A Deep Learning Framework for Inferring Extraterrestrial Intelligence from Transit Photometries Consistent with Various Theorized Kilostructures

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ABSTRACT

Hypothesized extraterrestrial technological intelligences have been theorized to construct large structures orbiting their host star. These structures may be detected using their transit light curves. In this research, we trained a deep neural network on epoch photometries queried from GAIA Dr3 and synthetic light curves simulated for these various theorized transiting geometries. Our completed model learns this data up to 88 percent training accuracy, and can be applied to future astrometric surveys, such as the Roman Telescope or Magellan.

BACKGROUND

➢ All observable systems emit a measurable luminosity from their host star which can be fitted to a flux value:

$$\Phi = \frac{L}{4\pi d^2} = \frac{4\pi R_*^2 \sigma T^4}{4\pi d^2} \tag{1}$$

➢ This flux can be measured using photometry. When any object passes in front of the star, it blocks out a small portion of light:

$$\Delta\Phi = \frac{\sigma T^4}{\pi d^2} \cdot (\pi R_*^2 - \pi r^2) \tag{2}$$

➢ The silhouette of the transiting satellite varies depending on its orientation in orbit with respect to the observer:

$$s(t) = ||(\mathbf{I} - \hat{l}\hat{l}^\top)(\vec{c}_0(t) - \vec{c}_*(t))|| \tag{3}$$

➢ This helps us turn our change in area into a function of time:

$$A_{\text{blocked}}(t) = A(s(t), R_*, r) \tag{4}$$

➢ This is how we derive distinct light curves through the transit method, observing the change in flux measured:

$$\Delta\Phi(t) = \frac{\sigma T^4}{d^2} \cdot A(s(t); R_*, r) \tag{5}$$

➢ Most notable transiting bodies are either exoplanets or moons of gas giants, whose geometries are mainly spherical. This keeps their flux "dips" relatively constant.

➢ What happens to that dip when a large, unnatural structure, that could only be constructed by an advanced civilization, orbits their system's star?

➢ For this, we test three proposed classes of *kilostructures*:
- The O'Neill Cylinder: A habitat proposed by Gerard K. O'Neill in a 1974 of *Physics Today* [2]
- The Stanford Torus: A habitat proposed in a NASA design study in 1975 [3]
- The tidally locked pyramid: A structure published by Luc F. A. Arnold in the Astrophysics Journal in 2005

DATA

Using equation (5) and fixed orientations, we simulate the light curves of our chosen transiting kilostructures as shown:

