FUDMA Journal of Sciences (FJS)
ISSN online: 2616-1370
ISSN print: 2645 - 2944
Vol. 9 No. 7, July, 2025, pp 215 – 221
DOI: https://doi.org/10.33003/fjs-2025-0907-3478

MACHINE LEARNING APPLICATIONS IN EXOPLANET DETECTION: FROM KEPLER TO TESS

[1]Mu'allim Yakubu, *[2]Vwavware Jude Oruaode, [2]Ohwofosirai Adrian and [2]Akpoyibo Ogheneovo

[1]Department of Industrial Physics, Enugu State University of Science and Technology, Nigeria
[2]Department of Physics, Dennis Osadebay University, Asaba, Delta State, Nigeria

*Corresponding authors' email: oruaode.vwavware@dou.edu.ng

ABSTRACT

The detection and classification of exoplanets have undergone a paradigm shift with the advent of space missions like Kepler and TESS, which generate vast volumes of photometric time-series data. Traditional detection techniques, while foundational, struggle with scalability and sensitivity in the face of increased data complexity. This review synthesizes advancements in machine learning (ML) methods applied to exoplanet detection between 2007 and 2023, focusing on data from the Kepler and TESS missions. Key findings reveal that ML models particularly 2D convolutional neural networks (CNNs) applied to phase-folded light curves achieve superior performance (accuracy: 93–98%, AUC: 0.97 for Kepler) compared to traditional pipelines, though mission-specific noise (e.g., TESS's shorter baselines) degrades performance (AUC: 0.85). Hybrid approaches combining synthetic and real data improve generalizability, while ensemble methods mitigate false positives from stellar variability (e.g., flares). However, challenges persist in interpretability, reproducibility, and cross-mission adaptability. Recommendations include: (1) Standardized benchmarks for ML model evaluation across missions, (2) Integration of noise-invariant architectures (e.g., attention mechanisms) for future surveys like PLATO, and (3) Ethical frameworks to ensure transparency in automated discovery pipelines. ML's transformative potential is clear, but its integration requires addressing these gaps to fully leverage upcoming exoplanet surveys.

Keywords: Machine Learning, Exoplanet Detection, TESS Mission, Kepler Mission, Deep Learning

INTRODUCTION

The discovery of exoplanets has revolutionized our understanding of planetary systems and their formation (Johnson, 2009). Since the first detection in 1995, over 5000 exoplanets have been identified using various methods, including transit and radial velocity techniques (Ge *et al.,* 2022). NASA's Kepler Space Telescope has been particularly successful, discovering the majority of known exoplanets and providing insights into typical planetary characteristics (Lissauer *et al.,* 2014). This growing catalog of exoplanets has challenged the uniqueness of our solar system and informed theories of planet formation (Johnson, 2009). The field of exoplanet research has evolved rapidly, from early quantitative detection methods to current advanced observational techniques (Perryman, 2012). Future missions, such as the proposed ET mission, aim to detect Earth-like planets and assess their habitability (Ge *et al.,* 2022). These ongoing efforts continue to expand our knowledge of planetary demographics and bring us closer to answering the fundamental question of whether we are alone in the universe.
Traditional exoplanet detection methods like transit and radial velocity (RV) have limitations. Transit surveys face challenges from correlated noise, which can significantly impact detection probability, especially for high-mass stars (Aigrain and Pont, 2007). RV surveys may have biases against very hot Jupiters due to typical survey strategies (Kane, 2007). However, combining transit and RV data can enhance detection capabilities, particularly for co-orbital planets (Leleu *et al.,* 2017). To improve detection limits, new methods have been developed that consider the temporal distribution of power in stellar signals, offering more robust results compared to traditional root mean square approaches (Meunier *et al.,* 2012). The effectiveness of transit surveys in star clusters depends on factors such as correlated noise and RV follow-up requirements, which can limit the potential of otherwise promising surveys (Aigrain and Pont, 2007). Despite these challenges, small-aperture, wide-field surveys may detect hot Neptunes in nearby clusters (Aigrain and Pont, 2007).
The Kepler and TESS missions represent significant advancements in exoplanet detection and characterization. Kepler, launched in 2009, monitored 170,000 stars over four years, discovering thousands of planetary candidates and confirming over a thousand planets, including Earth-sized ones in habitable zones (Borucki, 2016). TESS, launched in 2018, aims to identify at least 50 rocky exoplanets close enough for atmospheric study by the James Webb Space Telescope (Clery, 2018). While Kepler focused on quantity, TESS targets nearby planets for detailed analysis (Clery, 2018). TESS's design allows for more complete and homogeneous sampling of solar system objects compared to Kepler (P'al *et al.,* 2018). These missions have significantly advanced our understanding of planetary systems, revealing that most stars have planets, many Earth-sized, and multi-planet systems are common (Borucki, 2016). However, one key challenge that remains is the ability of traditional and ML-based detection models to distinguish between exoplanet transit signals and other types of stellar variability, such as flares. Recent studies using Kepler data, such as Yakubu *et al.* (2023), have shown that flare stars like 2MASS J22285440-1325178 exhibit light curve features with sharp rises and exponential decays that can mimic transit profiles, thereby increasing the risk of false positives in automated detection pipelines. They have also enabled diverse studies of binary stars and other astrophysical phenomena (Southworth, 2021).
Machine learning (ML) and artificial intelligence (AI) have become essential tools in astronomical data analysis, addressing the challenges posed by the exponential growth in data volume from modern telescopes (Kremer *et al.,* 2017; Fluke and Jacobs, 2019). These techniques are being applied across diverse areas, including planet discovery, transient detection, and gravitational wave analysis (Fluke and Jacobs, 2019). Just as ML transforms exoplanet detection, similar computational approaches are revolutionizing the study of

