Data Mining Indicators of Heart Disease

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ABSTRACT

Heart disease remains one of the leading causes of mortality worldwide, affecting individuals across various demographics. Despite advancements in healthcare, identifying and mitigating the risk factors associated with heart disease remains a critical challenge. This project aims to leverage machine learning techniques on a comprehensive dataset sourced from the Centers for Disease Control and Prevention (CDC) to predict the likelihood of heart disease based on key indicators.

Efficiently mining large-scale datasets like the CDC's Behavioral Risk Factor Surveillance System offers invaluable opportunities to uncover hidden patterns and insights relevant to heart disease prevention and management. By exploring factors such as high blood pressure, cholesterol levels, and behavioral attributes, we can extract meaningful correlations and predictive features. Through advanced machine learning techniques, we aspire to develop robust models capable of accurately identifying individuals at risk of heart disease. These models not only provide predictive capabilities but also offer actionable insights for personalized interventions and targeted healthcare strategies. By leveraging data mining methodologies, this project aims to contribute to the ongoing efforts in public health by empowering stakeholders with actionable intelligence to mitigate the impact of heart disease on individuals and communities.

KEYWORDS

Exploratory Data Analysis; Data Mining; Heart Disease; Data Visualization; Statistical Analysis

ACM Reference format:

Mohamed Elsayed, 2022. Heart Disease Prediction: Impact of Decision Trees and KNN Algorithms. https://www.kaggle.com/code/georgyzubkov/heart-disease-exploratory-data-analysis

1 Literature Survey

George Zubkov's work on exploratory data analysis sheds light on the primary factors contributing to cardiovascular diseases. Key issues identified include physical inactivity, mental health concerns, stress, and unhealthy habits such as alcohol consumption and excessive sugar intake.

In Mohamed Elsayed's research on heart disease prediction, Decision Trees and KNN algorithms are employed to forecast factors impacting heart conditions. The study emphasizes that individuals with difficult walking, a history of stroke, diabetes, and poor physical health are primary factors. The accuracy achieved using KNN was reported to be 0.71.

2 Proposed Work

2.1 Data Cleaning:
- Review and analyze data set
- Address missing values (if we use the NaN-included dataset)
- Update binary answers
- Remove duplicates & outliers
- Identify and correct data anomalies or inconsistencies
- Normalize numerical variables if necessary (e.g., scale or transform features to have a mean of 0 and a standard deviation of 1)

2.2 Data Preprocessing:
- Assign unique identifier
- Assign 'HEART ATTACK: Y/N' as 'HEART DISEASE: Y/N'
- Initial visualizations
- Split the dataset into training, validation, and testing sets
- Standardize or normalize numerical features to ensure they have similar scales

- Apply techniques to address multicollinearity among features
- Perform dimensionality reduction techniques (e.g., principal component analysis) if dealing with high-dimensional data

3.3 Data Integration:
- If enough time permits:
- Integrate health insurance rates per state to find correlations with heart disease
- Compare 2022 & 2020 analysis

3 Data Set

- Indicators of Heart Disease Data Set
400K+ Records (Some include NaN values)
Heath interview answers from 400K+ individuals
- "established in 1984 with 15 states, BRFSS now collects data in all 50 states, the district of columbia, and three u.s. territories. BRFSS completes more than 400,000 adult interviews each year, making it the largest continuously conducted health survey system in the world." –cdc
- "a heart attack is often an indicator of heart disease."-google
- dataset will be downloaded on all members' machines and connected via github

4 Evaluation Methods

Cross-Validation: Cross-validation involves splitting the dataset into multiple subsets (folds), training the model on a subset of the data, and evaluating its performance on the remaining subset. This process is repeated multiple times, with different subsets used for training and testing, and the results are averaged to obtain a more robust estimate of the model's performance.

Holdout Validation: Holdout validation involves randomly splitting the dataset into a training set and a separate validation set. The model is trained on the training set and evaluated on the validation set. This method provides an estimate of the model's performance on unseen data.

Bootstrapping: Bootstrapping involves generating multiple random samples (with replacement) from the original dataset and training the model on each sample. The model's performance is then evaluated on the original dataset or a separate validation set. Bootstrapping allows for estimating the variability of the model's performance and obtaining confidence intervals for performance metrics.

