



# Recovery of *TESS* Stellar Rotation Periods with Deep Learning

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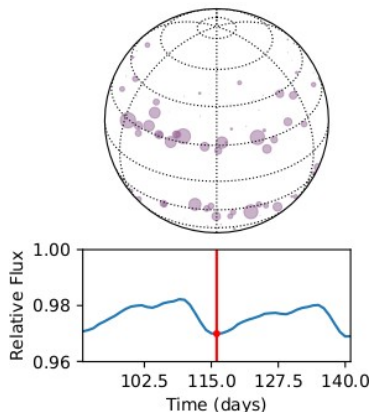


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Convolutional Neural Networks (CNNs) have the power to peer through *TESS* systematics to predict stellar rotation periods. We use CNNs to obtain periods for stars in *TESS* full-frame images (FFIs).

## Data

Our training dataset consists of 1 million simulated light curves. The simulations, made using *butterpy* [\*], are based on sunspot emergence and evolution code. Using *butterpy*, we vary rotation, latitudinal differential rotation, atmospheric activity level, and spot evolution to produce noiseless light curves.

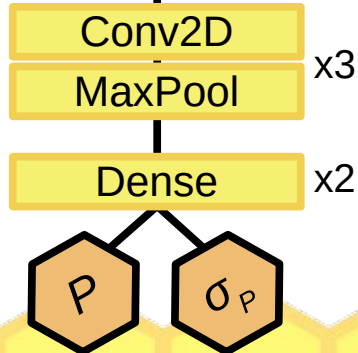
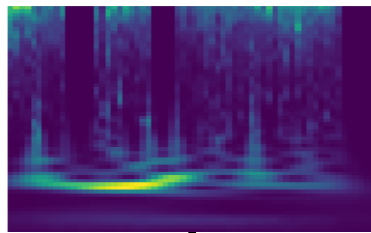


A realistic training set should contain realistic *TESS* systematics.

We extract galaxy light curves from *TESS* FFIs and inject them into our synthetic light curves to emulate *TESS* data products.

## Architecture

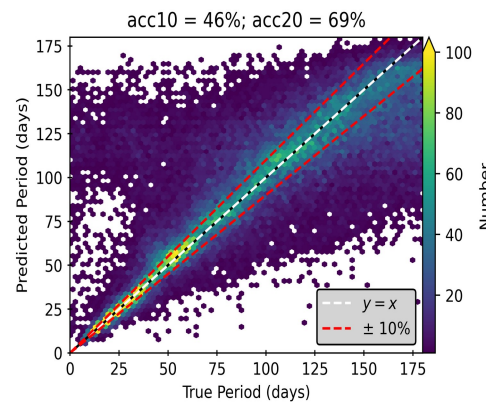
The noise-injected, synthesized light curves are normalized sector-by-sector, and we compute their wavelet power spectra (WPS). We feed the 2D WPS as an image into a CNN. The CNN uses 2D convolution and 1D max-pooling to optimize extraction of frequency information while learning to recognize noise and systematic features.



CNNs take advantage of computer vision technology and can learn the difference between noise and signal.

## Train

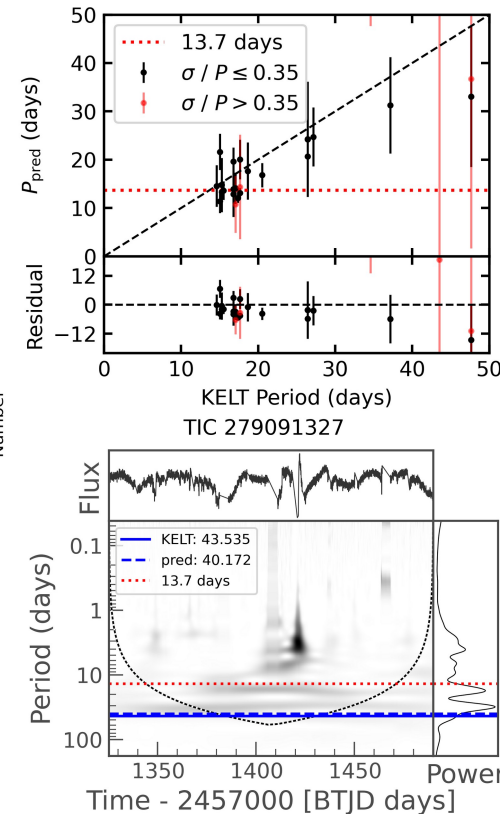
We partition the input dataset 80%/10%/10% into training, validation, and test sets. The CNN fully trains in about 4 hours on an NVIDIA RTX-2080. Using a Laplacian log-likelihood loss function allows us to predict both the rotation period and its uncertainty.



Predicting the period uncertainty lets us select objects with more confident estimates. With this selection, we recovery 46% (69%) of objects' periods to within 10% (20%) accuracy.

The trained network can predict periods for new input data in a fraction of a second!

## Evaluate/Predict Periods

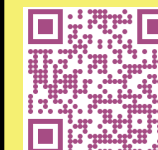
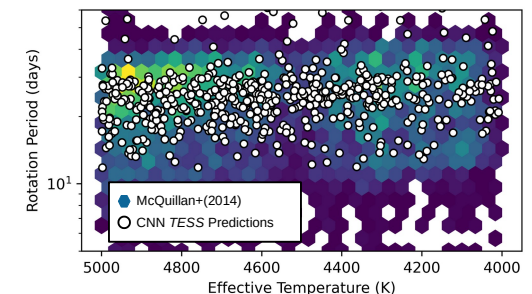


We successfully recover periods for KELT stars with existing measurements.

Even in cases where traditional periodograms are dominated by systematics, our CNN recovers the correct rotation period.

## Takeaways

- We recover known rotation periods from *TESS* data using Deep Learning.
- Our CNN can see beyond *TESS* systematics to predict periods.
- Predicting period uncertainty gives an added measure of confidence in our estimates.
- We are using the trained network to predict new rotation periods for *TESS* FFI stars.



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2104.14566

[\*] [github.com/zclaytor/butterpy](https://github.com/zclaytor/butterpy)