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Reducing Stroke Risk

June 2021

Executive Summary

The purpose of this project was to analyze a stroke related dataset to determine if it could be used to train a machine learning model to target individuals for risk reduction strategies by their health care providers. In addition, identifying correlations between stroke risk and other dimensions was a desired secondary outcome. Not only are strokes a leading cause of death in the United States, but the long-term consequences to a survivor can be life altering. The cost of associated medical treatments burden society. The dataset used in this work was obtained under a personal license freely distributable for any non-commercial ventures. The initial data analysis found that the target dimension of having had a stroke was considerably imbalanced towards patients with no stroke history. This problem makes training a model more challenging. Accuracy becomes less of a primary metric as always predicting no would yield a high accuracy, but entirely miss the goal of risk mitigation. Assuming everyone is at risk would waste too many resources. Ultimately, a model was found that was moderately successful at finding at risk individuals while minimizing the targeting of others who were not. This model could be used to target resources without being overly burdensome on the entire population.

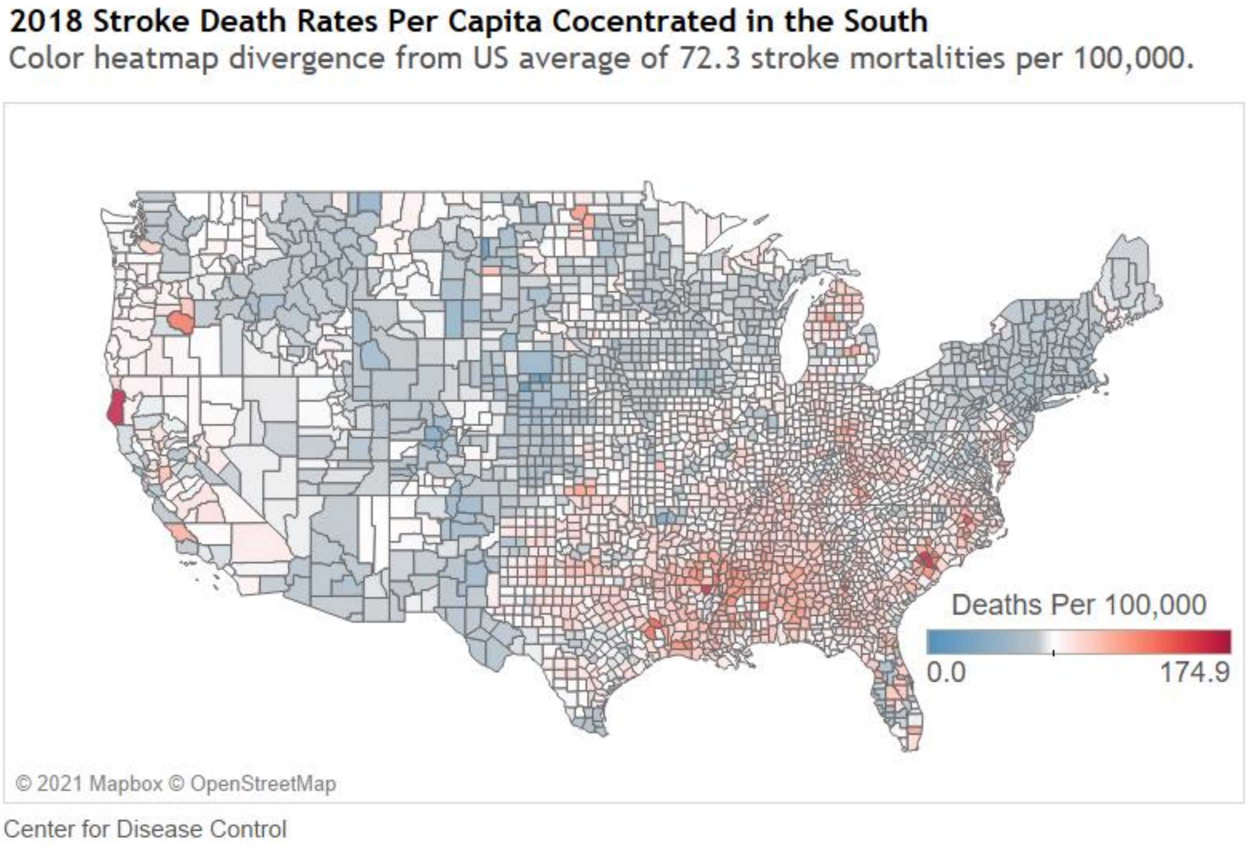
Abstract

In 2019, the World Health Organization reported stroke as the second leading cause of death (World Health Organization, 2020). Even for those who survive a stroke, there is often a slow recovery with life-long consequences (CDC, n.d.). Being able to predict that likelihood, would allow for recommendations on preventative measures by health care workers. This research sought to explore that potential with the goal of providing a tool for identifying that risk by using a machine learning binary classification model based on the dimensions found within the stroke prediction dataset. The research also sought to determine if there were any significant correlations found within those dimensions to having had a stroke.

Introduction

