AI Clinical Decision support in predicting hospital readmission for diabetes patients.

Daniel Akama Nyamweya

Problem Overview

- This project explores machine learning–based prediction of hospital readmissions using a real-world, multi-class clinical dataset.
- The goal is not only to build predictive models, but to understand why they make certain predictions through explainable AI (XAI), ensuring usability and applicability in real-world clinical decision support systems (CDSS).

Literature review (modeling)

- Recent literature emphasizes that the success of AI-based CDS tools depends not only on accuracy but also on interpretability, workflow fit, and clinical validation. For instance, contemporary work by **(Chaddad, A., et al. 2023)** observed that interpretable machine learning models are better than opaque neural networks in clinician trust and adoption rates when predicting.
- Explainable CDS systems have begun integrating user-centric design principles, allowing healthcare staff to visualize patient-specific risk factors in real time. Furthermore, there has been a surge in hybrid CDS frameworks that combine AI predictions with clinical guidelines. These insights strengthen the rationale for this research focus on explainable, and easily integrable CDS solutions.

Literature review (modeling)

- Large studies such as **(Strack et al., 2014b)** analyzed a large clinical database to assess diabetes care during hospitalization and identify potential improvements. It found that HbA1c measurements were rarely conducted in hospitalized diabetic patients. The analysis, using multivariable regression, showed that the likelihood of early readmission was influenced by whether HbA1c was measured, with variations depending on the primary diagnosis. The findings suggest that better monitoring of HbA1c in hospital settings could improve patient outcomes and reduce healthcare costs.

Literature review (dataset)

- Source Validation - The dataset originates from a trusted and peer-recognized repository (UCI Machine Learning Repository). It includes real-world clinical information such as demographics, lab tests, diagnoses (ICD codes), medications, and readmission outcomes. The dataset has been used in multiple peer-reviewed studies for developing predictive models, confirming its acceptance and reproducibility in research **(Strack et al., 2014b).**

Literature review (XAI)

- Apply SHAP values to interpret feature contributions for each prediction. Develop real-time decision support outputs that could integrate into EHR dashboards (e.g., patient risk scores with highlighted contributing factors).**(Mienye et al., 2024)**

Justification of population chosen

We decided to work with UCI Diabetes 130-US Hospitals for years 1999 to 2008 dataset.

- It has over 100k hospital admissions for diabetic patients across 130 hospitals in the United States. It Includes demographic information, admission/discharge details, diagnoses, medications, and readmission status.
- Population: Adult patients over 18 years with a primary or secondary diagnosis of diabetes.

Justification of population chosen (cont)

Some of the features include:

- Demographics: Age, gender, race.
- Hospital & Admission Info: Admission type (emergency, urgent, elective), discharge disposition, length of stay.
- Medical Diagnoses: Primary and secondary ICD-9 codes.
- Treatments & Medications: Insulin and oral diabetes medication changes (metformin, sulfonylureas, etc.)
- Laboratory Results: HbA1c measurements, glucose serum test results.
- Comorbidities: Hypertension, cardiovascular disease, obesity indicators via ICD-9.

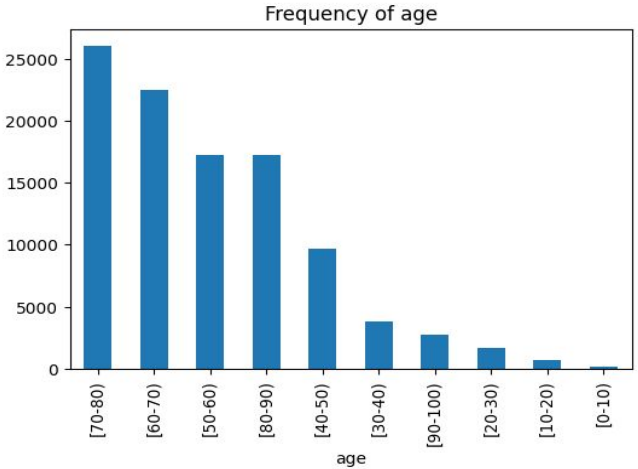
Justification of population chosen (cont)

Some of the features we engineered:

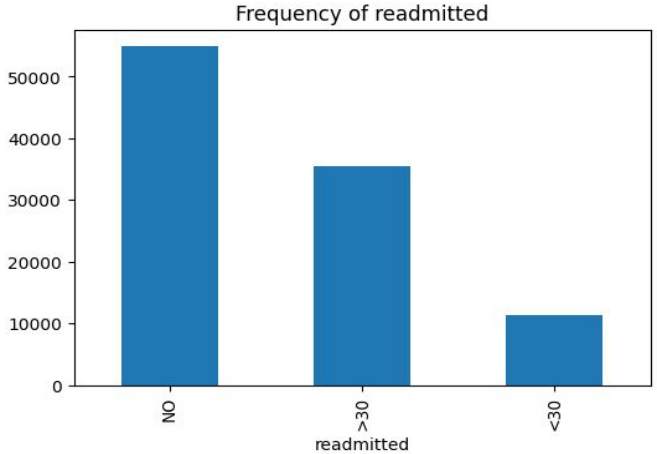
- age_group - converts numeric age to categorical risk buckets.
- comorbidity_score - counts the number of diagnoses.
- total_meds - aggregates medications or drug columns.
- prev_readmit - captures patient’s readmission history.

Exploratory analysis and Interpretation

Diabetes more prevalent in older people.

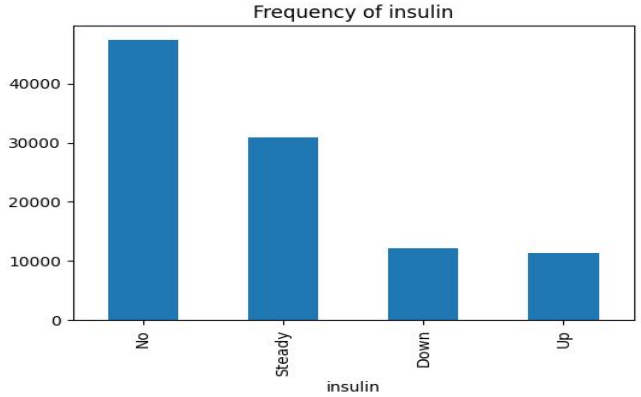


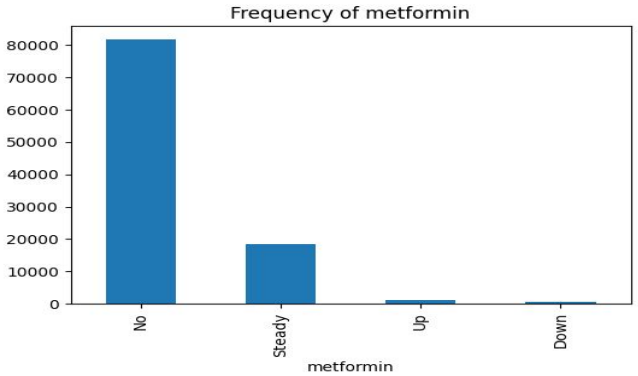
Diabetes more prevalent in older people.

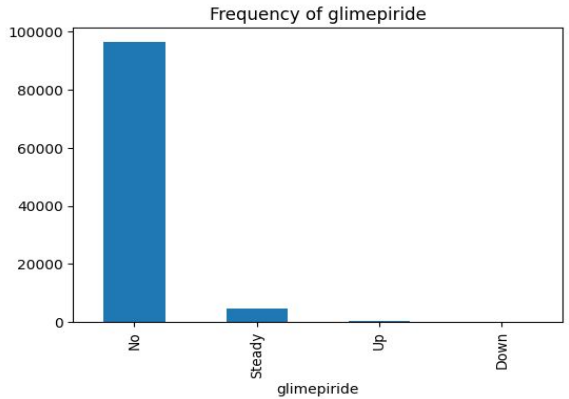


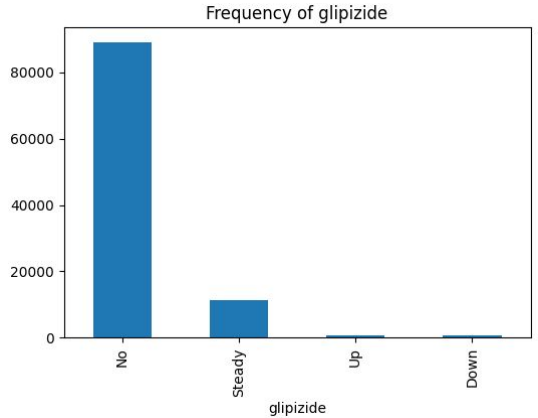
Dataset highly imbalanced.