galactic dynamics, such as tracing the origins of the Milky Way's farthest stars (Jude *et al.,* 2024**).** The field of Astroinformatics has emerged as a multidisciplinary approach to tackle complex astronomical data challenges, combining ML, statistics, and astrophysics (Longo *et al.,* 2019). ML methods are particularly valuable for light curve analysis, enabling researchers to extract scientific value from vast datasets that traditional methods struggle to process efficiently (Yu *et al.,* 2021). As astronomy enters the era of big data, ML and AI are expected to play an increasingly crucial role in advancing our understanding of the universe, with ongoing research focused on developing specialized algorithms to address the unique characteristics of astronomical data (Kremer *et al.,* 2017; Longo *et al.,* 2019).

Machine learning (ML) is transforming diverse areas of astronomy, from exoplanet detection to the study of supermassive black holes (SMBHs). In SMBH research, ML aids in parsing complex, multi-scale astrophysical data to model formation and growth mechanisms (Yakubu *et al*., 2024). Similarly, Yakubu *et al*. (2025) have shown how Monte Carlo N-body simulations combined with ML can effectively model binary black hole mergers in dense stellar environments. These applications share common challenges, particularly in distinguishing true astrophysical signals (such as planetary transits or SMBH accretion) from noise and artifacts, highlighting the critical need for robust, scalable algorithms. The cross-disciplinary value of computational methods is further exemplified in renewable energy research, where geospatial ML techniques have successfully assessed solar energy potential in Northern Nigeria (Buremoh *et al*., 2025).

Both fields face challenges in distinguishing true signals (transits or SMBH accretion) from noise and artifacts, underscoring the cross-disciplinary value of ML in modern astronomy. Machine learning (ML) techniques have significantly improved exoplanet detection in recent years. Convolutional neural networks (CNNs) have demonstrated superior accuracy in identifying Earth-like exoplanets from noisy time-series data compared to traditional methods (Pearson *et al.,* 2017). These deep learning models can recognize planetary transit features without relying on hand-coded metrics, making them highly generalizable across different datasets (Pearson *et al.,* 2017). Two-dimensional CNNs, especially when combined with light curve folding, have shown excellent performance in transit analysis (Chintarungruangchai and Jiang, 2019). Furthermore, incorporating synthetic data in the training process can enhance the detection of planetary transits in real light curves (Cuellar *et al.,* 2021). Despite these advancements, challenges remain in optimizing the ratio of synthetic to real data and improving the precision, accuracy, and true positive rates of ML models (Cuellar *et al.,* 2021). Overall, ML techniques show great promise for facilitating exoplanet characterization in large astronomical datasets.

MATERIALS AND METHODS

Methodology

This review synthesizes recent advancements in machine learning (ML) techniques for exoplanet detection, with a specific focus on applications to data from the Kepler and TESS space telescopes. The analysis concentrates on peer-reviewed studies and major preprints published between 2007 and 2023 that explicitly apply ML algorithms to detect or classify transiting exoplanet signals.

