A Comparative Analysis and Predictive Model for Reporting Depression in U.S. Adults

Kiran Mai Jaiswal Charpuria, Kruthika Gaddam, Mohith Surya Kiran Kasula, Bala Samantula, Sri Harsha Sudalagunta, April Taylor, Alan Varkey
[kichar, kgaddam, mkasula, bsamantu, ssudala, taylorad, alvarkey] @iu.edu

Indiana University-Purdue University, Indianapolis, USA

Abstract. A comparative analysis and predictive model for the reporting of depression in adults was performed. Discrepancies were investigated between self-reporting and healthcare professional reporting of depression. The findings were then used to predict specific groups who are more likely to experience depression.

Keywords: Depression; Reporting; NHANES database; NAMCS database; Predictive model

1 Project Scope

1.1 Introduction

People with mental health disorders are at an increased risk of social, educational, racial, and physical difficulty[1]. The incidence of depression globally in 2019 is 280 million, and the World Health Organization reports an estimated 28% increase in 2020 due to the Covid pandemic[2]. The American Academy of Pediatrics, American Academy of Child and Adolescent Psychiatry, and Children's Hospital Association declared a national mental health emergency for children and adolescents in the United States[3].

Despite the rise in depression and the effects of the disorder across all age groups, there remains a personal and medical stigma to a depression diagnosis[4]. Even mental healthcare providers have demonstrated stigma toward patients with mental health disorders[5]. Stigma, whether self-imposed or experienced, particularly affects the disclosure of mental health issues. Garcia et al.[6] demonstrated that standardized screening increased the diagnosis of depression in disparaged groups. Appropriate screening in an emotionally safe healthcare setting is a critical first step to addressing the global issue of depression

The focus of this project was the screening and diagnosis of depression in adults. Due to access limitations to depression data, minors were excluded. The object of this comparison was to analyze the reporting behaviors of the adult population and the diagnosis behaviors of healthcare providers regarding depression and then to create a model for predicting depression reporting.

1.2 Aims

To evaluate any significant differences between self-reported and provider-reported cases of depression in adults in the U.S.

To identify and correlate the main factors impacting the reporting of depression by self-reporters and providers in adults in the U.S. and identify the groups that report depression the most.

To develop a multi-variant model that predicts the diagnosis of depression cases from the features of age, gender, income, co-morbidity, medical insurance, education level, and race.

1.3 Purpose

This project investigated discrepancies between self-reporting and healthcare professional reporting of depression, and the findings were used to predict specific groups, for example, a specific age range, who were more likely to experience depression. The results can be used to improve screening standards for healthcare professionals to increase the diagnosis of depression in groups predicted to have depression.

1.4 Hypotheses:

Null Hypothesis. There will be no increase in the reporting of depression by adults as compared to the reporting of major depressive disorder by healthcare providers in medical records in the US.

Alternate Hypothesis. There will be an increase in reporting depression by adults compared to major depressive disorder by healthcare providers in medical records in the US.

2 Methodology

This project was a comparative analysis between adults and healthcare providers. The project used two datasets to compare depression indicators from the NHANES dataset with depression indicators from the NAMCS dataset. Once the data was compared, machine learning models were developed to predict the factors impacting the depression indicators in 1) adults and 2) healthcare providers. Tools for the project included Python Jupyter notebook, phpMyAdmin, Google Colab, and Microsoft Teams.

Stages of Project:

1. Data Collection and Extraction
2. Data Cleaning and Storage
3. Data Analysis
    a. Exploratory Data Analysis
    b. Prediction Modeling
4. Data Visualization

2.5 Team members Contributions

Everyone was incredibly supportive of our team, as everyone participated in the project actively. We met every Friday at 11 A.M., and for those who couldn't make it, we made it a habit to update notes on the canvas to keep track of our project and receive feedback from our professors and TAs so they could monitor our progress. We scheduled meetings even when there were no submissions to make it a habit to be in touch and obtain a corporate feel, which was a positive aspect of this. Canvas was utilized efficiently for discussions to conclude while considering everyone's viewpoints. In addition to the lecturers' lecture materials and videos, we exchanged YouTube videos in our group as we came from different backgrounds and had varying levels of knowledge about Python, ML, GitHub, and colab. Microsoft teams were effectively used to upload files and record meetings. We utilized Wrike, a project management platform, to keep track of activities because we were divided into sub-teams and had weekly responsibilities to complete.

	Team Members						
Tasks	April Taylor	Kruthika Gaddam	Bala Samantula	Sri Harsha Sudalagunta	Mohith Surya Kiran Kasula	Kiran Mai Jaiswal Charpuria	Alan Varkey
Project Management							
Background/Research							
Proposal Development							
Editing/Proofreading							
Data Collection							
Data Analysis							
Hypothesis Testing							
Project Presentation							
Report Development							
Data Cleaning							
Model Development and Testing							
Data Visualization							

Data Description

Data from two existing publicly available datasets was utilized for this project. Both datasets consisted of secondary data collected by the National Center for Health Statistics (NCHS) and contained data from surveys and physical examinations of persons in the United States (U.S.) from 2017 to 2018[7]. The project used 2018 survey data for both datasets because more recent full datasets were limited due restrictions to in-person contact during the Covid pandemic. The project team also considered the possible compounding effect the Covid pandemic may have on depression rates and decided to assess the pre-pandemic state of depression.

NHANES. The NCHS routinely conducts the National Health and Nutrition Examination Survey (NHANES) to gather information on the health of the general U.S. population. Nutrition, disease, health behaviors and demographic information are among the data collected from participants through a "mobile examination center" [8]. The 2018 source dataset included data from 9,254 persons[9].

NAMCS. The NCHS also routinely conducts the National Ambulatory Medical Care Survey to gather information on the direct patient care received in ambulatory care centers. Examples of available data from this dataset include patient diagnosis codes, insurance coverage, provider types and practice descriptors[10]. The 2018 source dataset included data from 9,953 patient record forms submitted by 496 physicians[11].

