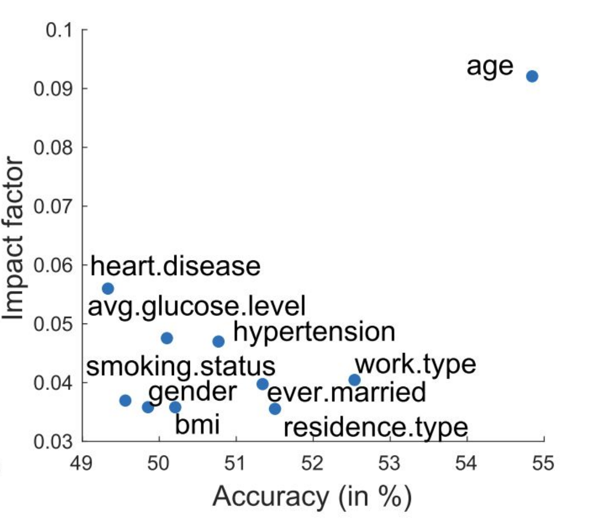
Team SMSU: Accuracy and Bias in Predicting Stroke Occurrence

By: Shaan Malhotra, Uzair Memon, Mohamed Abuelreich, Sathya Rajesh

Objectives

- Analyze literature relevant to our topic
- Recreate stroke occurrence models used in one of the pieces of literature
- Create our own stroke occurrence prediction models
- Compare the accuracy of the two sets of models
- Analyze the bias present in the literature’s models and our own
- Mitigate Bias in our own models
- Re-examine our models

Article #1: “Identifying Stroke Indicators Using Rough Sets” by Pathan et al.

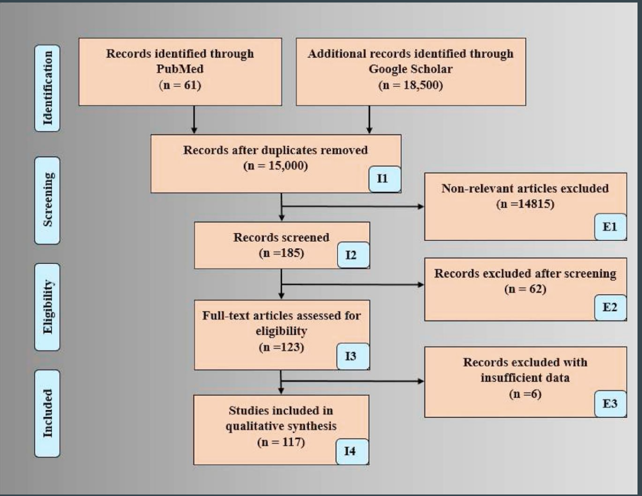


(d) Proposed approach

- Discusses the use of data mining techniques for the accurate prediction of stroke based on risk factors associated with electronic health records (EHRs)
- The choice of feature-selection methods can help improve prediction accuracy and efficient data management of archived input features.
- The article proposes a novel rough-set based technique for ranking the importance of various EHR records in detecting stroke, which can be applied to any dataset comprising binary feature sets.
- Concludes that **age, average glucose level, heart disease, and hypertension** were the most essential attributes for detecting stroke in patients.
- The proposed technique is benchmarked against other popular feature-selection techniques and obtained the best performance in ranking the importance of individual features in detecting stroke.
- Emphasizes the importance of selecting only the most discriminatory

Pathan, Muhammad Salman, et al. "Identifying stroke indicators using rough sets." IEEE Access 8 (2020): 210318-210327.

Article #2: “Understanding the bias in machine learning systems” by Suri et al.



- Assess the difference in risk of bias (RoB) in ML and non-ML cardiovascular disease predictors
- PRISMA model:
  - 117 Studies: 24 pure ML and 14 pure non-ML
  - 3 Bias bins:
    - Low Bias (5 ML vs 3 NML)
    - Medium Bias (10 ML vs 4 NML)
    - High Bias (9 ML vs 7 NML)
  - Common Attributes:
    - smoking (86%), hypertension (76.6%), BMI (70%), family history (63.4%), and ethnicity (38.4%)
- Analytical slope method:
  - bias in the ML papers were significantly less than the bias in the non-ML papers, a roughly 43% difference

Suri, Jasjit S., et al. "Understanding the bias in machine learning systems for cardiovascular disease risk assessment: The first of its kind review." Computers in biology and medicine (2022): 105204.