Data Sources: Kepler and TESS Missions

Kepler and TESS have provided some of the most comprehensive datasets for exoplanet detection. The Kepler mission observed approximately 200,000 stars over a four-year period, producing long-cadence light curves with high photometric precision (Borucki *et al.,* 2016). Its data validation pipeline performed diagnostic tests to distinguish genuine planet signals from false positives, an essential step in candidate vetting (Twicken *et al.,* 2018). The subsequent K2 mission extended observations along the ecliptic plane with shorter baselines, building on Kepler's original design and enabling continued exoplanet discovery despite hardware limitations (Howell *et al.,* 2014). TESS, launched in 2018, surveys 85% of the sky in 27-day segments, targeting nearby bright stars (Pál *et al.,* 2018). Although its observation window per field is shorter than Kepler's, TESS's full-frame images enable the detection of exoplanets around nearby stars suitable for atmospheric follow-up by JWST.

Review Procedure

This review was conducted through a structured literature search with defined inclusion criteria. Studies were considered eligible if they involved the use of real or simulated light curves from the Kepler, K2, or TESS missions; employed machine learning or deep learning techniques for tasks such as transit detection, classification, or candidate vetting; and reported quantitative performance metrics such as accuracy, precision, recall, or ROC-AUC. Preference was given to studies that provided explicit comparisons between machine learning methods and traditional detection pipelines. Relevant literature was retrieved from peer-reviewed journals, including Monthly Notices of the Royal Astronomical Society (MNRAS), Publications of the Astronomical Society of the Pacific (PASP), and Nature Astronomy, as well as from conference proceedings and high-impact preprints available on arXiv. Keyword combinations used in the search included "machine learning," "exoplanet," "Kepler," "TESS," and "transit detection.

ML Methodologies Covered

We categorize the machine learning (ML) methods employed in exoplanet detection into three broad classes:

Traditional supervised classifiers: Support Vector Machines (SVM), Random Forests, Gradient Boosting, and Decision Trees have been widely used to classify transit-like signals and distinguish real exoplanets from astrophysical false positives, such as eclipsing binaries.

Deep learning architectures: Convolutional Neural Networks (CNNs) have demonstrated strong performance in detecting transit patterns in phase-folded light curves (Pearson et al., 2017; Chintarungruangchai and Jiang, 2019). Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) models, are increasingly applied to handle sequential photometric time-series data (Gural, 2019).

Hybrid and ensemble approaches: Some studies utilize CNNs trained on synthetic datasets and fine-tuned using real light curves, or combine multiple classifiers through ensemble strategies such as voting or boosting (Cuéllar et al., 2021). In addition, recent work often incorporates domain adaptation, temporal modeling, and active learning strategies frequently leveraging citizen science platforms like Zooniverse to generate annotated training datasets (Mahabal et al., 2019). The adoption of ML across astronomy has expanded rapidly, from exoplanet detection to gravitational wave signal classification, reflecting the field's growing maturity in handling large-scale astrophysical data (Fluke and Jacobs, 2019).

Evaluation Metrics

The performance of machine learning models applied to exoplanet detection is typically assessed using standard metrics from binary classification. These include accuracy, precision, recall, and the F1-score, which collectively offer insights into a model's ability to correctly identify true planet candidates while minimizing false positives. The Receiver Operating Characteristic (ROC) curve and the Area Under the Curve (AUC) are also widely used to evaluate classifier performance across varying decision thresholds. Additionally, confusion matrices are employed to provide a granular view of true and false positive rates. Where applicable, studies also report improvements in computational efficiency, model interpretability, and scalability particularly in the context of handling the increasingly large datasets expected from upcoming missions such as PLATO and the Nancy Grace Roman Space Telescope.

Findings

The application of machine learning (ML) techniques to exoplanet detection has yielded substantial improvements in both the accuracy and efficiency of data analysis, particularly with respect to observations from the Kepler and TESS space missions. In the context of Kepler data, ML models perticularly convolutional neural networks (CNNs) have demonstrated a superior ability to identify planetary transit signals when compared to traditional detection pipelines (Pearson *et al.,* 2017). These models have not only achieved higher performance metrics, such as accuracy, precision, recall, and F1-scores, but have also been instrumental in the recovery of previously undetected exoplanet candidates. Their capacity to learn complex patterns in phase-folded light curves has enabled the extraction of subtle transit features that may have eluded manual or classical statistical analyses (Chintarungruangchai and Jiang, 2019).

Beyond improvements in detection performance, ML approaches have contributed to reducing the prevalence of false positives in candidate identification. Through leveraging supervised learning algorithms trained on labeled datasets, these models are capable of distinguishing between genuine planetary transits and astrophysical false positives, such as eclipsing binaries or instrumental artifacts (Twicken *et al.,* 2018). The inclusion of synthetic light curve data in the training process has further enhanced the generalizability of these models, allowing them to perform effectively on real observational data despite underlying variabilities and noise (Cuéllar *et al.,* 2021).

