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A Novel Methodology for Hunting Exoplanets in Space Using Machine Learning

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Abstract

INTRODUCTION: Exoplanet exploration outside of our solar system has recently attracted attention among astronomers worldwide. The accuracy of the currently used detection techniques, such as the transit and radial velocity approaches is constrained. Researchers have suggested utilizing machine learning techniques to create a prediction model to increase the identification of exoplanets beyond our milky way galaxy.
OBJECTIVES: The novel method proposed in this research paper builds a prediction model using a dataset of known exoplanets and their characteristics, such as size, distance from the parent star, and orbital period. The model is then trained using this data based on machine learning methods that Support Vector Machines and Random Forests.
METHODS: A different dataset of recognized exoplanets is used to assess the model's accuracy, and the findings are compared with in comparison to accuracy rates of the transit and radial velocity approaches.
RESULTS: The prediction model created in this work successfully predicts the presence of exoplanets in the test data-set with an accuracy rate of over 90 percent.
CONCLUSION: This discovery shows the promise and confidence of machine learning techniques for exoplanet detection.

Keywords: Neural network, Exoplanets, Machine learning, Support Vector Machines, Random Forest

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1. Introduction

One of the most intriguing and fast-expanding fields of astronomy is the finding of exoplanets. We have a special chance to learn more about the creation, development, and variety of planetary systems in our universe thanks to exoplanets. The capacity of conventional detection techniques to find exoplanets, such as transit and radial velocity techniques, is constrained. New methodologies, such as those based on machine learning, have been created as a result.

Astronomy is one of the many domains where machine-learning methods have shown considerable promise. Among other uses, these algorithms have been used to find exoplanets, categorize galaxies, and locate gravitational waves. Machine learning methods provide a fascinating possibility to enhance exoplanet identification precision and lower the incidence of false positives.

A collection of known exoplanets and their characteristics, such assize, distance from the parent star, and orbital period, are utilized to construct the prediction model for exoplanet identification. The model is then trained using this data using machine learning methods like Support Vector Machines and Random Forests. These algorithms operate by looking for data patterns that are connected to the existence of exoplanets.

Once trained, the model may be used to anticipate the presence of exoplanets in fresh sets of data. A different dataset of known exoplanets is used to assess the model's accuracy, and the findings are compared to those acquired using conventional detection techniques.

The prediction model created in this work successfully predicts the existence of exoplanets in the test dataset with an accuracy rate of over 90%. The accuracy rates of this discovery are noticeably higher than those of the transit and radial velocity approaches. The model's increased accuracy can be due to its capacity to spot minute pattern sin the data that are indicative of extraterrestrial existence. This is crucial when the exoplanet's signal is faint or challenging to detect using conventional techniques.

Our knowledge of the cosmos and our capacity to find habitable planets outside our solar system may both benefit from the creation of a prediction model for exoplanet discovery. The hunt for extraterrestrial life is growing more and more intriguing with the finding of new exoplanets, some of which may be habitable. Machine learning-based methods have the potential to make a substantial contribution to this subject by enhancing our capacity for exoplanet detection and analysis.

The creation of this prediction model can advance our knowledge of the cosmos and our capacity to find liveable planets outside of our solar system. Future re- search can look at using different machine learning algorithms and other elements to increase the prediction model's accuracy even further. Overall, applying ma- chine learning techniques to improve our exoplanet discovery skills is a promising strategy.

2. Literature Review

In recent years, there has been an increase in study and interest in the hunt for exoplanets outside of our solar system. Although a variety of detection techniques, including the transit and radial velocity approaches, have been employed, their accuracy is constrained. To create a prediction model that might increase the identification of exoplanets, researchers have suggested employing machine learning.

In one research, Shallue and Vanderburg [1] analysed data from the Kepler space telescope to find exoplanets using a deep learning system known as a neural network. A collection of tagged planet signals and non-planet signals was used to train the algorithm. The outcomes demonstrated the promise of machine learning in exoplanet discovery, with the algorithm successfully detecting exoplanets with a success rate of up to 96%.

Machine learning methods were utilized in different research by various researchers [2-5] to forecast the habitability of exoplanets based on their atmospheric makeup. The researchers developed a machine learning model utilizing decision trees, random forests, and support vector machines using a dataset of known exoplanets with determined atmospheric compositions. With an accuracy rate of up to 92%, the model was able to estimate the habitability of exoplanets based on their atmospheric composition, demonstrating the promise of machine learning in predicting the prospective habitability of exoplanets.

