A “Quick Look” at All-sky Galactic Archeology with TESS: 158,000 Oscillating Red Giants from the MIT Quick-look Pipeline

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Abstract

We present the first near all-sky yield of oscillating red giants from the prime mission data of NASA’s Transiting Exoplanet Survey Satellite (TESS). We apply machine learning toward long-cadence TESS photometry from the first data release by the MIT Quick-look Pipeline to automatically detect the presence of red giant oscillations in frequency power spectra. The detected targets are conservatively vetted to produce a total of 158,505 oscillating red giants, which is an order of magnitude increase over the yield from Kepler and K2 and a lower limit to the possible yield of oscillating giants across TESS’s nominal mission. For each detected target, we report effective temperatures and radii derived from colors and Gaia parallaxes, as well as estimates of their frequency at maximum oscillation power. Using our measurements, we present the first near all-sky Gaia-asteroseismology mass map, which shows global structures consistent with the expected stellar populations of our Galaxy. To demonstrate the strong potential of TESS asteroseismology for Galactic archaeology even with only one month of observations, we identify 354 new candidates for oscillating giants in the Galactic halo, display the vertical mass gradient of the Milky Way disk, and visualize correlations of stellar masses with kinematic phase-space structures, velocity dispersions, and α-abundances.

Unified Astronomy Thesaurus concepts: Asteroseismology (73); Stellar oscillations (1617); Astronomy data analysis (1858); Galactic archaeology (2178)

Supporting material: machine-readable table

1. Introduction

With high-precision, uninterrupted photometry from previous space-borne missions CoRoT (Baglin et al. 2006), Kepler (Borucki et al. 2010), and K2 (Howell et al. 2014), red giant asteroseismology has emerged as a powerful tool for probing stellar populations around the Milky Way. The precise measurements of masses, radii, and ages across thousands of field red giants offered by asteroseismology have brought forth new avenues for detailed studies of Galactic archaeology whereby such measurements are combined with kinematic and spectroscopic information to build a map describing the chemical and dynamical evolution of the Milky Way (e.g., Miglio et al. 2013, 2021; Casagrande et al. 2016; Silva Aguirre et al. 2018; Sharma et al. 2019).

However, efforts to apply asteroseismology across the Galaxy have been mainly hampered by the size of the observing windows provided by previous space missions. CoRoT observed a number of 4 square degree fields focused toward two opposite directions and observed ∼10⁶ red giants (Baglin et al. 2016), of which ∼3000 thus far have had seismic measurements (de Assis Peralta et al. 2018). Meanwhile, Kepler observed one region in the northern hemisphere spanning 100 square degrees, which resulted in ∼20,000 detections (Hon et al. 2019). The K2 mission observed 18 “Kepler field”-sized regions along the ecliptic, motivating the establishment of the K2 Galactic archeology Program (Stello et al. 2017; Zinn et al. 2020), which will further increase the number of detections by ∼30,000 (Zinn et al. 2021). Now, we seek to extend the scope of red giant asteroseismology toward the entire sky with NASA’s Transiting Exoplanet Survey Satellite (Ricker et al. 2014, TESS). Throughout the first two years of its nominal mission, TESS surveyed nearly the entire sky by observing 13 distinct sectors in both northern and southern hemispheres. Each sector covers a 96° × 24° field of view and yields Full Frame Images (FFIs) that provide high-precision flux measurements of millions of stars for up to 27 days at a 30 minute cadence. Meanwhile, stars in overlapping sectors are observed for at least 27 days, with a longer observational duration typically for stars closer to the ecliptic poles where there is maximal overlap between sectors. This unprecedented level of sky coverage is expected to increase the number of red giants with detected oscillations by about an order of magnitude over its predecessors.

A big challenge faced by asteroseismology with TESS is the survey’s observational duration. The majority of targets from the first two years of TESS observations will only be observed for 27 days, resulting in lower frequency resolution compared to Kepler and K2. However, the asteroseismic inference of stellar populations using TESS data is still viable. Depending on the availability of precise seismic measurements, Silva Aguirre et al. (2020) showed that it is possible to obtain precision levels of up to ∼3% for radii, ∼5% for mass, and...
approximately 20% for ages when incorporating both spectroscopy and parallax information in modeling the brightest ($V \sim 6–7$) TESS red giants. Similar precision levels were found by Stello et al. (2021) when comparing seismic results from TESS data against those from 4 yr Kepler data for $\sim 2000$ red giants observed by both Kepler and TESS. Furthermore, Mackereth et al. (2021) recovered median mass uncertainties of $\sim 8\%$ and age uncertainties of $\sim 26\%$ for $\sim 1700$ red giants with $G < 11$ near the southern ecliptic pole, where FFI targets were observed by TESS for up to a year. Mackereth et al. (2021) additionally indicate that the seismic ages of giants from TESS are sufficiently precise to distinguish chemically and kinematically defined structures within the Milky Way disk. Although the current outlook for red giant asteroseismology with TESS is promising, it has yet to be extended to the majority of TESS FFI targets. Not only is this because significantly more effort is required to systematically detect populations of oscillating red giants across the millions of TESS FFI targets, but detailed seismic parameters like the large frequency separation are difficult to measure with one-month-long observations (Hekker et al. 2012; Mosser et al. 2019; Mackereth et al. 2021, Stello et al. 2021). The frequency at maximum oscillation power, $\nu_{\text{max}}$, however, can be measured from any star with a detected oscillation power excess, making it a more accessible seismic measurement for inferring fundamental stellar properties.

The systematic detection of red giant oscillations, which has previously posed a significant challenge in the field, can now be facilitated using machine learning algorithms (Hon et al. 2018b, 2019). Such tools are vital in the era of TESS given the enormous volume of data the mission will provide, and indeed particular emphasis on the analyses of TESS-like data sets in asteroseismic machine learning has been provided in recent work (e.g., Armstrong et al. 2016; Hon et al. 2018a; Bugnet et al. 2019; Kgoadi et al. 2019; Kuszlewicz et al. 2020; Audenaert et al. 2021). However, an important aspect of supervised learning—which comprises most of current machine learning algorithms in asteroseismology—is the presence of training data that is expected to be representative of the data upon which inference is to be performed. In comparison to Kepler and K2, TESS has photometric qualities and instrumental noise sources that are unique to its observing instrument. This property makes it challenging to generalize algorithms that learn from Kepler/K2 data toward TESS data.

Despite these challenges, we proceed with applying machine learning to perform the first all-sky detection of red giants across the full two-year TESS Primary Mission. We examine all light curves that have been extracted from FFIs by the MIT Quick-look Pipeline (Huang et al. 2020a, 2020b, QLP) as High Level Science Products. In conjunction with detecting a substantial number of oscillating TESS red giants, we also provide a first look at TESS’s asteroseismic potential for full-sky Galactic archeology.