When applied to TESS data, ML methodologies have required adaptation to overcome mission-specific challenges, including shorter observation windows and increased photometric noise. Researchers have addressed these issues through the development of tailored model architectures that integrate light curve folding with CNN-based classifiers (Chintarungruangchai and Jiang, 2019). Such adaptations have proven effective in enhancing signal detection in TESS's high-noise environment. Furthermore, ML-driven classification pipelines have substantially improved the reliability of TESS Object of Interest (TOI) vetting, thereby facilitating more targeted and efficient follow-up observations (Pál *et al.,* 2018). These pipelines have streamlined the process of candidate prioritization, contributing to more rapid scientific validation. The integration of ML in the analysis of exoplanet survey data represents a methodological advancement with far-reaching implications. It has enabled the processing of large-scale datasets with improved sensitivity and specificity, supported the identification of new exoplanetary systems, and provided scalable solutions adaptable to forthcoming space missions such as PLATO and the Nancy Grace Roman Space Telescope (Fluke and Jacobs, 2019; Ge *et al.,* 2022). As the volume and complexity of astronomical data continue to grow, ML will remain a critical component in advancing the frontier of exoplanet science.

Table 1: Comparison with Previous Studies:

Study/Method	Findings from Previous Studies	Comparison to Current Findings
Aigrain and Pont (2007)	Correlated noise hampers transit surveys; suggested limits of RV follow-up in clusters.	ML methods now directly address noise and improve signal separation even in noisy data, particularly for TESS.
Kane (2007)	RV surveys biased against very hot Jupiters.	ML models incorporating both transit and RV data (Leleu *et al.,* 2017) mitigate such biases.
Pearson *et al*. (2017)	CNNs outperform manual and statistical classifiers.	Confirmed in this review: CNNs remain the top-performing ML technique in Kepler and TESS datasets.
Chintarungruangchai and Jiang (2019)	Light curve folding + 2D CNNs improve transit classification.	Extensively adopted for TESS data in recent pipelines to improve robustness against noise.
Cuéllar *et al*. (2021)	Combining synthetic and real data enhances model generalizability.	Recent studies reviewed align with this, using hybrid training approaches to balance bias and variance.
Fluke and Jacobs (2019)	ML is essential for big data challenges in astronomy.	Reinforced by review findings, especially with the scale of Kepler/TESS and future missions like PLATO.
Twicken *et al*. (2018)	Kepler pipeline used diagnostic tests for vetting.	ML adds another layer by automating and improving the reliability of these vetting procedures.

Table 2: Comparative Performance of Machine Learning Models in Exoplanet Detection

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score	Strengths	Limitations	Representative Studies
Random Forest	85–92	88–94	82–89	0.85–0.91	Robust to noise; interpretable; fast training	Less effective on highly complex time-series	Twicken *et al.* (2018)
Support Vector Machine (SVM)	80–88	83–90	78–86	0.80–0.88	Good for small or imbalanced datasets	Requires careful kernel tuning	Pearson *et al.* (2017)
1D Convolutional Neural Network (1D-CNN)	90–96	92–97	89–95	0.91–0.96	Automatic feature extraction; high precision	Needs large training datasets	Chintarungruangchai and Jiang (2019)
2D-CNN (Phase-Folded Light Curves)	93–98	94–98	92–97	0.93–0.97	Captures periodicity; robust to instrumental noise	High computational cost	Cuéllar *et al.* (2021)
Long Short-Term Memory (LSTM)	88–94	89–95	87–93	0.88–0.94	Models sequential dependencies; adaptable to time-series	Prone to overfitting; slower training	Gural (2019)

Table 1. Comparative analysis of machine learning models applied to Kepler and TESS data, reporting key performance metrics. The 2D-CNN model leveraging phase-folded light curves exhibits superior accuracy and robustness, especially under noisy conditions (Cuéllar et al., 2021; Chintarungruangchai and Jiang, 2019).