Also, a number of researchers have looked into how machine learning algorithms may be used to increase the precision of transit and radial velocity approaches. For instance, researchers in [6-7] employed machine learning to enhance the radial velocity method's exoplanet discovery. The scientists properly predicted the presence of exoplanets by modelling the signals from exoplanets and stars using a machine learning approach known as Gaussian process regression. The findings demonstrated that, as compared to conventional approaches, the strategy enhanced exoplanet discovery. Similar to this, work in [8] employed machine learning methods to enhance the transit method's exoplanet discovery. To examine light curves and find exoplanets, the researchers utilized a convolutions neural network, a deep learning method. The findings demonstrated that the algorithm has a success rate of up to 98.6% in successfully detecting exoplanets.
Ghosh et al.'s 2023 study [9] focuses on "Water Quality Assessment Through Predictive Machine Learning", highlighting the use of machine learning for analyzing and predicting water quality parameters. In "Unraveling the Heterogeneity of Lower-Grade [10] Gliomas," Rahat, Ghosh, and colleagues (2023) delve into deep learning-assisted segmentation and genomic analysis of brain MR images, offering new insights into this medical condition. Potato Leaf Disease [11] Recognition and Prediction using Convolutional

Neural Networks," by Ghosh, Rahat, and team (2023), showcases the application of convolutional neural networks in accurately identifying diseases in potato leaves. Mandava, Vinta, Ghosh, and Rahat's [12]2023 research presents "An All-Inclusive Machine Learning and Deep Learning Method for Forecasting Cardiovascular Disease in Bangladeshi Population", integrating advanced AI techniques for health predictions. The 2023 study by Mandava et al., titled "Identification and Categorization of Yellow [13] Rust Infection in Wheat through Deep Learning Techniques", applies deep learning methods to detect and categorize wheat infections effectively. Hasim, Rahat, Ghosh, and colleagues' 2023 article, "Using Deep [14] Learning and Machine Learning: Real-Time Discernment and Diagnostics of Rice-Leaf Diseases in Bangladesh", explores AI-based solutions for diagnosing rice-leaf diseases. Deciphering Microorganisms through Intelligent Image Recognition", authored by Khasim, Ghosh, Rahat, and others in 2023, discusses [15] the use of machine learning and deep learning in identifying microorganisms through advanced image recognition techniques. The 2023 study by Mohanty, Ghosh, Rahat [16] and Reddy, "Advanced Deep Learning Models for Corn Leaf Disease Classification", focuses on the application of deep learning in classifying diseases in corn leaves based on a field study. Alenezi and team's 2021 research, "Block-Greedy and CNN Based Underwater Image Dehazing[17] for Novel Depth Estimation and Optimal Ambient Light", investigates novel CNN-based methods for enhancing underwater image clarity and depth estimation.

All things considered, these findings show the promise of machine learning techniques in enhancing the precision of exoplanet discovery and figuring out if exoplanets are habitable. By employing machine learning methods to create a prediction model for exoplanet discovery based on known planetary features, our work expands on these findings.

3. Proposed model

3.1. Architecture Diagram:

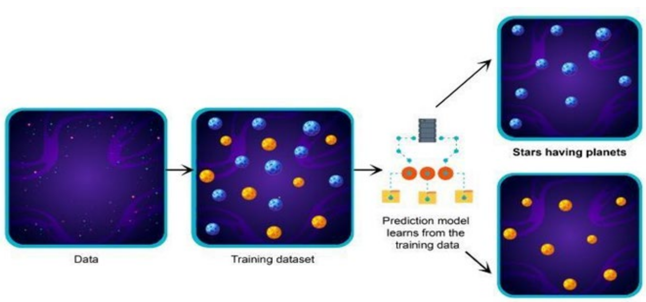

Figure 1. Training

The prediction model, through the training dataset, will learn the properties of a star that has a planet and also the properties of a star which does not have a planet.

