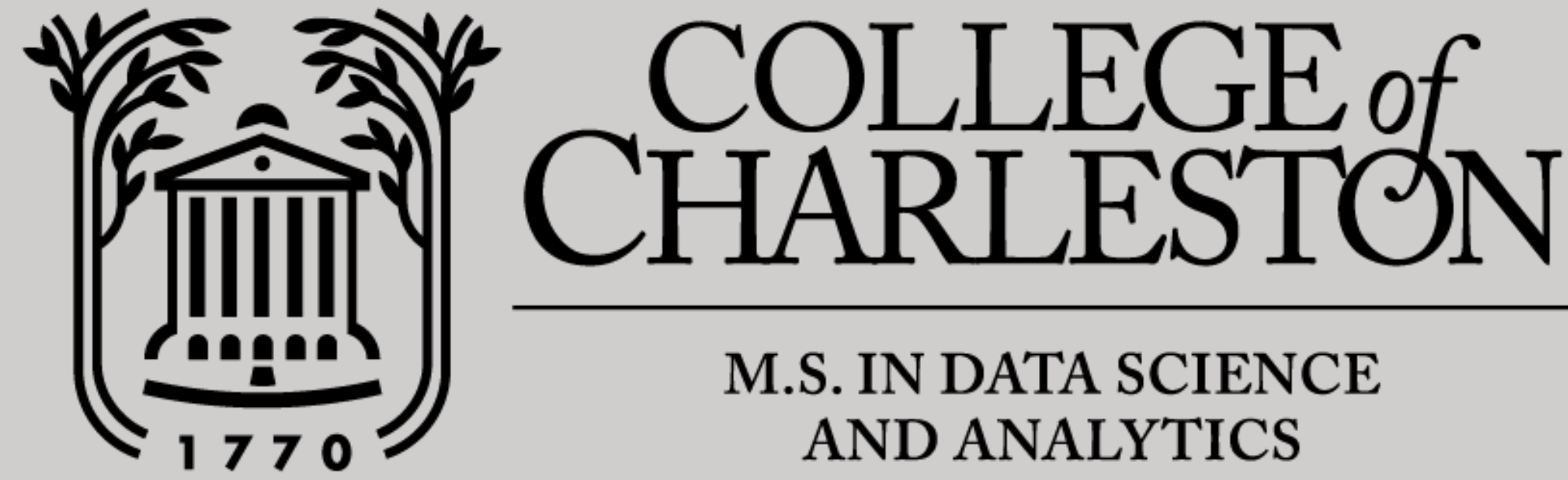


Unlocking the Secrets of Heart Transplant Success with Machine Learning



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Introduction

- Machine learning (ML) models can be used to predict medical outcomes
- United Network for Organ Sharing (UNOS) collects transplant data from across the US
- The dataset used has data on over 40,000 heart transplants
- Current ML models are more accurate than scoring systems in predicting heart transplant failure and mortality¹
- This study uses an XGBoost model to identify patients at risk of heart transplant failure before 365 days post-transplant
- Studies with other UNOS datasets have found success with Random Forest and XGBoost algorithms²

The Process

Collect Data from the Medical University of South Carolina

Feature Engineering

- Converted 365DaySurvival to bool
- Converted PROTEIN_URINE to bool
- Mapped features to new values:

Gender		ABOMAT	
M	0	ABO incompatible	0
F	1	ABO compatible	1
		ABO identical	2

Data Cleaning

- Removed object columns
- Selected columns based on physician feedback
- Removed objects with null values

