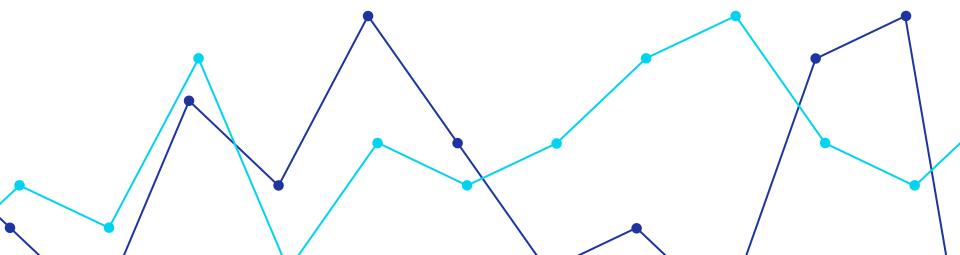
Healthcare - Persistency of a Drug

Model Evaluation and Conclusions

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Synthetic Minority Over-Sampling Technique (SMOTE)

In our analysis, SMOTE was utilized to address the significant class imbalance present in the dataset. Here's how it was applied:

- **Applied to Predictor Variables:** While SMOTE is typically used to balance the target variable in classification problems, in our unique case, we used SMOTE to address imbalances in key predictor variables (like race, gender, and age group) due to their skewed distribution.
- **Enhancing Model Training:** By creating a more balanced representation of different demographic groups, SMOTE allowed our models to learn from a dataset that more closely resembles a general population.
- **Improving Model Generalization:** The use of SMOTE aimed to improve the robustness and generalization of our models, ensuring they perform well not just for the majority group but across all segments of the population.

Baseline Model

	rt:	tion Repo	. Classifica	Baseline Model			
support	f1-score	recall	precision				
258	0.00	0.00	0.00	0			
427	0.77	1.00	0.62	1			
685	0.62			accuracy			
685	0.38	0.50	0.31	macro avg			
685	0.48	0.62	0.39	weighted avg			

Logistic Regression Model

Tuned Lo	gistic	Regressio	n Classific	cation Repo	ort
		precision	recall	f1-score	support
	0	0.76	0.64	0.70	258
	1	0.80	0.88	0.84	427
accu	racy			0.79	685
macro	avg	0.78	0.76	0.77	685
weighted	avg	0.79	0.79	0.79	685
Resampled	Tuned	l Logistic	Regression	Classific	ation Report
	P	recision	recall	f1-score	support
	0	0.69	0.73	0.71	258
	1	0.83	0.81	0.82	427
accur	acy			0.78	685
macro		0.76	0.77	0.76	685
	56	0.78	0.78	0.78	685

Random Forest Regression Model

Tuned Rai	ndom	Forest Class	ification	Report	
		precision	recall	f1-score	support
	0	0.75	0.66	0.70	258
	0				
	1	0.81	0.87	0.84	427
accui	racv			0.79	685
macro		0.78	0.76	0.77	685
weighted	avg	0.79	0.79	0.79	685
Resampled	l Tune	ed Random For	est Class	sification	Report
		precision	recall	f1-score	support
	0	0.66	0.72	0.69	258
	1	0.82	0.78	0.80	427
accur	acv			0.75	685
	_	0.74	0.75		
macro			0.75		685
weighted		0.76	0.75	0.76	685

XGBoost Model

Tuned XGBoost	Classifica	ation Repor	t	
	precision	recall	f1-score	support
0	0.77	0 67	0.71	250
0	0.77			258
1	0.81	0.88	0.84	427
accuracy			0.80	685
macro avg	0.79	0.77	0.78	685
7				
weighted avg	0.80	0.80	0.80	685
Resampled Tun	ed XGBoost	Classifica	tion Report	t
Resampled Tun		Classifica recall		t support
Resampled Tund		recall		
	precision	recall	f1-score	support
0 1	precision 0.69	recall 0.71	f1-score 0.70 0.82	support 258 427
0 1 accuracy	precision 0.69 0.82	0.71 0.81	0.70 0.82 0.77	258 427 685
0 1	precision 0.69 0.82	0.71 0.81	0.70 0.82 0.77	support 258 427

Stacking Model

Stacking	Mode	l Classific	ation Repo	ort	
		precision	recall	f1-score	support
	0	0.76	0.65	0.70	258
	1	0.81	0.88	0.84	427
accui	сасу			0.79	685
macro	avg	0.79	0.76	0.77	685
weighted	avg	0.79	0.79	0.79	685
Resampled	Sta	cking Model	Classifica	ation Repor	t
		precision	recall	f1-score	support
	0	0.76	0.65	0.70	258
	1	0.81	0.88	0.84	427
accur	асу			0.79	685
macro	avg	0.79	0.76	0.77	685
weighted	avg	0.79	0.79	0.79	685

Final Recommendations

After testing different metrics with different data, XGBoost is the best choice for further development.

- **Highest Accuracy:** The Tuned XGBoost model consistently showed the highest accuracy (80%) compared to the other models. This indicates its superior ability to correctly classify instances overall.
- **Balanced Performance:** XGBoost demonstrated a good balance between precision and recall, especially for Class 1 (Persistency_Flag = True), which is crucial in medical predictions. High recall is particularly important to ensure that the model doesn't miss out on true cases.
- **Robust to Imbalance:** XGBoost inherently manages class imbalance well, especially with proper tuning of its parameters. It applies weighting schemes to the classes, making it more sensitive to the minority class.

Conclusion

The Tuned **XGBoost** model stands out as the most suitable choice given its current performance and potential for improvement. However, addressing the underlying issue of data **imbalance** and **diversity** is key to achieving higher accuracy and building a model that is truly reflective and fair for the entire population. Additionally, continual refinement in feature engineering, model tuning, and validation will play a crucial role in enhancing model accuracy and reliability.