cont

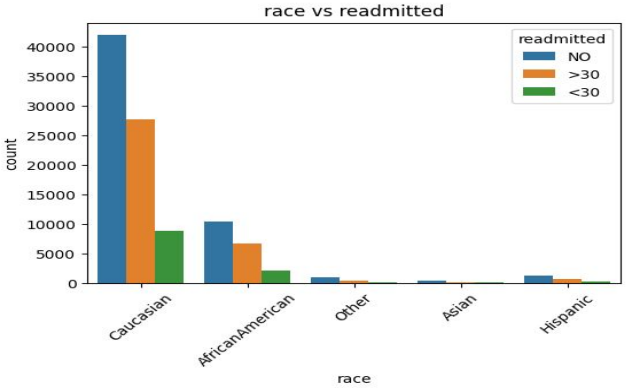

Frequency of insulin
40000
30000
20000
10000
0
No
Steady
Down
Up
insulin

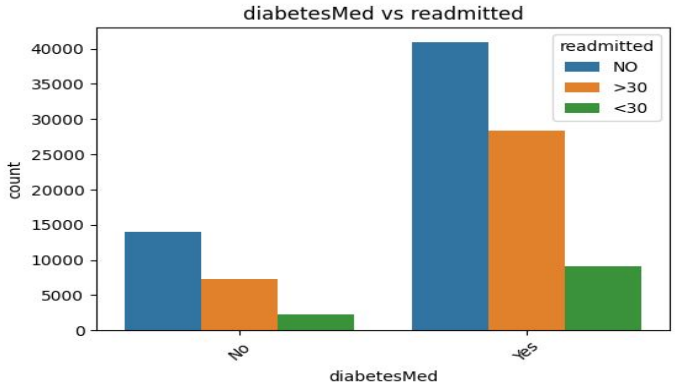

Frequency of metformin
80000
70000
60000
50000
40000
30000
20000
10000
0
No
Steady
Up
Down
metformin

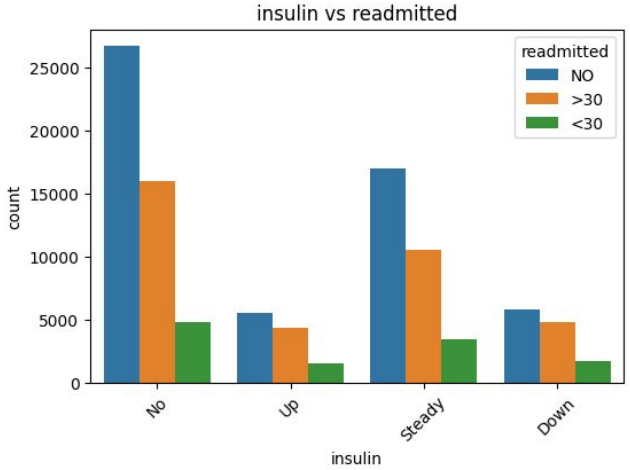

Frequency of glimepiride
100000
80000
60000
40000
20000
0
No
Steady
Up
Down
glimepiride