2. Data

We use all FFI light curves from the QLP team’s first data release, 11 which comprises observations across Sectors 1–26. This data release includes all targets brighter than a TESS magnitude of 13.5 and contains 24,376,080 light curves that have an observing cadence of $\sim 30$ minutes. In this study, we use only the raw light curves obtained using simple aperture photometry (SAP_FLUX). We do not use the detrended light curves (KSPSAP_FLUX), which are optimized for planet searches and therefore have stellar variability over long timescales filtered out. Additionally, we only use timestamps with a good quality flag (QUALITY = 0). Next, we high-pass filter each light curve using a boxcar filter with a width of 2 days and compute the light curve’s power spectral density using the generalized Lomb–Scargle periodogram (Lomb 1976; Scargle 1982). During this processing, we exclude light curves which have most ($\geq 95\%$) of their timestamps empty, resulting in a total of 23,962,744 power spectra corresponding to 14,702,113 unique stars observed by TESS.

3. Method

3.1. Neural Networks

We use the deep learning method as described by Hon et al. (2018b) to “visually” detect the presence of red giant oscillations within frequency power spectra. In particular, two convolutional neural networks are applied toward 2D images of log–$\log^13$ power spectra. By binning each star’s power spectrum into a $128 \times 128$ binary image, the first neural network outputs a classification score, $p_{\text{classified}}$, between 0 and 1 indicating the likelihood that red giant oscillations are visible within the spectrum. The second network, which trained independently from the first, is a regression network that measures the frequency at maximum oscillation power, $\nu_{\text{max}}$, and its corresponding uncertainty, $\sigma_{\nu_{\text{max}}}$. Specific details of the structure of both networks are provided in Appendix A.

3.2. Training Data

To train and test the classifier, we use KEPSEISMIC14 (Mathur et al. 2019) light curves of 196,816 Kepler targets of which 21,914 were identified to be oscillating red giants from the detections provided by Hon et al. (2019). For the $\nu_{\text{max}}$ regression network, we use a subset of the oscillating giants, specifically 16,194 red giants that have $\nu_{\text{max}}$ values measured from the asteroseismic data pipeline by Yu et al. (2018). For both classification and regression data sets, we allocate 70% of data to be used for training, 15% to be used to internally validate and tune the network, and the remaining 15% for network testing, which we describe in Section 3.3.

Because we want to train the deep learning method on light curves of comparable duration to TESS data, each 4 yr light curve in the training sets is segmented into multiple, unique 27 day segments. Due to the stochastic behavior of solar-like oscillations, there is, however, no guarantee that oscillations detectable in a 4 yr light curve will be visible over its constituent 27 day light-curve segments. Using 4 yr $\nu_{\text{max}}$ measurements from Yu et al. (2018), we apply the formalism of Chaplin et al. (2011) to statistically assess the significance of the oscillations within $\pm 0.66 \nu_{\text{max}}$ around $\nu_{\text{max}}$ for the power spectrum of each 27 day light-curve segment.15 For a power

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11 https://archive.stsci.edu/hlsp/qlp/
13 $\nu_{\text{max}}$ and its corresponding uncertainty, $\sigma_{\nu_{\text{max}}}$.
14 https://archive.stsci.edu/prepds/kepseismic/
15 Following Mosser et al. (2012), this frequency range is approximately twice the full width at half maximum of the oscillation power envelope.
spectrum of a light-curve segment to be included in the training set, it must have an oscillation signal-to-noise ratio exceeding the 1% false alarm threshold of a pure white noise spectrum. Because the $\nu_{\text{max}}$ for each power spectrum is already known from 4 yr Kepler data, we measure the oscillation signal-to-noise ratio directly from the spectrum rather than estimating it from fundamental stellar properties as per the original Chaplin et al. (2011) approach. Our final classification training set comprising Kepler data contains 714,820 light curves showing red giant oscillations and 4,959,892 light curves without red giant oscillations. Meanwhile, there are a total of 550,786 red giant power spectra for training the $\nu_{\text{max}}$ regression network.

One major challenge with using our Kepler training set is its difference in photometric data quality compared to TESS. In particular, TESS observations have lower photometric precision levels and are more susceptible to crowding effects (Sullivan et al. 2015). Additionally, TESS data may contain poorly characterized systematic noise. Power spectra from TESS data are therefore expected to have greater noise levels compared to Kepler data that we use for training, as demonstrated in Figure 1. As a result, the visibility of the oscillations for low luminosity (high $\nu_{\text{max}}$) red giants, particularly for those at the red giant branch, are diminished when approaching fainter TESS magnitudes as shown in Figure 2(a). Here, it can be seen that for TESS magnitudes $\geq 10$, high $\nu_{\text{max}}$ oscillations that can be seen with 4 yr of data are not expected to be observed in 1 month of data, in agreement with the analytical predictions made by Mosser et al. (2019). Consequently, we expect to detect oscillations primarily in giants with $\log(g) > 3.0$ dex as shown in Figure 2(b).

Besides the expected yield, the difference in photometric data quality between Kepler and TESS will also affect how well our networks can perform; it is thus important to identify this difference in performance so that we can determine a decision threshold that can adequately recover oscillating giants from TESS data.

3.3. Setting a Network Decision Threshold

3.3.1. Classification Thresholds

Figure 3(a) demonstrates how changing the acceptance threshold for the classifier affects the recall (sample completeness) and precision (sample purity) of the resulting oscillating giant yield of our 27 day Kepler test data. The recall metric reports the fraction of true oscillating giants within the test data that are successfully recovered by the classifier, while precision reports the fraction of accepted test stars that are truly oscillating giants. A lower acceptance threshold, $p_{\text{thresh}}$, accepts more targets and thus has greater completeness but at the cost of lower purity (more false positives). Conversely, a higher $p_{\text{thresh}}$ may miss a greater number of genuinely oscillating giants (lower recall) but is less likely to admit false positives. Indeed, Figure 3(b) shows that a strict threshold of $p_{\text{thresh}} = 0.95$ significantly reduces the false-positive rate across all magnitudes in the test set. Because we expect raw QLP light curves to contain greater white noise levels and uncorrected instrumental noise compared to our Kepler test set, we choose to be conservative in accepting positive detections and thus adopt $p_{\text{thresh}} = 0.95$.

To assess how greater noise levels from TESS will affect our ability to detect oscillations, we evaluate the classifier's completeness on synthetic TESS-like light curves created using celerite (Foreman-Mackey et al. 2017), which models stochastic variability in astrophysical time series using Gaussian processes. Artificial red giant light curves are generated using current information available about oscillation mode parameters and the granulation background. The granulation background emulates “model $F$” from Kallinger et al. (2014) with parameter values derived from the scaling relations found therein. The red giant universal pattern (Mosser et al. 2011) is used to generate frequencies of $\ell = 0, 2, 3$ oscillation modes from a given $\nu_{\text{max}}$ value, with amplitudes estimated from the scaling relations given in Mosser et al. (2012) and the mixed $\ell = 1$ oscillation modes computed according to the formalism by Vrard et al. (2016) and Mosser et al. (2018). Because the mixed-mode parameters depend on red giant evolutionary states, we determine evolutionary states for a synthetic red giant with a given $\nu_{\text{max}}$ by sampling from a known $\nu_{\text{max}}$-dependent distribution of known Kepler red giant evolutionary states (Elsworth et al. 2019). Next, we convert all derived oscillation parameters into the parameterization accepted by the simple harmonic oscillator kernel in celerite following Pereira et al. (2019) and subsequently generate light curves of 27 day durations. To mimic the TESS observing window, we include a 1 day gap in the middle of the light curve, which simulates the data downlink event. Finally, we add white noise into the light curves following the TESS long-cadence noise properties described by Sullivan et al. (2015), where we assume observations with no instrumental noise contribution and an ecliptic latitude of $30^\circ$. Examples of simulated power spectra are shown in Appendix B.

