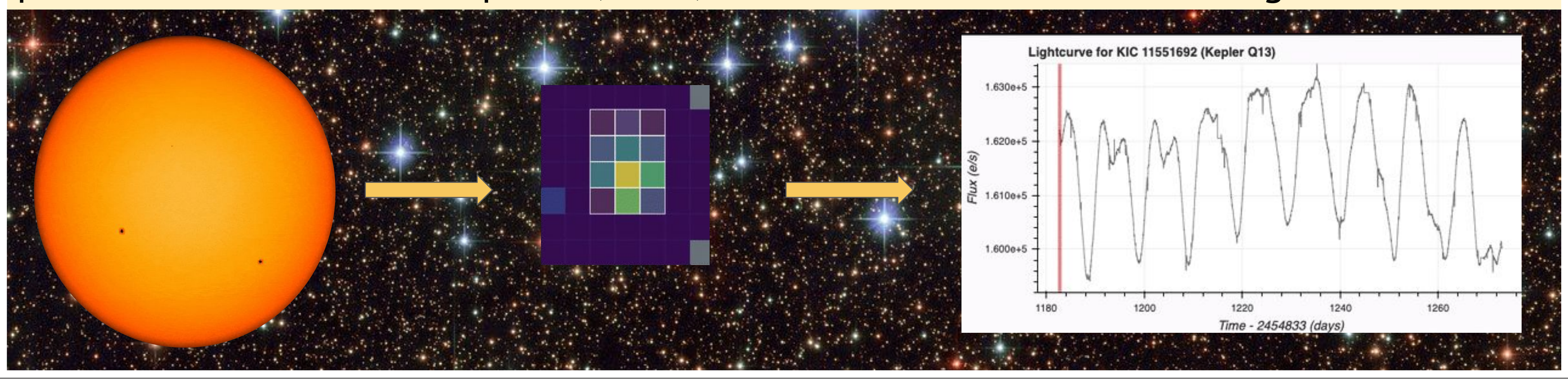
RotNet : Fast and Scalable Estimation of Stellar Rotation Periods Using Convolutional Neural Networks

J. Emmanuel Johnson[1], Sairam Sundaresan[2], Tansu Daylan[3], Lisseth Gavilan[4], Daniel K. Giles[5], Stela Ishitani Silva[6], Anna Jungbluth[7], Brett Morris[8], Andrés Muñoz-Jaramillo[9]

[1]University of València, [2]Intel Labs, [3]MIT, [4]NASA ARC, [5]IIT, [6]Catholic University, [7]Oxford University, [8]University of Bern, [9]SwRI

INTRODUCTION

The **magnetic field of stars** strongly affects the **habitability of nearby planets**. Currently, very little is known about the magnetic activity of stars other than the Sun. Magnetically active stars can show dark spots on their surface **(starspots)**. Distant stars are imaged as **a set of pixels** whose **brightness changes** are monitored with time. Several stellar parameters can be inferred from these light curves including the number of spots, sizes and rotation characteristics. The most critical parameter is the rotation period, P_Θ, which is correlated to stellar age and size.



TIME SERIES TO IMAGE TRANSFORMATIONS

To take advantage of **transfer learning** with SOTA pre-trained ResNet-18 convolutional neural networks, we used geometry preserving transformations [1] of our time series to images. We create a 3-channel image using the Grammian Angular Field (**GAF**), Markov Transition Field (**MTF**), and the Recurrence Plot (**RP**).

CHALLENGES

Can we use 1-D time series of the changing photon flux (light curves **due to starspots** on the surface) to estimate a **star's rotation period**?

- ***Redundant***: Many parameters describe the data equally well.
- ***Few-labels***: Lack of ground-truth on large-data scales.
- ***Physics SOTA***: computationally expensive and time consuming.

