### **Problem 01: Analysis of Exoplanets Based on Orbital Time Period**

#### **Approach to Dataset and Histogram Generation**

1. **Data Collection**:
   * Accessed the exoplanet catalog via the provided link.
   * Filtered data to include only confirmed exoplanets detected using the Radial Velocity (RV) method.
   * Exported relevant parameters, particularly the orbital period (in Earth days).
2. **Data Cleaning**:
   * Removed entries with missing or erroneous orbital period data.
   * Limited the orbital period range to 0–400 Earth days to focus on short to moderately long-period planets, avoiding skewness from extreme outliers.
3. **Histogram Generation**:
   * Used Python’s matplotlib and seaborn libraries for visualization.
   * Binned data into intervals of 10 days, plotted the histogram, and added labels for clarity.

#### **Key Insights**

1. **Concentration of Short-Period Exoplanets**:
   * Most exoplanets detected via the RV method exhibit orbital periods less than 50 days. This is due to:
     + **Observational Bias**: Closer planets cause larger and more frequent Doppler shifts, making them easier to detect.
     + **Detection Sensitivity**: Short-period planets induce stronger gravitational tugs, producing higher velocity amplitudes.
2. **Scarcity of Long-Period Exoplanets**:
   * Longer orbital periods result in weaker Doppler shifts and require more extended observation times to detect multiple cycles.
   * Current technology limits and observational time constraints hinder the detection of Earth-like planets with orbital periods similar to Earth, Venus, or Mars.

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### **Problem 02: Radial Velocity Method for Finding Exoplanets**

#### **Analysis of 51 Pegasi Radial Velocity Data**

1. **Scatter Plot**:
   * Loaded the radial velocity dataset.
   * Plotted time (Julian date) on the X-axis and radial velocity (m/s) on the Y-axis.
   * Observed periodic oscillations indicative of the planet’s influence.
2. **Initial Period Estimate**:
   * Identified a repeating pattern visually, estimating an orbital period of approximately 4.2 days.
3. **Lomb-Scargle Periodogram**:
   * Applied the periodogram formula to identify the period with the highest power.
   * Estimated a precise orbital period of ~4.23 days.
4. **Phase Folding**:
   * Folded the radial velocity data using the derived orbital period.
   * Plotted the phase-folded radial velocity curve to reveal the periodic motion of the star.

#### **Key Observations:**

* The derived orbital period matches historical observations of 51 Pegasi b.
* Noise in the folded curve may be due to measurement uncertainties or additional system factors.

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### **Problem 03: Pulsars in Deep Space**

### Numerical Dataset Analysis

### Data Preprocessing:

### Scaled numerical features using StandardScaler from scikit-learn.

### Split data into training and validation sets (80:20 ratio).

### Model Development:

### Trained a Random Forest model with hyperparameter tuning (e.g., tree depth and the number of estimators).

### Performance Evaluation:

### Metrics used: Accuracy, precision, recall, F1 score, and ROC-AUC.

### Achieved high precision, reducing false positives.

### Performance Summary:

### Accuracy: 93.25%

### Precision: 88.97%

### Recall: 91.54%

### F1 Score: 90.23%

### ROC-AUC: 96.78%

### Advantages and Limitations:

### Advantages:

### Faster training and easier preprocessing.

### High interpretability using metrics like feature importance.

### Limitations:

### Limited to structured data.

### Performance depends on feature engineering.

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### Image Dataset Analysis

### Preprocessing:

### Resized images to 64x64 pixels.

### Normalized pixel values and created batches for training.

### CNN Model:

### Designed a 4-layer CNN with convolutional, pooling, and fully connected layers.

### Used cross-entropy loss and Adam optimizer.

### Applied mixed precision training (GradScaler) and GPU acceleration.

### Performance Evaluation:

### Validation Accuracy: 87.5%.

### Training Loss: Converged to ~0.02 after 10 epochs.

### Advantages and Limitations:

### Advantages:

### Able to capture complex spatial patterns in images.

### Does not require manual feature engineering; instead, it learns features automatically.

### Limitations:

### Requires significant computational resources (e.g., GPUs).

### Slower training process due to model complexity.

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### Comparison and Discussion

### Numerical Models (Random Forest):

### Faster training and interpretation.

### Suitable for structured datasets with defined features.

### Ideal when computational efficiency and interpretability are critical.

### Image Models (CNN):

### Better for complex, high-dimensional image data.

### Requires more computational resources but excels in tasks requiring intricate pattern recognition.

### In summary, the Random Forest model achieved higher accuracy (93.25% vs. 87.5%) and efficiency, making it preferable for structured data. However, the CNN model excelled in recognizing complex image patterns, highlighting its strength for unstructured data tasks like image classification.

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### **Problem 04: Orbital Resonances**

#### **Approach**

1. **Inner Planet’s Orbital Period**:
   * Using Kepler’s Third Law:
   * Substituted and :
2. **Outer Planet’s Semi-Major Axis and Orbital Period**:
   * For a 3:2 resonance:
   * From Kepler’s law:
3. **Discussion**:
   * Resonances can enhance tidal heating, potentially affecting planetary atmospheres and habitability.
   * Gravitational interactions may destabilize orbits over time but can also promote long-term stability if resonances persist.

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### **Problem 05: Escape Velocity from a White Dwarf**

#### **Approach**

1. **Escape Velocity Formula**:
   * Using energy conservation:
   * Substituted and .
2. **Calculation**:
   * Values:
     + .
     + .
   * Result:
3. **Discussion**:
   * High escape velocities intensify accretion disk dynamics and electron degeneracy pressure.
   * White dwarfs exhibit extreme gravitational effects, influencing nearby matter and potentially triggering supernovae.