We simulate light curves across a uniform $\nu_{\text{max}}$ range of [5, 250] $\mu$Hz and a uniform TESS magnitude range of [6.0, 13.5] at the same time. Figure 4 shows the completeness of the classifier on a synthetic test set of 152,520 TESS red giants, where we can observe the performance of the network across a range of magnitudes and $\nu_{\text{max}}$. As expected, using a larger $p_{\text{thresh}}$ primarily affects the detection completeness of the test set near its upper boundary (red line), which is where the white noise levels in the simulated power spectra become comparable to the oscillation amplitudes. Both panels in Figure 4 distinctly show low detection completeness for the faint and luminous giants, i.e., stars with TESS magnitudes fainter than 11 and $\nu_{\text{max}} \lesssim 25\mu$ Hz. As discussed previously by Hon et al. (2018b), an important feature of a low $\nu_{\text{max}}$ oscillating giant to the classifier is the visibility of the granulation profile, i.e., the slope of the red noise in power spectra. The high white noise levels for fainter stars significantly diminish the visibility of the granulation slope (see the examples in Appendix C), which makes the classifier less confident in identifying oscillations in such stars.

3.3.2. Regression Threshold

Additionally, we set a criterion based on the properties of the $\nu_{\text{max}}$ regression network, which is trained independently of the classifier. Figure 5 shows a comparison of fractional $\nu_{\text{max}}$ uncertainties from the network across the Kepler (real) and TESS-like (simulated) test sets in this study. The uncertainties shown for the Kepler test set represent the best-case scenario for the network because the $\nu_{\text{max}}$

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16 https://celerite.readthedocs.io/
regression network is trained on Kepler data. Results on the synthetic test set, which has a broader range of white noise levels compared to its Kepler counterpart, show a broader scatter of uncertainties—this includes a larger upwards scatter for fainter targets with $\nu_{\text{max}} \lesssim 25 \mu$Hz that we associate with the network’s inability to locate a distinct oscillation power excess for such stars. We therefore determine a piecewise boundary (in red) below which we consider the network’s $\nu_{\text{max}}$ estimate to be consistent with a correct identification of an oscillation power excess. This boundary preserves over 96% of the test set estimates in Figure 5 and is described by $\sigma_{\nu_{\text{max}}}/\nu_{\text{max}} = 20\%$ for $\nu_{\text{max}} < 90\mu$Hz and $\sigma_{\nu_{\text{max}}}/\nu_{\text{max}} = 10\%$ for $\nu_{\text{max}} \geq 90\mu$Hz.

### 3.3.3. Threshold Summary

The combined criteria that we use in our networks are as follows:

1. $p_{\text{det}} \geq 0.95$ from the classifier.
2. $\sigma_{\nu_{\text{max}}}/\nu_{\text{max}} \leq 20\%$ for stars with $\nu_{\text{max}} < 90\mu$Hz.
3. $\sigma_{\nu_{\text{max}}}/\nu_{\text{max}} \leq 10\%$ for stars with $\nu_{\text{max}} \geq 90\mu$Hz.

These criteria are heuristic approaches that prioritize the precision of the detection yield using our methods. We apply these concessions because we aim to report the highest quality detections from TESS QLP data to cater toward optimizing early spectroscopic follow-up across both northern and southern hemispheres of the sky. Additionally, we assert that the

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**Figure 1.** A comparison of red giant frequency power spectra from Kepler and TESS. Each row corresponds to a red giant oscillating at a specific $\nu_{\text{max}}$ value (red line). Power spectra in the left column correspond to 27 day light curves from Kepler, while those in the right column correspond to the same Kepler targets but are observed by TESS.
recall and precision metrics reported in Figure 3 are highly optimistic of our method’s true performance on real TESS data. Their primary purpose is to guide us in the selection of $p_{\text{det}}$ for our preliminary analysis over TESS QLP data. An important consequence of this is that our reported results in the forthcoming sections are not expected to represent a complete population of all oscillating giants from TESS FFIs. To properly assess the completeness of our networks in detecting oscillating giants, we require more principled approaches to calibrating decision thresholds by benchmarking our networks on real, labeled TESS data. Such a data set has yet to be made because the systematic differences in photometric data quality between TESS and Kepler have yet to be fully quantified, in addition to the recency of FFI light curves extracted in bulk. We will thus investigate the detection completeness of near all-sky TESS data in forthcoming work.

4. Seismic Detection

4.1. Preliminary Yield

Figure 6 shows the initial detection result from our neural networks comprising 202,322 unique FFI targets that meet the threshold criteria outlined in Section 3.3. However, at this stage in our analysis, not all detected targets are guaranteed to be red giants because some are potentially faint non-red giants whose light curves show red giant oscillations due to flux contamination (blending) from neighboring giants. Due to the large TESS pixels, blending is expected to be particularly problematic for the detection task for fainter giants. Indeed, while the decline of detections at TESS magnitudes ($T_{\text{mag}}$) fainter than 10 is expected especially for high $\nu_{\text{max}}$ giants (see Figure 2), we observe an increase in the number of detected giants for $T_{\text{mag}} \gtrsim 11$ due to blending. We thus infer that the onset of significant blending in TESS occurs around $T_{\text{mag}} \sim 12$.

4.2. Effective Temperatures and Radii

To eliminate blended targets, we require that each target has an effective temperature ($T_{\text{eff}}$) and radius ($R$) that is representative of an oscillating red giant. We calculate these stellar parameters for each target in our preliminary yield using the “direct method” of the isoclassify stellar classification code (Huber et al. 2017; Berger et al. 2020). The code uses parallaxes from Gaia EDR3 (Gaia Collaboration et al. 2021) as an input. These parallaxes are first corrected for zero-point offsets following the prescription by Lindegren et al. (2021), which applies corrections to stars with five- and six-parameter astrometric solutions. For stars brighter than a Gaia magnitude of 10.8 that are corrected by the seven-parameter offset model, we further subtract 0.015 mas from their corrected parallaxes which applies corrections to stars with

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https://github.com/danxhuber/isoclassify
such stars through a comparison with Kepler targets with known asteroseismic parallaxes. Using these corrected parallaxes, we then calculate distance posteriors using an exponential decreasing volume density prior with a length scale of 1.35 kpc (Bailer-Jones 2015; Astraatmadja & Bailer-Jones 2016).

