Quantifying the lunar impact on astronomical observations using a machine learning framework for visibility prediction

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Introduction

Empirically excluding regions near the Moon not only reduces the available sky area but also restricts the operational flexibility of scheduling strategies, thereby decreasing overall resource utilization efficiency. Consequently, dynamic evaluation of observational feasibility is needed during scheduling. Existing models generally lack descriptions of the relationship between lunar illumination and target visibility. Thus, establishing a model capable of quantitatively characterizing the impact of moonlight and predicting target visibility under varying conditions has become a key scientific issue for advancing intelligent observation scheduling systems.

Visibility of a target

Quantitatively describing the impact of moonlight and predicting target visibility under varying conditions requires jointly considering target brightness, background sky brightness, and atmospheric effects.

Observation time *t*

$$t = \frac{T_{\mathrm{obs}} - T_{\mathrm{sunset}}}{T_{\mathrm{sunrise}+1\mathrm{day}} - T_{\mathrm{sunset}}}$$

Altitude *h*

$$\sin h = \sin\varphi \sin\delta + \cos\varphi \cos\delta \cos(S - \alpha)$$

Extinction *I*

$$\begin{cases} X = \dfrac{1.002432\cos^2 z + 0.148386\cos z + 0.0096467}{\cos^3 z + 0.149864\cos^2 z + 0.0102963\cos z + 0.000303978} \\ z = 90^\circ - h \end{cases}$$

$$I = I_0 \cdot \mathrm{e}^{-\tau X}$$

Lunar phase *θ*

$$\theta = \varphi_\odot - \varphi_\oplus$$

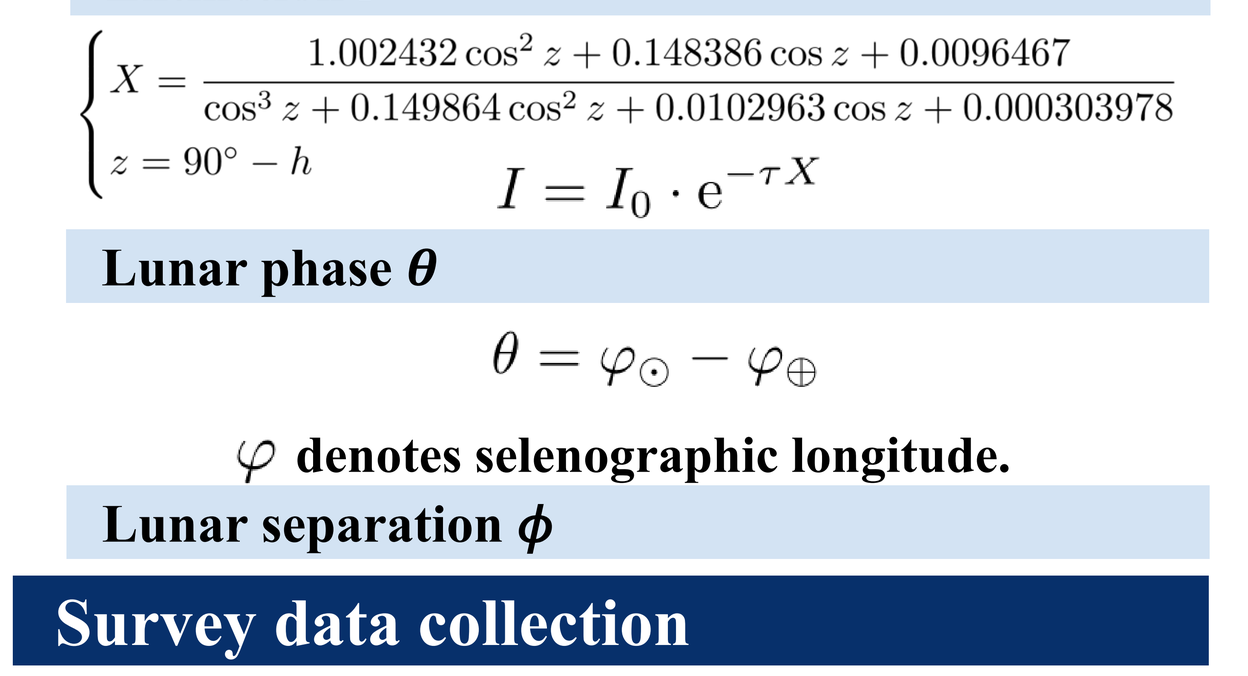
φ **denotes selenographic longitude.**

Lunar separation *ϕ*

Survey data collection

- **From 31 March 2023 to 22 June 2024**
- **With denser sampling at smaller separations and sparser sampling at larger separations, green dots**

