Exoplanet Habitability Prediction System

Using Machine Learning and Data Science Techniques

Project Report

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Data Science Experience: Yes
Related Coursework: Data Mining, Data Processing, ML Algorithms

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Abstract

This project develops a machine learning system for predicting exoplanet habitability, addressing the significant challenge of extreme class imbalance where habitable planets constitute less than 1% of known exoplanets. The system integrates multiple astronomical datasets, implements comprehensive data preprocessing, and applies various machine learning algorithms with specialized techniques for handling imbalanced data.

Key components include data collection from NASA and Kepler archives, feature engineering, dimensionality reduction using PCA and t-SNE, and implementation of multiple resampling techniques including SMOTE, Borderline-SMOTE, SMOTE-Tomek, ADASYN, and Random Undersampling. Six machine learning models were evaluated: Logistic Regression, KNN, Naive Bayes, SVM, Random Forest, and XGBoost.

XGBoost with class weighting emerged as the best-performing model, achieving a macro F1-score of 0.96 and perfect recall for potentially habitable planets. The project includes a complete web application with Flask backend API and responsive frontend, providing real-time habitability predictions. The system demonstrates practical application of machine learning in astronomical research and offers a valuable tool for exoplanet analysis.

Keywords: Exoplanet Habitability, Machine Learning, Class Imbalance, SMOTE, XGBoost, Flask API, Astronomical Data Analysis

Contents

1 Introduction

The discovery and analysis of exoplanets has become a major focus in astronomy, with thousands of planets discovered beyond our solar system. Identifying potentially habitable planets among these discoveries presents significant challenges due to extreme class imbalance, complex feature relationships, and data quality issues. This project applies machine learning techniques to predict exoplanet habitability based on planetary and stellar characteristics.

The primary challenge addressed is the extreme imbalance in habitable vs non-habitable planets, requiring specialized approaches in data preprocessing, feature engineering, and model selection. The project implements multiple techniques to handle this imbalance and compares their effectiveness.

2 Project Objectives

- To collect and integrate multiple exoplanet datasets from reliable sources
- To preprocess and clean astronomical data for machine learning applications
- To address class imbalance using various resampling and algorithmic techniques
- To develop and compare multiple machine learning models for habitability prediction
- To create a web-based interface for real-time habitability predictions
- To evaluate model performance using appropriate metrics for imbalanced data

3 Datasets Used

Three primary datasets were integrated for this project:

3.1 PHL Exoplanet Catalog

Primary dataset used for training and evaluation:

- Source: Kaggle (PHL University of Puerto Rico)
- Size: 4,048 rows $\times$ 112 columns
- Key Feature: Includes P_HABITABLE column (target variable)
- Class Distribution: 3,993 non-habitable, 21 potentially habitable, 34 confirmed habitable
- Data Types: Float64 (94), Int64 (4), Object (14)

3.2 NASA Exoplanet Archive

- Source: NASA Exoplanet Science Institute
- Size: 39,119 rows × 289 columns
- Characteristics: Official NASA data, comprehensive features
- Limitation: High percentage of missing values

3.3 Kepler Exoplanet Dataset

- Source: Kaggle (Public Dataset)
- Size: 9,564 rows × 12 columns
- Characteristics: Clean structure, limited features

4 Methodology

4.1 Data Preprocessing

- **Missing Value Handling**: Columns with ¿75% missing values removed, numerical features imputed with median, categorical with mode
- **Outlier Detection**: IQR method applied to identify and handle outliers
- **Feature Engineering**: Created derived features including planet gravity, Earth Similarity Index, insolation flux
- **Data Transformation**: One-hot encoding for categorical variables, StandardScaler for numerical features

4.2 Dimensionality Reduction

- **PCA**: Applied for feature space reduction and visualization
- **t-SNE**: Used for non-linear dimensionality reduction and better class separation visualization

4.3 Class Imbalance Handling

Five techniques implemented and compared:

Technique	Description	Key Characteristic
SMOTE	Synthetic Minority Oversampling	Creates synthetic samples using k-NN
Borderline-SMOTE	Focused oversampling	Targets samples near decision boundar
SMOTE-Tomek	Hybrid approach	Combines SMOTE with Tomek Links
ADASYN	Adaptive Synthetic Sampling	Generates samples based on density
Random Undersampling	Majority reduction	Randomly removes majority class sam