Strokes affect almost 800,000 Americans each year according to the Center for Disease Control (CDC, n.d.). Most strokes are ischemic and are caused by vascular blockage. From 2014 to 2015, 46 billion dollars was spent on strokes related costs (CDC, n.d.). Slightly over 12 percent of strokes are fatal within the first month which increases to 25 percent during the first year (Higuera, 2019). Even for those that survive, loss of motor skills, vision loss and mood swings can lead to disability (Higuera, 2019). The Southern United States is particularly impacted by stroke mortalities. Figure 1 shows how the Southern United States has a high concentration of stroke related deaths.

Figure 1



2018 Stroke Death Rates Per Capita Cocentrated in the South

Color heatmap divergence from US average of 72.3 stroke mortalities per 100,000.

Center for Disease Control

With all that in mind, a dataset was acquired from Kaggle with related dimensions (2020). This was used to train a model to target those individuals at risk. That dataset was processed using a systemized methodology addressing all stages of the data science process. The dataset consisted of eleven variables. These included an identity key, gender, age, hypertension status, heart disease status, if the patient ever been married, type of work, type of residence, average glucose level, body mass index (BMI), smoking status, and the target stroke variable.

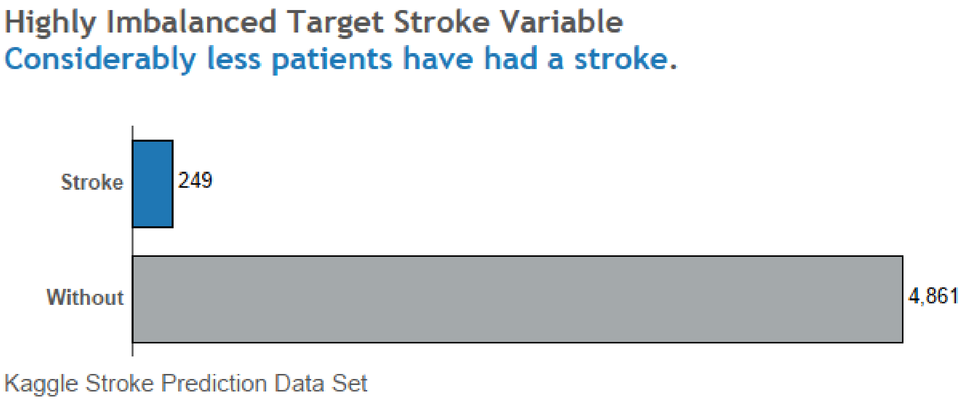
Methods

The CRISP-DM methodology was implemented for this project (Siegel, 2016). As such, six iterative stages were followed.

- Business (Domain) Understanding
- Data Understanding
- Data Preparation
- Modeling
- Evaluation
- Deployment

In the context of this paper, the first four will be covered in the current methods section. The evaluation and deployment phases of CRISP-DM can be found in the results and conclusion sections. Domain knowledge was acquired first. This involved researching stroke related publications referenced above. The data was analyzed in the data understanding phase and explored using statistical measures. In traditional data science, this is also referred to as exploratory data analysis. It was in this stage that missing data was discovered for the BMI variable. Marked skew was noted on the numeric variables for BMI and average glucose levels (See Appendix for reference histograms). The data was then cleansed and prepared accordingly. Missing BMI data was replaced with a nearest neighbor model. To address the non-normal distribution of the data, the affected dimensions were normalized before model training. The ultimate concern with this dataset was a large imbalance between those who had had a stroke and those who had not as noted in Figure 2. Less than five percent were labeled as stroke victims.