Create, Train, and Test XGBoost Model

Evaluate Metrics and Features

Results

Data Distribution in Original Dataset

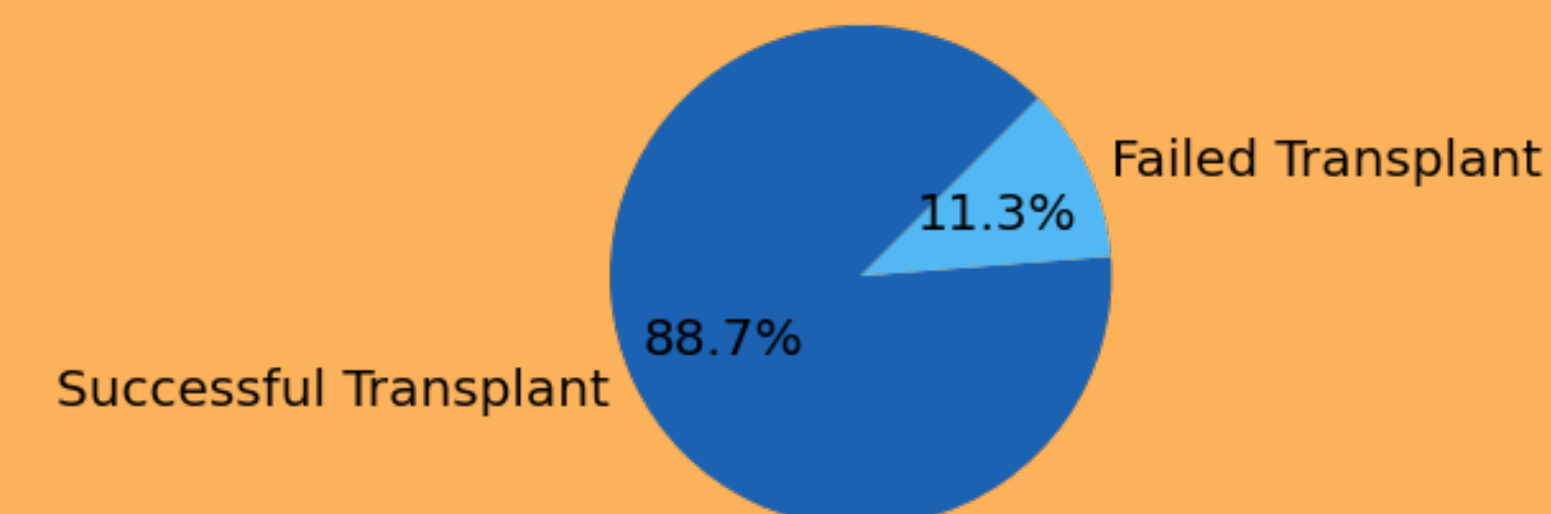


Figure 1: Data distribution showing uneven class distributions in dataset

- The dataset is highly skewed, as shown in Figure 1
- Unbalanced classes will likely result in an overfit model favoring the dominant class

- Confusion matrix in Figure 2 built with Scikit-Learn library after model testing
- Test results show high accuracy, but low specificity