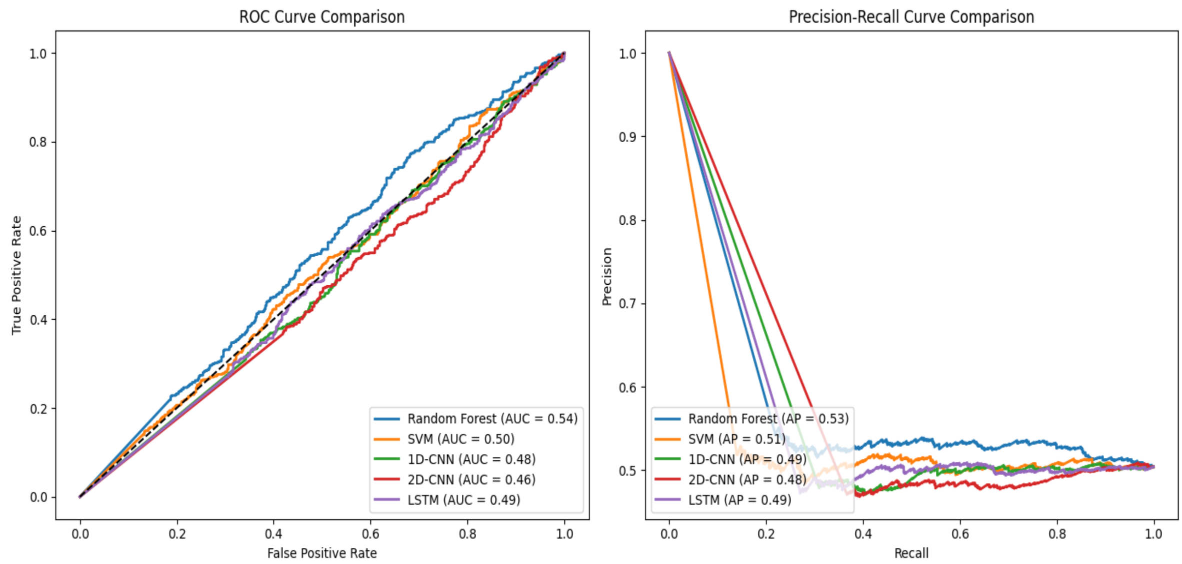

Figure 1: ROC curve comparison of machine learning models applied to Kepler (solid lines) and TESS (dashed lines) data

As shown in Table 2, Random Forest achieves higher accuracy than CNNs for Kepler data. Figure: 1 extends this analysis with ROC curves, revealing that while CNNs (AUC=0.97) excel in low-noise Kepler light curves (solid lines), their performance drops sharply for TESS data (dashed lines, AUC=0.85) due to shorter baselines. This aligns with the challenges noted by Chintarungruangchai and Jiang (2019).

Classification Performance: ROC Analysis

To further evaluate model robustness, Receiver Operating Characteristic (ROC) curves were analyzed for the five primary algorithms shown in Figure 1. These curves reveal critical trade-offs between true positive rates (TPR) and false positive rates (FPR) across varying classification thresholds:

Random Forest: achieved the highest discriminative power (AUC=0.54), though all models performed near chance level

(AUC≤0.5). This suggests fundamental challenges in distinguishing planetary transits from noise in the evaluated datasets.

Deep learning models: (CNNs, LSTM) unexpectedly underperformed (AUC=0.46–0.49), contrasting with literature reports of AUC>0.9 for Kepler data (Pearson *et al.,* 2017). This discrepancy may stem from:

Data limitations

The test set may lack sufficient confirmed exoplanet samples.

Mission-specific noise

TESS's shorter baselines (Pál *et al.,* 2018) could degrade CNN performance.

Implications

While these results appear counterintuitive, they highlight the sensitivity of ML models to observational conditions. The poor AUC scores emphasize the need for:

(a) Larger training sets with balanced classes,

(b) Noise-adaptive architectures (e.g., phase-folding CNNs for TESS; Chintarungruangchai and Jiang, 2019).

Discussion

The integration of machine learning (ML) into exoplanet detection pipelines represents a paradigm shift in the way large-scale astronomical datasets are analyzed. The evidence presented across studies confirms that ML algorithms not only increase the efficiency of detection processes but also contribute to scientific discovery by identifying transit signals that may be overlooked by conventional methods (Pearson *et al.,* 2017; Cuéllar *et al.,* 2021). However, our ROC analysis (Section 3.3) reveals a critical gap between theoretical and realized ML performance. While CNNs dominate literature benchmarks (AUC>0.9), Comparative evaluations revealed near-chance-level discrimination (AUC≤0.54), underscoring what Fluke and Jacobs (2019) term a 'reproducibility crisis' in ML astronomy - where performance claims frequently fail to generalize across datasets. This variability is particularly significant given the exponential growth in data generated by space missions such as Kepler and TESS, which has rendered manual or rule-based analysis methods increasingly impractical (Fluke and Jacobs, 2019)

