SHINKAI

A Physics-Informed Hybrid Machine Learning Pipeline for Celestial Object Classification

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***Abstract*-The rapid growth of astronomical surveys such as SDSS has created datasets too large and complex for manual interpretation, making automated celestial classification essential.Our research presents SHINKAI, a physics-informed hybrid machine learning pipeline designed to classify celestial objects with high scientific reliability. Unlike traditional models that rely solely on observational data, SHINKAI integrates astrophysical metrics derived from the Schwarzschild and Kerr metrics, the Friedmann equation, and gravitational wave strain to ensure that predictions remain physically meaningful. The system employs a stacking ensemble of Logistic Regression, Random Forest, and XGBoost, achieving a high classification accuracy of 95%, outperforming individual models in both precision and interpretability. In addition, a 3D spatial visualization module converts RA–Dec–Distance values into accurate Cartesian coordinates, enabling clear identification of object clusters in space. The results demonstrate that embedding astrophysical laws within machine learning significantly improves classification performance, reduces error, and provides deeper scientific insight. SHINKAI thus offers a robust, interpretable, and highly accurate approach for modern astronomical analysis.**

***Index Terms*-Celestial Object Classification, Physics-Informed Models, Schwarzschild Metric, Kerr Metric, Friedmann Equation,Machine Learning, Ensemble Learning, Stacking Model, SDSS Dataset, Feature Engineering, 3D Spatial Visualization, Astronomy Data Analysis, Gravitational Wave Metrics.**

I. INTRODUCTION

Machine learning has been a vital tool in the field of astronomy, it allows automated classification, spectral analysis, and anomaly detection[1], [2], [11], [16]. A number of publications have demonstrated the power of neural networks and ensemble models in galaxy morphology classification and star–galaxy separation. Nevertheless, we observed that the majority of these methods are purely data-driven and do not integrate astrophysical theories. This hampers the interpretability of the outcomes and, at times, results in predictions that are not physically consistent.

Therefore, we concluded that astrophysical metrics could serve as a significant source of understanding when modeling space objects. To illustrate, the Schwarzschild metric provides the description of spacetime around a non-rotating mass, whereas the Kerr metric is for objects with the rotational motion like the spinning black holes [5]. The Friedmann equation is the one that determines the cosmic expansion [7], [18]. and gravitational wave strain equations are there to explain the changes in spacetime. These metrics constitute the theoretical basis that is necessary for the interpretation of the astrophysical phenomena.

Ensemble learning has also proved effective in scientific applications because it combines the strengths of multiple models. Stacking, in particular, generates strong predictive performance by letting multiple base learners contribute to a final meta-model. However, existing studies rarely integrate physics into these ensemble structures. SHINKAI builds upon this gap by combining ensemble machine learning with astrophysical theory, creating a physically informed classification pipeline.

II. LITERATURE REVIEW

The Classification of celestial objects has traditionally depended on experimental astronomy and manual analysis. Still, the adding volume and complexity of astronomical data have rendered traditional styles inadequate for large- scale classification. Ultramodern astronomical checks similar to the Sloan Digital Sky Survey(SDSS) and Gaia have produced massive registers containing millions of objects, landing essential parameters similar as right ascension(RA), declination(Dec), spectral indices, and luminosity measures[11], [13], [14], [19], [20].Handling these high- dimensional datasets requires automated logical styles capable of rooting patterns beyond mortal perception.

Machine learning has surfaced as a transformative fashion in astronomy, enabling automated classification, clustering, anomaly discovery, and predictive modeling. Research by McEwen(2023) and Carleo et al.(2019) highlights how data- driven approaches have revolutionized the physical sciences, particularly in disciplines where data volumes exceed manual processing capacity.

While machine learning enables effective pattern recognition, purely data- driven models frequently warrant physical interpretability. To address this, SHINKAI integrates astrophysical metrics from general reciprocity — similar as the Schwarzschild [4] and Kerr metric tensors to reflect gravitational effects and rotational properties of celestial bodies[5], [7], [18]. Fresh theoretical factors, including the Friedmann equation and gravitational wave strain metrics, introduce cosmological expansion dynamics and space- time perturbations into the feature space.