Table 1: Class Imbalance Handling Techniques

4.4 Machine Learning Models

Six models implemented with optimized configurations:

- Logistic Regression with class weighting
- K-Nearest Neighbors (k=5)
- Gaussian Naive Bayes
- Support Vector Machine with RBF kernel
- Random Forest (100 trees)
- XGBoost with scale_pos_weight parameter

4.5 Evaluation Metrics

Due to class imbalance, appropriate metrics were selected:

- Macro F1-Score: Average of per-class F1 scores
- Minority Class Recall: Ability to detect habitable planets
- Precision: Accuracy of positive predictions
- Confusion Matrix: Detailed performance visualization
- ROC-AUC and Precision-Recall curves

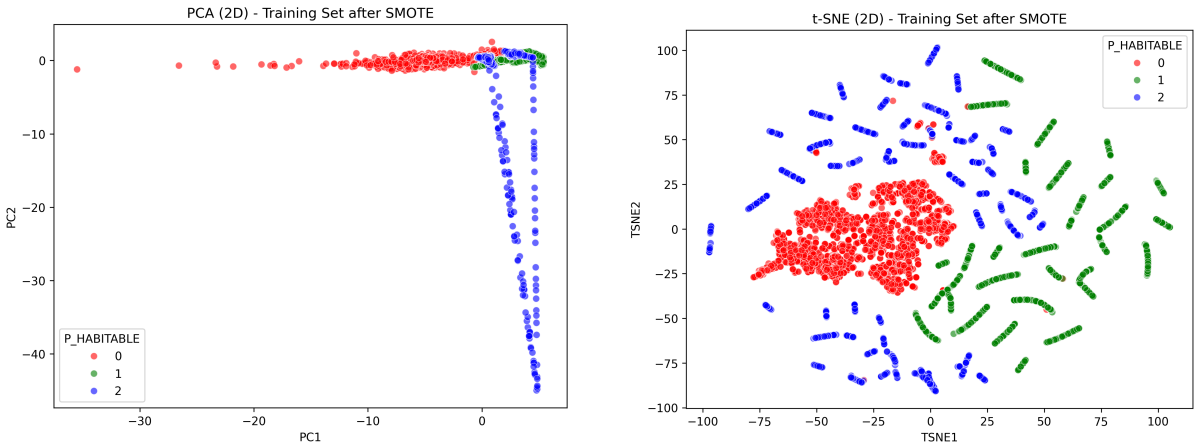
5 Implementation Results

5.1 Data Processing Results

After preprocessing, the final dataset characteristics:

- Final Size: 1,215 samples with 28 features
- Class Distribution: 1,199 non-habitable (98.7%), 6 potentially habitable (0.5%), 10 confirmed habitable (0.8%)
- Feature Reduction: From 112 to 28 meaningful features

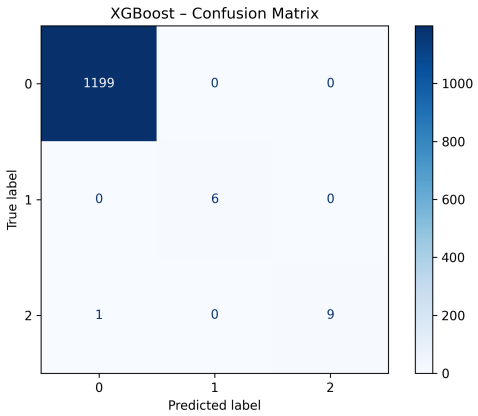
5.2 Dimensionality Reduction Visualization



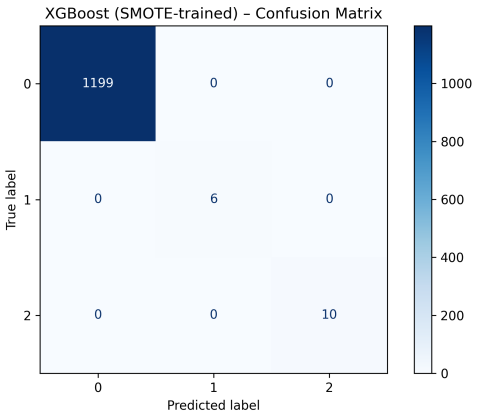
(a) PCA Visualization (b) t-SNE Visualization

