CSUN SPaRA program

CSUN ANAGNOST COLLEGE OF ENGINEERING & COMPUTER SCIENCE

Forecasting Runner Injuries from Wearable Data using Recurrent Neural Networks

Brandon Ismalej, Xunfei Jiang, Department of Computer Science

Abstract

Wearable sensors continuously capture training load and physiological patterns in athletes. Although **wearable sensors provide rich daily data**, identifying early indicators of **injury risk remains a challenge.**

In this project, we apply **deep recurrent neural networks to forecast runner injuries** from multivariate training load sequences.

Dataset & Analysis

Dataset: Injury Prediction in Competitive Runners [1]

- **74 elite runners tracked over 7 years** (2012-2019) single Dutch team; middle- and long-distance
- **583 injuries & 42,183 healthy training session**s collected via GPS watches, heart rate monitors, and subjective assessments
- **Training data** included distance, duration, intensity zones (Z1-Z5), and **engineered** ACWR (Figure 1)
- **Rolling 7-day sequences** used to predict next-day injury, shown in Figure 2

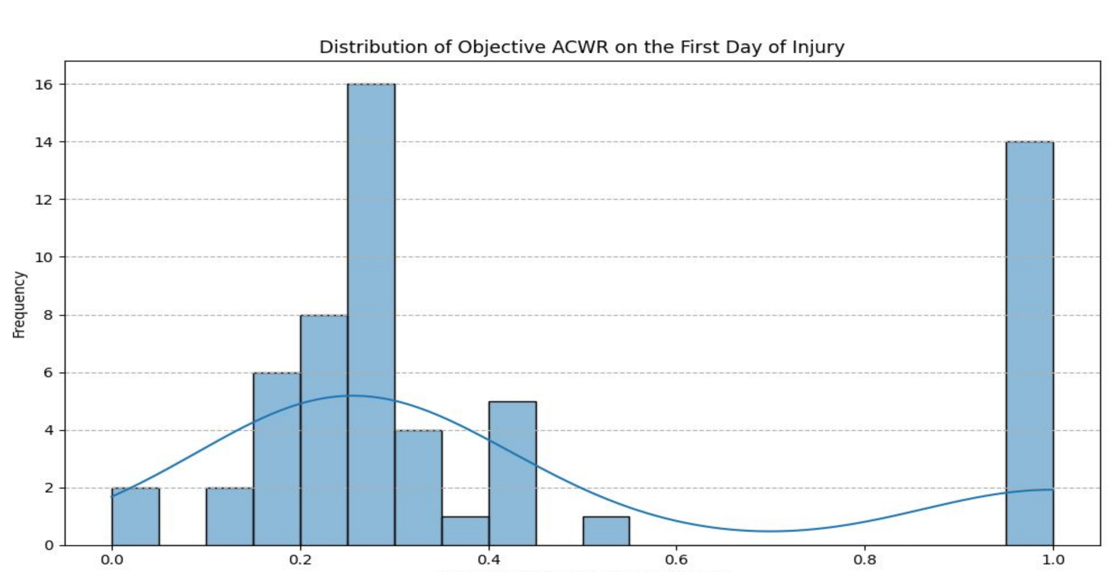

Figure 1: Acute Chronic Workload Ratio Among Injuries

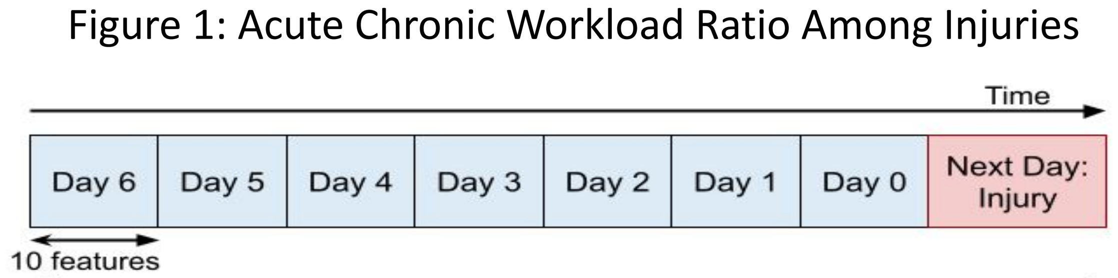

Figure 2: 7 Day Sequences of Training Data for Forecasting Next-Day Injury

Training Results

Neural Network Training:

- Bidirectional **Gated Recurrent Unit** (GRU) (Figure 3)
- **Focal Loss** function used
  - To mitigate effects of class imbalance
  - Prioritizes learning from rare cases by penalizing misclassification of the minority class (injuries)