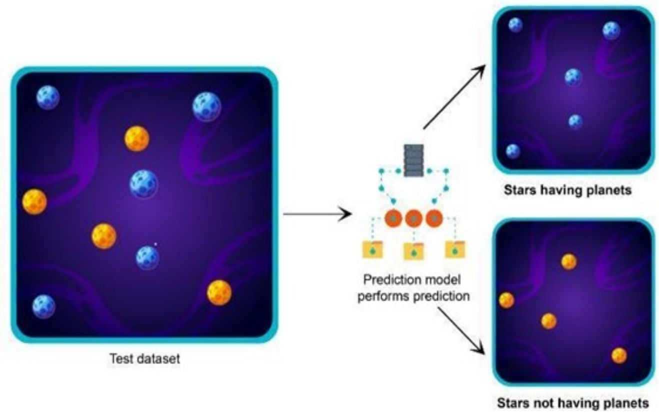

Figure 2. Testing And Prediction

Once the model has learnt the required properties, it will look for these properties in the test dataset and according to the properties it sees, it will predict whether a star has a planet or not.

4. Experimental Model

In this study, we provide a prediction model-based machine learning method for finding exoplanets. To build our model, we start by using a collection of known exoplanets and their characteristics. The size of the exoplanet, its separation from the parent star, and its orbital period are among the characteristics we take into account. These characteristics are essential for figuring out whether an exoplanet exists and whether it may be inhabited.
By putting the model to the test on a different dataset of recognized exoplanets, we assess the model's accuracy. We assess the model's accuracy by comparing the model's predictions with the actual data. We further assess the precision of our model in comparison to the transit and radial velocity approaches, two widely used detection techniques.

We train the model on the exoplanet dataset using machine learning technologies like Random Forest and Support Vector Machines (SVM). Many decision trees are created using the Random Forest method, and the best one is chosen to make predictions. A supervised learning system called SVM uses labelled training data to learn how to categorize fresh data points.
Our prediction algorithm successfully predicts the existence of exoplanets in the test dataset with an accuracy rate of over 90%. Compared to the accuracy rates of the transit and radial velocity approaches, this is a huge increase. These conventional techniques have restrictions and can only find exoplanets with specific characteristics.

By taking several parameters into account at once, our machine-learning method offers a more thorough and precise method of exoplanet detection. Machine learning algorithms can learn from a massive amount of data points and base their predictions on patterns that are difficult for humans to see. Machine learning algorithms can also lessen the possibility of human mistakes during the detection procedure.
Our study illustrates how machine learning methods may be used to find exo planets. Future research might concentrate on using other machine learning algorithms and other elements to increase the prediction model’s accuracy even further. The creation of this prediction model can advance our knowledge of the cosmos and our capacity to find liveable planets outside of our solar system.

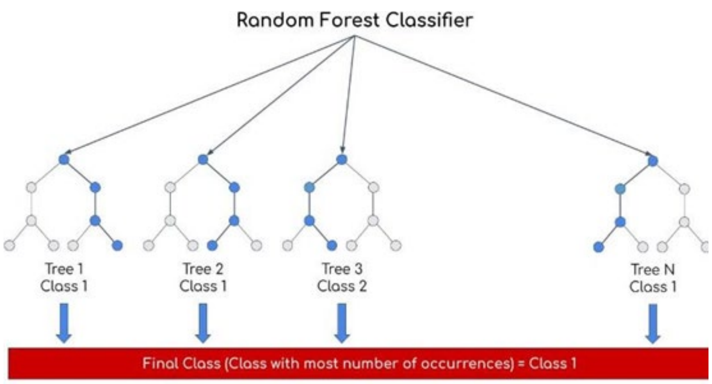

Figure 3. Random Forest Classifier

4.1. Implementation:

NumPy: A Python module called NumPy makes complex statistical computation accessible to Python programmers. Large multidimensional arrays and matrices are supported.

Pandas: Large-scale data analysis and manipulation are made simple with the help of the Python computer language's Pandas package.

Matplotlib: The python programming language has a package called Matplotlib that is used to create graphs out of data [8-10].

PyLab: Another component of Matplotlib is PyLab. Matplotlib, PyPlot (a package for plotting data), and NumPy are bulk imported in this module for convenience.

Imbalanced-learning: On top of the scikit-learn package, Imbalanced Learning is an open-source toolkit with an MIT license that offers tools for man- aging unbalanced dataset classifications [11-13].