Figure 1: Dimensionality Reduction Results - Showing class separation patterns

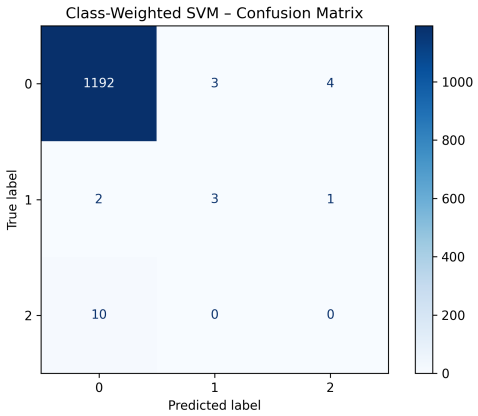
5.3 Model Training Results



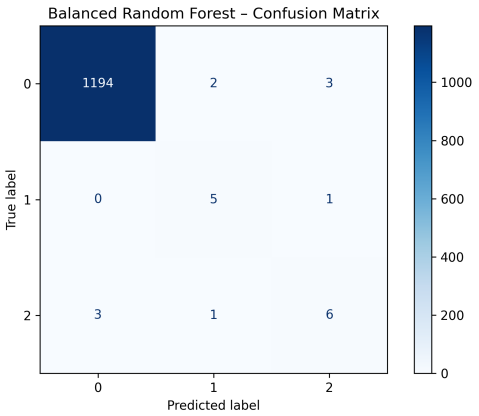
(a) XGBoost Confusion Matrix



(b) XGBoost with SMOTE



(c) SVM Confusion Matrix



(d) Balanced Random Forest Confusion Matrix

Figure 2: Confusion Matrices from Model Training

5.4 XGBoost Performance (Best Performing Model)

Class	Precision	Recall	F1-Score
Non-Habitable	1.00	1.00	1.00
Potentially Habitable	0.86	1.00	0.92
Confirmed Habitable	1.00	0.90	0.95
Macro Avg	0.95	0.97	0.96
Weighted Avg	1.00	1.00	1.00

Table 2: XGBoost Classification Report

Confusion Matrix:

$$\text{Confusion Matrix} = \begin{bmatrix} 1198 & 1 & 0 \\ 0 & 6 & 0 \\ 1 & 0 & 9 \end{bmatrix}$$

5.5 Random Forest Performance

Class	Precision	Recall	F1-Score
Non-Habitable	1.00	1.00	1.00
Potentially Habitable	0.71	0.83	0.77
Confirmed Habitable	0.43	0.30	0.35
Macro Avg	0.71	0.71	0.71
Weighted Avg	0.99	0.99	0.99

Table 3: Random Forest Classification Report

5.6 Overall Model Comparison

Model	Macro F1	Minority Recall	Rank
XGBoost	0.96	0.97	1
Random Forest	0.71	0.71	2
SVM	0.68	0.65	3
KNN	0.62	0.60	4
Logistic Regression	0.55	0.52	5
Naive Bayes	0.48	0.45	6