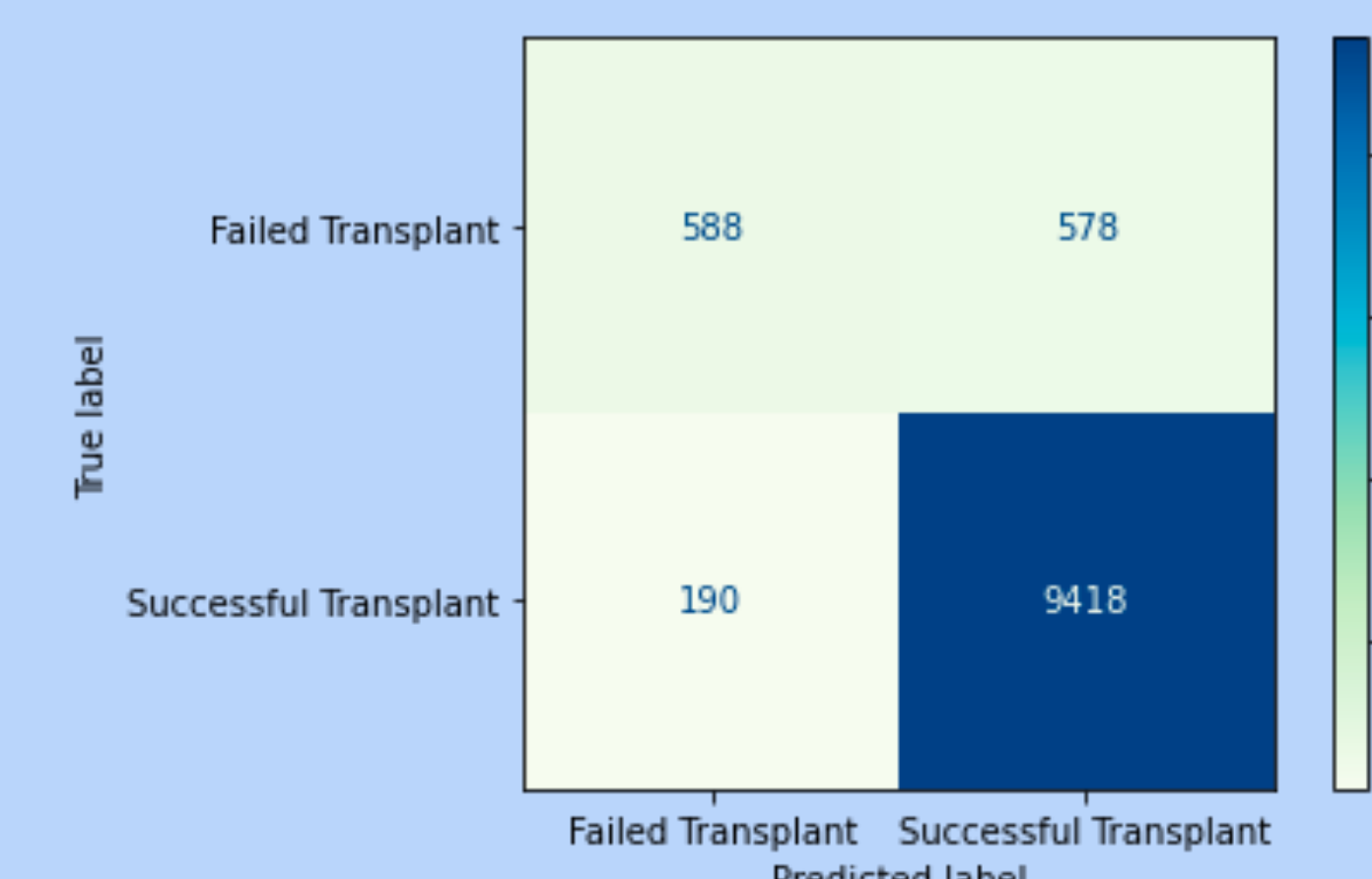
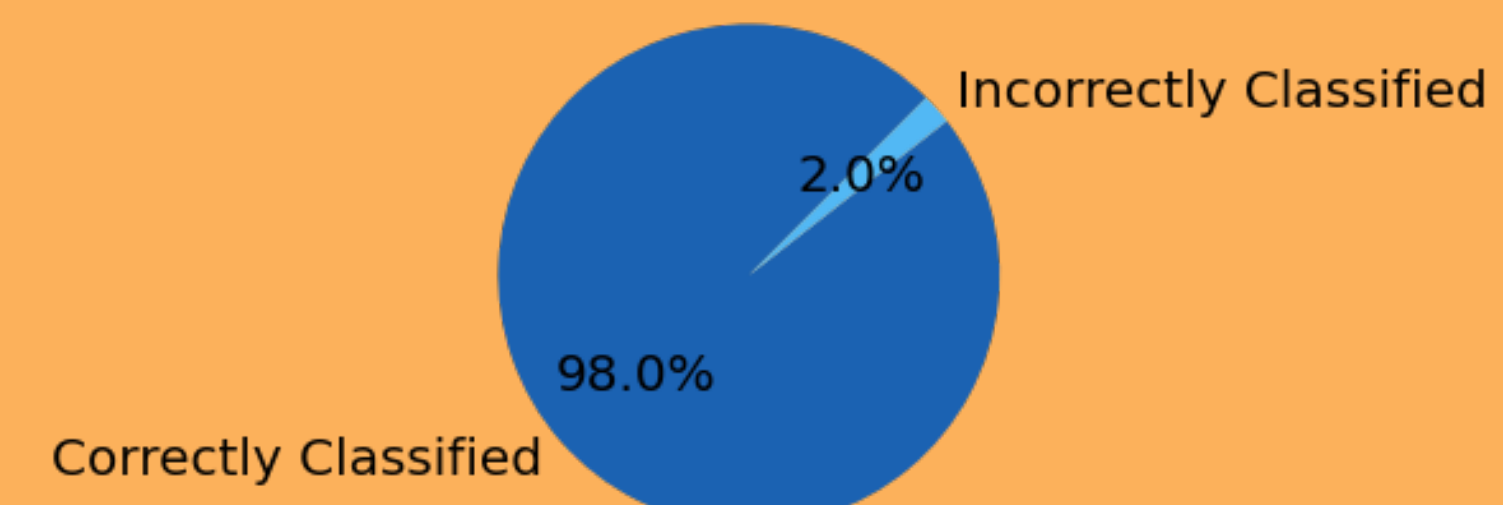