3 Data Collection and Extraction

Collection. The NHANES dataset is sectioned into multiple subset data files based on topic or survey instrument. The subset datasets are available from the NCHS website as XPORT files (xpt) along with codebooks for interpretation[8]. The subsets which included variables pertaining to this project were chosen. The NAMCS data is available on a NCHS website in a SAS file (sas7bdat) in a zip file. The NCHS provides a micro-file data codebook for interpretation[12]. The source files (Figure 1) were downloaded and stored in a shared repository (Teams) and the class repository (Canvas). The source files were not stored directly in MySQL due to error messages when attempting to upload the files in their original state.

The files were uploaded into Jupyter, for processing with Python. The SAS and xpt files were converted to csv files using the Python Panda method. The 5 NHANES CSV files were merged into one CSV file using a Python Panda merge method with parameters for an outer merge. The SEQN column was used as a primary key in each set to allow for the retention of all rows and columns from all five datasets. Since not all surveys were conducted on all participants, the merging of the datasets led to multiple empty cells in the merged NHANES set. The empty cells were filled with '0' to aid in the data analysis process.

Extraction. Both surveys include a broad amount of health data. This project did not analyze the full datasets. It focused on the data within each dataset that was anticipated to correlate with depression or depression reporting (Figure 1). The datasets were reduced with the Pandas method of selecting only the columns designated for this project. Medications were also excluded from both datasets, except for the Boolean variable of "medication for depression." Medications are varied in their indication for use, and the datasets did not provide information on initiation or discontinuation dates for correlation with depression onset or improvements. Due to this complexity, the team chose not to include this variable in the project, despite the potential to indicate or predict depression.

PROJECT SOURCE FILES	
2018 NHANES	
Demographics	DEMO_J.XPT
Disabilities	DLQ_J.XPT
Depression Screener	DPQ_J.XPT
Medical Conditions	MCQ_J.XPT
Health Insurance	HIQ_J.XPT
2018 NAMCS	
Office-based visits	namcs2018_sas.sas7bdat

Figure 1. NHANES & NAMCS Source files

Removing irrelevant data. The data was further reduced to only data relevant to the project aims. After merging the NHANES subsets, the datasets were cleaned of duplicates.

AGE. Age was limited to adults only in both sets. The NCHS restricts the release of depression scores for minors in the NHANES survey, therefore participate data for those under age 18 was removed for all variables. Age was limited in the NAMCS dataset with the selection of only the column, "AGE" which limited the participant's data to those aged over 17.

Handling Missing Data.

NHANES. Per the NHCS [13] recommendation, data was evaluated for missing values and was prespecified to be imputed if more than 10% were missing using multiple imputation method (Figure 2). Th following values in the set indicated no data was available:

NAMCS Missing Values(%)			NHANES Missing Values(%)			
Code	**-9**		**Code**	**9/99**	**7/77**	**Blank**
RACER	0%		INDHHIN2	0.1%	2.0%	0.0%
RACEUN	28.6%		HIQ031A	0.7%	0.1%	0.0%
PAYTYPER	2.5%		HIQ031B	0.0%	0.0%	0.0%
DIAG1	0.4%		HIQ031D	0.0%	0.0%	0.0%
DIAG2	34.2%		HIQ031E	0.0%	0.0%	0.0%
DIAG3	57.9%		HIQ031H	0.0%	0.0%	0.0%
DIAG4	73.1%		HIQ031I	0.0%	0.0%	0.0%
DIAG5	84.3%		HIQ031AA	0.0%	0.0%	0.0%
OWNSR	4.5%		DMDEDUC2	0.0%	0.2%	0.0%
AGE	0.0%		DMDEDUC3	0.0%	0.0%	0.0%
SEX	0.0%		DLQ140	0.0%	0.0%	1.6%
DEPRN	0.0%		DLQ150	0.1%	0.0%	1.6%
NOCHRON[1]	67.0%		DLQ170	0.2%	0.0%	48.0%
DEPRESS	0.0%		DPQ010	0.1%	0.7%	7.5%
MENTAL	0.0%		DPQ020	0.1%	0.0%	7.5%
PSYCHOTH	0.0%		DPQ030	0.1%	0.5%	7.5%
NOPROVID	0.0%		DPQ040	0.1%	0.1%	7.5%
PHYS	0.0%		DPQ050	0.1%	0.0%	7.5%
PHYSASST	0.0%		DPQ060	0.1%	0.1%	7.5%
NPNWM	0.0%		DPQ070	0.1%	0.0%	7.5%
RNLPN	0.0%		DPQ080	0.1%	0.0%	7.5%
MHP	0.0%		DPQ090	0.1%	0.0%	7.5%
OTHPROV	0.0%		RIDAGEYR	0.0%	0.0%	0.0%
PROVONE	0.0%		RIAGENDR	0.0%	0.0%	0.0%
SPECCAT	0.0%		RIDRETH3	0.0%	0.0%	0.0%
	[1] Blank		>10%			

Figure 2. NAMCS & NHANES Missing Data Evaluation

- missing = blank
- "don't know" = 9/99
- refused = 7/77

For all variables in the reduced dataset, the above were considered in the missing data calculations. Not all survey questions were asked or appropriate for all participants. For those variables, blanks were converted from NaN to "0".

PHQ-9 Questions. The blank data in the PHQ questions was reviewed in detail to ensure the blank values that were converted to "0" for the depression screening questions did not skew the PHQ total score to lower values or the overall rate of depression in NHANES. Each question for the PHQ had a 7.5% missing rate. This consisted of about 743 participants for which all questions were blank for the PHQ-9. This indicates the participants did not consent to the depression survey. The team chose not to drop these participants to preserve the other data obtained for the other variables (including other depression indicators) as well as the missing data rate being less than the prespecified 10%.

As further discussed in section 3.a, the NHANES dataset depression indicator proportion was higher than the NAMCS total depression indicator proportion. The team did not feel the missing surveys responses significantly affected the outcome of the findings.