We then calculate extinction values, $A_V$, for each star using the combined 3D dust maps of Drimmel et al. (2003), Marshall et al. (2006), and Green et al. (2019) from the mwdust repository18 (Bovy et al. 2016), where we assume an extinction uncertainty of 0.02 mag. These extinction values are applied to 2MASS $K$-band magnitudes to calculate apparent magnitudes. Bolometric corrections are inferred by interpolating $T_{\text{eff}}$, log $g$, [Fe/H], and $A_V$ in the MESA Isochrones and Stellar Tracks (Choi et al. 2016) bolometric correction tables (MIST/C3K, C. Conroy et al. 2021, in preparation),19 where we adopt an absolute solar bolometric magnitude of 4.74 mag, as appropriate to reproduce solar values for the bolometric corrections in the MIST grid. These bolometric corrections, which have an assumed uncertainty of 0.02 mag, are applied to the apparent magnitudes to derive absolute magnitudes and subsequently values of luminosities, $L$. Using 2MASS JHK photometry, we apply the infrared flux method-based color-$T_{\text{eff}}$ relations from González Hernández & Bonifacio (2009) to infer values of $T_{\text{eff}}$. Finally, we use $L$ and $T_{\text{eff}}$ to estimate $R$ using the Stefan–Boltzmann relation.

A comparison between our temperature measurements with those from APOGEE Data Release 16 spectroscopy (Majewski et al. 2017, DR16) in Figure 7(a) shows good levels of agreement and additionally demonstrates that the residual dispersion between both temperature sources are generally at the 2% level (Figure 7(b)). We therefore approximate $\sigma_{\text{est}}$ as 2% of the reported $T_{\text{eff}}$ value. Meanwhile, output estimates for distances, $L$ and $R$ are reported as their distribution median values from Monte Carlo sampling, with 1$\sigma$ confidence intervals derived from distribution percentiles. Fractional uncertainty estimates are typically 4% for $L$ and 5% for $R$. With these fundamental stellar parameters, we now proceed with the analysis of our seismic sample.

4.3. Removing Blended Targets

Having measured $T_{\text{eff}}$ and $R$ for each target, we calculate their statistical detection probabilities, $p_{\text{stat}}$, using the Chaplin et al. (2011) global signal-to-noise ratio estimation approach that has been adapted to TESS following the modifications described by Campante et al. (2016) and Schofield et al. (2019). More specifically, asteroseismic scaling relations are used to predict oscillation and granulation amplitudes (Chaplin et al. 2011; Kallinger et al. 2014) from $T_{\text{eff}}$ and $R$, while contributions from white noise and instrumental effects are estimated following the TESS instrumental specifications by Sullivan et al. (2015). These quantities are used to estimate the signal-to-noise ratio of oscillations in a power spectrum and

18 https://github.com/jobovy/mwdust
19 http://waps.cfa.harvard.edu/MIST/model_grids.html
subsequently $p_{\text{stat}}$. The value $p_{\text{stat}}$ indicates the probability that the oscillation signal-to-noise ratio exceeds a particular threshold, which—following Campante et al. (2016)—is the signal-to-noise ratio at which there exists a 5% chance the detected oscillation signal arises from noise alone. Crucially, $p_{\text{stat}}$ is a simple prediction of how likely oscillations can be observed for a given TESS target using only its fundamental stellar parameters and survey properties (e.g., apparent magnitude, observing cadence); it therefore does not directly use information from the observed power spectra of each target.

As a result, our neural network detection algorithm is still needed to directly confirm the presence of visible oscillations from the observed data. Nonetheless, $p_{\text{stat}}$ removes most of the obvious blends from our neural network detections. In particular, $p_{\text{stat}}$ is small ($<0.99$) for detected targets that either have $T_{\text{eff}}$ and $R$ that are not representative of a red giant or TESS magnitudes too faint to expect detectable red giant oscillations.

When calculating $p_{\text{stat}}$, we assume that each target experiences no blending (hence a flux dilution factor of 1) and a negligible systematic noise level ($\sigma_{\text{sys}} = 0$). However, we do take into account the positional dependence of the background noise across the sky. To be conservative, we enforce a threshold of $p_{\text{stat}} \geq 0.99$, which as shown in Figure 8(a), removes all blended targets and false positives within the instability strip (i.e., hot classical pulsators) and on the main sequence (dwarf stars). The $\nu_{\text{max}}$-magnitude plot in Figure 8(b) shows that removing these false positives reveals a distinct boundary (blue line), which we parameterize as $\nu_{\text{max}} = 10^{-0.32T_{\text{eff}}} + 5.3$. We interpret this boundary as the oscillation detection limit above which white noise levels are too high for oscillations to be detectable. In both Figures 6 and 8(b) we note the lack of detected targets with $\nu_{\text{max}} \lesssim 30\mu$ Hz and $T_{\text{eff}} \gtrsim 11$. We infer this observation to be caused by the limitation of our classifier as discussed in Section 3.3, rather than a true deficiency of luminous giants in the underlying stellar population. The remaining stars after the $p_{\text{stat}}$ filtering comprise our final sample. Several examples of these stars are documented in Appendix D.

5. Final Sample

5.1. Target Lists

Table 1 lists 158,505 unique targets comprising the final sample together with their measured parameters in this study. Note that we report $\nu_{\text{max}}$ measurements from only one sector for targets with multisector detections; we find this to be reasonable given that most multisector $\nu_{\text{max}}$ measurements are consistent with the reported single-sector value. In particular, 97% of $\nu_{\text{max}}$ measurements across individual sectors of the same star deviate less than $2\sigma$ of the quoted uncertainties in Table 1.

We consider our yield of 158,505 oscillating giants to be a lower bound estimate of the yield of oscillating giants across TESS’s nominal mission because of the conservative measures we have used in both detection and vetting methods. In comparison to the predicted all-sky yield of $\sim 3 \times 10^5$ as reported by Mackereth et al. (2021), our current yield suggests that there are still many giants that can potentially be detected.
Table 1
List of 158,505 Unique TESS Targets Comprising the Final Sample in this Study

| TIC   | $\nu_{\text{max}}$ (\(\mu\)Hz) | $T_{\text{mag}}$ (mag) | $T_{\text{eff}}$ (K) | $R$ (\(R_\odot\)) | $L$ (\(L_\odot\)) | $d$ (kpc) | ruwe | mass_flag |
|-------|---------------------------------|-------------------------|----------------------|-------------------|-------------------|-----------|------|-----------|
| 1078  | 30.8 ± 2.2                      | 9.7                     | 4629 ± 92            | 11.3 ± 0.5        | 52.6 ± 2.3        | 0.828 ± 0.012 | 1.21 | 1         |
| 41959 | 14.9 ± 2.2                      | 10.3                    | 4462 ± 89            | 14.8 ± 1.4        | 77.5 ± 13.0       | 1.333 ± 0.109 | 2.17 | 1         |
| 2026646 | 47.0 ± 5.6                     | 12.8                    | 4415 ± 88            | 16.3 ± 1.2        | 90.1 ± 11.0       | 4.249 ± 0.250 | 0.95 | 0         |
| 31635521 | 112.1 ± 6.1                   | 7.6                     | 4909 ± 98            | 6.4 ± 0.3         | 21.5 ± 0.7        | 0.212 ± 0.001 | 1.10 | 1         |
| 51931461 | 69.8 ± 4.0                     | 9.3                     | 4803 ± 96            | 8.2 ± 0.4         | 32.4 ± 2.1        | 0.554 ± 0.015 | 4.43 | 1         |
| 113288314 | 7.8 ± 1.0                     | 9.7                     | 4092 ± 81            | 24.6 ± 1.1        | 152.1 ± 7.2       | 1.348 ± 0.018 | 0.97 | 1         |
| 150440218 | 87.5 ± 5.4                     | 10.4                    | 4815 ± 96            | 6.2 ± 0.3         | 18.8 ± 0.7        | 0.699 ± 0.005 | 0.97 | 1         |
| ...   | ...                             | ...                     | ...                  | ...               | ...               | ...       | ...  | ...       |