Frequency of glipizide
80000
60000
40000
20000
0
No
Steady
Up
Down
glipizide

Bivariate visualizations

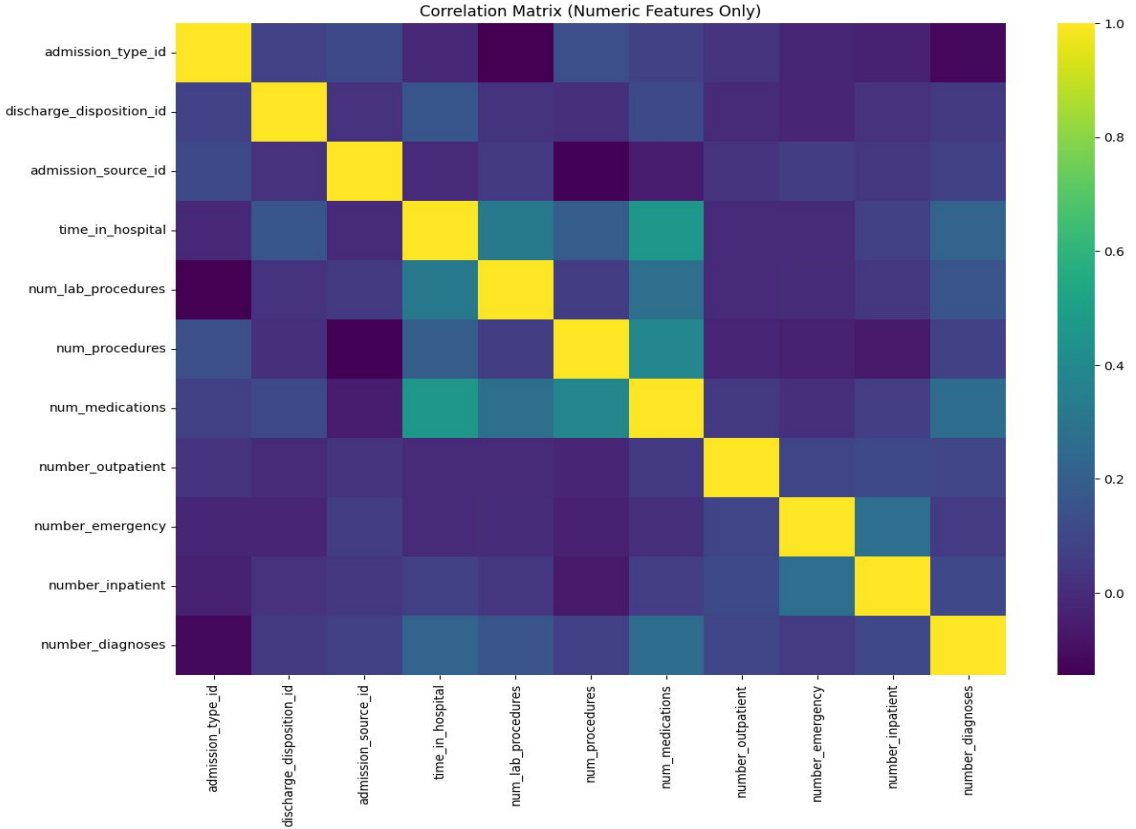






Correlation Matrix

Absence of strong multicollinearity (correlation values close to ±1) indicates that these variables can be jointly included in predictive modeling without causing significant redundancy or distortion of the model coefficients. Overall, the matrix suggests a diverse set of predictors that may each add value when analyzing or predicting clinical outcomes.