DLQ-170 How depressed did you feel? This question was the only variable with more than 10% missing within NHANES. The team chose not to impute this variable considering that a participant may feel uncomfortable or uncertain answering this question. Also, a positive was captured in the depression indicator. Imputing may falsely increase the dependent variable.

NAMCS. For most of the variables in the NAMCS, the data was imputed by NAMCS, therefore no adjustments were required. Diagnosis (including no chronic illness), payer type and practice type were not imputed.
Race. Initially, the variable for race, "RACEUN" was chosen, however, it was discovered that 29% of that variable was missing and was also not imputed. On further investigation, the "RACER" variable was an acceptable alternative. The "RACER" variable contained less categories within racial groups (black, white, other) which provides less insight into the depression of multiple races. However, the "RACER" variable is imputed by NCHS, and the team agreed having a complete dataset for this variable was more important for this project considering the risk of limited findings from missing values.

Diagnoses. Diagnosis codes, "DIAG" 1-5, were not imputed by NCHS. Due to the nature of U.S. office visits scheduling, most patients are seen for short appointments where only a primary diagnosis (DIAG1) is treated. Rarely are up to 5 diagnoses treated in one office visit (DIAG 1-5). Imputing a diagnosis would introduce inaccurate findings considering the 339 diagnosis categories and numerous subcategories in each diagnosis category. Missing percentages were calculated for these variables, but empty cells were not imputed. Positive findings for diagnoses were used for each participant in the data analyses and predictive models.

No Chronic Illness. A significant amount of missing data (67%), for "no chronic illness" was found, however this category would be difficult to impute accurately considering the wide range of chronic illnesses that could be imputed. As with the depression survey, the team chose not to drop these participants to retain the other data obtained from these surveys.

3.6 Data Cleaning and Storage

Feature Engineering. After cleaning, the datasets were prepared for data analysis by conducting feature engineering. Most of the variables were categorical and were transformed into Boolean (0/1) features. Several variables were combined or transformed by normalization or standardized across datasets for consistency and simplicity. The variables combined and/or renamed include insurance, education, age, gender, and race.

Education. The NHANES source dataset included two education variables; under age 20 and over age 20. Considering that our sample population is all adults over 17, the team created an EDUC feature that merged the two variables of education and consolidated the multiple primary education categories into one category. This allowed for a simplified 5 category education feature.

Insurance. Health insurance was a common variable between the NHANES and NAMCS datasets. However, the datasets differed in the categorization of the types of insurance. The insurance columns for each dataset were consolidated to 4 common U.S. insurance types: private, state-funded, Medicare, and no insurance.

Race. Race was also a common variable between the datasets. However, NAMCS categorized the imputed RACER variable into three categories while NHANES used 6. For standardization, NHANES categories were consolidated into black, white, and other and both datasets were renamed to be consistent features names.

Comorbid Conditions. Both datasets included medical diagnoses information. NHANES survey captured Boolean answers for chronic medical conditions. The team chose chronic conditions that were anticipated to correlated with a depression reporting. The NAMCS survey captured all diagnosis codes as described in the prior section. However, each code was grouped per participant and per visit. The team separated the diagnosis codes into 16 medical condition features using Python Pandas as a yes/no Boolean feature for each NAMCS participant. The diagnoses codes for depression were excluded from these features and were used in the creation of the Depression Indicator (see below).

Normalizing depression data. The depression data was normalized to a single depression classification by creating a the "Depression Indicator" (DI) feature for each dataset. For each participant, any positive dependent variable (depression) was considered a "yes" for the Depression Indicator. For example, if a participant received a PHQ total of 10 or more and reported having a chronic condition of depression, that participant was considered as a "yes" for reporting depression. If a provider reported a patient with a depression diagnosis code and depression medication treatment that patient was considered as a "yes" for reporting depression. Any indication of depression

was classified on a binary (yes/no) scale for standardization across the datasets. The variables from each set to compile DI included:

- NHANES
  - PHQSCR: PHQ Total>10-- (indicative of depression)
  - DLQ140: Feelings of depression-- >=Monthly,
  - DLQ150: Medications for depression-- Yes
  - DLQ170: Depression Level-- A lot, A little or in between a lot and a little
- NAMCS
  - DEPRN-- depression chronic disease
  - DEPRESS-- depression screen
  - MENTAL-- mental health counseling referral
  - PSYCHOTH—psychotherapist referral

Once feature engineering was complete, NHANES contained 26 features and NAMCS contained 41 features used for hypothesis testing and modeling.

4 Data Analysis

To view and comprehend our data, Python was used. Many built-in Python libraries were utilized, including pandas, NumPy, Seaborn, Matplotlib, and Scipy. Matplotlib is a Python library for creating interactive visualizations such as bar charts and pie charts. Seaborn is a visualization library based on Matplotlib used to generate heatmaps. Scipy is a Python package used for scientific computing and hypothesis testing. To help comprehend the data, we developed the visualizations listed below.

4.1 Descriptive Statistics.

Descriptive statistics allow data to be presented more easily, making interpretation meaningful. Since most variables were categorical, only the mean and median were calculated for the continuous variables of age in the NHANES and NAMCS datasets and "PHQ Score" in the NHANES dataset. The mode, standard deviation, variance, and interquartile range were determined for all categorical variables to understand the distribution and dispersion. Skewness and kurtosis were calculated to identify outliers.

Two features were determined to cause large kurtosis. The data was examined, and it was not found to have outliers. The feature of no insurance only had one participant with a “yes.” This was not unexpected due to the large numbers of participants with other insurances and the changes in U.S. policy in recent years around insurance access for the uninsured. “No Provider” was the other feature with a large kurtosis. This feature was not a valuable feature as it was only for patients who visited the clinic without seeing a provider. Normalization of the data was not required for the categorical data therefore was not performed. even though we specified it in our proposal. The results of the descriptive statistics were compiled into a tabular description for easier comprehension (see appendix).