Figure 2

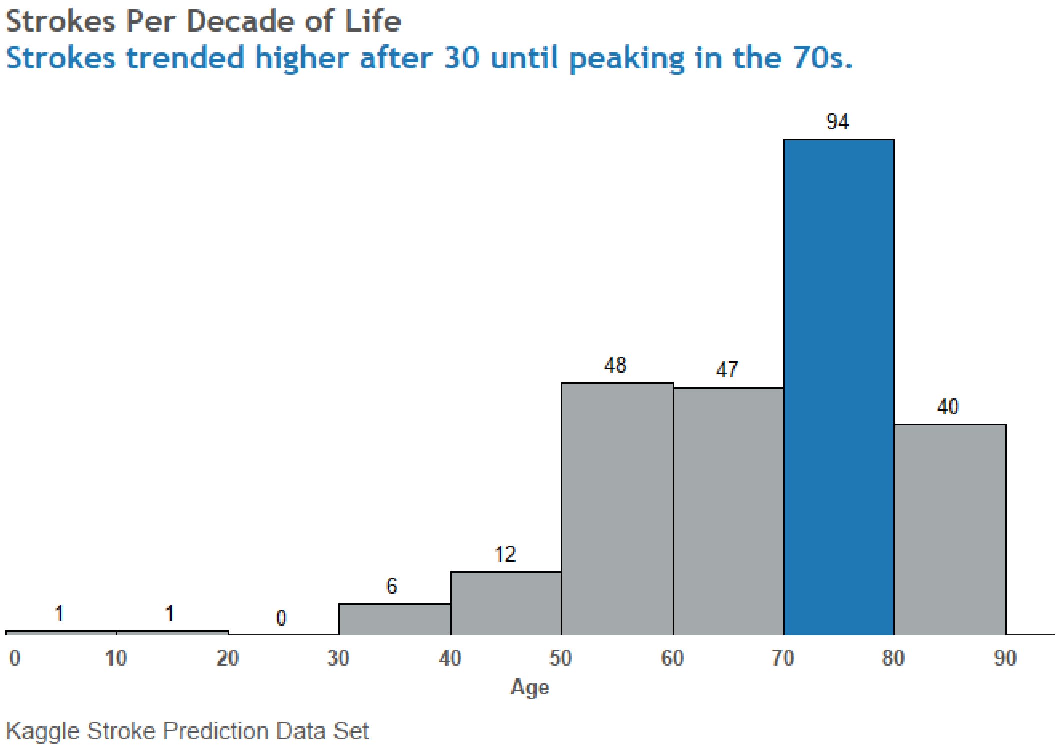


To address this concern oversampling techniques were applied. Oversampling involves redrawing from the underrepresented value randomly until an adequate balance for training is achieved. It should be applied after the data is split into training, test and validation sets to avoid overfit caused by data leaking into the test and validation sets. Multiple ensemble or aggregation models were used and then further combined into a blended final model. Overall accuracy is not the ideal metric for measuring best fit in an imbalanced dataset. As such, recall or maximizing relevant results was used to tune the blended model.

Results

The model was moderately successful at predicting stroke risk. It was 78 percent accurate at predicting individuals who had not had a stroke. It was 76 percent accurate at predicting patients who had. This left the overall accuracy at 77 percent. This balanced out with the area under the curve score of 77 percent which is used to measure how well predictions rank. This result struck a reasonable risk versus reward threshold. Only age showed a moderate degree of correlation across three statistical measures. Age was also noted as the primary feature in multiple models blended to make up the final model. This was in line with total counts for strokes for each decade of life as shown in Figure 3.