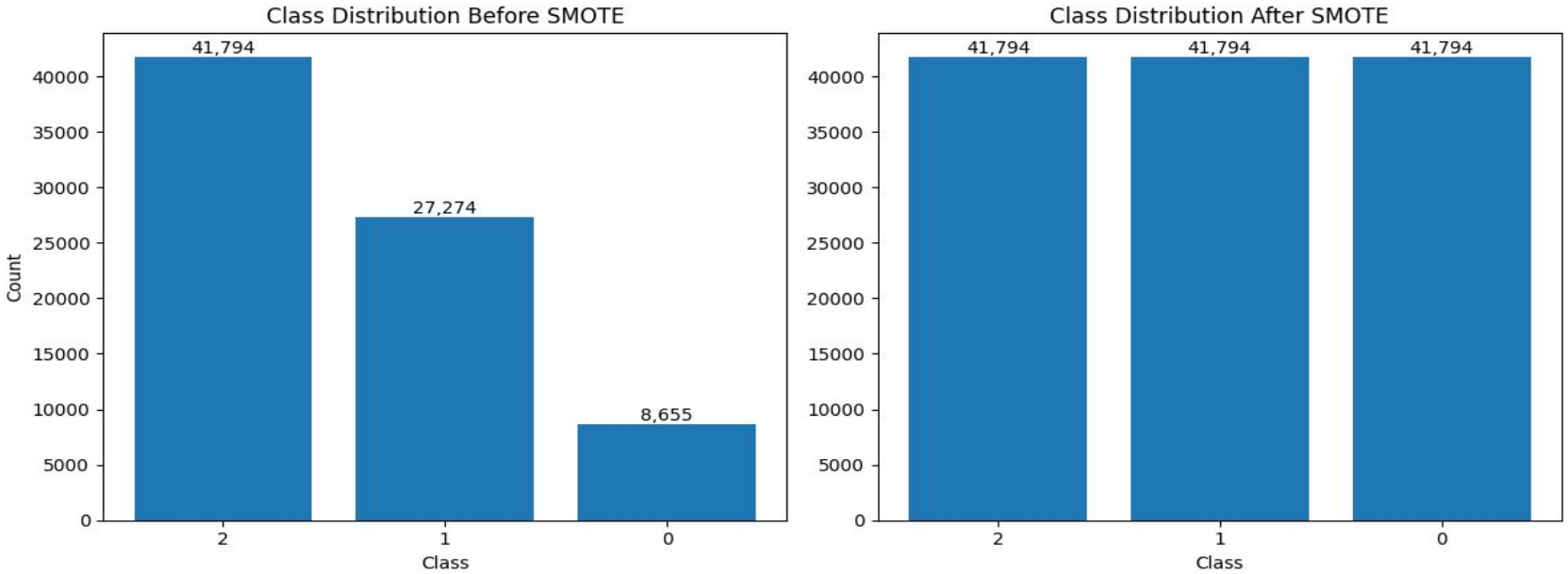


Preprocessing implemented.

1. Missing values removal (>40%) and imputation.
2. Categorical features encoding (33 features)
3. Outliers removal - focused heavily on 3 features:
    a. Time in hospital.
    b. Number of lab procedures.
    c. Number of medications.
4. Feature engineering (age_groups, comorbidity_score, total_meds)
5. Patient-level splitting - group shuffle split to prevent data leakage.

Modeling.

Smote for oversampling.



Metrics comparison table

Model	Accuracy	Precision Macro	Recall Macro	F1 Macro	AUC Macro
Logistic Regression	0.491938	0.408377	0.409394	0.397107	0.590863
Random Forest	0.568245	0.444377	0.419362	0.415099	0.648764
MLP Classifier	0.552275	0.439324	0.414773	0.414421	0.619938
XGB Classifier	0.573791	0.46759	0.43372	0.434999	0.660554

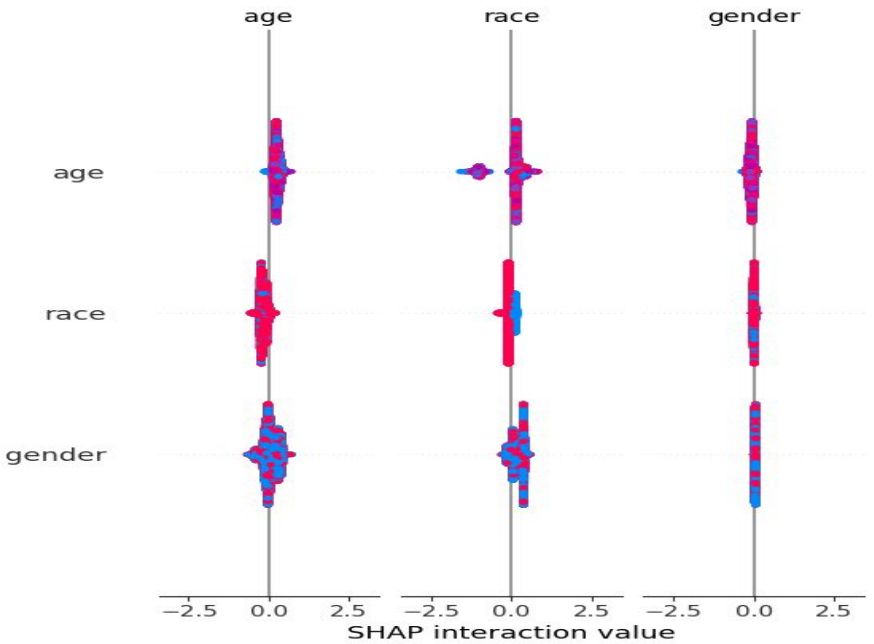
- Despite XGBoost being the best-performing model, the absolute values of accuracy, recall, and AUC across all models remain moderate. This suggests that the dataset may have limitations such as class imbalance even with SMOTE, feature sparsity, or limited clinical granularity that make prediction inherently challenging.
- These findings reinforce the importance of incorporating explainability (XAI), better feature engineering, and potentially additional contextual or temporal features to enhance model performance in future iterations.

XAI - why the choice?