Among the two data sets, the common variables were age, gender, race, and insurance type. These shared variables were compared across the datasets (Figure 3), (Figure 4) and analyzed for differences in depression reporting (Figure 5), (Figure 6), (**Error! Reference source not found.**), (Figure)

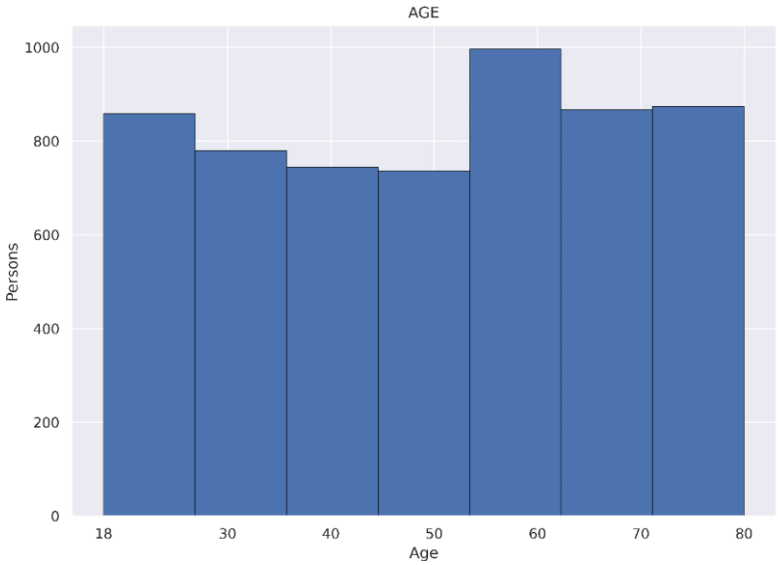


Figure 3. Age Distribution for NHANES

The largest group of persons with an indication of depression in the NAMCS group was those aged 60 to 70. with the distribution skewed to the older population. This can seen in Figure 4.

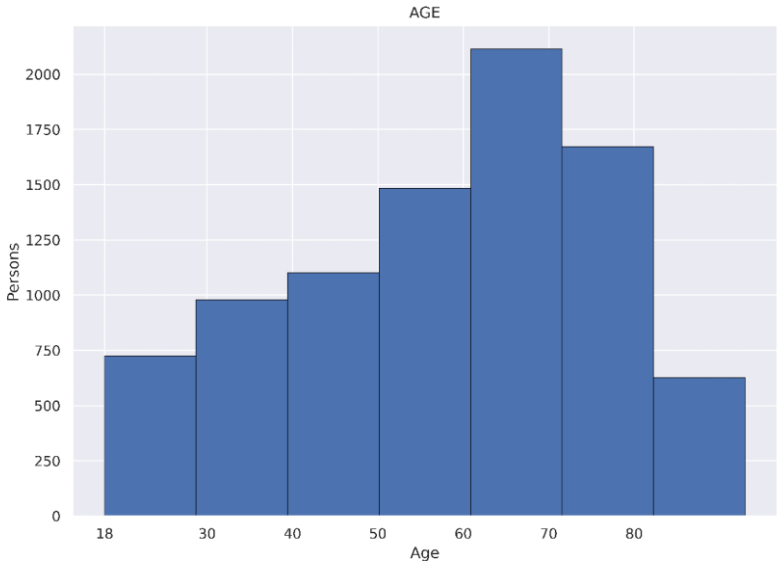
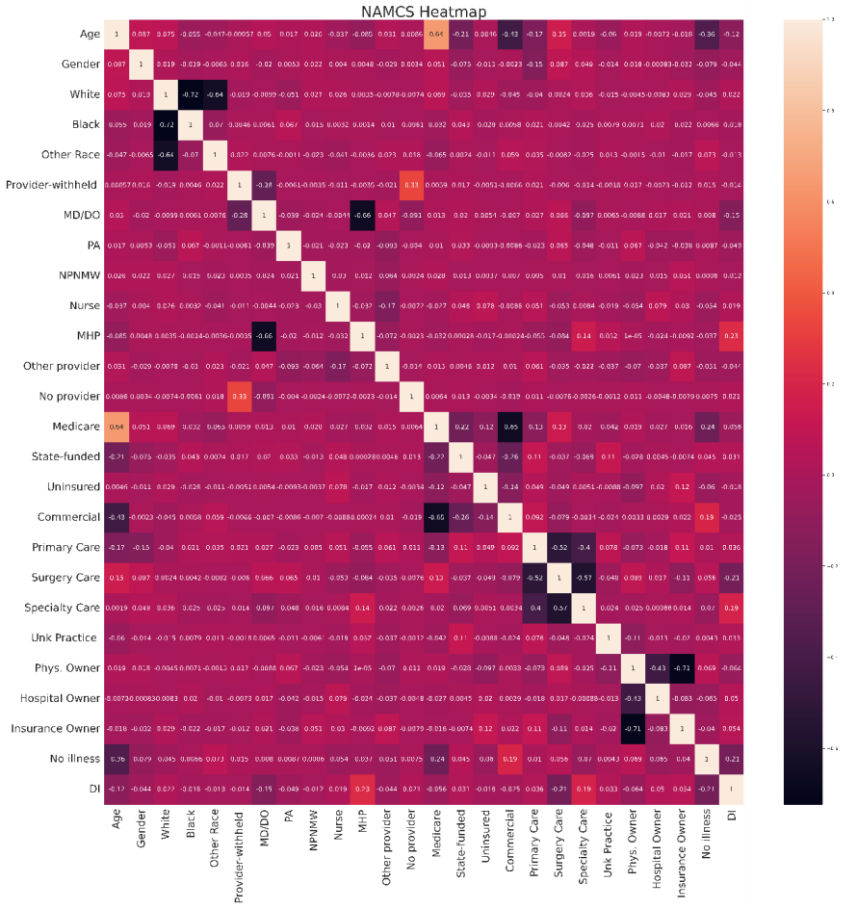


Figure 4. Age Distribution for NAMCS

Figure 5 shows Depression Indicator (DI) vs Race in NAMCS dataset. The 0 indicates ‘Yes’ and 1 as ‘No’ in the below graph.