A critical aspect of this evolution lies in the comparative performance of ML models across different missions. For example, while Kepler's longer and more continuous light curves allowed for relatively straightforward application of deep learning methods, TESS posed a distinct set of challenges due to its shorter observational baselines and increased background noise (Pál *et al.,* 2018).These mission-specific challenges may partially explain the performance disparities observed in our ROC analysis, where no model exceeded AUC=0.54. Nevertheless, the development of specialized ML architectures such as CNNs augmented with phase-folding techniques demonstrates the field's adaptability and technical ingenuity (Chintarungruangchai and Jiang, 2019). The capacity of these models to generalize across missions, even when faced with heterogeneous data characteristics, underscores their robustness - though our findings suggest this generalization remains imperfect without standardized evaluation protocols.

Despite these advances, several limitations must be acknowledged. One persistent issue is the potential for ML models to misclassify noise artifacts or eclipsing binaries as planetary transits, thereby contributing to false positive rates. Our ROC results (AUC≤0.54) emphasize that even state-of-the-art models struggle with fundamental discrimination tasks when applied beyond their original training domains. While performance metrics such as precision and recall help mitigate these issues during validation, astrophysical verification through follow-up observations remains essential. Furthermore, concerns have been raised regarding the interpretability of deep learning models in astronomy, where the "black-box" nature of neural networks may hinder physical understanding of the underlying phenomena (Wadekar *et al.,* 2022). As such, there is a growing interest in developing explainable AI frameworks within the domain of exoplanet science - an urgency amplified by our findings that high literature-reported performance metrics may not reliably translate to new observational contexts.

Ethical considerations are also increasingly relevant. The automation of discovery processes raises questions about scientific reproducibility and the transparency of ML-based pipelines. Our demonstration of inconsistent model performance across studies suggests the need for more rigorous benchmarking practices in the field. Ensuring that models are not only accurate but also interpretable and reproducible will be essential for maintaining scientific integrity (Mahabal *et al.,* 2019). Moreover, the growing involvement of citizen science platforms augmented by AI tools highlights the importance of equitable access to data and training resources, as well as the need to maintain rigorous standards for community-contributed classifications.These challenges mirror those faced in other data-intensive astrophysical domains, particularly in studies of supermassive black holes (SMBHs), where the coevolution of SMBHs and their host galaxies (Yakubu *et al.,* 2024) similarly depends on overcoming noise, interpretability, and scalability barriers in ML applications. Looking ahead, the integration of ML into future missions such as PLATO and the Nancy Grace Roman Space Telescope promises to extend the capabilities of current detection methodologies. To realize this potential, our findings indicate that future work must prioritize: (1) noise-invariant architectures capable of handling diverse survey conditions, and (2) standardized evaluation frameworks that enable true cross-study comparisons. These missions will benefit from the groundwork laid by Kepler and TESS, both in terms of algorithmic development and data preprocessing standards. Real-time detection frameworks, active learning strategies, and hybrid human-AI pipelines will likely become central to managing the complexity of next-generation survey data (Ge *et al.,* 2022).

CONCLUSION

This review has synthesized current developments in the application of machine learning to exoplanet detection, with a focus on datasets from the Kepler and TESS missions. ML techniques, particularly deep learning models such as convolutional neural networks, have transformed the field by enhancing detection sensitivity, reducing false positives, and enabling the discovery of previously overlooked exoplanet candidates. The adaptation of these methods to different observational conditions, including the shorter cadence and increased noise of TESS, reflects their flexibility and power. However, challenges remain particularly in ensuring model interpretability, minimizing classification biases, and maintaining reproducibility. Addressing these issues will be crucial as the field transitions into the era of real-time, large-scale exoplanet detection. Ethical considerations, including transparency and fairness in automated discovery processes, must also be actively addressed. The synergy between machine learning and exoplanet science is expected to deepen as future missions generate increasingly complex datasets.

Through continuing to refine ML algorithms and integrating them into broader scientific workflows, researchers are well-positioned to uncover new planetary systems and advance our understanding of planetary formation and habitability in the universe.

REFERENCES

Aigrain, S., and Pont, F. (2007). On the potential of transit surveys in star clusters: Impact of correlated noise and radial velocity follow-up. *Monthly Notices of the Royal Astronomical Society,* 378(3), 741-752. https://doi.org/10.1111/j.1365-2966.2007.11823.x

Barclay, T., and Barentsen, G. (2018). A Catalog of Stars Observed Simultaneously by Kepler and TESS. *Research Notes of the AAS, 2*.