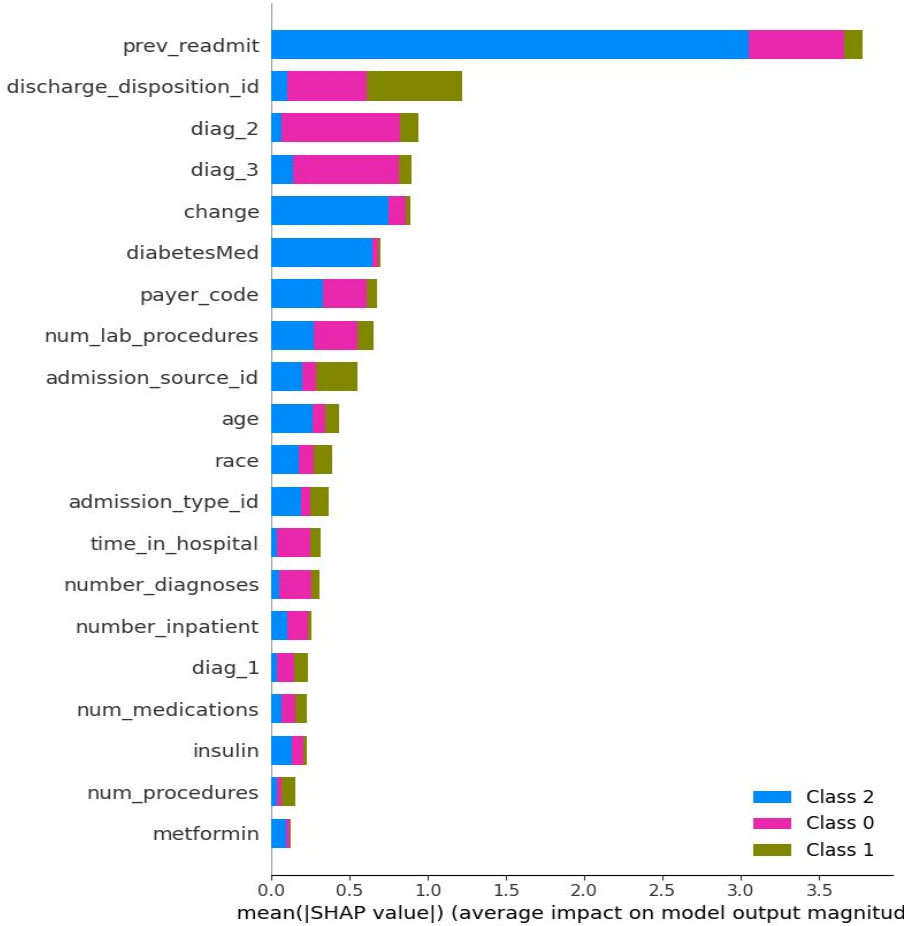
Global SHAP visualization.

Summary plot

- Features at top are the most influential for readmission risk. (gender, race, age)
- Color = feature value (red = high, blue = low)
- X-axis = impact on prediction