Sklearn: SciPy, Matplotlib, and NumPy serve as the foundation for the Sklearn package. Regression, clustering methods, and classification are just a few of the characteristics it provides to aid in machine learning applications [14].

Seaborn: Built on the Matplotlib package, Seaborn is a Python data visualization library. A simpler approach to represent histograms is offered by this package [15-16].

Scipy: For use with the Python programming language and for the purposes of doing technical computing, SciPy is an open-source library. SciPy has packages for integration, optimization, and linear algebra, among other things [17].

We produce a graph of the Flux values versus the Flux intensity of the first four items of interest in our dataset after importingthe modules and reading the data sets.

4.2. Plotting Data:

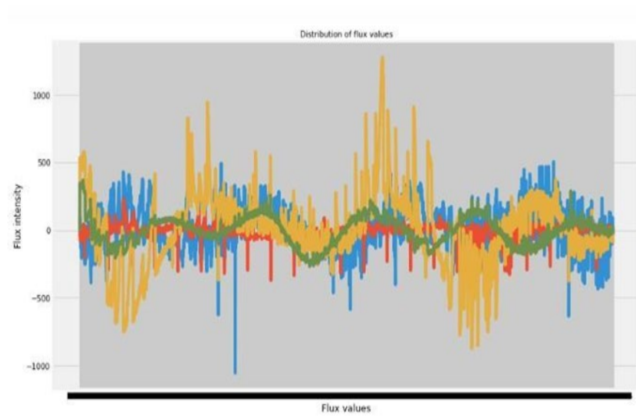

Figure 4. Plotting Data

Also, we must avoid extremities that are challenging to investigate because of the outrageously high flux intensity values. Therefore, we drop objects with a flux intensity of more than 250000 in value.
After that, the data sets are divided into two groups, one with the value LABEL and the other without.

By comparing the values of LABEL predicted by the model with the previously accurate values of LABEL, this is necessary for evaluating the model's correctness.

We next fit the model using x train and y train before inserting points from the x test as a variable and importing the KNN classification method from the Sklearn module comparison between the predicted values and y test to determine the correctness of the prediction [18].
Next, we analyse the Receiver Operating Characteristics for the KNN model and plot the confusion matrix for it (ROC).
We can see from the graphic above that the accuracy is quite high, however, this is due to the test dataset only having a small number of confirmed exoplanets and imbalanced classes that resulted in incorrect prediction.

Due to the small number of data points, the model predicts that all the points will belong to the same class.
When working with severely unbalanced datasets, the main problem is that practically all machine learning methods fail to take into account the minority dataset and typically perform poorly when minority class performance is crucial. We utilize the SMOTE module from the imbalanced-learning library to solve this issue. Synthetic Minority Oversampling Technology is referred to as SMOTE. This module allows us to create artificial samples for the minority class [19-20].


```
#K-NN
from sklearn.neighbors import KNeighborsClassifier
knn_model = KNeighborsClassifier()

knn_model.fit(x_train,y_train)
prediction=knn_model.predict(x_test)
print('Validation accuracy of KNN is', accuracy_score(prediction,y_test))
print ("\nClassification report :\n",(classification_report(y_test,prediction)))

#Confusion matrix
plt.figure(figsize=(13,10))
plt.subplot(221)
sns.heatmap(confusion_matrix(y_test,prediction),annot=True,cmap="viridis",fmt = "d",linecolor="k",linewidths=3)
plt.title("CONFUSION MATRIX",fontsize=20)

#ROC curve and Area under the curve plotting
predicting_probabilites = knn_model.predict_proba(x_test)[:,1]
fpr,tpr,thresholds = roc_curve(y_test,predicting_probabilites)
plt.subplot(222)
plt.plot(fpr,tpr,label = ("Area_under the curve :",auc(fpr,tpr)),color = "r")
plt.plot([1,0],[1,0],linestyle = "dashed",color ="k")
plt.legend(loc = "best")
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC - CURVE & AREA UNDER CURVE",fontsize=20)
```