Confusion Matrix: A confusion matrix provides a tabular representation of the model's predictions compared to the actual class labels. From the confusion matrix, various performance metrics such as accuracy, precision, recall, and F1 score can be calculated.

5 Tools

- KAGGLE
- GITHUB
- JUPYTERLAB
- EXCEL
- PYTHON
- PANDAS
- SKLEARN
- MATPLOTLIB
- SNS
- DISCORD

6 Milestones

Data Preparation:
- Clean the dataset by addressing missing values, outliers, and inconsistencies.
- Perform feature engineering and data preprocessing tasks.
- Split the dataset into training, validation, and testing sets.

Model Development:
- Choose appropriate data mining techniques and algorithms.
- Develop and train predictive models.
- Optimize model parameters and hyperparameters for improved performance.

Model Evaluation:
- Evaluate model performance using appropriate metrics.
- Validate models using cross-validation or holdout techniques.

Results Interpretation and Reporting:
- Interpret model results and analyze insights gained.
- Document the data mining process and prepare a final report summarizing findings.
- Present results to stakeholders, discussing implications for decision-making.

7 Milestones Completed

Data Preparation:

- The data has been preprocessed by converting the Yes/No answers to 1/0. The AgeCategory has also been converted and one-hot encoded. HadHeartAttack has been converted to HasHeartDisease.
- Split the dataset into training, validation, and testing sets. Do we need this?

Model Development:

- The mining techniques have been selected – correlation, k-means, contingency table…
- Correlation, k-means and contingency table have been completed.

Model Evaluation:

- The correlation matrix shows which features are correlated with each other and which features are not correlated. The contingency table and bar plot display the instances of heart disease that occur if someone had a stroke and in a certain age category.
- PCA isn't achievable with the majority of this dataset since it is categorical/binary data. We have attempted to apply MCA to the dataset, but we haven't been able to get it to work.

Results Interpretation and Reporting:

- Results and interpretation for correlation, k-means, contingency and PCA/MCA have been documented in the notebook.

8 Milestones ToDo

Data Preparation:

- Clean the dataset by addressing missing values, outliers, and inconsistencies.

Model Development:

- Develop and apply other models based on group discretion.
- Optimize model parameters and hyperparameters for improved performance.

Model Evaluation:

- Evaluate model performance using appropriate metrics.
- Validate models using cross-validation or holdout techniques.

Results Interpretation and Reporting:

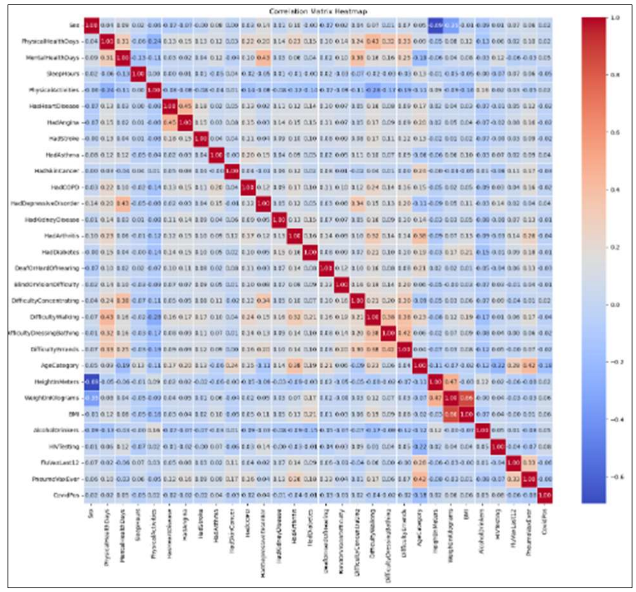
- Interpret model results and analyze insights gained for other models developed.
- Document the data mining process and prepare a final report summarizing findings.
- Present results to stakeholders, discussing implications for decision-making.

9 Results Thus Far

Full plots can be viewed within the Jupyter notebook.