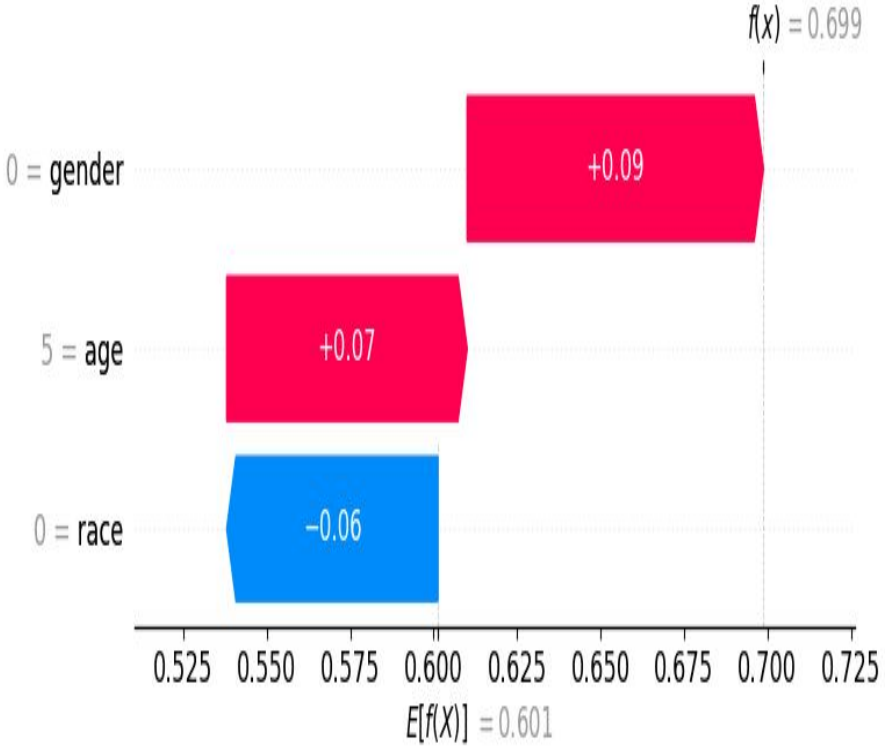


Bar plot of global feature importance



Local SHAP graph for sample index 10

- The patient's gender increases the predicted risk, shown by a positive SHAP value that pushes the final prediction higher.
- Age also contributes positively, indicating that the patient's age category is associated with an elevated readmission probability relative to the population baseline.
- Race contributes negatively, meaning the patient's specific race category decreases the predicted probability compared to the average case in the dataset.



Conclusion

- Given these performance limitations, implementing a full user interface (UI) at this stage would not be practical or responsible. A UI implies readiness for operational deployment, yet the model is not accurate enough to support clinical or administrative decision-making. Deploying a weak model behind a user-friendly interface could create a false sense of confidence, leading to potential misinterpretations or inappropriate actions.

- For this reason, the project instead shifted towards explainable AI (XAI) methods such as SHAP to explore and understand why the models behave as they do and to identify which features contribute meaningfully to predictions.

- Overall, the project demonstrates that while predictive modeling is feasible, significant improvements to data quality, feature richness, and model interpretability are required before operationalizing the system.

Next Steps

1. Deepen Explainability (XAI):
Expand SHAP analyses to include dependence plots, summary plots, and feature-level insights. This will help identify which features are truly meaningful and which require refinement or removal.

2. Improve Feature Engineering:
- Incorporate richer temporal features (e.g., sequence of encounters, time since last admission).
- Build comorbidity indices (Charlson, Elixhauser).
- Aggregate medication and lab result patterns.
- Explore interaction terms and non-linear transformations.

3. Experiment With Advanced Models:
- Gradient boosting with custom loss functions.
- Recurrent or transformer-based models for sequential data.
- Survival models if time-to-readmission becomes relevant.

4. Re-evaluate Deployment After Model Improvements:
Only if performance metrics reach clinically acceptable levels should a UI or decision-support tool be considered. Until then, development should remain focused on model refinement and explainability.

References

1. GroupShuffleSplit. (n.d.). Scikit-learn. https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.GroupShuffleSplit.html
2. GeeksforGeeks. (2025, November 13). SMOTE for Imbalanced Classification with Python. GeeksforGeeks. https://www.geeksforgeeks.org/machine-learning/smote-for-imbalanced-classification-with-python
3. Strack B, DeShazo JP, Gennings C, Olmo JL, Ventura S, Cios KJ, Clore JN. Impact of HbA1c measurement on hospital readmission rates: analysis of 70,000 clinical database patient records. Biomed Res Int. 2014;2014:781670. doi: 10.1155/2014/781670. Epub 2014 Apr
4. PMID: 24804245; PMCID: PMC3996476. https://pmc.ncbi.nlm.nih.gov/articles/PMC3996476/ 2. Chaddad, A., Peng, J., Xu, J., & Bouridane, A. (2023). Survey of Explainable AI Techniques in Healthcare. Sensors, 23(2), 634. https://doi.org/10.3390/s2302063 3. Lundberg, S., & Lee, S. (2017, May 22). A unified approach to interpreting model predictions. arXiv.org. https://arxiv.org/abs/1705.07874
5. Rajkomar, A., Dean, J., & Kohane, I. (2019). Machine learning in medicine. New England Journal of Medicine, 380(14), 1347–1358. https://doi.org/10.1056/nejmra1814259 5. UCI Machine Learning Repository. (n.d.). https://archive.ics.uci.edu/dataset/296/diabetes+130-us+hospitals+for+years+199 9-2008

References

6. Mienye, I. D., Obaido, G., Jere, N., Mienye, E., Aruleba, K., Emmanuel, I. D., & Ogbuokiri, B. (2024). A survey of explainable artificial intelligence in healthcare: Concepts, applications, and challenges. Informatics in Medicine Unlocked, 51, 101587. https://doi.org/10.1016/j.imu.2024.101587

7. Shortliffe, E. H., & Sepúlveda, M. J. (2018). Clinical decision support in the era of artificial intelligence. JAMA, 320(21), 2199. https://doi.org/10.1001/jama.2018.17163