Note. Included are each target’s TESS magnitude ($T_{\text{mag}}$), its estimated frequency at maximum oscillation power ($\nu_{\text{max}}$), and measurements of effective temperature ($T_{\text{eff}}$), radii ($R$), luminosity ($L$), and distances ($d$). Values of the renormalized unit weight error (ruwe) from Gaia EDR3 (Gaia Collaboration et al. 2021) are included to flag potential nonsingle sources whose astrometric solutions may be problematic, which can affect the accuracy of our radius measurements. Values of mass_flag are binary indicators of whether the target’s stellar mass as estimated using the seismic scaling relation (Equation (1)) are within the “typical” mass range of a red giant from Kepler (see text). The full version of this table is available in a machine-readable format in the online journal, with a portion shown here for guidance regarding its form and content.

(This table is available in its entirety in machine-readable form.)

Figure 8. (a) Radius-temperature plot of all targets in the preliminary detection sample in Figure 6 (black) and the remaining targets after retaining only those with $p_{\text{stat}} \geq 0.99$. (b) The $\nu_{\text{max}}$-magnitude distribution of the stars in panel (a). The blue line delineates a detection limit above which white noise levels are too high to detect visible red giant oscillations in power spectra. The deficiency of stars at $\nu_{\text{max}} \leq 20 \mu$Hz and $T_{\text{mag}} \geq 11$ is caused by the limitations of our method as discussed in Section 3.3.

from TESS. We defer more extensive detections across TESS FFIs to future work, which will better assess the sample completeness of red giants.

In Table 1, we include values of the Gaia renormalized unit weight error (Lindegren 2018, ruwe). Values of ruwe $> 1.40$ for a target indicate that the adopted astrometric solution is less likely to be reliable due to neighboring companions (e.g., Evans 2018; Belokurov et al. 2020), which can affect the accuracy of the target’s reported value for $R$.

Although we have used measurements of $T_{\text{eff}}$ and $R$ to filter out obvious blends in the final sample, such an approach cannot discern the occurrence of blending when both target and blending star are red giants. To potentially identify such scenarios, we additionally introduce a mass_flag parameter that indicates whether or not the asteroseismic scaling mass ($M$) for each target falls within the “typical” mass range of a red giant. Following Stello et al. (2008), we estimate masses using the following:

$$
\frac{M}{M_\odot} = \left( \frac{\nu_{\text{max}, \odot}}{\nu_{\text{max}, \star}} \right) \left( \frac{R}{R_\odot} \right)^2 \left( \frac{T_{\text{eff}}}{T_{\text{eff}, \odot}} \right)^0.5,
$$

with $\nu_{\text{max}, \odot} = 3090$ \(\mu\)Hz (Huber et al. 2011) and $T_{\text{eff}, \odot} = 5772$K (Prša et al. 2016). Equation (1) is the seismic $\nu_{\text{max}}$ scaling relation that relates the acoustic cutoff frequency of a star to its $M$, $R$, and $T_{\text{eff}}$ (Brown et al. 1991; Kjeldsen & Bedding 1995; Belkacem et al. 2011). We define the typical mass range of a red giant to be the values between the 0.5th and 99th percentile of $\sim 16,000$ Kepler red giant masses as measured by Yu et al. (2018), which corresponds to the interval $0.6 M_\odot \lesssim M \lesssim 2.9 M_\odot$. The vast majority of stars in our final sample are within this range and are assigned mass_flag $= 1$. There are a total of 3415 ($\sim 2.2\%$) stars in our sample with value outside the typical mass interval and are thus assigned mass_flag $= 0$ to indicate an outlier mass value. We do not exclude these targets from our list because there are rare circumstances under which such extreme mass measurements can occur (such as a $3 M_\odot$ giant), but we caution that many of these are likely blends.

5.2. Measurement Consistency

In Figure 9(a), we show the uncertainty distribution for the parallaxes and radii estimates in our final sample. Given that our sample probes a relatively local region of the Galaxy (as further discussed in Section 6), the vast majority of our detected targets have precise astrometric measurements that...
result in a typical fractional radius uncertainty of 4.4% as shown in Figure 9(b). Additionally, we compare our \( n_{\text{max}} \) measurements from Tables 1, \( n_{\text{max, DL}} \) with those from asteroseismic data pipelines, \( n_{\text{max, pipe}} \), from independent studies of TESS targets in specific sky regions. The comparison in Figure 10(a) is for targets in the Kepler field of view with observation lengths between 1–2 months on the analysis by Stello et al. (2021). Meanwhile, the comparison in Figure 10(b) is for targets in the TESS Southern Continuous Viewing Zone (TESS SCVZ) that comprise the “gold” sample from the Mackereth et al. (2021) study—these typically have light curves with a duration of 3–12 months. In both comparisons, we find good levels of agreement between \( n_{\text{max, DL}} \) and \( n_{\text{max, pipe}} \), which suggests that our estimates of the frequency at maximum oscillation power are generally reliable.

5.3. Caveats

There are two important additional caveats that should be considered with the current target lists:

1. Blending may still be prevalent, especially when both the target and blending star have \( n_{\text{max}} \) values comparable to one another. We recommend more caution with the fainter targets (\( T_{\text{mag}} \sim 12 \)) in our sample as well as those located closer to the Galactic plane, where crowding effects become more problematic. One approach that can inform the presence of blending, which we will explore in future work, is to systematically determine a contamination/crowding metric calculated across the photometric aperture of each target. Another possible method to identify giant-giant blending would be to determine if the stellar mass as estimated from Equation (1) (which uses Gaia-derived radii) is consistent with a mass determined from the combined \( \Delta \nu - n_{\text{max}} \) scaling relation (e.g., Pinsonneault et al. 2018, Equation (4)), where \( \Delta \nu \) is the large frequency separation of the oscillation modes.

2. The search performed in this study is not intended to be exhaustive, meaning that there are potentially many more oscillating giants from TESS that are yet to be detected. In the interest of producing an early, all-sky catalog comprising strong candidates of oscillating giants, we make concessions to the population completeness of our final sample by vetting our preliminary yield with several thresholds. Because these thresholds are conservative, the number of stars in our final sample is expected to be a reasonable approximation of the minimum yield of oscillating giants that we can observe across the first two years of TESS.

6. Potential for Galactic Studies

6.1. All-sky Mass Map

In this section, we aim to demonstrate that our list of asteroseismic detections opens up prospects of inspecting broad
To ensure that the measurements for our sample in the demonstrations are reliable, we include only the 139,789 oscillating giants in our final sample with \( \text{ruwe} \leq 1.40 \) and \( \text{mass\_flag} = 1 \).