NAMCS Heatmap
Age
Gender
White
Black
Other Race
Provider-withheld
MD/DO
PA
NPNMW
Nurse
MHP
Other provider
No provider
Medicare
State-funded
Uninsured
Commercial
Primary Care
Surgery Care
Specialty Care
Unk Practice
Phys. Owner
Hospital Owner
Insurance Owner
No illness
DI

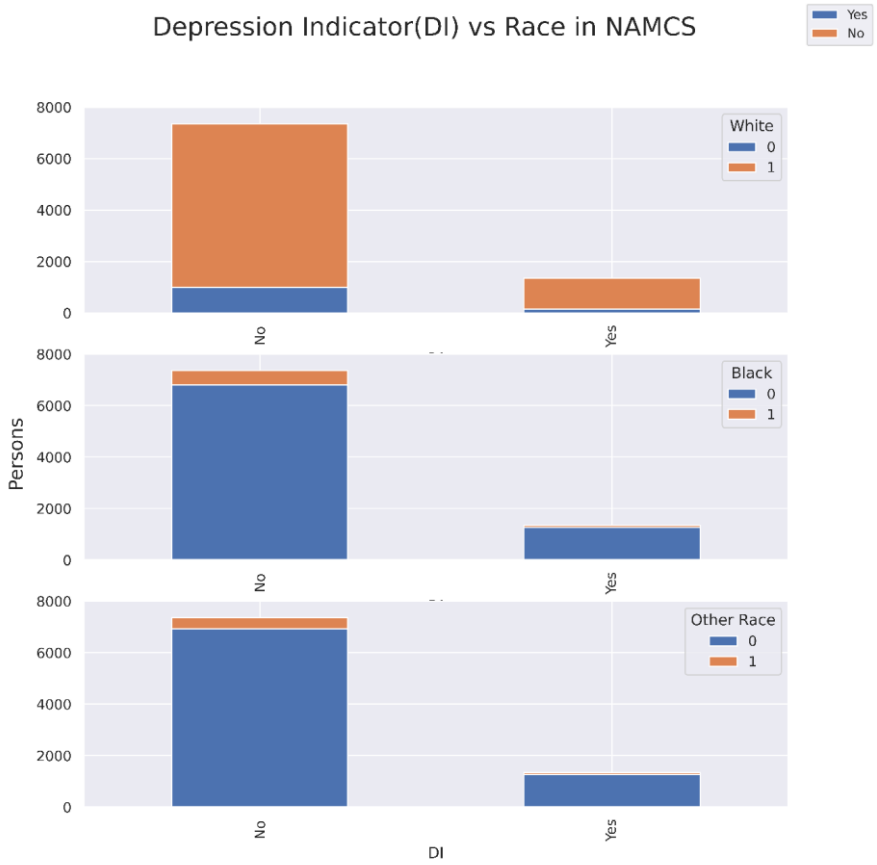


Figure 5. DI by Race in NAMCS

The below graph shows the Depression indicator (DI) by gender in NAMCS dataset. Both males and