Article #3: "Predicting Stroke from Electronic Health Records" by Nwosu et al.

- Principal Component Analysis (PCA): provide information for which attributes were responsible for the majority of the variance in the response variable
    - 3 parts: scree plot, biplot, subspace representation
    - Showed that we should use all the attributes for building the models
- Built 3 models for predicting stroke
    - Decision tree, random forest, and neural network

Approach	**Average accuracy (over 1000 experiments)**
Decision Tree	74.31%
Random Forest	74.53%
Neural Network	75.02%

Nwosu, Chidozie Shamrock, et al. "Predicting stroke from electronic health records." 2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). IEEE, 2019.

Our Dataset

- Sourced from kaggle
  - Originally from an electronic health record provided by McKinsey & Company
- Medical and demographic information for 5,110 patients
- 12 attributes in total
  - 11 input variables
  - 1 response variable (whether or not the patient had a stroke)
- Key observations:
  - More women patients than men patients
  - Only 548 patients had a stroke
  - Major imbalance in classes (will require downsampling)

Variables in our dataset

- Age: double
- Gender: male, female, other
- BMI: double
- Smoking status: either 0 or 1, with formerly smoking being labeled as 1
- Work type: prive, self-employed, government job
- Residence type: urban or rural
- Average glucose levels: double
- Hypertension: yes or no
- Heart disease: yes or no
- Ever married: yes or no

Data cleanup

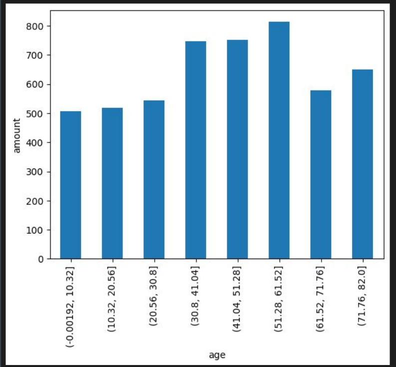
- For this particular dataset, there was only a minimal amount of data cleanup/processing needed
- Smoking status was converted into a binary value
  - They either smoked or didn't, and anyone who was “unknown” was changed to NaN
- Ages were binned
  - 7 bins, 8-10 years in size each

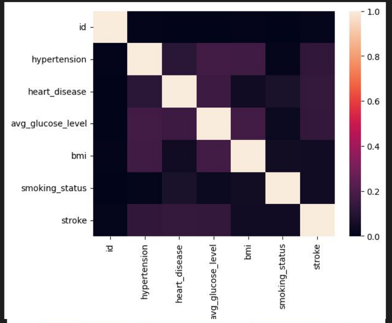
EDA

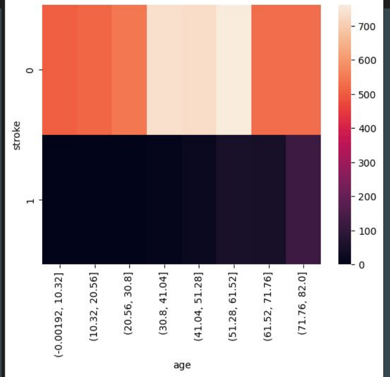
- When looking at the age distribution of the dataset, it is seen that the majority of the people in the dataset are between 30-61

- The strongest factors correlated to having a stroke are hypertension, heart disease, and average glucose levels

- Unsurprisingly, the older people in the dataset had a higher rate of stroke than their younger counterparts.