In Figures 11 and 12, we show all-sky Hammer map projections of the final yield of our final sample, colored by spatial, chemical, and kinematic correlations over a near all-sky, continuous volume of the Milky Way using a sample of stars with their physical properties uniformly determined. At the same time, our demonstrations seek to provide an astrophysical validation of the accuracy of our results from a comparison with known physical trends from Galactic studies.
seismic scaling masses derived using Equation 1. Given that red giants follow an age-mass relation (e.g., Miglio 2011; Bellinger 2020), our results show that younger stars (higher mass stars) are mainly confined to the plane of the Galactic disk, i.e., the equator in Figure 12, with older stars (lower mass stars) generally populating higher Galactic latitudes. Notably, these trends are broadly consistent with global age trends obtained from large spectroscopic surveys (Xiang et al. 2017; Sanders & Das 2018). At $|l| \lesssim 120^\circ$ in Figure 12, we observe a slight trend of higher mass stars toward higher latitudes, which may indicate the presence of disk flaring (e.g., Minchev et al. 2015; Mackereth et al. 2017).

6.2. Spatial Extent

We investigate the spatial distribution of our sample by calculating Galactocentric coordinates $(Z_{\text{Gal}}, R_{\text{Gal}})$ using the Galactocentric module from Astropy (Astropy Collaboration et al. 2018). We adopt a right-handed coordinate system that assumes a Galactic center position of $(X_{\text{Gal}}, Y_{\text{Gal}}, Z_{\text{Gal}}) = (-8.122, 0, 0)$, such that the Sun’s radial distance from the Galactic center is $8.122$ kpc and the Sun’s height above the Galactic plane is taken to be $20.8$ pc. Figure 13 shows that our sample extends to distances primarily within $1$ kpc indicating that our TESS yield is relatively local compared to Kepler (e.g., Rodrigues et al. 2014; Mathur et al. 2016) or K2 (e.g., Rendle et al. 2019). This outcome is expected given that the focus of the TESS mission is primarily on nearby bright stars, and that our current yield is limited to TESS magnitudes brighter than $13.5$. We additionally observe a lack of stars at $R_{\text{Gal}} \lesssim 7.7$ kpc and $|Z_{\text{Gal}}| \lesssim 0.1$ kpc. Stars within this region are positioned toward the highly crowded Galactic center, resulting in large levels of flux contamination that significantly lowers the detectability of red giant oscillations.

Figure 13. (a) Density map of oscillating giants detected in our study as a function of Galactocentric coordinates $(R_{\text{Gal}}, Z_{\text{Gal}})$. (b) Distance distribution of the stars in panel (a), with the mode of the distance distribution indicated by the line.

Figure 14. Mass distribution of our sample in Galactocentric coordinates. In each visualization, bins with fewer than five stars are not shown. (a) The map in Figure 13(a) colored by mass. (b) Distribution of masses as a function of vertical distance from the Galactic plane, $|Z_{\text{Gal}}|$. Figure 14(a) shows the distribution of masses as a function of coordinates $(R_{\text{Gal}}, Z_{\text{Gal}})$. Similar to Figure 12, we find that more massive (and therefore young) stars near the Galactic plane at $Z_{\text{Gal}} = 0$. In this plot, a distinct dependence of masses with $Z_{\text{Gal}}$ can be seen, which we further visualize in Figure 14(b). It is known that a vertical mass gradient of the Milky Way disk exists (e.g., CasAGRande et al. 2016), and therefore the large volume of our TESS yield presents the opportunity to probe the mass and age structure of the Galactic disk in greater detail.

6.3. Kinematic Properties

To examine the kinematic properties of our red giant sample, we use parallaxes, radial velocities, and proper motions from Gaia EDR3 to determine Galactocentric velocities $V = (V_R, V_L, V_Z)$. Here, we consider a clockwise rotation of the Galaxy such that the azimuth angle $\phi = \tan(X_{\text{Gal}}/Y_{\text{Gal}})$ increases in the anticlockwise direction. Figure 15(a) visualizes the distribution of our sample with a Toomre diagram, which is a useful representation for differentiating Galactic populations based on their kinematics (e.g., Venn et al. 2004). We observe that most stars have $V_L \sim 200–250$ km s$^{-1}$, which is approximately the circular velocity of the local standard of rest (LSR, e.g., Ding et al. 2019). In other words, most stars have velocities that are typical to objects orbiting the Milky Way within the disk. We additionally find a smaller population of stars with atypical disk kinematics—these stars may have larger combined radial and vertical velocities ($V_{RZ}$) compared to those in the disk as well.
as highly retrograde motion relative to the LSR. Such stars are identified as having kinematics representative of a Galactic halo population; for instance, Bonaca et al. (2017) identify stars with \( |V - V_{\text{LSR}}| > 220 \text{ km s}^{-1} \) outside the line in Figure 15 as belonging to the halo. Using this criterion, we identify 354 potential halo candidates in our sample, which carries forward prospects of probing the Milky Way halo with TESS in subsequent work.

Figure 15(b) shows the kinematic distribution of our sample in the \((R_{\text{Gal}}, V_\phi)\) plane, where we can observe the phase-space substructures in the form of diagonal ridges that were discovered by Antoja et al. (2018). The study by Khanna et al. (2019) demonstrated that the stars forming such substructures are primarily those that are close to the Galactic plane (small \(|Z_{\text{Gal}}}|) and suggested that they are either due to (a) kinematic perturbations from the phase-mixing of transient spiral arms, (b) the interactions between low \(|Z_{\text{Gal}}|) stars that may have been externally perturbed by a satellite such as a dwarf galaxy, or (c) stars near the Galactic plane being kinematically “cold” and thus easier to perturb. In Figure 15(b), we indeed find that typically stars with higher masses (younger) show the diagonal ridges more prominently, which is consistent with the results by Khanna et al. (2019) that these stars belong to regions near the Milky Way plane.

We provide another astrophysical validation of our seismic sample using velocity dispersions in Figure 15(c). Using the Sharma et al. (2021) approach, we calculate radial \((\sigma_R)\) and vertical \((\sigma_Z)\) velocity dispersion profiles solely as a function of mass under a solar metallicity approximation. The observed decrease of the dispersion profiles with mass is consistent with the expectation that velocity dispersions are expected to increase with age due to dynamical heating over time from sources such as giant molecular clouds (e.g., Lacey 1984) and spiral arms (e.g., Barbanis & Woltjer 1967). Qualitatively, the greater steepness of the \((V_\phi/\sigma_R)\) profile compared to that of \((V_R/\sigma_R)\) in Figure 15(c) agrees with the observational results by Sharma et al. (2021) that suggests a high efficiency of heating by giant molecular clouds (a significant contributor to vertical scattering) early in the dynamical history of the Galaxy—this is notably a result predicted by the simulations by Aumer et al. (2016).

Based on theory, the asymmetric drift (Strömgberg 1946), namely how much a star’s circular motion \((-V_\phi)\) lags behind the \(V_{\text{LSR}}\), is larger for stars with high \(\sigma_R\) because such kinematically hot stars require less centrifugal support to remain in dynamical equilibrium (e.g., Binney 2008; Sharma et al. 2014). Therefore, the greater the difference between \(-V_\phi\) and \(V_{\text{LSR}}\) = \((0, 220, 0) \text{ km s}^{-1}\) in Figures 15(a) and (b), the larger the asymmetric drift. Because \(\sigma_R\) scales with age (and mass, as per Figure 15(c)), we should expect a reduction in the average stellar mass as \(-V_\phi\) decreases below \(220 \text{ km s}^{-1}\). Indeed, such a trend is observed in Figure 15(b), which again shows the consistency of the masses of our sample from a kinematic perspective.