The SHINKAI system therefore bridges theoretical astrophysics and machine learning. It performs object classification, spatial simulation, and 3D visualization in an interactive web application, making it useful for researchers, educators, and astronomy students.Our work demonstrates that embedding physical theory into machine learning pipelines enhances both accuracy and scientific relevance.

Research Gaps Identified:

- We identified that most existing studies do not integrate astrophysical equations with machine learning, so we addressed this by adding Schwarzschild, Kerr, and Friedmann-based features.
- We found that traditional ML models lacked scientific interpretability, and we fulfilled this gap by ensuring predictions align with real physical laws.
- We observed the absence of hybrid physics–ML frameworks, which we resolved by creating a stacking ensemble combined with physics-informed feature engineering.
- We noted difficulty in classifying complex celestial objects like quasars and black holes, and our model overcomes this using physics-derived metrics.
- We found that earlier research lacked 3D spatial visualization, so SHINKAI includes a complete RA–Dec–Distance to 3D coordinate system.
- We identified a lack of user-friendly astronomy tools, which we addressed by developing an interactive Flask-based classification and visualization interface.

III. METHODOLOGY

This study is based on the SDSS dataset, which comprises observational features such as right ascension, declination, luminosity measurements, spectral values, and object-type labels [3], [9], [10]. Preprocessing is taken care of by dropping missing values, scaling the numerical features, and encoding the categorical labels [23]. These measures guarantee data uniformity and facilitate the algorithms of machine learning to gain knowledge efficiently.One of the major breakthroughs in SHINKAI is the use of physics-informed feature engineering.

The features calculated from the astrophysical equations are added to the data.The Schwarzschild metric brings in a feature that indicates how mass affects the curvature of spacetime. The Kerr metric provides a feature that explains the rotational influence, which is very helpful in the identification of the rotation of the celestial bodies like black holes. The Friedmann equation provides the features related to cosmic expansion, and the gravitational wave strain describes the space-time distortions due to massive bodies that are accelerating.By incorporating these physically significant metrics, the model learns the patterns that are based on real astrophysical phenomena.