Models that we made
KNN

```
subset = dataset.groupby('stroke').sample(n=249, random_state=27)
subset.stroke.value_counts()
#taking a subset of the data to have equal number of stoke patients, if this step is not done you'll get
#95% accuracy because the there is an imbalance between people that have stokes and people that don't
#In the 5000 person dataset, only 249 people actually have a stoke.
```

```
0    249
1    249
Name: stroke, dtype: int64
```

```
x_train, x_test, y_train, y_test = train_test_split(subset, labels, random_state=42, test_size=0.2)
#split the data, 80% train and 20% test
```

```
scaler = StandardScaler()
x_train = scaler.fit_transform(x_train)
x_test = scaler.transform(x_test)
```

```
classifier = KNeighborsClassifier(n_neighbors=11, p=2,metric='euclidean')
classifier.fit(x_train, y_train)
```

```
cm = confusion_matrix(y_test, y_pred)
print (cm)
```

```
[[36 15]
 [12 37]]
```

```
print(accuracy_score(y_test, y_pred))
```

```
0.73
```

Random forest

```
x_train, x_test, y_train, y_test = train_test_split(subset, labels, random_state=0, test_size=0.20)
#80% test, 20% test
```

```
rf = RandomForestClassifier()
rf.fit(x_train, y_train)
```

```
RandomForestClassifier()
```

```
y_pred = rf.predict(x_test)
```

```
cm = confusion_matrix(y_test, y_pred)
print (cm)
```

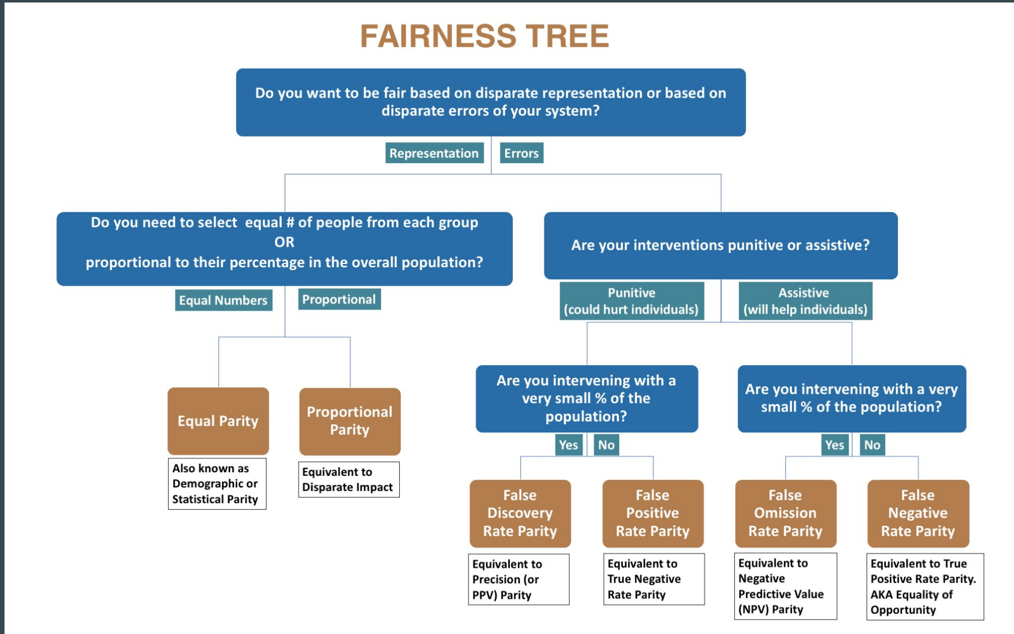
```
[[35 14]
 [ 8 43]]
```

```
print(accuracy_score(y_test, y_pred))
```

```
0.78
```

Analysis of Bias in the Research Article's Models

- Protected attributes we focused on: gender, age, residence type
- Aequitas tool:
    - Reference Groups (majority):
        - Gender: Female
        - Age: 33.50-54.00
        - Residence type: Urban
    - Disparity Intolerance: 80%
    - Tests we used:
        - Equal Parity
        - Proportional Parity
        - False Positive Rate Parity
        - False Omission Rate Parity
        - False Negative Rate Parity



http://aequitas.dssg.io/

Results

- Neural Network:
  - All tests failed

Audit Results: Summary

Equal Parity - Ensure all protected groups are have equal representation in the selected set.	Failed	Details
Proportional Parity - Ensure all protected groups are selected proportional to their percentage of the population.	Failed	Details
False Positive Rate Parity - Ensure all protected groups have the same false positive rates as the reference group).	Failed	Details
False Negative Rate Parity - Ensure all protected groups have the same false negative rates (as the reference group).	Failed	Details
False Omission Rate Parity - Ensure all protected groups have equally proportional false negatives within the non-selected set (compared to the reference group).	Failed	Details