Figure 2: Confusion matrix generated from the test data predictions

Classification Rates for Successful Heart Transplants



Classification Rates for Failed Heart Transplants

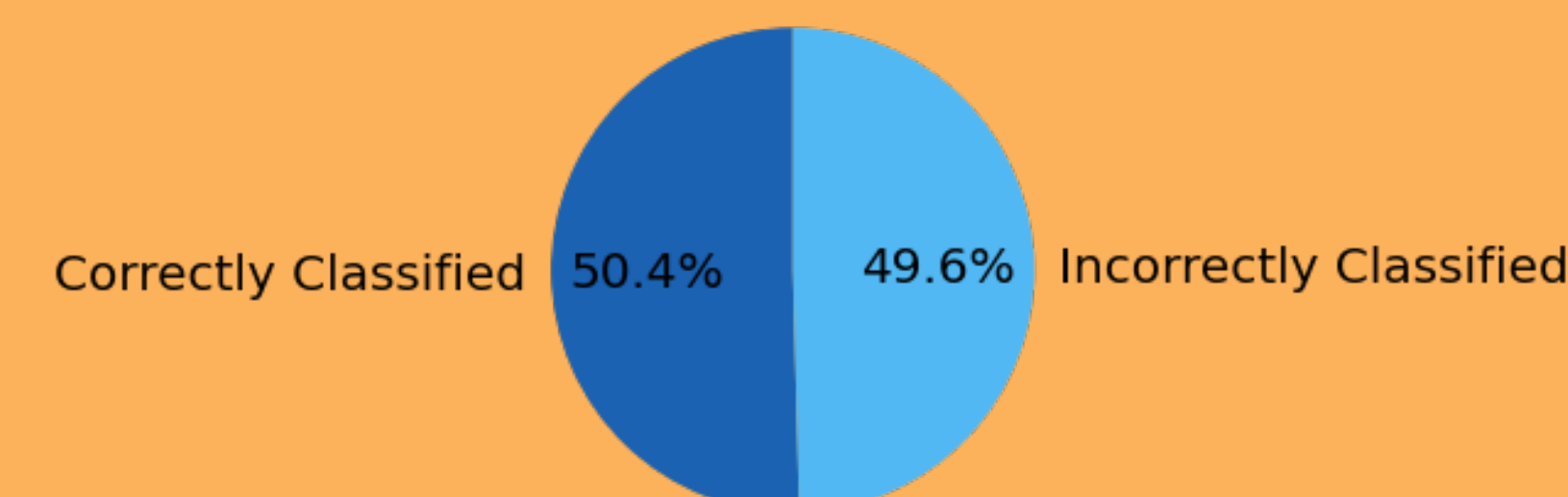


Figure 3: Classification rates for both classes

- Almost all successful transplants were classified correctly while only half of failed transplants were, as shown in Figure 3
- Table 1 shows good model performance for all metrics except specificity

Metric	Score
Accuracy	0.929
Precision	0.942
Recall	0.98
Specificity	0.504
F1 Score	0.961
AUC ROC	0.742

Table 1: Evaluation metrics calculated from model predictions

- Transplant year and donor age are the top features used in classification, per Figure 4
- Features with a larger SHAP value range play a larger role in classification