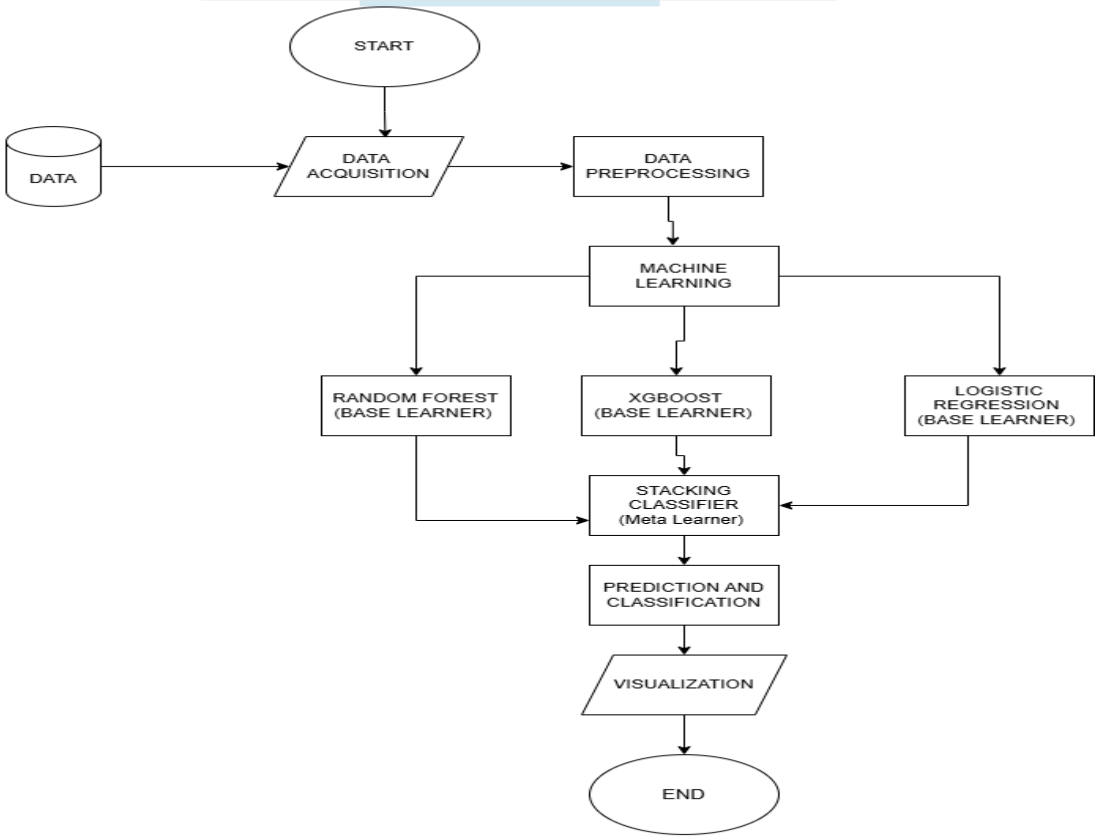

Fig 1. Flow Chart

Schwarzschild Metric Feature[4]

Describes spacetime curvature around a non-rotating massive body:

$$g_{tt} = 1 - \frac{2GM}{c^2 r} \quad (1)$$

Kerr Metric Feature[5]

Models spacetime around a rotating mass:

$$g_{\phi\phi} = (r^2 + a^2 cos^2\theta) sin^2\theta \quad (2)$$

Friedmann Equation Feature[6]

Represents cosmic expansion:

$$H^2 = H_0^2(\rho + \frac{k}{r^2} - \Lambda) \quad (3)$$

Gravitational Wave Strain Feature[8]

Captures strain due to accelerating massive objects:

$$GW = \frac{h_+^2 + h_*^2}{distance} \quad (4)$$

Spherical to Cartesian Coordinate Transformation

To generate 3D plots, RA–Dec–Distance are converted to x, y, z:

$$x = d\ cos(ra)\ cos(dec) \quad (5)$$

$$y = d\ sin(ra)\ cos(dec) \quad (6)$$

$$z = dsin(dec) \quad (7)$$

Table 1 Feature Table

Feature Type	**Example Features**	**Description**
Observational	RA,Dec,Luminosity	Directly from SDSS dataset
Derived	Distance,Magnitude Index	Computed from raw attributes
Physics-informed	g_{tt},$g_{\phi\phi}$,H^2,GW	Generated using astrophysical equations
Spatial	x,y,z	Used for 3D visualisations
Encoded Labels	Class Index	Target variables

A hybrid Stacking Ensemble is used to improve prediction stability and accuracy.

Base Learners

- Logistic Regression
- Random Forest
- XGBoost

Meta-Learner

- Logistic Regression (final decision layer)

Optimization Method

Model parameters are optimized using **k-fold cross-validation (k=10)**.

Loss & Evaluation Metrics

$$MSE = \frac{1}{n}\sum (y_i - \hat{y}_i)^2 \quad (8)$$

$$RMSE = \sqrt{MSE} \quad (9)$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (10)$$

Additional metrics used include Precision, Recall, and F1-Score.