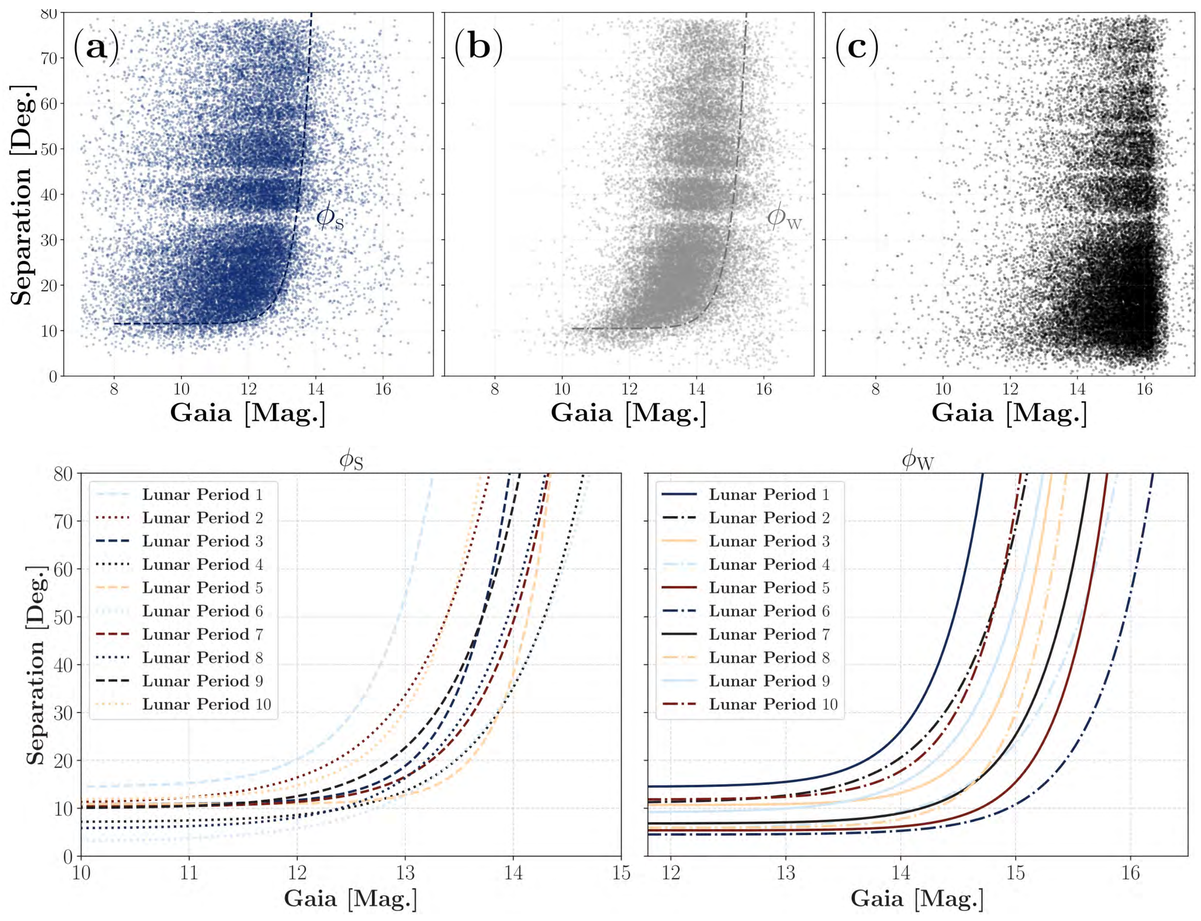
$$\mathbb{S} = \{4^\circ, 6^\circ, 8^\circ, 10^\circ, 12^\circ, 15^\circ, 18^\circ, 21^\circ, 25^\circ, 30^\circ, 40^\circ, 50^\circ, 60^\circ, 75^\circ\}$$