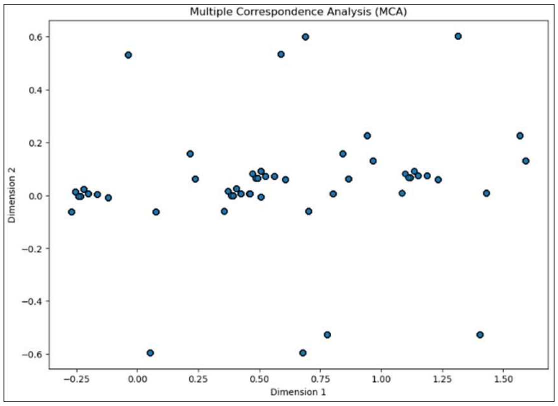
Correlation:

- Plotting the correlation matrix between the features showed which features are correlated and which features are not correlated. With a correlation cutoff of 0.15, HasHeartDisease has the greatest correlation to HadAngina, HadStroke, DifficultyWalking and AgeCategory. Angina is chest pain cause by reduced blood flow to the heart.



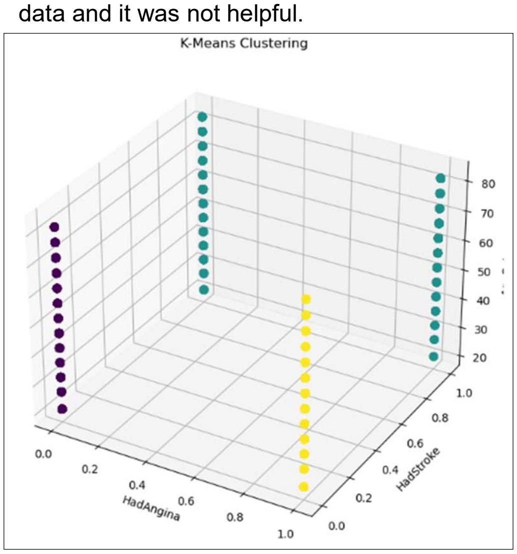
PCA/MCA:

- After attempting to apply PCA, we learned that PCA cannot be used on categorical/binary data. We found another method of dimension reduction for categorical/binary data – multiple correspondence analysis (MCA). MCA allows for categorical analysis across multiple features/categories.
- There isn't much guidance on how to implement MCA using Python. There are Python libraries for MCA – MCA and Prince, but neither have robust documentation and examples to aid in applying the methods. We applied PCA and created a scatter plot from the results, but the plot didn't show enough detail to allow for full analysis.
- The AgeCategory data had to be one-hot encoded to apply MCA.



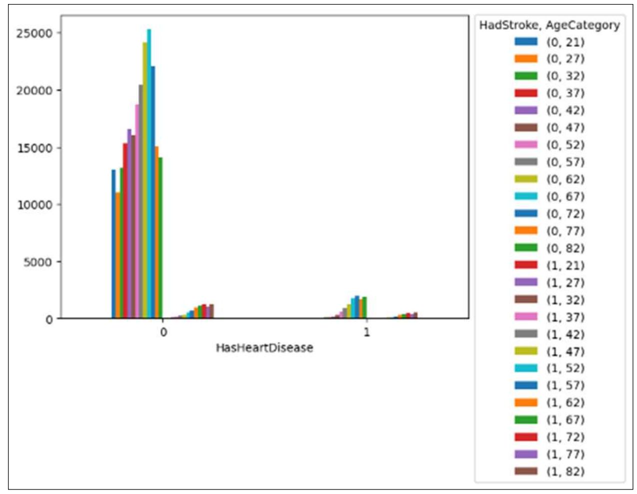
K-Means:

- The initial plan was to apply K-Means to the data to see which ‘groups’ of feature data were similar to each other. The groups would then show us the profiles of people based on the features reported that were most similar to each other. However, K-Means is not an appropriate model for categorical/binary data. Applying K-Means to the data set generated straight lines of 1/0 data and it was not helpful.



Contingency:

- Although PCA and K-Means were not helpful forms of analysis, visualizing the contingency table from MCA was helpful. Using the contingency table, we were able to visualize the relationship between HasHeartDisease, HadStroke and Age Category.
- Based on the plot visual, if someone hasn't had a stroke, they aren't likely to have heart disease. In addition, if they do have heart disease, they still aren't greatly likely to have had a stroke. However, AgeCategory does appear to have an effect on having heart disease and having a stroke.



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[2] Mohamed Elsayed, "Heart Disease Prediction", Kaggle, Available: [https://www.kaggle.com/code/andls555/heart-disease-prediction/notebook#10|-Comparison]