



Analysis of Hospitalized Diabetes Patients between 1999-2008

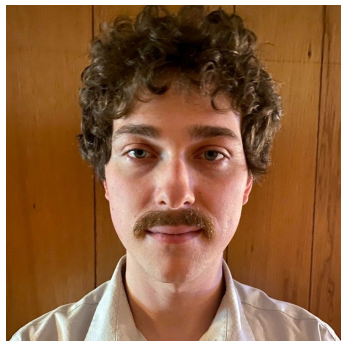
Keith-Jordan Wilkinson, Eddy Doering, Cory Chitwood, Kai Gui



Introduction



Keith-Jordan
Wilkinson



Eddy Doering



Cory Chitwood



Kai Gui



[linkedin.com/in/keith-jordan-wilkinson](https://www.linkedin.com/in/keith-jordan-wilkinson)

[linkedin.com/in/efdoering](https://www.linkedin.com/in/efdoering)

[linkedin.com/in/cchitwood](https://www.linkedin.com/in/cchitwood)

[linkedin.com/in/kaigui](https://www.linkedin.com/in/kaigui)

Tools:



IDEs



Introduction

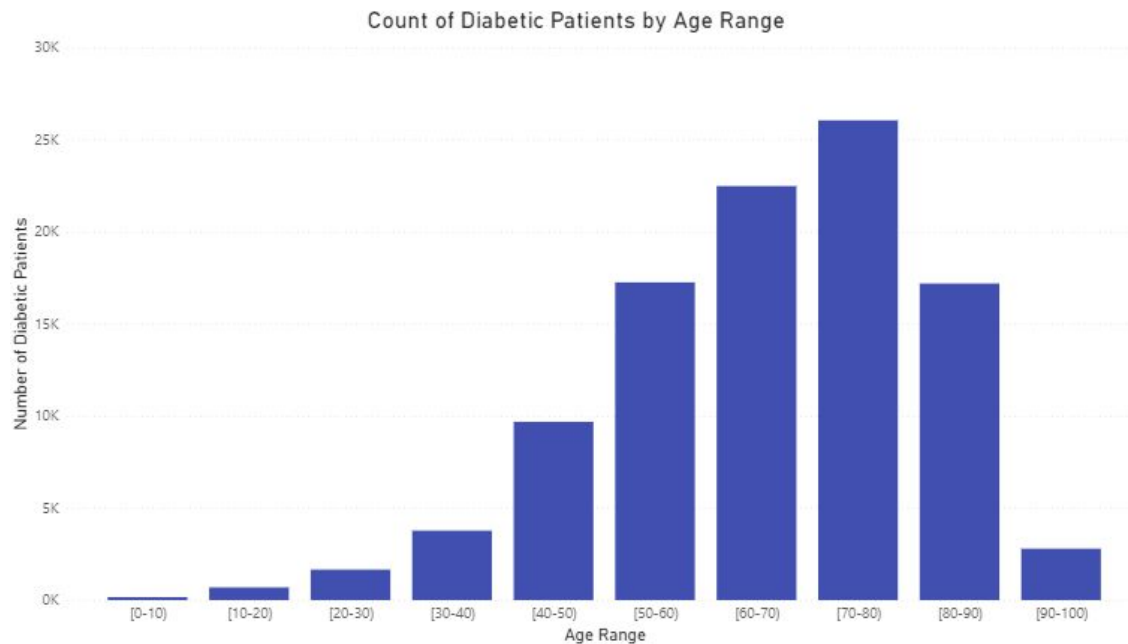
- Diabetes affects 10% of the U.S. population, 8th leading cause of death.
- Hospital readmittance is associated with poor patient outcomes.
- Dataset: Diabetes 130-US hospitals for years 1999-2008 (UCI)
 - Can ML predict if hospitalized diabetes patients will be readmitted?
- This information may improve patient outcomes and diabetes care



Questions

1. What is the most common age range for diabetes patients?
2. What are common diagnoses with diabetes patients?
3. How does time spent hospitalized change with patients age?
4. Are there any racial disparities in hospital visits for diabetes patients vs. national demographics?
5. What features can predict readmittance rates?