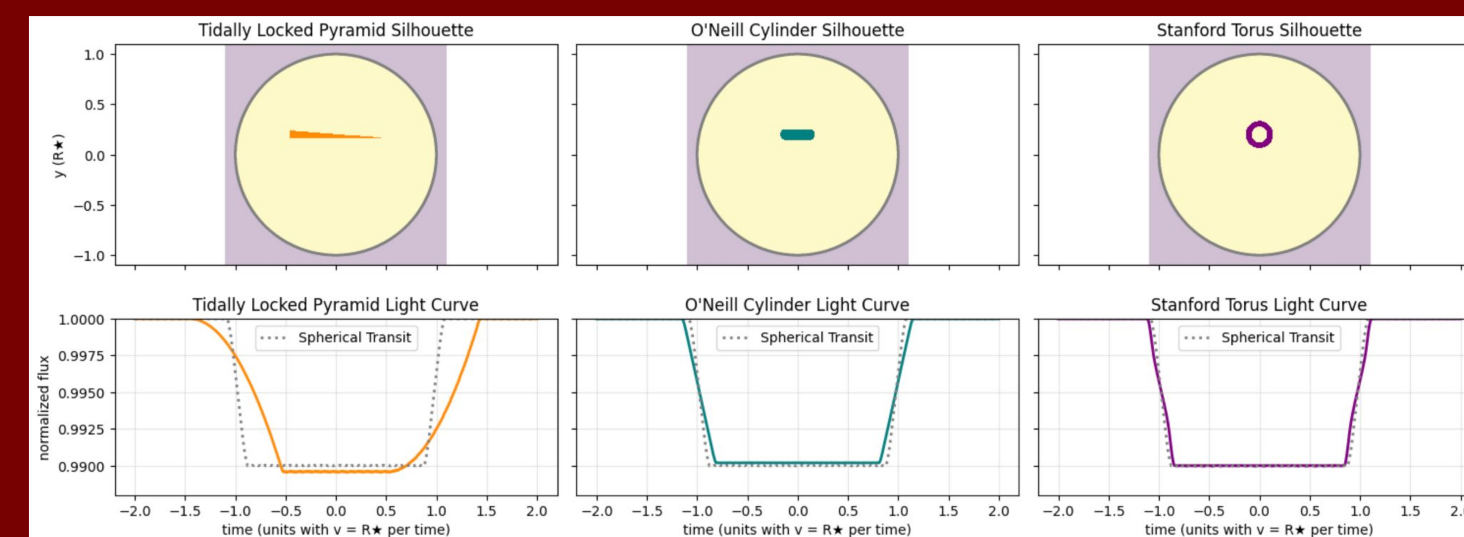
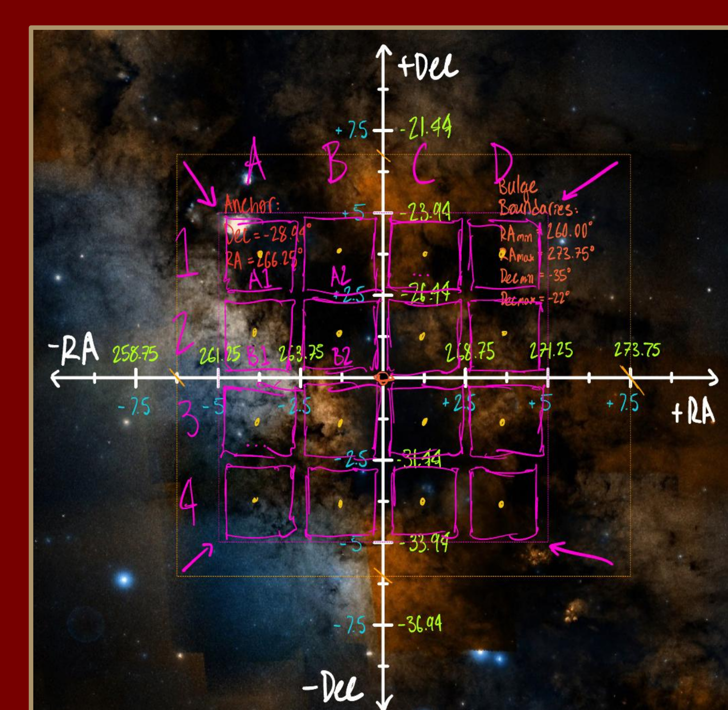


Figure 1: Geometries & Light Curves of Tested Kilostructures Compared to Natural, Spherical Geometries

To bury our synthetic light curves amidst enough real, comparative sources, we draw our real epoch photometries from GAIA's data release 3. [1] Our sourcing range is a series of 16 connected box queries, each 2.5 degrees across, centered around Sagittarius A*, as shown in figure 2 below.