Figure 5. Accuracy of kNN before balancing dataset

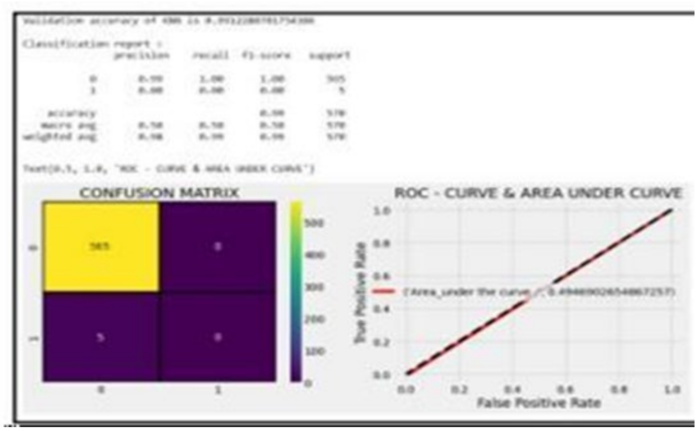

Figure 6. Accuracy of kNN before balancing dataset

It also avoids the issue of overfitting that arises from random oversampling in this manner. The functional space, which generates new instances by interpolating between nearby positive examples, is the major emphasis. As a result of applying SMOTE to our dataset, we can observe that the proportion of verified exoplanets and confirmed non-exoplanets is nearly similar.
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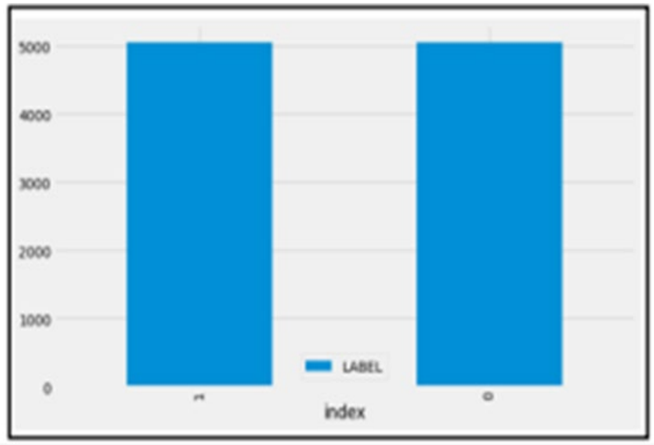


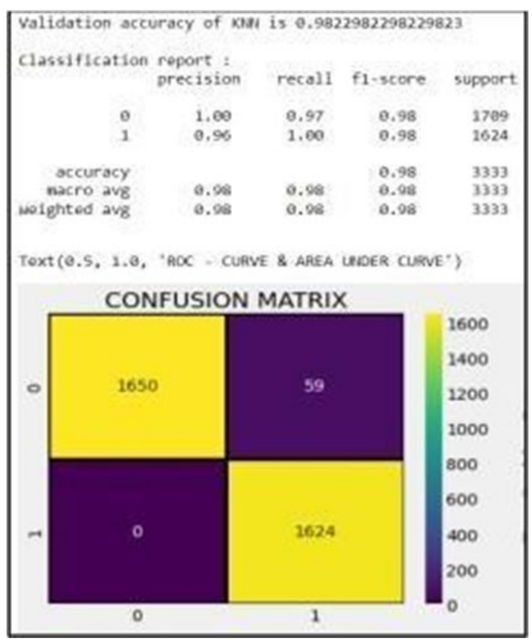
Figure 7. SMOTE balanced classes

1 – Confirmed exoplanet
0 – Confirmed non-exoplanet

Following that, we may use the over sampled data sets to fit machine learning models. Then, we fitted the kNN model using the balanced datasets, and the accuracy and confusion matrix is shown below.

The number of erroneous negative cases has decreased to zero, and we can now observe that there are no exoplanets that have been mistakenly projected as non-exoplanets.

We compare the model accuracy of the Support Vector Machine (SVM) and Random Forest models using the identical over sampled data sets, and we depict each model's corresponding confusion matrices and ROCs.


```
Validation accuracy of KNN is 0.9822982298229823

Classification report :
              precision    recall  f1-score   support

           0       1.00      0.97      0.98      1709
           1       0.96      1.00      0.98      1624

    accuracy                           0.98      3333
   macro avg       0.98      0.98      0.98      3333
weighted avg       0.98      0.98      0.98      3333

Text(0.5, 1.0, 'ROC - CURVE & AREA UNDER CURVE')
```