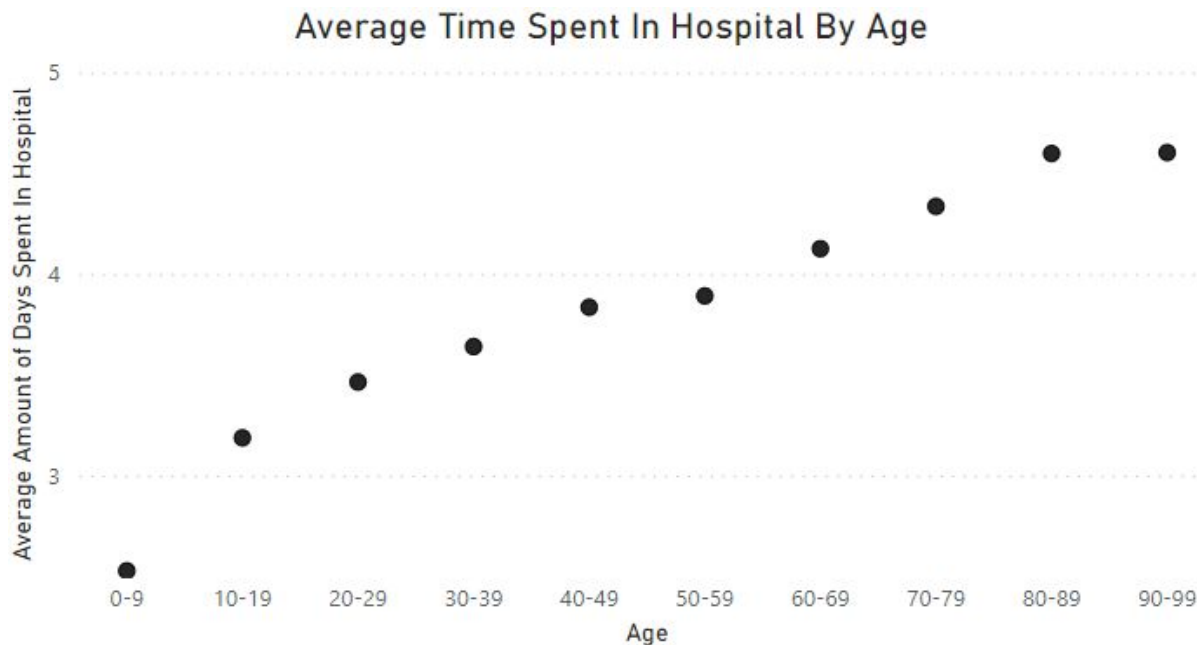
Visuals (1/4)



- Patient count increases from ages 40 to 80
- Patient count drops steeply at ages 80-100
- Between ages 0-30, there are very few hospitalized diabetes patients

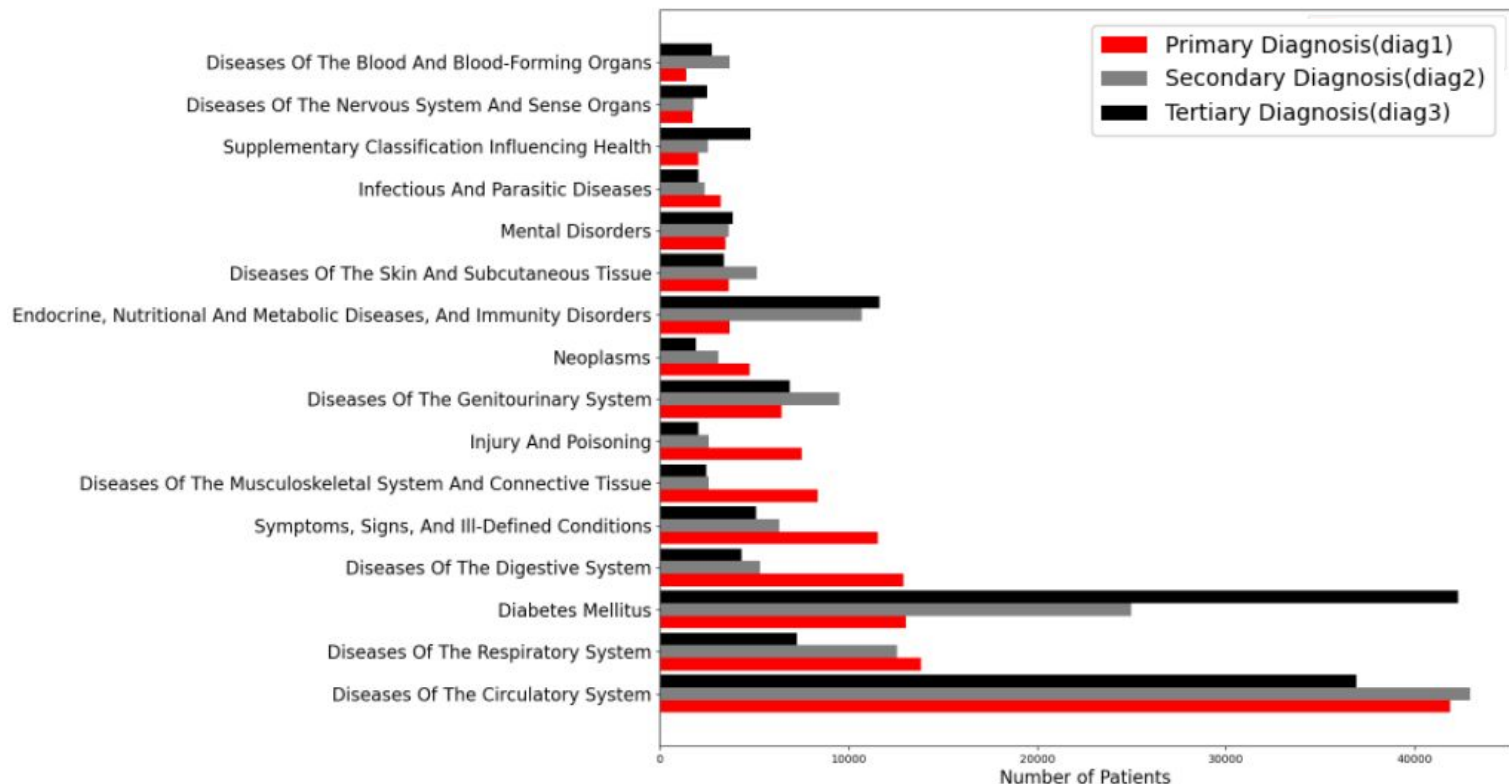
Visuals (2/4)