- Random Forest:
  - Only FNRP passed

Audit Results: Summary

Equal Parity - Ensure all protected groups are have equal representation in the selected set.	Failed	Details
Proportional Parity - Ensure all protected groups are selected proportional to their percentage of the population.	Failed	Details
False Positive Rate Parity - Ensure all protected groups have the same false positive rates as the reference group).	Failed	Details
False Negative Rate Parity - Ensure all protected groups have the same false negative rates (as the reference group).	Passed	Details
False Omission Rate Parity - Ensure all protected groups have equally proportional false negatives within the non-selected set (compared to the reference group).	Failed	Details

- Decision Tree:
  - All tests failed

Audit Results: Summary

Equal Parity - Ensure all protected groups are have equal representation in the selected set.	Failed	Details
Proportional Parity - Ensure all protected groups are selected proportional to their percentage of the population.	Failed	Details
False Positive Rate Parity - Ensure all protected groups have the same false positive rates as the reference group).	Failed	Details
False Negative Rate Parity - Ensure all protected groups have the same false negative rates (as the reference group).	Failed	Details
False Omission Rate Parity - Ensure all protected groups have equally proportional false negatives within the non-selected set (compared to the reference group).	Failed	Details

Bias Mitigation

- Used the Aequitas output from the research article models as a starting point
- Tried to address the shortcomings showcased by each of the tests
- Improved random downsampling:
  - Expand to all the attributes that failed the equal and proportional parity test (gender and age)
- Improve data cleaning methods for “strange” outputs
  - Mainly reorganizing the age categories
- Total size of data provided to Aequitas
  - The research models only had viable predictions for 249 rows
  - Changed the training of the model to allow for 498 rows

Analysis of Bias in Our Models

- Before Bias Mitigation:
  - Needed to adjust based on changes made to the format of the data while training

Audit Results: Summary

Equal Parity - Ensure all protected groups are have equal representation in the selected set.	Failed	Details
Proportional Parity - Ensure all protected groups are selected proportional to their percentage of the population.	Failed	Details
False Positive Rate Parity - Ensure all protected groups have the same false positive rates as the reference group).	Passed	Details
False Discovery Rate Parity - Ensure all protected groups have equally proportional false positives within the selected set (compared to the reference group).	Passed	Details
False Omission Rate Parity - Ensure all protected groups have equally proportional false negatives within the non-selected set (compared to the reference group).	Failed	Details

- Random Forest:

Audit Results: Summary

Equal Parity - Ensure all protected groups are have equal representation in the selected set.	Passed	Details
Proportional Parity - Ensure all protected groups are selected proportional to their percentage of the population.	Passed	Details
False Positive Rate Parity - Ensure all protected groups have the same false positive rates as the reference group).	Passed	Details
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False Omission Rate Parity - Ensure all protected groups have equally proportional false negatives within the non-selected set (compared to the reference group).	Passed	Details

- KNN:

Audit Results: Summary

Equal Parity - Ensure all protected groups are have equal representation in the selected set.	Passed	Details
Proportional Parity - Ensure all protected groups are selected proportional to their percentage of the population.	Passed	Details
False Positive Rate Parity - Ensure all protected groups have the same false positive rates as the reference group).	Passed	Details
False Negative Rate Parity - Ensure all protected groups have the same false negative rates (as the reference group).	Passed	Details
False Omission Rate Parity - Ensure all protected groups have equally proportional false negatives within the non-selected set (compared to the reference group).	Passed	Details

Conclusions

- For our project:
    - Accuracy:
        - Research models: Decision tree (74.31%), Random Forest (74.53%), and Neural Network (75.02%)
        - Our models: Random Forest (78%), KNN (73%)
    - Bias:
        - Research models: bias was present for the outlined protected attributes (gander, age, residence type)
        - Our models: bias was initially present but after bias mitigation we greatly reduced any bias present
- For the field in general
    - Machine Learning models in the medical field are only going to expand in terms of abundance and functionality
    - Important to not just understand the biases but also learn strategies to combat them
        - Random downsampling
        - Building off of previously created models after examining their biases
        - Using tools like Aequitas
    - Keeping these strategies in mind when building models can help reduce bias

References

http://aequitas.dssg.io/

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Thank you for listening!