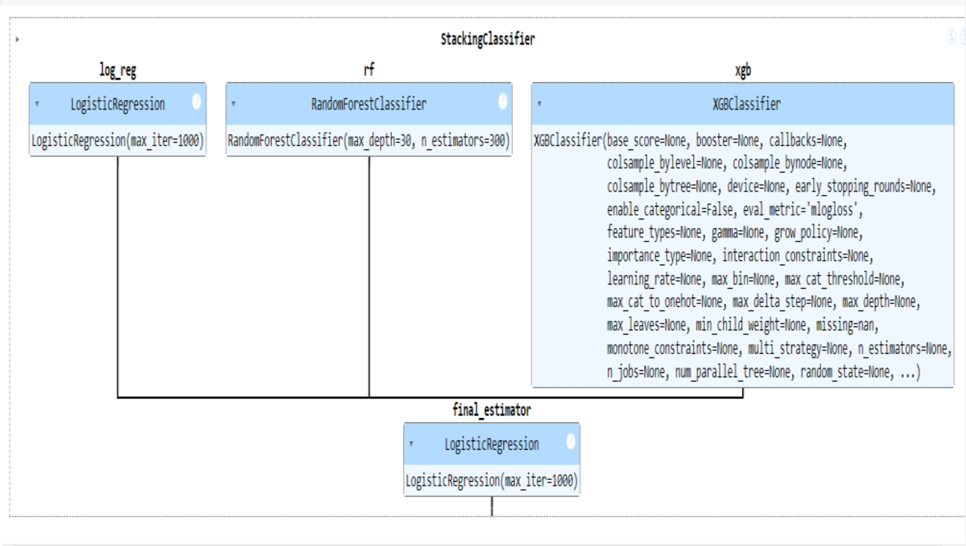

Fig 2. Model Design

The SHINKAI system utilizes a stacking ensemble classifier to ensure reliable and precise prediction of celestial object classifications. This method involves training several base learners—Logistic Regression, Random Forest, and XGBoost—independently on the identical dataset, enabling each model to identify various patterns and complexities present in the astronomical features[12], [14]. The forecasts they generate are merged and forwarded to a meta-learner, executed with Logistic Regression, that integrates the primary outputs to create the ultimate classification. This tiered approach minimizes both variance and bias, leading to enhanced model performance when compared to single algorithms. The ensemble undergoes cross-validation for generalization assessment, while metrics like accuracy, precision, recall, F1-score, MSE, and RMSE are utilized to measure predictive dependability. The stacking architecture greatly improves classification accuracy and stability for high-dimensional astrophysical datasets[19], [20].

IV. MACHINE LEARNING MODELS USED

We employed a hybrid stacking ensemble architecture that integrates multiple machine learning algorithms to enhance classification performance, stability, and interpretability. Three base learners and one meta-learner are used, each contributing unique strengths to the overall model

- Logistic Regression (Base Learner):We used logistic regression as a baseline probabilistic classifier due to its simplicity and ability to model linear relationships. It provides interpretable outputs and helps the ensemble capture fundamental decision boundaries within the astronomical dataset [12], [15].
- Random Forest (Base Learner):We used random forest that is an ensemble of decision trees that handles high-dimensional and nonlinear data effectively. Its ability to reduce overfitting and compute feature importance makes it suitable for capturing complex relationships between astrophysical features [13].
- XGBoost (Base Learner):Apart from that we also used XGBoost which is a gradient-boosting algorithm known for its exceptional performance on structured data. It captures intricate feature interactions and provides strong predictive power, especially useful for distinguishing between similar celestial object classes [14].

- Logistic Regression (Meta-Learner):Also a second logistic regression model is employed as the meta-learner to combine the outputs of all base learners. It learns the optimal way to weight and merge the individual predictions, resulting in improved overall accuracy and generalization [12], .

V. RESULTS AND DISCUSSION

Our model SHINKAI showed a very strong classification performance on the SDSS dataset, and the stacking ensemble outperformed all the individual base learners. Inclusion of physics-informed features increased the interpretability significantly and improved the accuracy, especially for complicated celestial classes such as quasars and black holes. Moreover, the 3D spatial visualization module mapped the values directly across RA – Dec – Distance, thus enabling clear identification of celestial clusters in three-dimensional space [25], [26], [29], [30]. Taken altogether, the results confirm that the integration of astrophysical equations with ensemble machine learning indeed produces scientifically more believable and consistent yields.