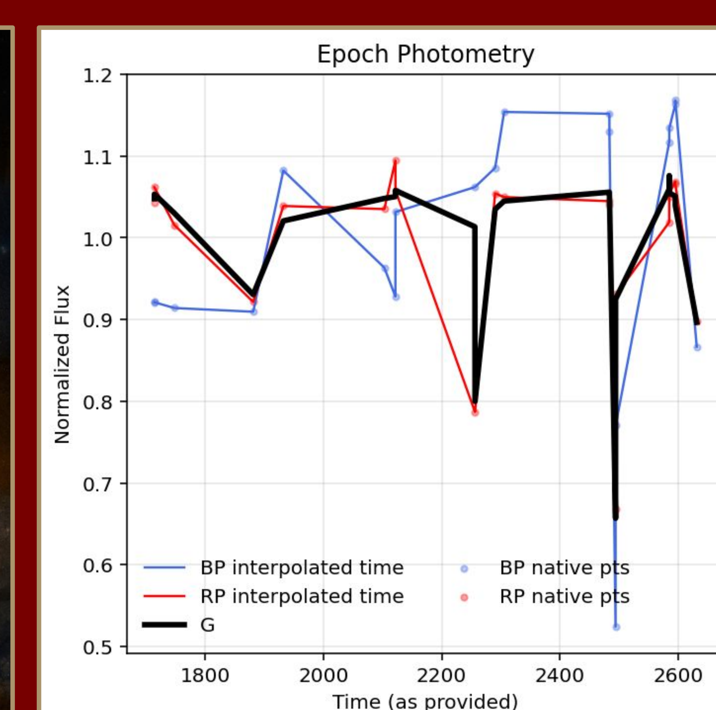


Figure 2: (left) Hand-drawn query range centered at Sagittarius A with approximate ICRS mapping*
Figure 3: (right) Sample epoch photometry of Gaia Dr3 Source ID 4109740749689569024

This provides us with a bright, well defined, dense stellar population. ADQL conditionals are used to return the desired parameters and remove contaminants such as binary stars and quasars. Each returned source ID allows us to query epoch photometries for our resulting 11,103 stars with observable transiting bodies. A sample epoch photometry for the star of source ID [number] is shown in figure 3 above.

METHODS

Our deep neural network operates through a dataloader, convolution, activation & vector heads. The dataloader applies a chromatic jitter to the synthetic positives, generating enough positives to imbed amongst the 11,103 negatives. The architecture is represented in figure 6 in the results section.

RESULTS

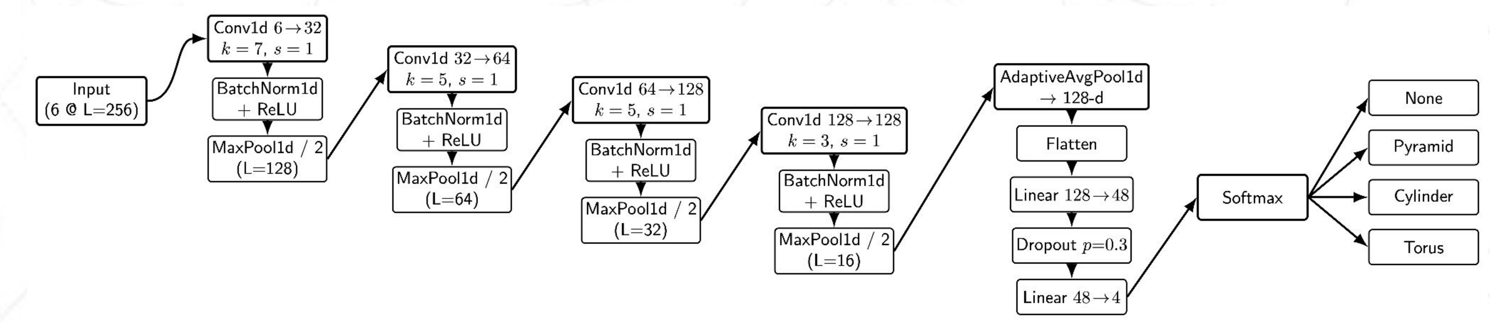
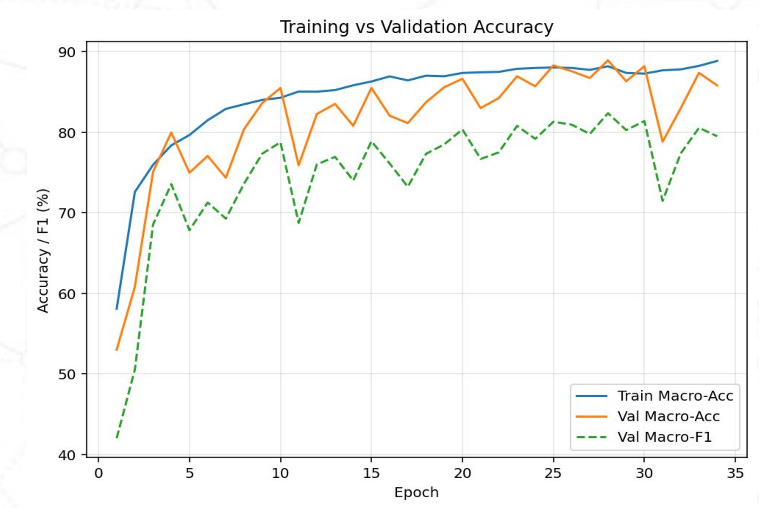