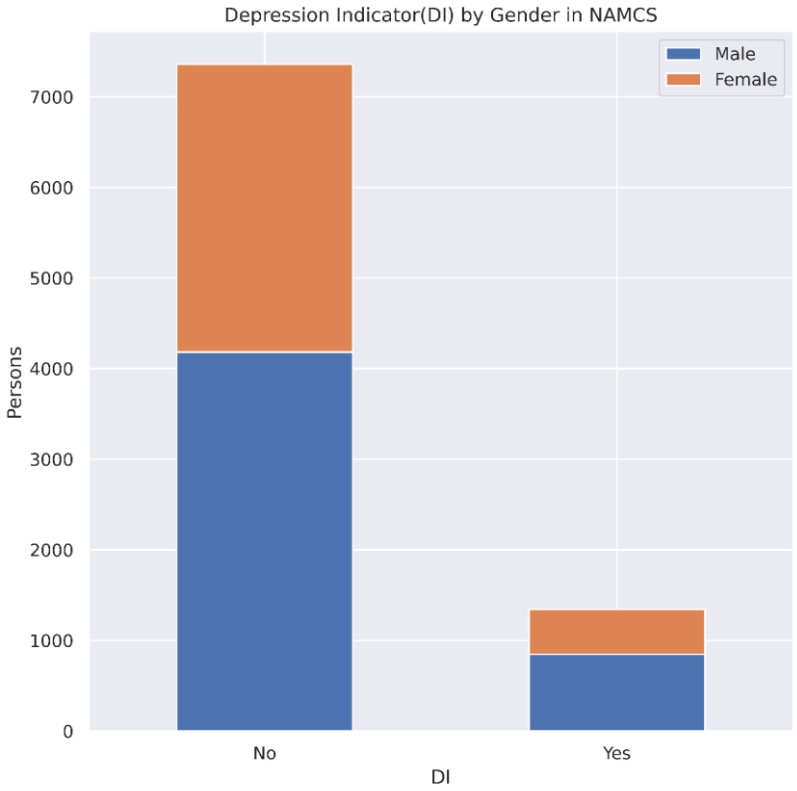


Figure 6. DI by Gender in NAMCS

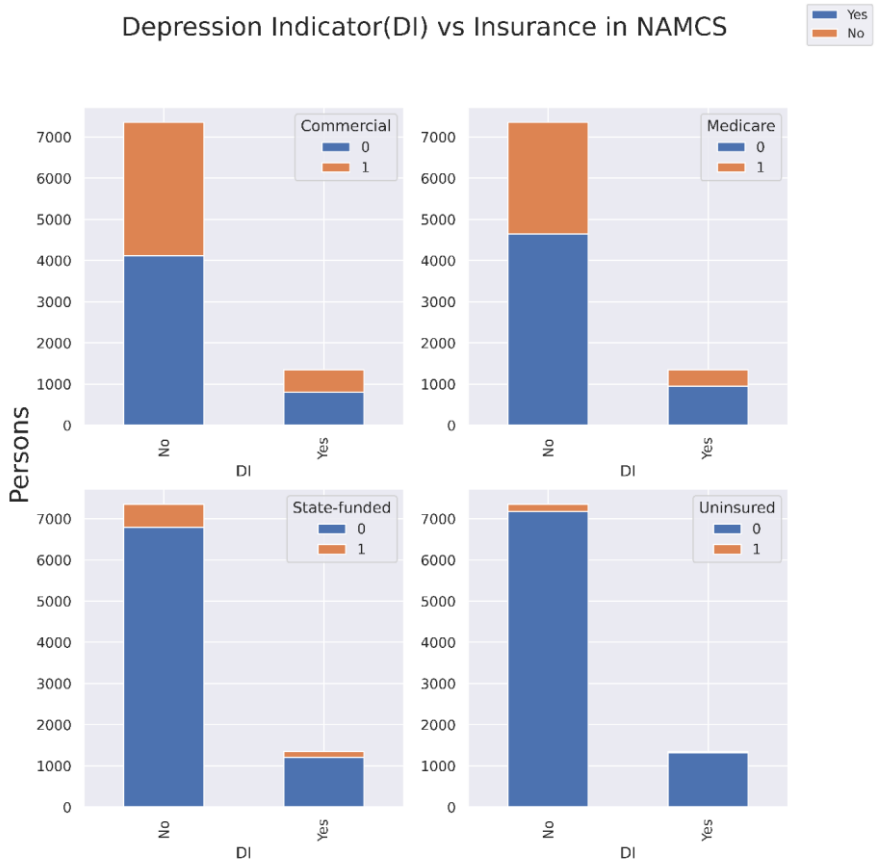
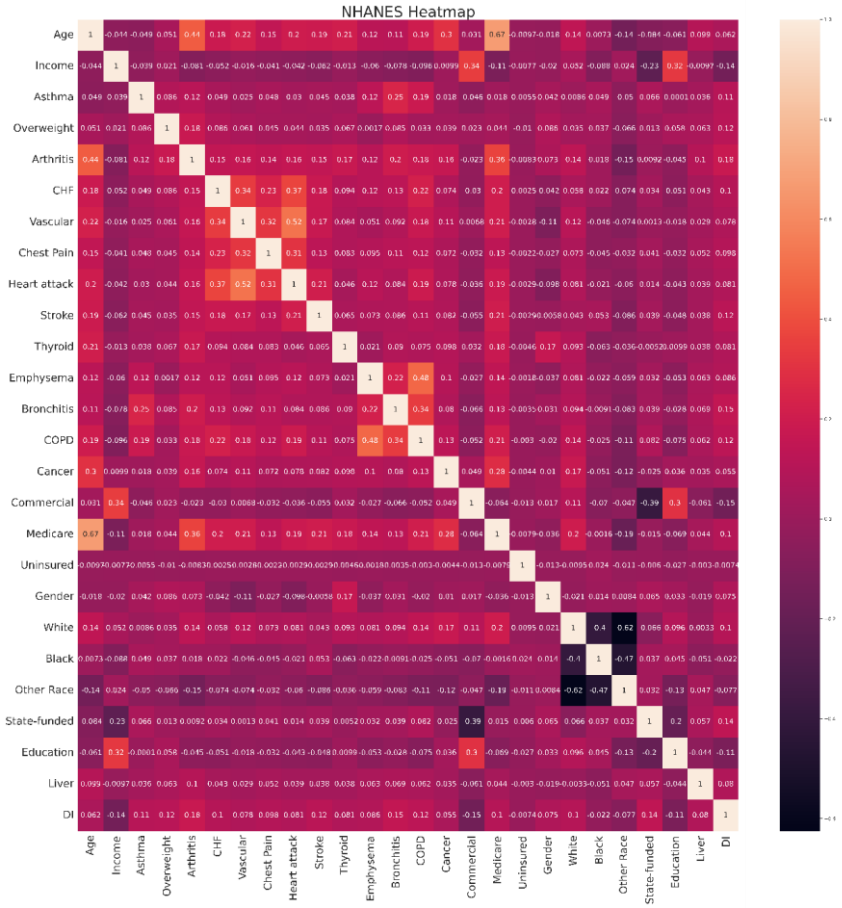
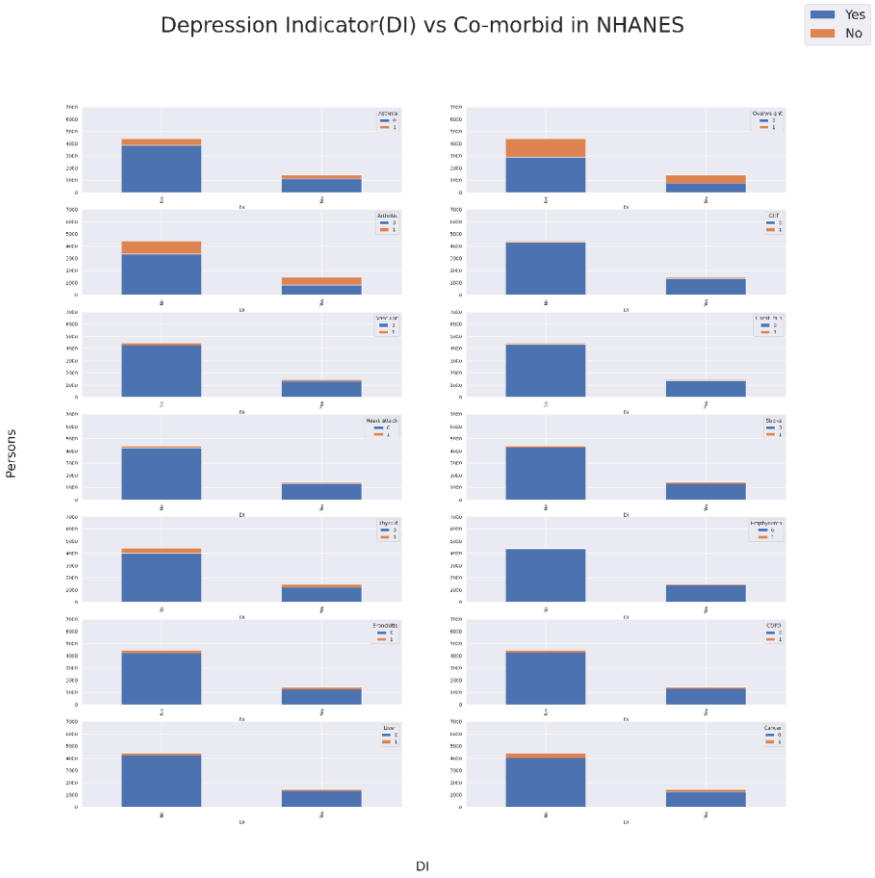
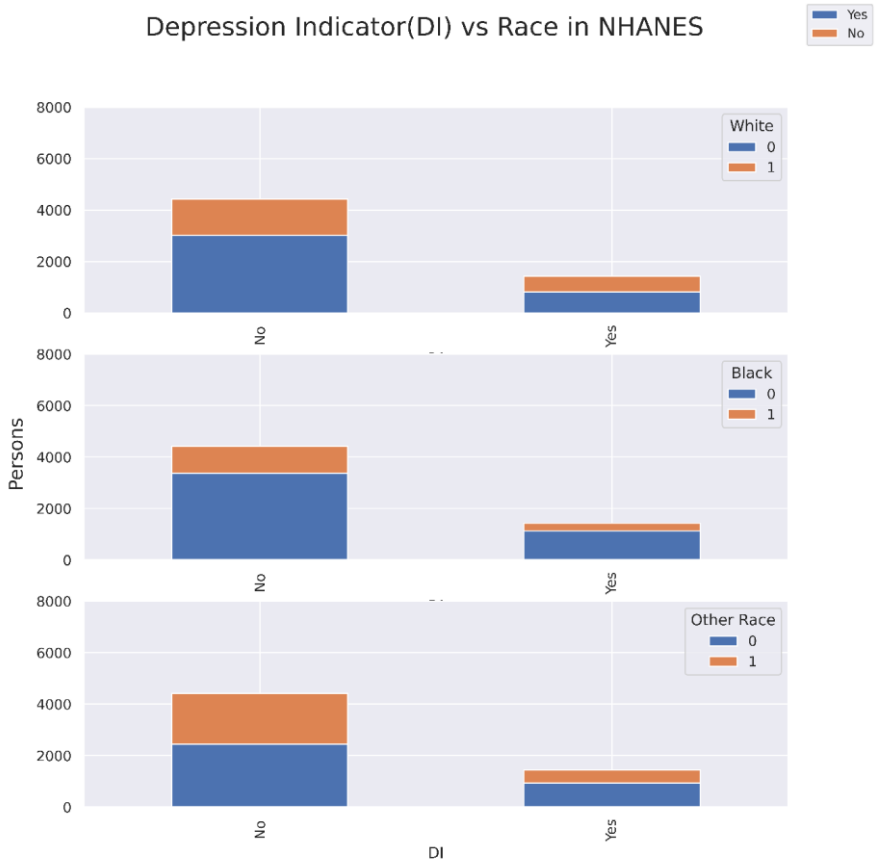