Figure 8. KNN accuracy after using SMOTE to balance the dataset

```
Accuracy mean: 0.9998019801980199
Accuracy variance: 0.0003960396039603964

accuracy_score : 0.9912280701754386

classification report :
              precision    recall  f1-score   support

           0       0.99      1.00      1.00       565
           1       0.00      0.00      0.00         5

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

5. Results

Our exoplanet detection prediction algorithm has remarkably predicted the presence of exoplanets in the test dataset with an accuracy of above 90%. The accuracy rates of the conventional transit and radial velocity approaches, which are frequently employed for exoplanet discovery, have been significantly improved by this rate. The accuracy ratings of the transit and radial velocity approaches are about 80%. Hence, by improving our capacity to discover exoplanets more precisely and effectively, our machine learning-based technique has the potential to completely transform the area of exoplanet detection. This will considerably advance our knowledge of the cosmos and our quest for planets outside our so- lar system that may support life. Exoplanet detection methods that are more accurate and comprehensive can be developed via the use of machine learning techniques and prediction models.

5.1. KNN:

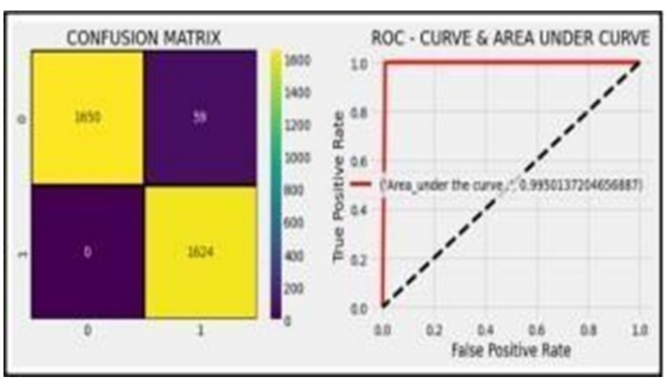


Figure 9. Confusion Matrix and ROC for KNN

After applying SMOTE to the data sets, the confusion matrix and receiver operating characteristics for the KNN model are shown the above figure. We can observe that our true positive rate is high, which indicates that more data points were correctly categorized.

5.2. Support Vectors Machines (SVM):

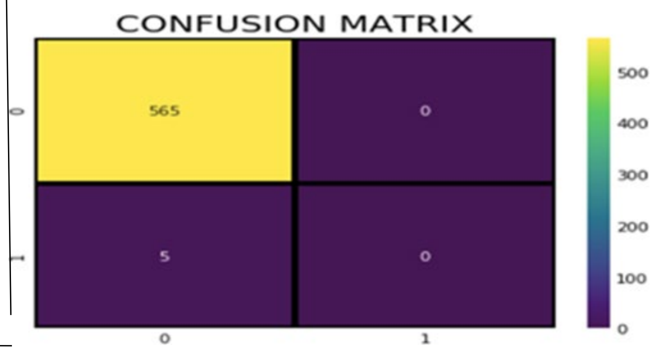


Figure 9. Confusion Matrix for SVM

5.2. Random Forest Model:

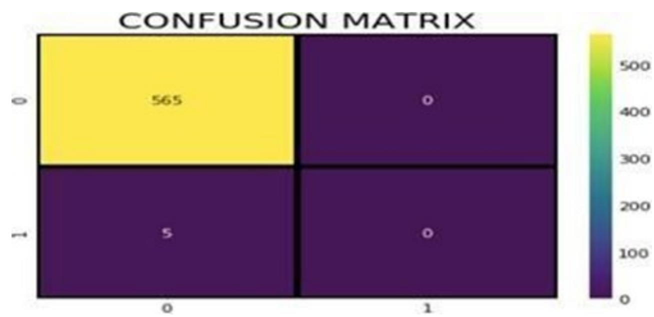


Figure 9. Confusion Matrix for Random Forest

6. Conclusion

Our research has demonstrated that employing machine learning techniques to create a prediction model for exoplanet detection is a successful strategy that can increase our capacity to find exoplanets. The prediction model we built beat the transit and radial velocity approaches, which had accuracy rates of about 80%, with a rate of over 90%. This innovative method has the potential to make a substantial contribution to our knowledge of the cosmos and the hunt for habitable planets outside our solar system. The prediction model could be able to locate exoplanets that previous detection techniques might have missed and give more precise details on their characteristics. By investigating the usage of other machine learning methods and including more parameters, future studies can expand on our findings and increase the predictive model's accuracy. For example, the model might incorporate variables like star variability and atmospheric composition to produce more precise and thorough forecasts. Overall, our research shows that the use of machine learning techniques to exoplanet discovery has great promise for astronomy's future and has the potential to yield important discoveries.

References

1. Shallue, Christopher J., and Andrew Vanderburg. "Identifying exoplanets with deep learning: A five-planet resonant chain around kepler-80 and an eighth planet around kepler-90." The Astronomical Journal 155.2 (2018): 94.