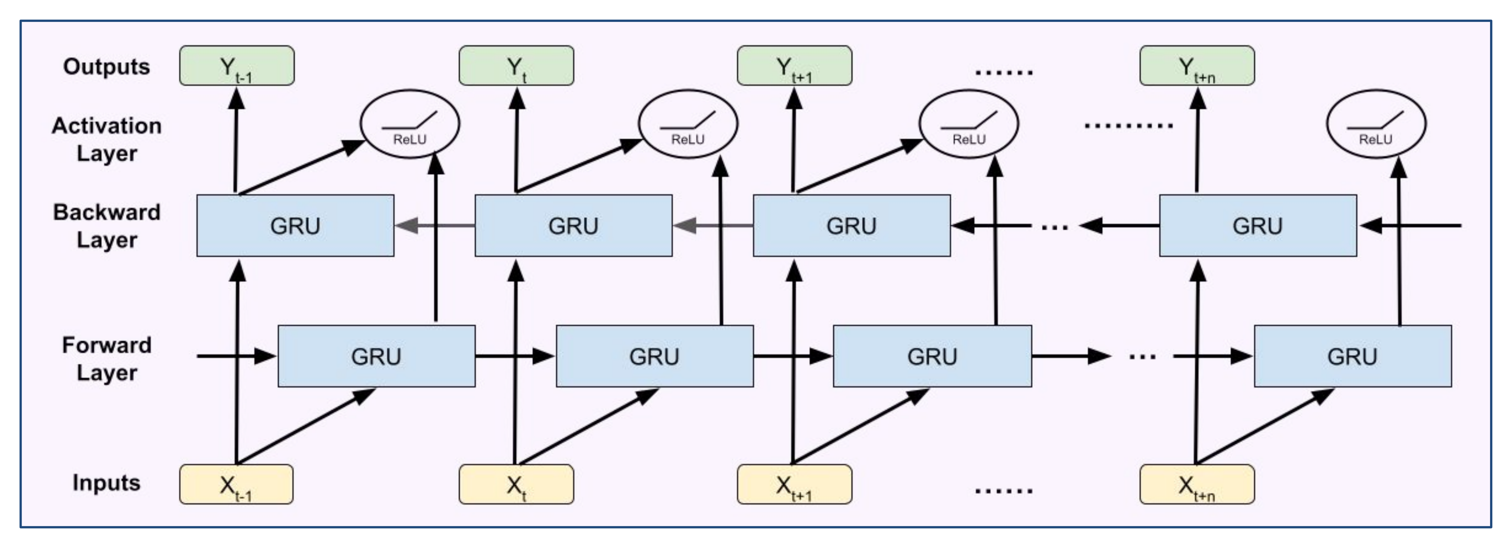

Figure 3: Bidirectional GRU Architecture

Current Results:

- Achieved 92.1% accuracy & 0.569 ROC-AUC on highly imbalanced runner-injury dataset (Table 1)
- Precision-recall performance remains low due to the extreme class imbalance; PR-AUC ~0.025.
- Performance remains below prior work, emphasizing the challenge of injury prediction.

Approach	Our Approach	Lovdal et al., 2021 [1]	Li et al., 2025 [2]
Data Balance Method	Focal Loss	None (raw)	VAE Augmentation
Model Type	Bidirectional GRU	XGBoost	VAE-Autoformer
Accuracy (%)	**92.10**	–	79.76
Recall (%)	**13.46**	58.4	92.25
Precision (%)	2.76	–	67.49
ROC-AUC	0.569	0.724	0.881

Table 1: Results Compared with Relevant Literature

Conclusions

- Injury prediction from training data remains a challenging, highly imbalanced classification task
- The **Bidirectional GRU achieved strong accuracy** but limited recall and ROC-AUC
- Deep recurrent models can serve as viable foundations for practical and informative injury forecasting pipelines, as shown in Figure 4

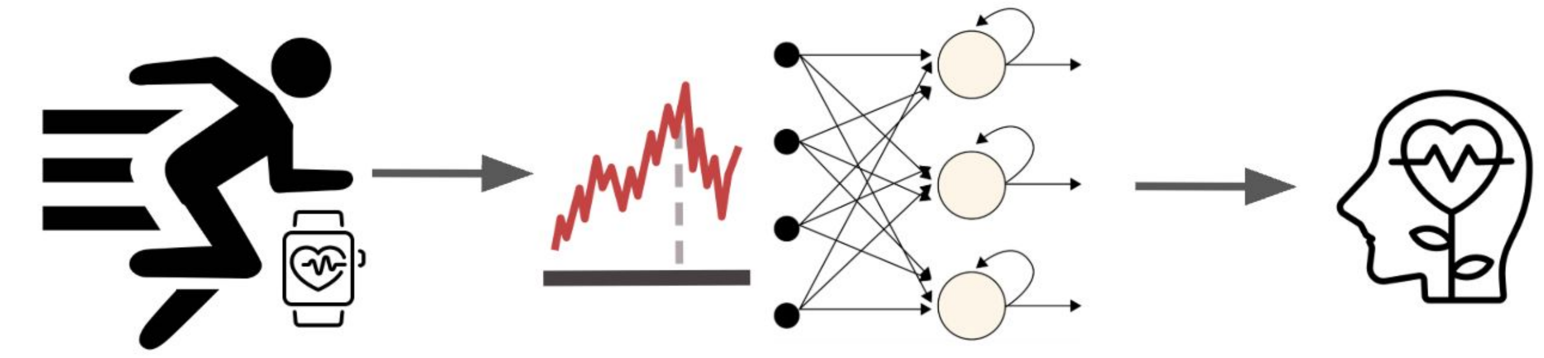

Figure 4: High Level Pipeline for Time Series Injury Forecasting

Future Work

- Integrate **VAE- or GAN-based data augmentation** to improve minority class representation
- Investigate multi-week contextual modeling and interpretability metrics for practical deployment

Acknowledgements

We would like to thank Zachary Frappier for his work in the exploratory data analysis and feature engineering.

References

[1] S. S. Lövdal, R. J. R. Den Hartigh, and G. Azzopardi, "Injury Prediction in Competitive Runners With Machine Learning," International Journal of Sports Physiology and Performance, vol. 16, no. 10, pp. 1522–1531, 2021, doi: https://doi.org/10.1123/ijspp.2020-0518.

[2] A. Li, R. Zhang, and C. Li, "Data augmented Autoformer for runner injury prediction," Alexandria Engineering Journal, vol. 132, pp. 64–73, Nov. 2025, doi: https://doi.org/10.1016/j.aej.2025.10.021.

Supported by CSUN STEM Pathways & Research Alliance (CSUN-SPaRA) and funded by the California State University System.