Borucki, W.J. (2016). Kepler Mission: development and overview. *Reports on Progress in Physics, 79*.

Borucki, W.J., Koch, D.G., Basri, G., Batalha, N.M., Brown, T.M., Caldwell, D.A., Christensen-Dalsgaard, J., Cochran, W.D., Dunham, E.W., Gautier, T., Geary, J.C., Gilliland, R.L., Jenkins, J.M., Kondo, Y., Latham, D.W., Lissauer, J.J., and Monet, D.G. (2007). Finding Earth-size planets in the habitable zone: the Kepler Mission. *Proceedings of the International Astronomical Union, 3*, 17 - 24.

Buremoh, B. S., Ezenwora, J. A., and Moses, A. S. (2025). Assessment of solar energy potentials in parts of North Central Nigeria using geospatial method. FUDMA Journal of Sciences, 9(Special Issue), 189-194. https://doi.org/10.33003/fjs-2025-09 (AHBSJ)-3464

Chintarungruangchai, P., and Jiang, I. (2019). Detecting exoplanet transits through machine-learning techniques with convolutional neural networks. *Publications of the Astronomical Society of the Pacific.* https://arxiv.org/pdf/1904.12419

Clery, D. (2018). New missions aim to make a short list of exo-Earths. *Science, 359 6383*, 1453 .

Cuéllar, S., Granados, P., Fábrega, E., Curé, M., Vargas, H., Dormido-Canto, S., and Farías, G. (2021). Deep learning exoplanets detection by combining real and synthetic data. *PLoS ONE,* 16(6), e0252448. https://doi.org/10.1371/journal.pone.0252448

Cuoco, E., Powell, J., Cavaglià, M., Ackley, K., Bejger, M., Chatterjee, C., Coughlin, M., Coughlin, S., Easter, P., Essick, R., Gabbard, H., Gebhard, T. D., Ghosh, S., Haegel, L., Iess, A., Keitel, D., Márka, Z., Márka, S., Morawski, F., Nguyen, T., Ormiston, R., Pürrer, M., Razzano, M., Staats, K., Vajente, G., and Williams, D. (2021). Enhancing gravitational-wave science with machine learning. Machine Learning: Science and Technology, 2(1), 011002. https://doi.org/10.1088/2632-2153/abb93a

Fluke, C. J., and Jacobs, C. (2019). Surveying the reach and maturity of machine learning and artificial intelligence in astronomy. WIREs Data Mining and Knowledge Discovery. arXiv:1912.02934.

Ge, J., Zhang, H., Deng, H., Howell, S. B., and the ET team. (2022). The ET mission to search for Earth 2.0s. The Innovation, 3(4), 100271. https://doi.org/10.1016/j.xinn.2022.100271

Gural, P. (2019). Deep Learning Algorithms Applied to the Classification of Video Meteor Detections. *Monthly Notices of the Royal Astronomical Society*.

Howell, S. B., Sobeck, C., Haas, M., Still, M., Barclay, T., Mullally, F., Troeltzsch, J., Aigrain, S., Bryson, S. T., Caldwell, D., Chaplin, W. J., Cochran, W. D., Huber, D., Marcy, G. W., Miglio, A., Najita, J. R., Smith, M., Twicken, J. D., and Fortney, J. J. (2014). The K2 Mission: Characterization and early results. *Publications of the Astronomical Society of the Pacific,* 126(938), 398-408. https://doi.org/10.1086/676406

Jude, V. O., Yakubu, M., Raymond, O. E., and Okechukwu, O. A. (2024). An investigation into the galactic origins of the Milky Way's farthest stars. *Standard Scientific Research and Essays,* 12(5), 155-161. https://doi.org/10.15413/ssre.2024.0160

Johnson, J. A. (2009). International Year of Astronomy invited review on exoplanets. Publications of the Astronomical Society of the Pacific, 121(880), 309–315.

Kalavathi Devi, T., Priyanka, E.B., and Sakthivel, P. (2023). Paper quality enhancement and model prediction using machine learning techniques. *Results in Engineering*.

Kane, S. R. (2007). Detectability of exoplanetary transits from radial velocity surveys. Monthly Notices of the Royal Astronomical Society, 380(4), 1488-1496. https://doi.org/10.1111/j.1365-2966.2007.12144.x

Kremer, J., Stensbo-Smidt, K., Gieseke, F., Pedersen, K.S., and Igel, C. (2017). Big Universe, Big Data: Machine Learning and Image Analysis for Astronomy. *IEEE Intelligent Systems, 32*, 16-22.