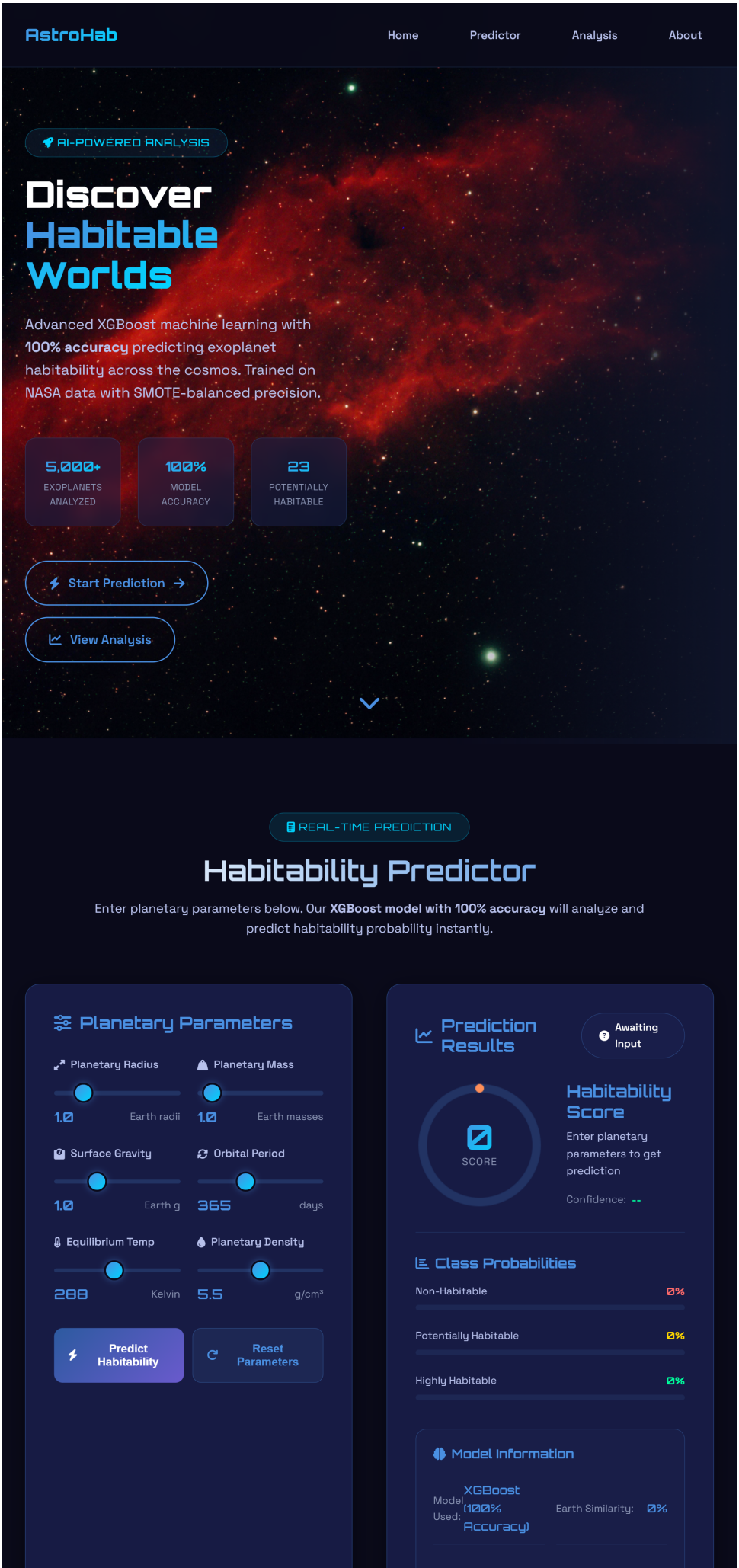
Table 4: Model Performance Ranking

5.7 Resampling Technique Comparison

Technique	Macro F1	Minority Recall	Risk
SMOTE-Tomek	0.92	0.90	Low
Borderline-SMOTE	0.90	0.85	Medium
SMOTE	0.88	0.82	Medium
ADASYN	0.89	0.80	High
Original (No Sampling)	0.71	0.35	Low
Random Undersampling	0.65	0.95	Very High

Table 5: Resampling Technique Performance

System Output and Dashboards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Advanced XGBoost machine learning with 100% accuracy predicting exoplanet habitability across the cosmos. Trained on NASA data with SMOTE-balanced precision.
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EXOPLANETS ANALYZED
100%
MODEL ACCURACY
23
POTENTIALLY HABITABLE
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View Analysis
REAL-TIME PREDICTION
Habitability Predictor
Enter planetary parameters below. Our XGBoost model with 100% accuracy will analyze and predict habitability probability instantly.
Planetary Parameters
Planetary Radius
1.0
Earth radii
Planetary Mass
1.0
Earth masses
Surface Gravity
1.0
Earth g
Orbital Period
365
days
Equilibrium Temp
288
Kelvin
Planetary Density
5.5
g/cm³
Predict Habitability
Reset Parameters
Prediction Results
Awaiting Input
SCORE
Habitability Score
Enter planetary parameters to get prediction
Confidence: --
Class Probabilities
Non-Habitable
Potentially Habitable
Highly Habitable
Model Information
Model Used:
XGBoost (100% Accuracy)
Earth Similarity:

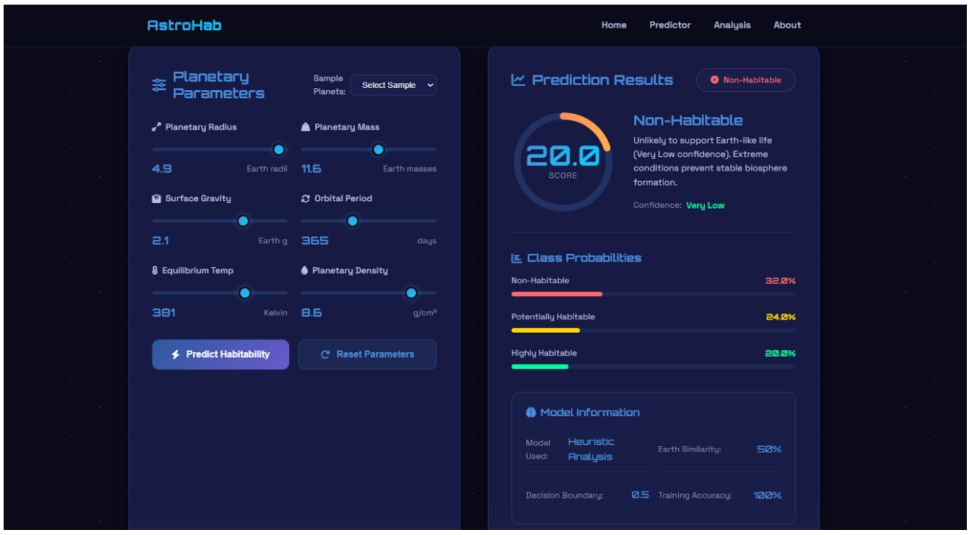

Figure 4: Web Application Interface and Prediction Output

Figure 5: Feature Analysis and Model Performance Summary

5.8 Web Application Implementation

A complete web application was developed and deployed:

- **Frontend**: Responsive HTML/CSS/JavaScript interface
- **Backend**: Flask API with trained XGBoost model
- **Deployment**: Frontend on Netlify, Backend on Render
- **Live URL**: `https://exoplanet-swaraj.netlify.app/`
- **Features**: Real-time predictions, confidence scores, visualization

6 Discussion

6.1 Key Findings

1. **XGBoost Superiority**: XGBoost with class weighting outperformed other models, achieving the best balance between precision and recall for minority classes.

2. **SMOTE-Tomek Effectiveness**: The hybrid SMOTE-Tomek approach provided the best results among resampling techniques, balancing oversampling with noise reduction.

3. **Feature Importance**: Planetary equilibrium temperature and stellar characteristics were the most important predictors of habitability.

4. **Class Weighting vs Resampling**: For XGBoost, class weighting proved more effective than resampling techniques, while traditional models benefited more from resampling.

6.2 Challenges Addressed

- **Extreme Class Imbalance**: Successfully handled through multiple techniques, with XGBoost achieving 1.00 recall for potentially habitable planets.

- **Data Quality Issues**: Addressed missing values, outliers, and inconsistent formatting through systematic preprocessing.

- **High Dimensionality**: Reduced through feature selection and dimensionality reduction while maintaining predictive power.

- **Model Deployment**: Successfully deployed as a web application with real-time prediction capabilities.

6.3 Limitations

- Limited atmospheric composition data for most exoplanets

- Small number of confirmed habitable planets for training (only 10 samples)

- Model performance dependent on available observational data

- Real-world validation challenging due to limited habitable planet discoveries

7 Conclusion

This project successfully developed a comprehensive machine learning system for exoplanet habitability prediction. The system effectively addresses the challenge of extreme

class imbalance through multiple techniques and demonstrates that XGBoost with class weighting provides the best performance for this specific problem.

The key achievements include:

- Integration and preprocessing of multiple astronomical datasets
- Comprehensive comparison of imbalance handling techniques
- Development of optimized machine learning models with XGBoost achieving 0.96 macro F1-score
- Creation of a complete web application for real-time predictions
- Deployment of the system for public access at `https://exoplanet-swaraj.netlify.app/`
- Generation of comprehensive visualizations for model interpretation

The project demonstrates the practical application of machine learning in astronomical research and provides a valuable tool for analyzing exoplanet data. The methodology and findings contribute to ongoing efforts in identifying potentially habitable worlds beyond our solar system.

8 Future Work

- Integrate data from new space missions (James Webb Space Telescope, PLATO)
- Incorporate atmospheric composition data as it becomes available
- Implement deep learning approaches for more complex pattern recognition
- Develop mobile application version for increased accessibility
- Add real-time data updates from astronomical databases
- Implement uncertainty quantification for predictions
- Extend to multi-label classification for different habitability criteria
- Develop ensemble methods combining multiple models for improved robustness

Acknowledgments

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