- Average hospitalization duration increases with age
- Complications associated with diabetes and surgical procedures may increase with age



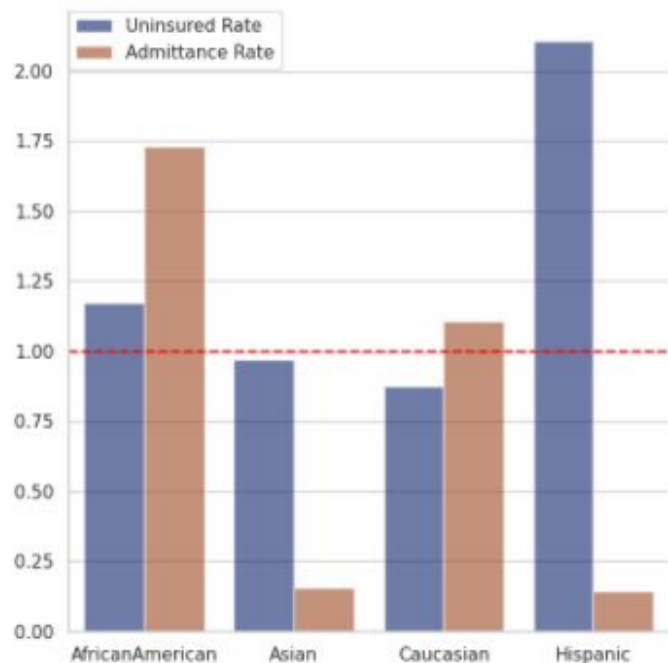
Visuals (3/4)

Primary, Secondary, and Tertiary Diagnosis of Diabetes Patients 1999-2008



Visuals (4/4)

Normalized Uninsured Rate vs Diabetes Admittance Rate



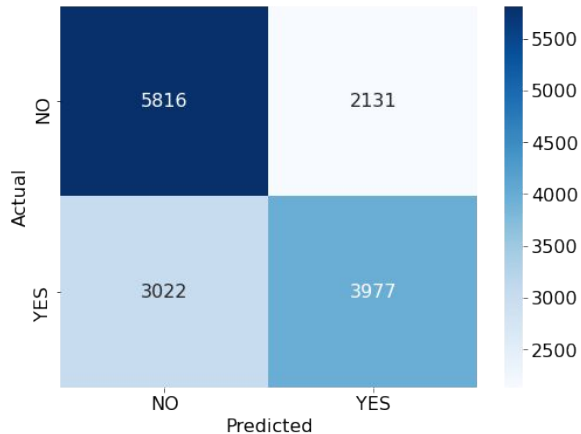
- Does higher uninsured percentage correlate with lower hospitalization rate?
- Hispanics and Caucasians follow hypothesis, African Americans and Asians do not.
- Other possible factors?
 - Language/cultural barriers?