$$Y = \begin{cases} 1, \text{ for SNR} \geq 10, \text{ Visible} \\ 0, \text{ for SNR} < 3, \text{ Invisible} \\ \times, \text{ for } 3 \leq \text{SNR} < 10, \text{ Unstable} \end{cases} \qquad X \begin{cases} t & \text{Mag} \\ h & I \\ \theta & \phi \end{cases}$$

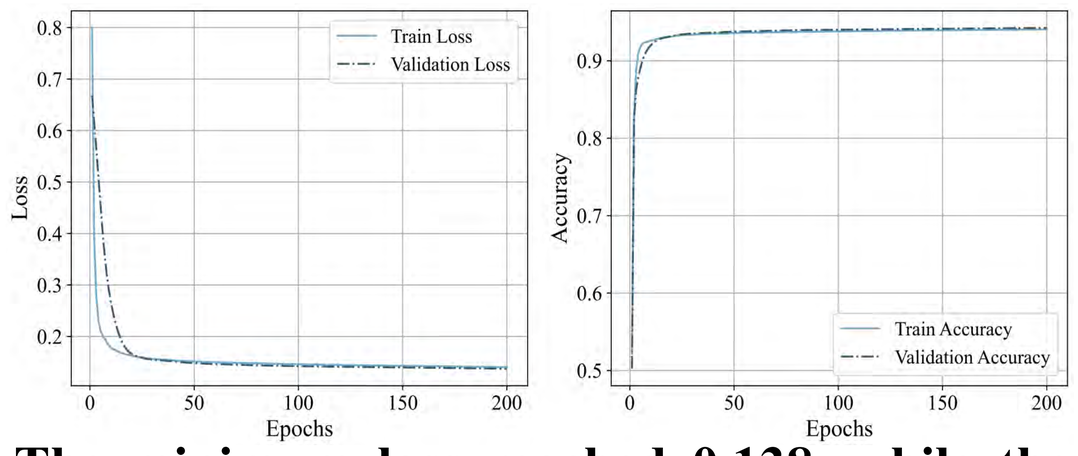
Results

Correlation between Separation-Gaia



Discriminative results

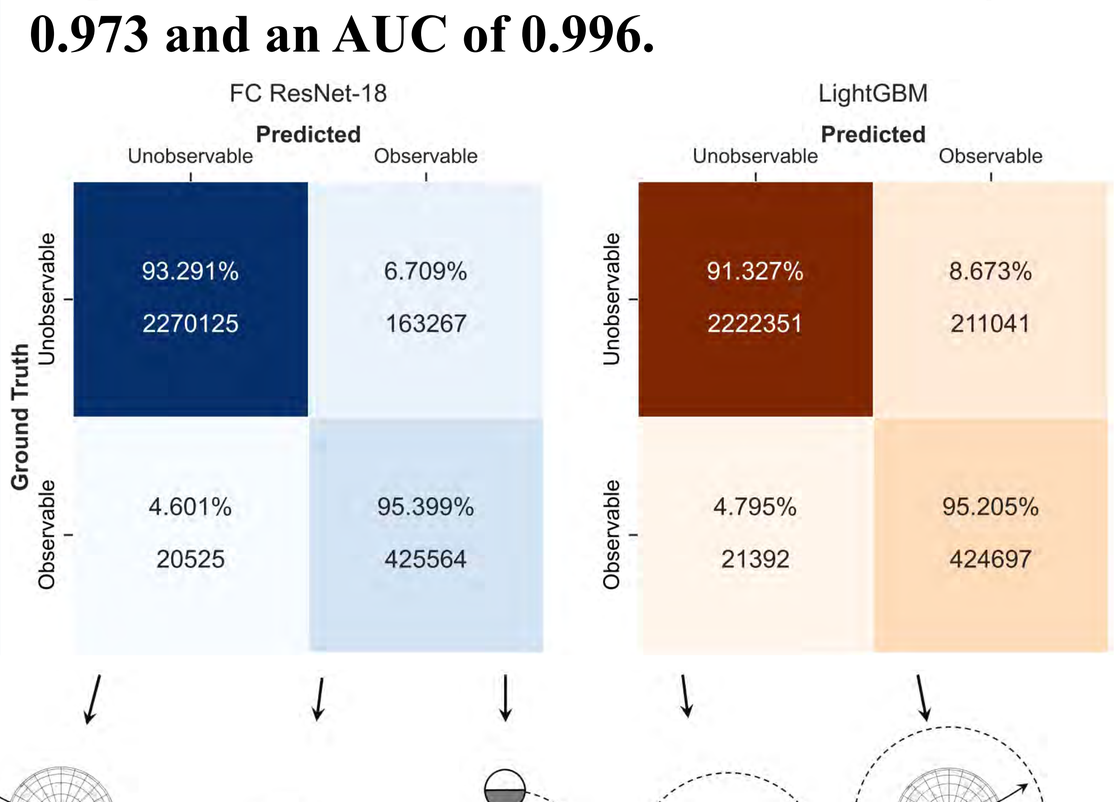
FC ResNet-18

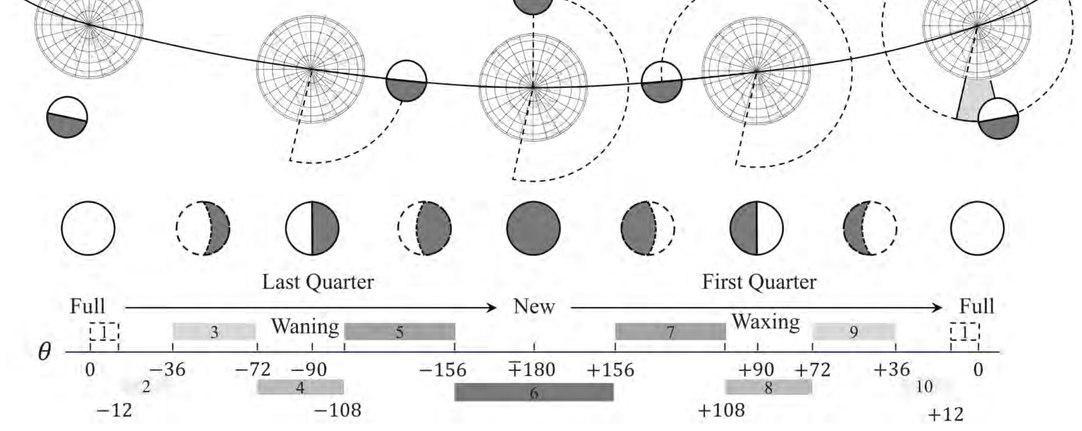


The minimum loss reached 0.138, while the maximum accuracy was 0.942, with an AUC of 0.988.

LightGBM

LightGBM model achieved an accuracy of 0.973 and an AUC of 0.996.





Lunar Period	1	2	3	4	5	6	7	8	9	10
Satellites	18105	34752	35952	33868	49410	39551	34213	45560	37650	19550
Denoising	18070	34720	35891	33840	49410	39546	34194	45534	37625	19538
FC ResNet-18	18070	34720	35868	32959	49407	39544	34180	45534	37625	19460
/ (%)	99.806	99.908	99.768	97.314	99.994	99.982	99.903	99.943	99.934	99.538
LightGBM	12847	28618	31895	32521	48767	38987	30825	41267	31464	15427
/ (%)	70.930	82.350	88.730	95.990	98.699	98.574	90.114	90.585	83.547	78.915

Conclusion

By integrating moonlight-affected observational data with star catalog information, and by combining two machine learning algorithms—FC ResNet-18 and LightGBM, the model enables accurate assessment of target visibility under different lunar phases.