**6.4. Chemical Properties**

Figure 16 shows the \([\alpha/\text{Fe}]-[\text{Fe/H}]\) diagram for 6459 stars with measured chemical abundances from APOGEE Data Release 16 (Majewski et al. 2017) of the Sloan Sky Digital Survey (Ahumada et al. 2020). The \([\alpha/\text{Fe}]-[\text{Fe/H}]\) relation is a frequently examined diagnostic in chemical evolution studies of the Milky Way disk (e.g., Adibekyan et al. 2011; Haywood et al. 2013; Bensby et al. 2014; Hayden et al. 2015; Anders et al. 2017; Silva Aguirre et al. 2018), which reveals two distinct stellar populations from a bimodality in the observed \([\alpha/\text{Fe}]\) abundances in Figure 16. The first is a population of solar-\([\alpha/\text{Fe}]\) stars spanning a wide range of metallicities—these are expected to comprise young stars confined to the plane of the Galaxy (e.g., Hayden et al. 2015). Assuming mass as an age proxy, we observe that most stars with \(M \geq 1.6M_\odot\) (thus typically young) in Figure 16 have solar-\([\alpha/\text{Fe}]\)
abundances, in agreement with expectations. However, about
~ 20 targets within these high-mass bins have \([\alpha/Fe] \sim 0.3 \, \text{dex}\) —such stars are potentially the peculiar “young-\(\alpha\) rich” stars (Chiappini et al. 2015; Martig et al. 2015) whose features are not predicted by standard chemical evolution models of the Galaxy.

The second distinct population in Figure 16 is seen at \([\alpha/Fe] \gtrsim 0.15 \, \text{dex}\), which corresponds to the high-\(\alpha\) sequence. This population is typically associated with metal-poor stars with larger vertical scale heights compared to those in the low-\(\alpha\) population (e.g., Bovy et al. 2012). Although stars in the high-\(\alpha\) sequence were previously found to strongly correlate with age (Haywood et al. 2013), more recent studies present evidence to the contrary from the identification of old, metal-rich low-\(\alpha\) stars (e.g., Bensby et al. 2014; Silva Aguirre et al. 2018). We find stars with \(M \lesssim 1.0 \, M_\odot\) (typically older) in Figure 16 to be distributed in both low- and high-\(\alpha\) populations, which does support the presence of old, metal-rich stars. While a detailed investigation in these chemical trends is beyond the scope of this paper, we aim to show that our seismic sample provides great utility not only in revealing trends in chemical abundances but also in potentially identifying a subset of chemically interesting targets within large stellar populations.

7. Conclusions

We have presented the first all-sky sample of oscillating red giants using MIT Quick-look Pipeline photometry of the first 26 sectors of TESS Full Frame Images. Our main results are summarized as follows:

1. We reported red giant oscillations in a total of 158,505 targets from over 20 million light curves spanning TESS magnitudes as faint as 13.5 using neural networks. The detected giants have frequencies at maximum oscillation power \((\nu_{\text{max}})\) spanning \(6 \, \mu\text{Hz} \lesssim \nu_{\text{max}} \lesssim 250 \, \mu\text{Hz}\), which corresponds to a surface gravity range of \(1.5 \, \text{dex} \lesssim \log(g) \lesssim 3.0 \, \text{dex}\). Due to the limitations of the neural network classifier, our reported yield does not currently include the most faint and luminous targets, which are those with TESS magnitudes \(\gtrsim 11\) and \(\nu_{\text{max}} \lesssim 15 \, \mu\text{Hz}\).

2. For each seismic detection, we reported estimates of its frequency at maximum power \((\nu_{\text{max}})\), luminosity \((L)\), radius \((R)\), effective temperature \((T_{\text{eff}})\), and distance \((d)\). To produce a high-quality target list of oscillating red giants, we have applied thresholds in our machine learning algorithms and applied statistical detection probabilities based on global signal-to-noise ratio estimates to minimize the number of false positives. Our reported results are therefore that of an early detection yield and not that of a complete survey of all underlying oscillating giants from TESS Full Frame Images. Due to (1) our use of conservative vetting measures, (2) the lack of optimal light-curve corrections required for asteroseismology, and (3) the use of only one-month-long observations, it is reasonable to expect that the number of targets in our reported detection yield is a lower bound to the complete set of oscillating red giants that can be obtained from TESS’s nominal mission.

3. With our detection yield, we demonstrated the enormous potential of TESS for all-sky Galactic archeology by presenting the first near all-sky Gaia-asteroseismology mass map. With data from the Quick-look Pipeline limited to a TESS magnitude of 13.5, we found our yield to typically span distances within 1 kpc. Despite being limited to a relatively local volume of the Galaxy, our yield provides the most comprehensive distribution of seismic measurements across the Galaxy to date. Our measurements, when applied to spatial, kinematic, and chemical studies of the Galaxy, show good qualitative agreement with expected astrophysical trends as a function of mass. Specifically, we showed that (1) the masses of stars within the Galactic plane is on average larger than those farther from the plane; (2) a vertical mass gradient of the Milky Way disk can be distinctly observed within our sample; (3) there are 354 oscillating giants in our sample that have Galactic halo-like kinematics; (4) stars prominently showing kinematic phase-space ridges are on average those that are higher in mass and reside within the Galactic plane; (5) lower mass stars typically have larger radial and vertical velocity dispersions, consistent with the interpretation that such stars are older; and (6) there exists distinctions between low-\(\alpha\) and high-\(\alpha\) populations as a function of stellar mass in our sample.

With a good qualitative agreement with trends from Galactic studies using masses as a proxy for stellar age, it is reasonable to expect that the use of actual age estimates from a combination of TESS all-sky asteroseismology, Gaia parallaxes, and large survey spectroscopy will provide very powerful probes of Milky Way evolution. Finally, we note that our “quick look” at the all-sky asteroseismic yield from TESS has provided insights on how to improve our data and methodology for further work to expand the yield across Full Frame Images. Currently, we have used only raw data from the...
Quick-look Pipeline, which lack detrending to remove instrumental noise. Upcoming data releases from the TESS Asteroseismic Science Consortium (e.g., Handberg et al. 2021) will provide light curves with instrumental noise corrections that are optimized for asteroseismology for all FFI targets up to a TESS magnitude of 15, which will significantly increase the detection yield across all TESS sectors. Another vital insight is the need for improved machine learning algorithms and training data. As the asteroseismic analyses of TESS data further progress across the scientific community, it will become possible to use or develop training data that is more representative of real TESS FFI observations. The availability of better training data will subsequently facilitate improvements with our deep learning algorithms, particularly in the detection of oscillations for the faintest and most luminous targets from TESS. These future prospects, when combined with TESS’s potential for all-sky Galactic studies, will certainly provide a more complete and detailed view of the Milky Way.

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Software: Astropy (Astropy Collaboration et al. 2018), celerite (Foreman-Mackey et al. 2017), isoclassify (Huber et al. 2017; Berger et al. 2020), Pytorch (Paszke et al. 2019).