DATA & PREPROCESSING

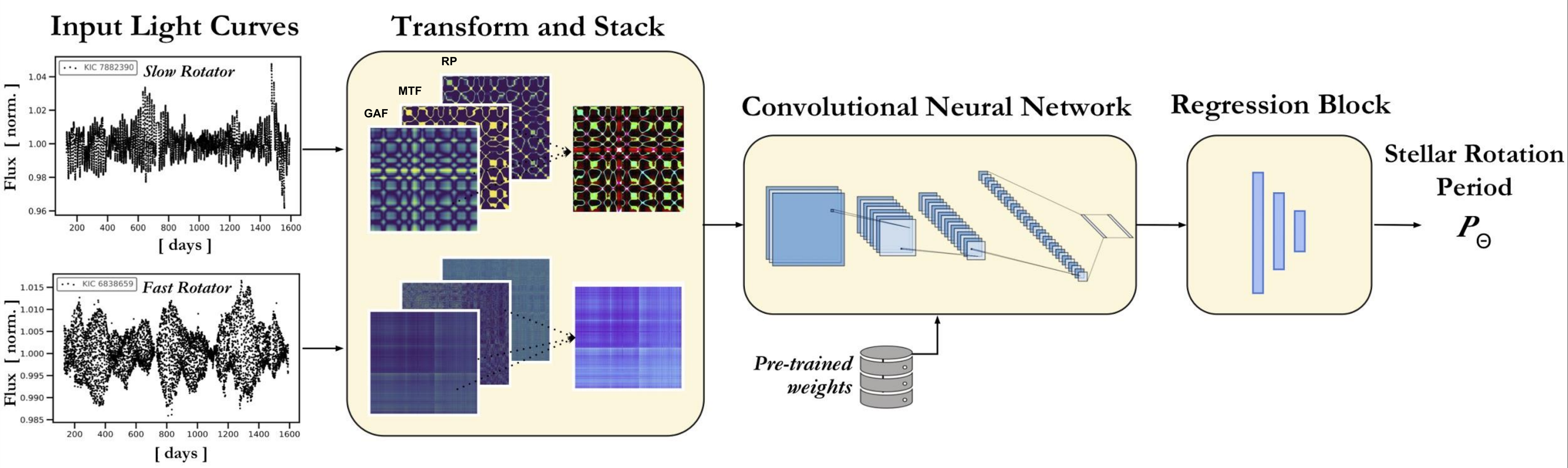
- **~100K** light curves in the catalog from *Kepler* mission
- **18,472** light curves with McQuillan rotation period estimates
- Each light curve is a time series, with ~60k data points which were rebinned to **1,080** time steps.
- P_Θ Transformation: Log Transform + Quantile Transform + MinMax Scaling

BASELINE METHODS

- AutoCorrelation Function (*Physics Community SOTA*)[2]
- Random Forest Regressor
- 1D Convolutional NN