Figure 3

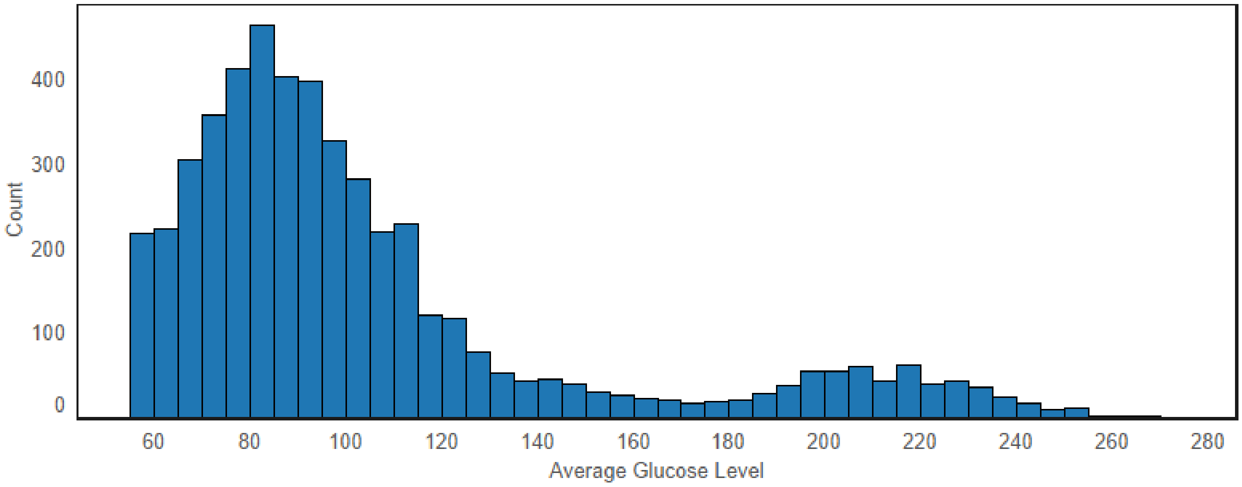


Conclusions

This model could be used as a guide in a clinical environment for targeting those more likely to have a stroke. The final model was processed and stored in a format for cross platform portability. Further training against more data would likely improve the predictive power. Given the variance shown in the heat map from Figure 1, it would also be worth researching models that included a geographic dimension.

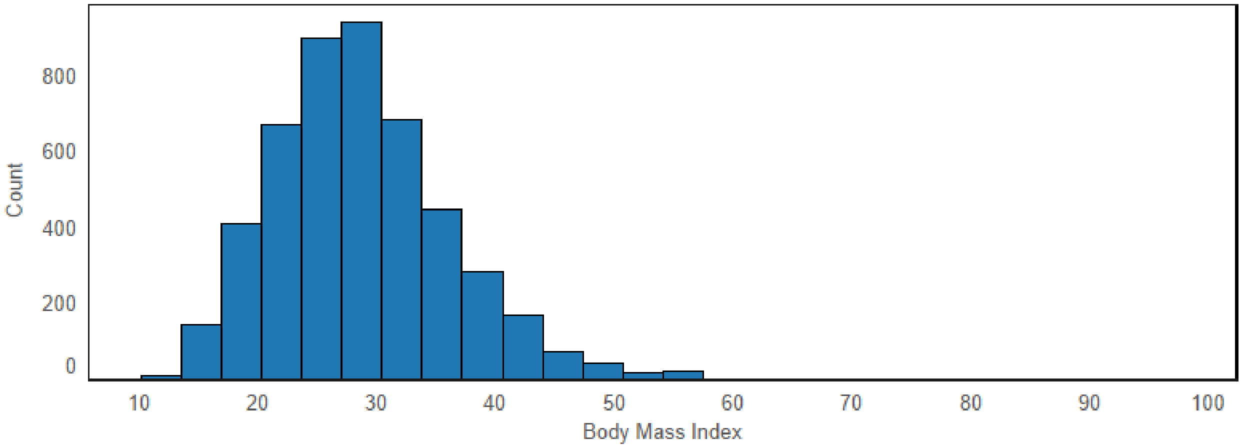
Appendix

Average Glucose Level Histogram
Approximate kurtosis of 1.7 and skew of 1.6



Kaggle Stroke Prediction Dataset

Body Mass Index Histogram
Approximate kurtosis of 3.3 and skew of 1.1



Kaggle Stroke Prediction Dataset

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