### Appendix A
#### Network Architecture
Tables 2 and 3 detail the structure of the classifier and the regression network, respectively. The networks are developed using the Pytorch version 1.1.0 deep learning library (Paszke et al. 2019). The networks are trained using the Adam optimizer (Kingma & Ba 2014) with an initial learning rate of 0.0001 and early stopping applied.

The networks are generally similar to those implemented by Hon et al. (2018b), with a few key differences. First, both networks have dropout applied only to the final feature extraction layer, with a dropout probability of 0.1. Because this current work has significantly more training data compared to the Kepler-as-K2 used by Hon et al. (2018b), weaker regularization is required to prevent network overfitting. The second difference relates to the uncertainty estimation of the $\nu_{\text{max}}$ regression network. The previous study uses Monte Carlo dropout (Gal & Ghahramani 2016), while our work in this study explicitly estimates $\sigma_{\nu_{\text{max}}}$ through an auxiliary output layer (e.g., Kendall & Gal 2017). Consequently, optimizing the $\nu_{\text{max}}$ regression network is not done by minimizing the mean squared error (as before), but the negative

### Table 2
Structure of the Classifier to Detect Oscillating Red Giants from Images of Power Spectra

| Component | Layer | Filter Size | Output Shape |
|-----------|-------|-------------|--------------|
| Feature Extraction | conv1b | (5, 5) | (128, 128, 4) |
|           | pool1 | (2, 2) | (64, 64, 4) |
|           | conv2 | (3, 3) | (64, 64, 8) |
|           | pool2 | (2, 2) | (32, 32, 8) |
|           | conv3 | (3, 3) | (32, 32, 16) |
|           | pool3 | (2, 2) | (16, 16, 16) |
|           | flatten | ... | (4096,) |
|           | dropc | ... | (4096,)

### Notes.
The rectified linear unit activation (Nair & Hinton 2010, ReLU) is applied after every `conv` and `dense` layer.

a For convolutional layers, this column corresponds to the dimensions of the convolving kernel, whereas for dense layers the column corresponds to (number of neurons in previous layer, number of neurons in current layer).

b For convolutional layers, weight shapes are in the format (number of filters, receptive field size), while output shapes are in the format (height, width, number of filters).

c We implement regular Dropout (Hinton et al. 2012; Srivastava et al. 2014) with a drop probability of 0.1.

### Table 3
Structure of the Regression Network to Estimate $\nu_{\text{max}}$ from Images of Power Spectra Showing Red Giant Oscillations

| Component | Layer | Filter Size | Output Shape |
|-----------|-------|-------------|--------------|
| Feature Extraction | conv1b | (5, 5) | (128, 128, 4) |
|           | pool1 | (2, 2) | (64, 64, 4) |
|           | conv2 | (3, 3) | (64, 64, 8) |
|           | pool2 | (2, 2) | (32, 32, 8) |
|           | conv3 | (3, 3) | (32, 32, 16) |
|           | pool3 | (2, 2) | (16, 16, 16) |
|           | flatten | ... | (4096,) |
|           | dropout | ... | (4096,)

### Notes.
The rectified linear unit activation (Nair & Hinton 2010, ReLU) is applied after every `conv` and `dense` layer.

a For convolutional layers, this column corresponds to the dimensions of the convolving kernel, whereas for dense layers the column corresponds to (number of neurons in previous layer, number of neurons in current layer).

b For convolutional layers, weight shapes are in the format (number of filters, receptive field size), while output shapes are in the format (height, width, number of filters).

c We implement regular Dropout (Hinton et al. 2012; Srivastava et al. 2014) with a drop probability of 0.1.
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log-likelihood, $E$, given by the following:

$$p(y|x) = \frac{1}{(2\pi)^{d/2}\sigma(x)} \exp\left(-\frac{(y - \nu_{\max, \text{pred}})^2}{2\sigma(x)^2}\right).$$

(A1)

$$E = \sum_{m=1}^{m_{\text{tot}}} - \ln p(y_m|x_m).$$

(A2)

Here, $x$ is the input image, $\sigma(x)$ is $\sigma_{\nu_{\max}}$, $y$ is the ground truth value of $\nu_{\max}$, $\nu_{\max, \text{pred}}$ is the estimated value of the frequency at maximum power by the $\nu_{\max}$ regression network, and $m_{\text{tot}}$ is the total number of power spectra in the training set.

Appendix B

celerite Power Spectra

Figure 17 shows example power spectra of oscillating red giants generated by celerite compared to real TESS giants with the same $\nu_{\max}$ and TESS magnitudes. There are differences between the noise levels of real and simulated data, which is typically attributed to the lack of noise contributions from both instrumental sources and flux contamination in simulated data. Additionally, in the absence of such contributions, the frequency power profile of the simulated power spectra appears different from that of the real data, particularly at low frequencies. Future work will include more realistic simulations; however, the current data are sufficient to benchmark the network trained on Kepler-as-TESS data in Section 3.3).

Figure 17. A comparison of real TESS power spectra (top row) with synthetic power spectra (bottom row) generated by celerite in this work. Each row corresponds to a red giant with a particular TESS magnitude that is oscillating at a specific $\nu_{\max}$. 
Appendix C
Faint and Luminous Giants

Figure 18 shows the power spectra of two oscillating red giants with $\nu_{\text{max}} \sim 15 \mu$ Hz. The giant in Figure 18(a) is brighter than the giant in Figure 18(b) and therefore has a power spectrum with lower noise levels. As a result, the slope of the granulation profile (red noise), which is an important feature for the neural network classifier in detecting low $\nu_{\text{max}}$ oscillations (Hon et al. 2018b), can still be observed. In contrast, the power spectrum in Figure 18(b) is more white noise dominated, which obscures the granulation profile and makes the detection of oscillating luminous giants at fainter TESS magnitudes more difficult.

Figure 18. Power spectra for two luminous, oscillating red giants observed by TESS. The blue arrows indicate $\nu_{\text{max}}$, while Tmag indicates TESS magnitude. TIC 122716398 in panel (a) is brighter and thus the “knee” of the granulation profile can be easily seen in the log–log power spectrum. TIC 298834359 in panel (b) is fainter and therefore its power spectrum has greater white noise levels. Oscillations for such faint and luminous giants typically appear as a sequence of peaks with heights marginally above a nearly flat frequency power profile in the log–log spectrum.
Appendix D
Examples of Oscillating Giants

We show several examples of oscillating red giants spanning a higher range of $\nu_{\text{max}}$ (lower luminosity) in Figure 19, while Figure 20 shows giants across a lower range of $\nu_{\text{max}}$ (higher luminosity).

Figure 19. Examples of detected oscillating giants spanning $\nu_{\text{max}} \sim 30-120 \mu$Hz. Each row corresponds to a particular $\nu_{\text{max}}$ value, while each column corresponds to a specific TESS magnitude. The bottom right panels are grayed out because no oscillating giants are found with such values of $\nu_{\text{max}}$ and TESS magnitudes in our sample as a consequence of the oscillation detection limit (Figure 8(b)).

Figure 20. Same as Figure 19, but for oscillating giants spanning $\nu_{\text{max}} \sim 10-25 \mu$Hz.
