**Josh Manchester — RNN Component**

**Title & Authors**

**Machine Learning for Exoplanet Detection: Identifying Exoplanets in Light Curves**  
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**Abstract**

My component of our research project proposes a Recurrent Neural Network (RNN) pipeline to detect exoplanets through light curves in the Kepler/K2 and TESS data. Building on best practices for time-series modeling and prior astronomy RNN applications, I will (1) prepare mission light curves with consistent detrending/normalization; (2) prototype LSTM/GRU models for sequence classification at the cadence of the missions; (3) evaluate with precision, recall, F1, ROC-AUC, and confusion analyses; and (4) compare against simple baselines and team CNN/Transformer variants. The larger project trains three complementary models (CNN, RNN, Transformer) on Kepler/TESS and synthetic sets.

**Introduction & Problem Statement**

Space missions like Kepler and TESS deliver continuous photometry (high resolution digital photos) enabling exoplanet transit detection via brightness dips (light curves), but distinguishing true transits from stellar variability (natural brightening and dimming of the light from a star) and variation in instrument data gathering remains challenging. An RNN can find patterns in the data over the time the data was collected, complementing convolutional and transformer approaches used by my team. My specific aim is to design, train, and evaluate an RNN that improves transit-signal discrimination and generalizes across Kepler/TESS cadences. (Team role: “Development and evaluation of a Recurrent Neural Network (RNN) for exoplanet detection from Kepler and TESS light-curve data.”)

**Related Work**

1. **Exploratory sequence representation of Kepler light curves.** Kügler et al. introduce an ESN-coupled autoencoder that encodes light curves via an RNN reservoir and optimizes reconstruction in sequence space (as opposed to readout space), highlighting the value of sequence-aware encoders for Kepler variability. This motivates using recurrent architectures to capture dynamics beyond pointwise features.
2. **RNNs for astrophysical transient detection in Kepler/TESS.** Vida et al. evaluate LSTM-based flare detection and report ~80–90% precision/recall at >5σ on short-cadence Kepler and successful transfer to TESS, demonstrating that carefully trained LSTMs can generalize across missions and effectively reject false positives (e.g., RR Lyrae maxima). While their task is flares, their methodology informs my preprocessing, windowing, class imbalance handling, and thresholding choices.
3. **RNNs for event timing/intensity modeling.** Du et al.’s RMTPP formalizes learning history-dependent intensity with RNNs for marked temporal point processes, showing how recurrent encoders capture complex event histories without brittle parametric assumptions. I will adapt the idea of encoding event histories (ingress/egress, gap structure) to augment classification with timing-aware auxiliary losses or features.

**Datasets (and state of the art notes)**

**Kepler/K2 (NASA):** High-quality, long-baseline photometry; multiple cadences; widely used for transit searches and variability studies. Prior sequence-aware methods (e.g., ESN-AE visualization) underline the richness of temporal structure to exploit.

**TESS (NASA):** All-sky, shorter baselines, different cadence; serves to test cross-mission generalization. Vida et al. showed LSTM models trained on Kepler can transfer to TESS for transient discovery tasks with strong precision/recall, suggesting feasibility for transit classification too (task differs but pipeline lessons apply).

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| **Dataset** | **Use in this component** | **Notes on SOTA/benchmarks** |
| Kepler (short/long cadence) | Train/val | RNNs effective on Kepler time-series; ESN-AE shows benefits of sequence-aware encoders. |
| TESS (2–10 min cadence sectors) | Test generalization | LSTM-based detectors have achieved ~80–90% P/R for flares; informs RNN design and transfer expectations. |
| Synthetic (transit injections) | Stress tests & controlled ablations | Matches overall project plan to include a synthetic dataset. |

**Methodology (RNN)**

**Preprocessing.** Mission-specific detrending; normalization per quarter/sector; interpolation rules only when safe; label alignment to avoid leakage from future samples (windowed labeling strategy informed by transient-detection literature).

**Architecture.** Compare GRU and LSTM stacks (2–3 layers, 128–256 units) with dropout; temporal global average pooling vs. final-state readout; sigmoid/softmax head depending on labeling granularity (sequence vs. subsequence). (Vida et al. favor stacked LSTMs; I’ll start there.)

**Training.** Class-imbalance weighting; focal/bce loss; early stopping on validation F1; strong augmentation via time masking and noise injection to emulate cadence gaps and systematics; hyperparameter search guided by validation P/R and AUC.

**Evaluation.** Precision, recall, F1, AUC; error analyses on false positives (stellar variability types) and false negatives (shallow/short transits); cross-mission transfer (Kepler→TESS) to test robustness, following the philosophy of prior Kepler→TESS RNN work.

**(Optional) Timing-aware auxiliary signal.** Inspired by RMTPP, encode inter-event intervals (candidate ingress/egress markers) to regularize the classifier or provide a multi-task head for event timing likelihood; this can help the RNN exploit the structure of transit sequences.

**Milestones & Deliverables (for Josh)**

**Week 1–2:** Reproducible Kepler/TESS data prep notebook; baseline non-recurrent classifier for sanity check.  
**Week 3–4:** LSTM/GRU prototypes; windowing/labeling choices locked; first Kepler validation results.  
**Week 5:** Cross-mission test on TESS; error taxonomy; ablations on window length and cadence.  
**Week 6:** Optional timing-aware auxiliary objective; finalize metrics/plots and RNN write-up.  
Deliverables: Trained RNN model with config, evaluation report/figures, and contribution text for the AAAI-format paper. (Sections required in the proposal stage: Title/Authors, Abstract, Introduction, Related Work, Roles/Deliverables, Dataset table with SOTA, Short Conclusion.)

**Short Conclusion**

RNNs (especially LSTMs) are a strong fit for temporal context in mission light curves and have demonstrated transfer across Kepler/TESS in related tasks. My contribution will deliver a well-tuned recurrent baseline for transit detection that complements the team’s CNN and Transformer systems and helps quantify the benefits of sequence-aware modeling in this domain

**References (minimum 3 peer-reviewed)**

Kügler, S. D., Gianniotis, N., & Polsterer, K. L. (2016). *An explorative approach for inspecting Kepler data*. **MNRAS**, 455(4), 4399–4405.

Vida, K., Bódi, A., Szklenár, T., & Seli, B. (2021). *Finding flares in Kepler and TESS data with recurrent deep neural networks*. **A&A**, 652, A107.

Du, N., Dai, H., Trivedi, R., Upadhyay, U., Gomez-Rodriguez, M., & Song, L. (2016). *Recurrent marked temporal point processes: Embedding event history to vector*. **KDD 2016**, 1555–1564.