Predicting Readmittance with Machine Learning

- Goal: Predict patient readmittance based on features of the initial stay
- Four different machine learning classification models were employed:
 - Random Forests
 - K-Nearest Neighbors
 - Ridge
 - SGD Classifier.
- Hyperparameters were tuned. Model performance was compared.

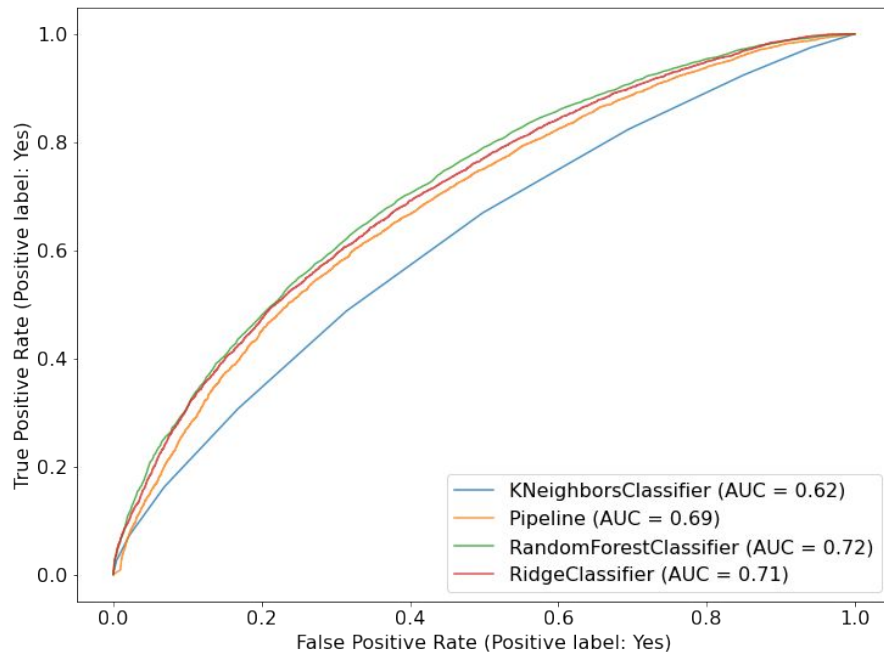
Summary of ML Models

| Model | Base Accuracy | Optimized Accuracy | Improvement | Optimized AUC | Approx. Runtime (min.) |
|----------------------------|---------------|--------------------|-------------|---------------|------------------------|
| Random Forest Classifier | 0.58421 | 0.65523 | 12.156% | 0.72 | 5 |
| Ridge Classifier | 0.57886 | 0.65068 | 12.406% | 0.71 | 2 |
| SGD Classifier | 0.54353 | 0.63233 | 16.339% | 0.69 | 15 |
| KNN Classifier | 0.49331 | 0.63648 | 29.023% | 0.62 | 25 |
| Ensemble Voting Classifier | N/A | 0.65175 | N/A | N/A | 60 |



- ML Classifiers Optimized: Random Forest, Ridge, SGD, K-Nearest Neighbors
- Random Forest and Ridge were the strongest performers in terms of accuracy, runtime, and AUC.

ROC Plot and Top Features



| Feature | Importance |
|--------------------|------------|
| num_lab_procedures | 0.0514 |
| num_medications | 0.0486 |
| number_inpatient | 0.0399 |
| time_in_hospital | 0.0365 |
| number_diagnoses | 0.0281 |
| num_procedures | 0.0248 |
| number_outpatient | 0.0173 |
| number_emergency | 0.0163 |
| gender_Male | 0.0137 |
| insulin_Yes | 0.0102 |

Conclusion

- Demographics of hospitalized diabetes patients were explored.
- Optimized ML Models predict hospital readmission better than chance.
- ML Model has room to improve. For future work, we recommend:
 - Develop models specific for select diagnoses/medical specialties.
 - Explore original database for additional features.