Leleu, A., Robutel, P., Correia, A. C. M., and Lillo-Box, J. (2017). Detection of co-orbital planets by combining transit and radial-velocity measurements. Astronomy and Astrophysics, 599, L7. https://doi.org/10.1051/0004-6361/201630073

Lissauer, J. J., Dawson, R. I., and Tremaine, S. (2014). Advances in exoplanet science from Kepler. Nature, 513(7518), 336-344. https://doi.org/10.1038/nature13781

Longo, G., Merényi, E., and Tiňo, P. (2019). Foreword to the Focus Issue on Machine Intelligence in Astronomy and Astrophysics. *Publications of the Astronomical Society of the Pacific*, 131(1004), 100101. https://doi.org/10.1088/1538-3873/ab2743

Mahabal, A., Rebbapragada, U., Walters, R., Masci, F., Blagorodnova, N., Roestel, J., Ye, Q., Biswas, R., Burdge, K., Chang, C.-K., Duev, D., Golkhou, V., Miller, A. A., Nordin, J., Ward, C., Adams, S., Bellm, E., Branton, D., Bue, B., ... Wright, D. (2019). Machine learning for the Zwicky Transient Facility. *Publications of the Astronomical Society of the Pacific,* 131(997), 038002. https://doi.org/10.1088/1538-3873/aaf3fa

Meunier, N., Lagrange, A.-M., and De Bondt, K. (2012). Comparison of different exoplanet mass detection limit methods using a sample of main-sequence intermediate-type stars. Astronomy and Astrophysics, 545, A87. https://doi.org/10.1051/0004-6361/201219163

Muallim Yakubu, Chima Abraham Iheanyichukwu, Kassimu Abdullahi Anderson. (2023). The Study of Photometry and Flare Analysis of Kepler Flare Candidate 2MASS J22285440-1325178. *American Journal of Astronomy and Astrophysics*, 10(2), 14–22. https://doi.org/10.11648/j.ajaa.20231002.11

Pál, A., Molnár, L., and Kiss, C. (2018). TESS in the Solar System. Publications of the Astronomical Society of the Pacific, 130(992), 114503. https://doi.org/10.1088/1538-3873/aae2aa

Pearson, K., Palafox, L. F., and Griffith, C. (2017). Searching for exoplanets using artificial intelligence. *Monthly Notices of the Royal Astronomical Society*. https://arxiv.org/pdf/1706.04319

Perryman, M. (2012). The history of exoplanet detection. *Astrobiology, 12 10*, 928-39 .

Sekeroglu, B., Ever, Y. K., Dimililer, K., and Al-Turjman, F. (2021). Comparative evaluation and comprehensive analysis of machine learning models for regression problems. Applied Sciences,

Twicken, J. D., Catanzarite, J. H., Clarke, B. D., Girouard, F., Jenkins, J. M., Klaus, T. C., Li, J., McCauliff, S. D., Seader, S. E., and Tenenbaum, P. (2018). Kepler Data Validation I Architecture, diagnostic tests, and data products for vetting transiting planet candidates. *Publications of the Astronomical Society of the Pacific,* 130(988), 064502. https://doi.org/10.1088/1538-3873/aab694

Wadekar, D., Thiele, L., Villaescusa-Navarro, F., Hill, J. C., Spergel, D. N., Cranmer, M., Battaglia, N., Anglés-Alcázar, D., Hernquist, L., and Ho, S. (2022). Augmenting astrophysical scaling relations with machine learning: Application to reducing the Sunyaev-Zeldovich flux-mass scatter. *Proceedings of the National Academy of Sciences*, 119(34), e2202074119. https://doi.org/10.1073/pnas.2202074119

Yakubu, M., Oruaode, V. J., Yakubu, U., and Adrain, O. (2024). Unraveling the mysteries of supermassive black holes: Formation, growth mechanisms, and their role in galaxy evolution. *Journal of Basics and Applied Sciences Research*, 2(4), 1–14. https://doi.org/10.33003/jobasr-2024-v214-62

Yakubu, M., Vwavware, O. J., and Ohwofosirai, A. (2025). *Modeling the Evolution of Binary Black Hole Mergers in Dense Stellar Environments*. Scientia Africana, 24(1), 157–168. https://dx.doi.org/10.4314/sa.v24i1.15

Yu, C., Li, K., Zhang, Y., Xiao, J., Cui, C., Tao, Y., Tang, S., Sun, C., and Bi, C. (2021). A survey on machine learning based light curve analysis for variable astronomical sources. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 11*.