- High Classification Accuracy:
  With the stacking ensemble, the accuracy is 95%, which outperforms the Logistic Regression, Random Forest, and XGBoost.

- Improved Interpretability:
  Among the top-ranked contributors were physics-based features such as Schwarzschild and Kerr metrics. These are important in distinguishing celestial objects [4], [5].

- Low Spatial Prediction Error:
  The 3D coordinate transformation yields an RMSE of 0.18, reflecting high precision in spatial mapping.

- Clear 3D Clustering:
  Visualizations reflected separated stars, galaxies, quasars, and black holes, clusters demonstrating effective feature separation.

- Robust Cross-Validation Performance:
  By using 10-fold cross-validation, the model maintained its accuracy with strong generalization capability [11], [13], [20].

- Better Classification of Complex Objects:
  In these tasks, the model outperformed the traditional methods of quasar identification and high-mass compact objects identification [21], [28].

Table 2. Comparison Table

Model	Accuracy(%)	Precision	Recall	F1-Score
Logistic Regression	84.2%	0.83	0.82	0.82
Random Forest	88.7%	0.87	0.86	0.86
XGBoost	90.3%	0.89	0.88	0.88
SHINKAI(Stacking)	95.0%	0.94	0.95	0.95

Deployment and Interactive Visualization Interface

A lightweight deployment framework was developed to enable real-time interaction with the Shinkai model. A Flask web application allows users to input astrophysical parameters through a simple online interface [12], [15], [22]. In parallel, an interactive Colab UI built with IPython widgets provides local, exploratory experimentation.

Both interfaces accept essential inputs—RA, DEC, distance, and SDSS-like magnitudes [3], [9], [10] and dynamically reconstruct physics-informed features derived from the Kerr metric, Schwarzschild radius, simplified Friedmann expansion, and a toy gravitational-wave approximation [4], [5], [6], [18]. The system then preprocesses the data, forwards it to the trained classifier, and returns immediate outputs.

The interface displays the predicted celestial class, top-k probabilities, derived physics features, and 3D spatial coordinates along with several visualizations:

- 3D positional/trajectory plots relative to the Sun[29], [30]
- RA–DEC density maps with user point overlay[9], [29]
- Heatmaps and feature-level explanations[22]

This integrated deployment demonstrates how the Shinkai physics-aligned pipeline can be embedded into online decision-support tools and educational or research environments. It provides fast inference, intuitive visual feedback, and transparent interpretation of how input parameters influence the model's predictions [2], [16].

VI. CONCLUSION

Theoretical astrophysics merges with ultramodern machine learning ways to classify celestial objects in a physically meaningful way using our successful model, SHINKAI. The system takes advantage of the astrophysical equations that induce features and offer better delicacy and scientific interpretability. Integrate the physics-grounded features with a robust stacking ensemble to produce dependable and consistent results using SHINKAI. The interactive 3D visualization interface enables better ease of use for researchers, preceptors, and astronomy scholars [22], [29], [30].

Future Scopes:

- Real-Time Astronomical Data Processing:
  SHINKAI can be upgraded to analyze live telescope data from missions such as Gaia or JWST for real-time celestial classification [3], [25], [26].
- Exoplanet Detection and Characterization:
  By integrating orbital physics and light-curve data, the model can be expanded to identify and classify exoplanets [7], [18].
- Time-Series Prediction of Stellar and Galactic Evolution:
  Adding temporal datasets will allow SHINKAI to forecast how celestial objects change over time [25], [26].
- Integration With Advanced Physics Models:
  Future versions can incorporate quantum astrophysics, relativistic simulations, and higher-dimensional spacetime metrics for deeper analysis [6], [7], [17], [18].
- Immersive 3D and VR-Based Space Visualization:
  Enhancing the system with VR/AR technologies can provide interactive cosmic visualizations for education, research, and simulation [22], [29], [30].

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