Sources

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2. Centers for Disease Control and Prevention. National Diabetes Statistics Report, 2020. Atlanta, GA: Centers for Disease Control and Prevention, U.S. Dept of Health and Human Services; 2020. Link
3. McIlvennan CK, Eapen ZJ , Allen LA. Hospital Readmissions Reduction Program. Circulation. 2015;131:1796–1803. DOI: 10.1161/CIRCULATIONAHA.114.010270
4. 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. 2014:781670. DOI: 10.1155/2014/781670
5. U.S. Census Bureau. HIC-9_ACS. Population Without Health Insurance Coverage by Race and Hispanic Origin: 2008 to 2019. Health Insurance Historical Tables - HHI Series. Link
6. Cherney, K. (2018, July 6). Age of onset for type 2 diabetes: Risk factors and more. Healthline. Retrieved November 8, 2021, from <https://www.healthline.com/health/type-2-diabetes-age-of-onset>.

Questions?

Capstone ERD

| diag | |
|------|------------------|
| PK | <u>diagID</u> |
| | diag_description |

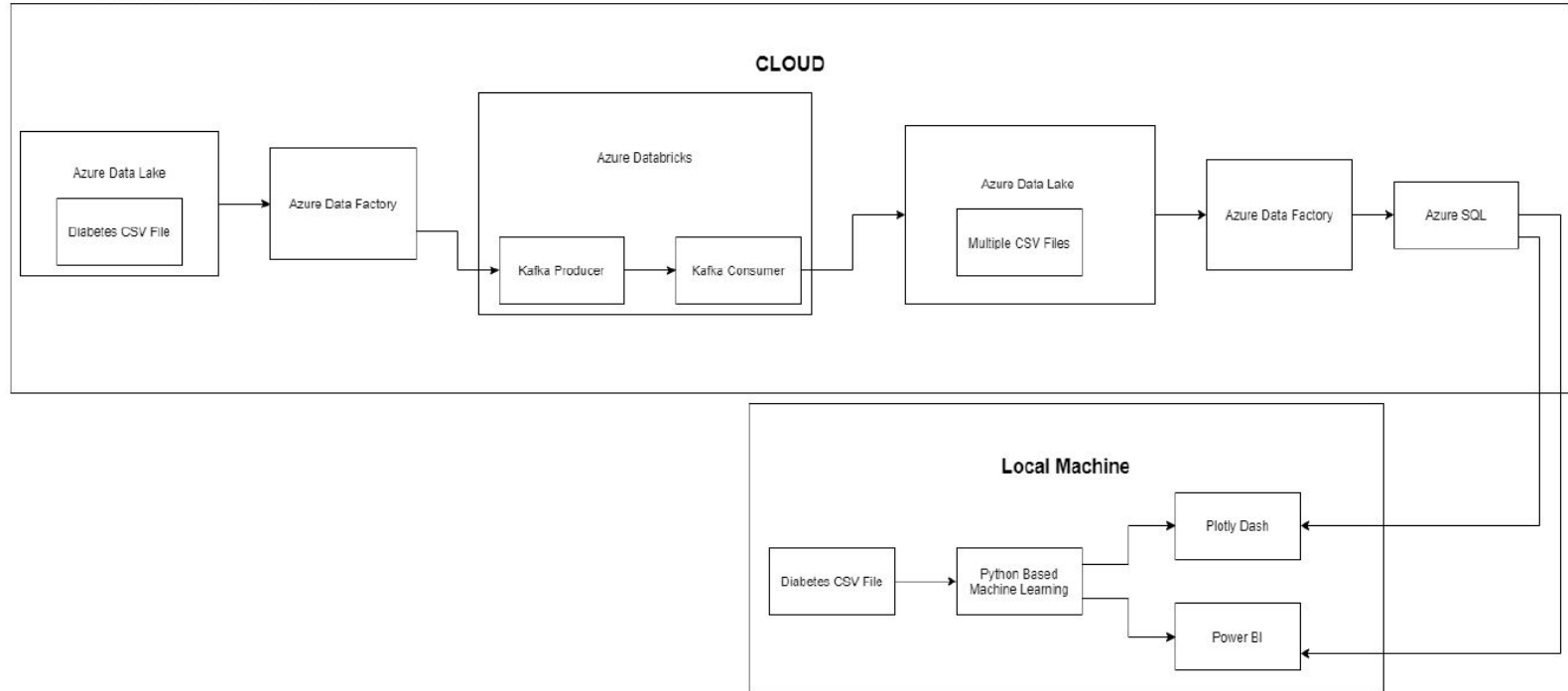
| diabetestemp | |
|--------------|--|
| PK | <u>EncounterID</u> |
| FK | patient_nbr race gender age weight admission_type_id discharge_disposition_id admission_source_id time_in_hospital payer_code medical_specialty num_lab_procedures num_procedures num_medications number_outpatient number_emergency number_inpatient diag_1 diag_2 diag_3 number_diagnoses max_glu_serum A1Cresult metformin repaglinide nateglinide chlorpropamide glimepiride acetohexamide glipizide glyburide tolbutamide pioglitazone rosiglitazone acarbose miglitol troglitazone tolazamide examide cloglipton insulin glyburide-metformin glipizide-metformin glimepiride-pioglitazone metformin-rosiglitazone metformin-pioglitazone change diabetesMed readmitted |

