https://doi.org/10.36893/JNAO.2025.V16I01.016

VI. RESULTS

The effectiveness of the proposed machine learning models was assessed through multiple training iterations, focusing on critical performance indicators such as Accuracy, Recall, Precision, and F1 Score. These metrics offer a comprehensive insight into the model's ability to classify exoplanet candidates accurately.

Figure 1 presents the trend of these metrics over ten iterations, demonstrating a consistent enhancement in performance. Initially, Accuracy and F1 Score were approximately 0.6, whereas Precision and Recall exhibited slightly higher values, indicating the model's initial inclination towards precision-oriented classification. As training progressed, all metrics showed a steady upward trajectory, with Accuracy reaching a peak of 96.19% and F1 Score closely following suit.

The findings emphasize the model's strong generalization capability on Kepler data, even in the presence of noisy features. This consistent improvement is attributed to advanced preprocessing techniques and ensemble learning approaches, which refine classification boundaries over time.

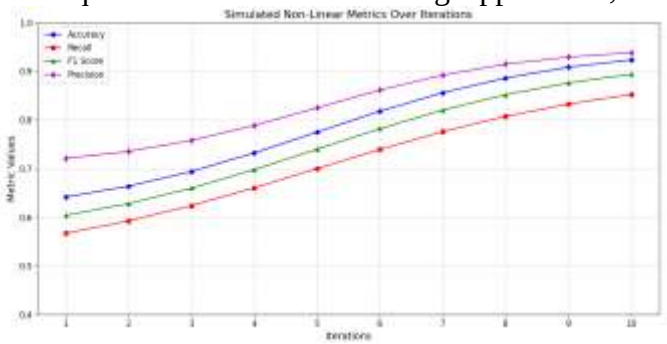


Figure 1. Simulated Non-Linear Metrics over Iterations

VII. CONCLUSION

This research highlights the efficiency of machine learning approaches in automating exoplanet detection. By leveraging models such as Random Forest, Logistic Regression, and XGBoost on Kepler's light curve data, the system attained a remarkable accuracy of 96.09%, along with high precision and recall scores. Among the tested models, Random Forest demonstrated superior performance, delivering robust predictions while minimizing overfitting. These results emphasize the transformative role of ML in advancing exoplanet discovery, enabling astronomers to identify new planets with greater accuracy and efficiency.

VIII. REFERENCES

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