Figure 4: Neural Network Architecture Dimensionalized into LeNet to FCNN Format

The accuracy and loss curves for the optimized model are shown in figures 5 and 6, respectively:



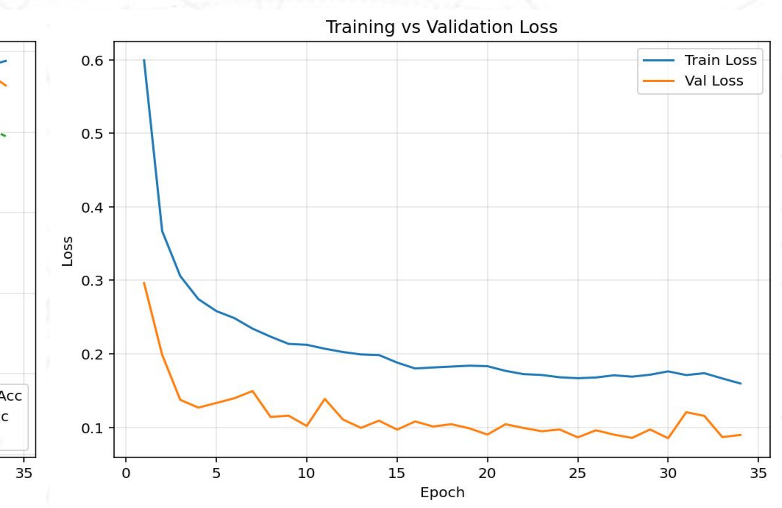


Figure 5: (left) Training, Validation, & Macro Metric Accuracy Curves across 34 Epochs of Training
Figure 6: (right) Training & Validation Loss Curves across 34 Epochs of Training

These results indicate slight overfitting, but within acceptable range for a dataset as abundant as ours. This was reduced as much as possible by intentionally sabotaging the learning rate to generate high volatility, tuning as needed, and then adding macro metrics to stop the model from rewarding itself too heavily for correctly classifying the non-kilostructure sources. The volatility was then corrected by decreasing momentum and adding plot smoothening, then final hyperparameter tuning.

CONCLUSION

While leaving room for further development, our model successfully predicted and classified the tested kilostructures with 88% training accuracy. We intend to use this classifier to search for transits of interest in future surveys. Moving forward, this work can guide other astrophysicists with interests in deep learning, and provide a foundation for other CNNs working with transit photometry.

REFERENCES

1. *This work has made use of data from the European Space Agency (ESA) mission Gaia* (https://www.cosmos.esa.int/gaia), *processed by the Gaia Data Processing and Analysis Consortium* (DPAC, https://www.cosmos.esa.int/web/gaia/dpac/consortium). *Funding for the DPAC has been provided by national institutions, in particular the institutions participating in the Gaia Multilateral Agreement.*
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4. *L. F. A.* Arnold, "Transit Lightcurve Signatures of Artificial Objects", *Astrophysical Journal*, Vol. 627, No. 1, July 2005.

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