| race_uninsured_2008 | |
|---------------------|---|
| PK | <u>Race</u> |
| | Total Uninsured Uninsured Error Percent Percent Error |

| insurnsnoe_agg_2008 | |
|---------------------|---------------------|
| PK | <u>Coverage</u> |
| | Estimate Percent |

Data Platform

Outline of Data Platform



| Model | Refactor "Readmitted | Encode MedList | Refactor MedList (Y/N) | Tuned | Drop Medical Specialty | Drop Emergency | Score | Percent Improvement |
|---------------------------------|----------------------|----------------|------------------------|----------|------------------------|----------------|--------------------|---------------------|
| Ridge Classifier | N | N | N | N | Y | N | 0.578860612 | 0 |
| Ridge Classifier | N | N | N | Y | Y | N | 0.583805733 | 0.854285317 |
| Ridge Classifier | Y | N | N | N | Y | N | 0.639636023 | 10.49914433 |
| Ridge Classifier | Y | N | N | Y | Y | N | 0.649939783 | 12.27915147 |
| Ridge Classifier | Y | Y | N | N | Y | N | 0.640773451 | 10.69563862 |
| Ridge Classifier | Y | Y | N | Y | Y | N | 0.650675766 | 12.40629483 |
| Ridge Classifier | Y | Y | N | N | N | N | 0.64893617 | 12.10577415 |
| Ridge Classifier | Y | Y | N | Y | N | Y | 0.647326507 | 11.82769981 |
| Ridge Classifier | Y | N | Y | Y | Y | N | 0.649404523 | 12.18668356 |
| Random Forest Classifier | N | N | N | N | Y | N | 0.584207775 | 0 |
| Random Forest Classifier | Y | Y | N | Y | N | Y | 0.645278726 | 10.45363531 |
| Random Forest Classifier | Y | Y | N | Y | N | N | 0.650006691 | 11.26293042 |
| Random Forest Classifier | Y | Y | N | Y | Y | N | 0.648735448 | 11.04532922 |
| Random Forest Classifier | Y | N | Y | Y | Y | N | 0.655225478 | 12.15624062 |
| SGD Classifier | N | N | N | N | N | N | 0.543526258 | 0 |
| SGD Classifier | N | N | N | N | Y | N | 0.546455996 | 0.539024331 |
| SGD Classifier | N | N | N | N | Y | Y | 0.550074378 | 1.204747712 |
| SGD Classifier | Y | N | N | N | Y | Y | 0.602219274 | 10.79856132 |
| SGD Classifier | Y | N | Y | N | Y | Y | 0.607928276 | 11.84892488 |
| SGD Classifier | Y | N | Y | Y | Y | Y | 0.632332248 | 16.33885923 |

| Model | Refactor "Readmitted" | Encode MedList | Refactor MedList (Y/N) | Tuned | Drop Medical Specialty | Drop "Emergency/Trama" Medical Specialty | Drop "?" Medical Specialty | Drop BUT "Internal Medicine" Medical Specialty | Score | Percent Improvement |
|----------------|--------------------------|----------------|------------------------|-------|------------------------|--|-------------------------------|--|-------------|---------------------|
| KNN Classifier | n | n | n | n | n | n | n | n | 0.493309247 | 0 |
| KNN Classifier | n | n | y | n | n | n | n | n | 0.49484812 | 0.311949003 |
| KNN Classifier | n | y | n | n | n | n | n | n | 0.492573264 | -0.149193001 |
| KNN Classifier | y | y | n | n | n | n | n | n | 0.568714037 | 15.28550115 |
| KNN Classifier | y | y | n | y | n | y | n | n | 0.59 | 19.60043402 |
| KNN Classifier | y | y | n | y | y | n | n | n | 0.586243811 | 18.83900719 |
| KNN Classifier | y | y | n | y | n | y | y | y | 0.636484687 | 29.0234658 |
| KNN Classifier | y | y | n | y | n | y | y | n | 0.614925373 | 24.65312121 |