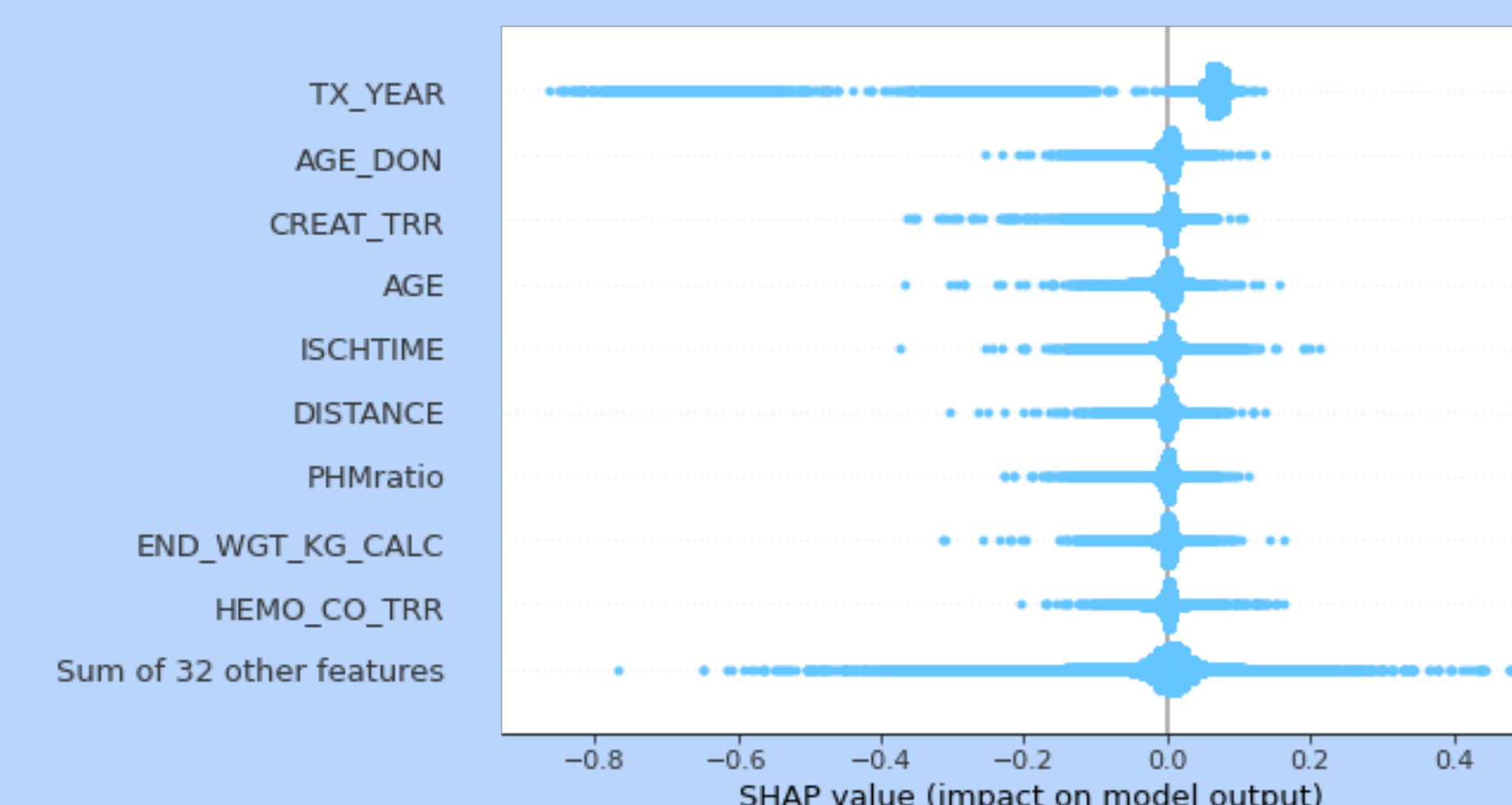


Figure 4: Top features impacting transplant success prediction

Conclusions

- The model accurately classifies 93% of successful heart transplants
- The model's specificity is low, only accurately classifying 50% of failed transplants
- Discrepancy in accuracy and specificity likely due to unbalanced classes
- The model is likely overfit and favors successful transplant classification
- The model is still successful and suggests that ML models can be used to predict heart transplant outcomes

Future Work

- Reduce the model complexity to address overfitting concerns
- Focus on a smaller subset of features
- Return to object-type features for feature engineering
- Try other algorithms, such as Random Forest

Acknowledgements

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Works Cited

- Naruka, V., Arjomandi Rad, A., Subbiah Ponniah, H., Francis, J., Vardanyan, R., Tasoudis, P., Magoulakia, D. E., Lazopoulos, G. L., Salmasi, M. Y., & Athanasiou, T. (2022). Machine Learning and Artificial Intelligence in cardiac transplantation: A systematic review. *Artificial Organs*, 46(9), 1741–1753. <https://doi.org/10.1111/aor.14334>
- Miller, R. J. H., Sabovčik, P., Cauwenberghs, N., Vens, C., Khush, K. K., Heidenreich, P. A., Haddad, P., & Kuznetsova, T. (2022). Temporal shift and predictive performance of machine learning for Heart Transplant Outcomes. *The Journal of Heart and Lung Transplantation*, 41(7), 928–936. <https://doi.org/10.1016/j.jhealun.2022.03.019>

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