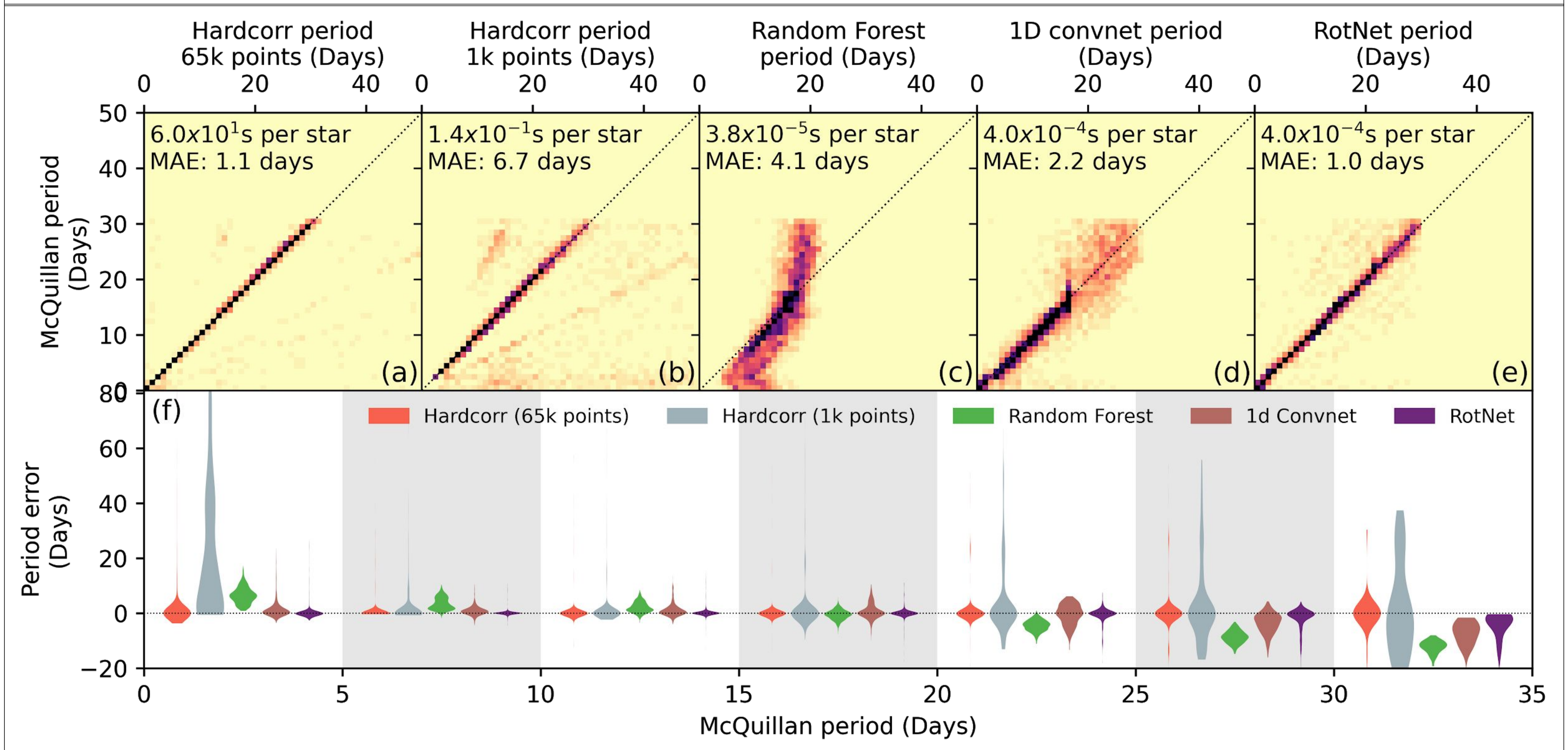
RotNet

1. Time series input
2. Stacked image transforms
3. Pretrained CNN Feature Extractor
4. Regression Block
5. Regressed Rotation Period



Results

- 2D Histograms for 3,700 stars in our test said versus benchmark McQuillan periods (cite)
- Time is measured on a single CPU
- Violin Plots display residual errors



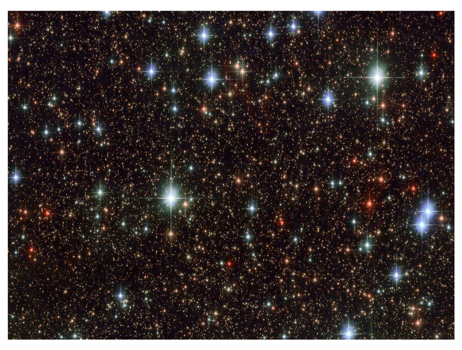
RESULTS

Despite limiting our input to fewer data points, our 2D CNN:

- Beats the SOTA accuracy
- 350x times faster than ACF (~1K data points)
- 10,000x times faster than ACF (~65K data points)
- Extensible framework for other stellar parameters

NEXT STEPS

- Evaluate the uncertainty of our predictions.
- Evaluate other time-series to image transformations
- Compare our ML results to inference methods.



Acknowledgements

This work was initiated at the NASA Frontier Development Lab (FDL) 2020 with partners including Google Cloud, Intel, IBM, and NVIDIA, amongst others. We also want to thank the mentors during the FDL period: Yarin Gal (Oxford), Gibor Basri (UC Berkeley), Antonino Lanza (INAF), and Valentina Salvatelli (IQVIA). Lastly, we thank Weights & Biases for their support.

References

[1] Zhiguang Wang and T. Oates. Encoding time series as images for visual inspection and classification using tiled convolutional neural networks. In AAAI Workshop - Technical Report 2015.

[2] A. McQuillan, T. Mazeh, and S. Aigrain. Rotation Periods of 34,030 Kepler Main-sequence Stars: The Full Autocorrelation Sample. The Astrophysical Journal Supplement Series ,211(2):24, April 2014.