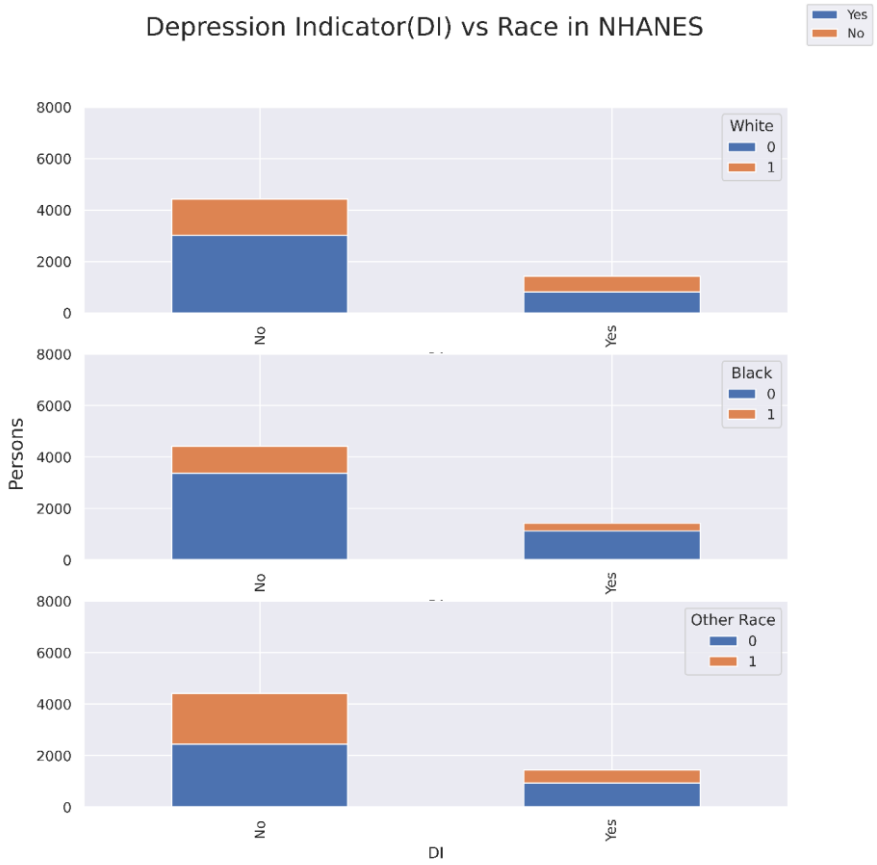
Figure 7. DI by Insurance Type in NAMCS


NHANES Heatmap
Age
Income
Asthma
Overweight
Arthritis
CHF
Vascular
Chest Pain
Heart attack
Stroke
Thyroid
Emphysema
Bronchitis
COPD
Cancer
Commercial
Medicare
Uninsured
Gender
White
Black
Other Race
State-funded
Education
Liver
DI