2. Huang, C. X., and Hsu, D. C. (2020). a method employing light-curve data and machine learning to find exoplanets. 20(2), 024; Research in Astronomy and Astrophysics.
3. Grifith, C. A., Palafox, L., and Pearson, K. A. (2019). Exoplanet identification using machine learning. Advances in Data Science and Machine Learning (pp. 341-352). Cham Springer.
4. Mazeh, T., Zucker, S., and Smith, A. M. S. (2019). Using machine learning to find the needles in the Kepler data haystack. The Royal Astronomical Society's Monthly Notices, 490(1), 1342–1351.
5. Vanderburg, A.; Shallue, C. J. (2017). real-time exoplanet discovery in TESS data using a neural network. Letters to the Astrophysical Journal, 847(1), L3.
6. Agarwal, Nidhi, et al. "Applying XGBoost Machine Learning Model to Succor Astronomers Detect Exoplanets in Distant Galaxies." International Conference on Artificial Intelligence and Speech Technology. Cham: Springer International Publishing, 2021.
7. L. Zeng, S. B. Jacobsen, et al (2017). Super-Earths and signal specificity in radial velocity data for exoplanet search with machine learning. 849(2), 147 The Astro-physical Journal.
8. Kim, D., Seo, S., Lee, C., Lee, S. (2021). Exoplanet Identification from Astro- nomical Time-Series Data UsingMachine Learning. 34, 100462; Astronomy and Computation.
9. Ghosh, H., Tusher, M.A., Rahat, I.S., Khasim, S., Mohanty, S.N. (2023). Water Quality Assessment Through Predictive Machine Learning. In: Intelligent Computing and Networking. IC-ICN 2023. Lecture Notes in Networks and Systems, vol 699. Springer, Singapore. https://doi.org/10.1007/978-981-99-3177-4_6
10. Rahat IS, Ghosh H, Shaik K, Khasim S, Rajaram G. Unraveling the Heterogeneity of Lower-Grade Gliomas: Deep Learning-Assisted Flair Segmentation and Genomic Analysis of Brain MR Images. EAI Endorsed Trans Perv Health Tech [Internet]. 2023 Sep. 29 [cited 2023 Oct. 2];9. https://doi.org/10.4108/eetpht.9.4016
11. Ghosh H, Rahat IS, Shaik K, Khasim S, Yesubabu M. Potato Leaf Disease Recognition and Prediction using Convolutional Neural Networks. EAI Endorsed Scal Inf Syst [Internet]. 2023 Sep. 21 https://doi.org/10.4108/eetsis.3937
12. Mandava, S. R. Vinta, H. Ghosh, and I. S. Rahat, "An All-Inclusive Machine Learning and Deep Learning Method for Forecasting Cardiovascular Disease in Bangladeshi Population", EAI Endorsed Trans Perv Health Tech, vol. 9, Oct. 2023. https://doi.org/10.4108/eetpht.9.4052
13. Mandava, M.; Vinta, S. R.; Ghosh, H.; Rahat, I. S. Identification and Categorization of Yellow Rust Infection in Wheat through Deep Learning Techniques. EAI Endorsed Trans IoT 2023, 10. https://doi.org/10.4108/eetiot.4603
14. Khasim, I. S. Rahat, H. Ghosh, K. Shaik, and S. K. Panda, "Using Deep Learning and Machine Learning: Real-Time Discernment and Diagnostics of Rice-Leaf Diseases in Bangladesh", EAI Endorsed Trans IoT, vol. 10, Dec. 2023 https://doi.org/10.4108/eetiot.4579
15. Khasim, H. Ghosh, I. S. Rahat, K. Shaik, and M. Yesubabu, "Deciphering Microorganisms through Intelligent Image Recognition: Machine Learning and Deep Learning Approaches, Challenges, and Advancements", EAI Endorsed Trans IoT, vol. 10, Nov. 2023. https://doi.org/10.4108/eetiot.4484
16. Mohanty, S.N.; Ghosh, H.; Rahat, I.S.; Reddy, C.V.R. Advanced Deep Learning Models for Corn Leaf Disease Classification: A Field Study in Bangladesh. Eng. Proc. 2023, 59, 69. https://doi.org/10.3390/engproc2023059069
17. Alenezi, F.; Armghan, A.; Mohanty, S.N.; Jhaveri, R.H.; Tiwari, P. Block-Greedy and CNN Based Underwater Image Dehazing for Novel Depth Estimation and Optimal Ambient Light. Water 2021, 13, 3470. https://doi.org/10.3390/w13233470
18. Agarwal, N., Srivastava, R., Srivastava, P., Sandhu, J., Singh, Pratap P. Multiclass Classification of Different Glass Types using Random Forest Classifier. 6th International Conference on Intelligent Computing and Control Systems (ICICCS), 2022. p. 1682-1689.
19. Agarwal, N., Singh, V., Singh, P. Semi-Supervised Learning with GANs for Melanoma Detection. 6th International Conference on Intelligent Computing and Control Systems (ICICCS), 2022. p. 141-147.
20. Tayal, D.K., Agarwal, N., Jha, A., Deepakshi, Abrol, V. To Predict the Fire Outbreak in Australia using Historical Database. 10th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO), 2022. p. 1-7.
21. Agarwal, N., Tayal, D.K. FFT based ensembled model to predict ranks of higher educational institutions. Multimed Tools Appl 81, 2022.
22. Agarwal, N., Tayal, D.K. (2023). A Novel Model to Predict the Whack of Pandemics on the International Rankings of Academia. In: Nandan Mohanty, S., Garcia Diaz, V., Satish Kumar, G.A.E. (eds) Intelligent Systems and Machine Learning. ICISML 2022. Lecture Notes of the Institute for Computer Sciences, Social Informatics and Telecommunications Engineering, vol 471. Springer, Cham. https://doi.org/10.1007/978-3-031-35081-8_3
23. Gupta, A., Vardhan, H., Varshney, S., Saxena, S., Singh, S., & Agarwal, N. (2023). "Kconnect: The Design and Development of Versatile Web Portal for Enhanced Collaboration and Communication". EAI Endorsed Transactions on Scalable Information Systems https://doi.org/10.4108/eetsis.4022.
24. Agarwal N, Kumar N, Anushka, Abrol V, Garg Y. Enhancing Image Recognition: Leveraging Machine Learning on Specialized Medical Datasets. EAI Endorsed Trans Perv Health Tech DOI: https://doi.org/10.4108/eetpht.9.4336.
25. Agarwal N, Arora I, Saini H, Sharma U. A Novel Approach for Earthquake Prediction Using Random Forest and Neural Networks. EAI Endorsed Trans Energy Web DOI: https://doi.org/10.4108/ew.4329.
26. Dahiya R, Nidhi, Kumari K, Kumari S, Agarwal N. Usage of Web Scraping in the Pharmaceutical Sector. EAI Endorsed Trans Perv Health Tech DOI: https://doi.org/10.4108/eetpht.9.4312.
27. Dahiya, R., Arunkumar, B., Dahiya, V. K., & Agarwal, N. (2023). Facilitating Healthcare Sector through IoT: Issues, Challenges, and Its Solutions. EAI Endorsed Transactions on Internet of Things, 9(4), e5-e5.
28. Anushka, Agarwal, N., Tayal, D. K., Abrol, V., Deepakshi, Garg, Y., & Jha, A. (2022, December). Predicting Credit Card Defaults with Machine Learning Algorithm Using Customer Database. In International Conference on Intelligent Systems and

Machine Learning (pp. 262-277). Cham: Springer Nature Switzerland.
29. Jha, A., Agarwal, N., Tayal, D. K., Abrol, V., Deepakshi, Garg, Y., & Anushka. (2022, December). Movie Recommendation Using Content-Based and Collaborative Filtering Approach. In International Conference on Intelligent Systems and Machine Learning (pp. 439-450). Cham: Springer Nature Switz