Depression Indicator(DI) vs Co-morbid in NHANES
Yes
No
Persons
DI


Depression Indicator(DI) vs Race in NHANES
Yes
No
White
Black
Other Race
0
1
8000
6000
4000
2000
0
Persons
No
Yes
DI


Depression Indicator(DI) by Gender in NHANES
Male
Female
7000
6000
5000
4000
3000
2000
1000
0
Persons
No
Yes
DI


Depression Indicator(DI) vs Race in NHANES
Yes
No
White
Black
Other Race
0
1
8000
6000
4000
2000
0
Persons
No
Yes
DI

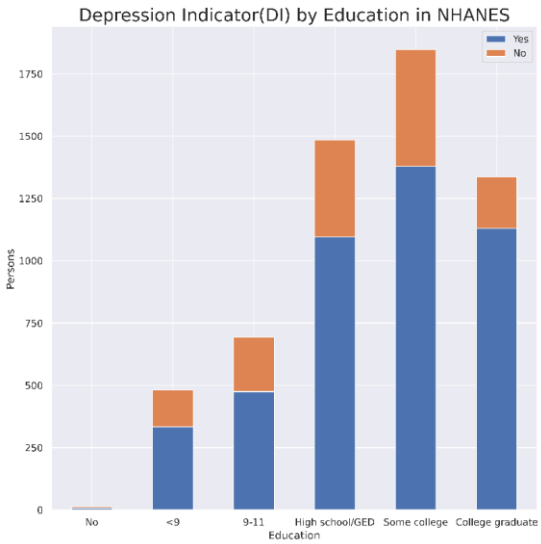


Figure 8 DI by Education for NHANES

The findings indicate a larger association among college going and High school age group depression than those of college graduates in the depression reported in the NHANES.

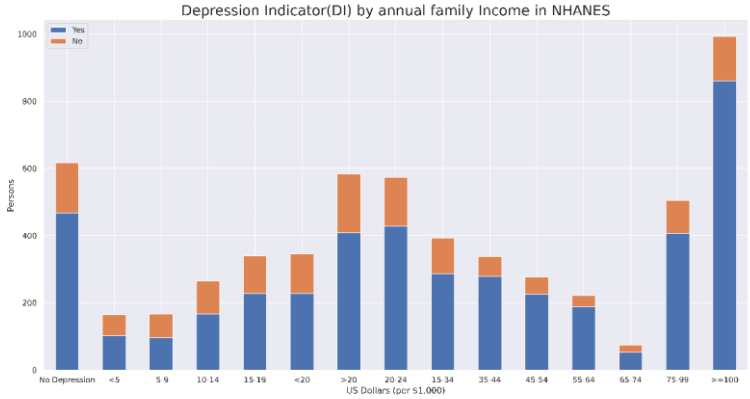


Figure 9 DI by Income for NAMCS

The findings indicate a larger association with >=100 followed by >20 and 20-24 income groups in the NAMCS which reported depression.

Hypothesis testing. The Chi-square test was used to assess any significant associations between the Depression Indicator (DI) and of each independent feature for each dataset and to determine the significant features to be used in the predicative modeling. For the null hypothesis, a significance of $p < 0.05$ was used as an indication to reject the null and a significant association between the groups. The chi-square contingency test in Python was used for the chi-square analysis. The results of the chi-square results determined that 23 and 29 of the features were significant features in NHANES and NAMCS, respectively (Figure) (Figure).

NHANES VARIABLES CHI SQUARE WITH DEPRESSION INDICATOR					
VARIABLE	CODE	P- VALUE	CRITICAL	STATIC	REJECT NULL
Age	AGE	0.03117	81.381	84.336	YES
Income	INDHHIN2	0.00000	23.685	210.484	YES
Asthma	MCQ010	0.00000	3.841	65.169	YES
Overweight	MCQ080	0.00000	3.841	79.925	YES
Arthritis	MCQ160A	0.00000	3.841	182.783	YES
CHF	MCQ160B	0.00000	3.841	56.897	YES
Vascular	MCQ160C	0.00000	3.841	35.056	YES
Chestpain	MCQ160D	0.00000	3.841	55.266	YES
HeartAttack	MCQ160E	0.00000	3.841	37.52	YES
Stroke	MCQ160F	0.00000	3.841	83.849	YES
Thyroid	MCQ160M	0.00000	3.841	37.901	YES
Emphysema	MCQ160G	0.00000	3.841	42.184	YES
Bronchitis	MCQ160K	0.00000	3.841	136.981	YES
COPD	MCQ160O	0.00000	3.841	88.838	YES
Cancer	MCQ220	0.00003	3.841	17.432	YES
Commercial	INSPRVT	0.00000	3.841	130.371	YES
Medicare	INSMCARE	0.00000	3.841	62.943	YES
Uninsured	INSNOCH	1.00000	3.841	0	NO
Gender	SEXML	0.00000	3.841	32.584	YES
White	RACEWH	0.00000	3.841	57.87	YES
Black	RACEBL	0.09907	3.841	2.72	NO
Other Race	RACEOT	0.00000	3.841	34.741	YES
State-Funded	INSSTATE	0.00000	3.841	109.903	YES
Education	EDUC	0.00000	9.488	87.52	YES
Liver	MCQ700	0.00000	3.841	36.454	YES

Figure 10. Chi-Square Testing Results NHANES

NAMCS VARIABLES CHI SQUARE WITH DEPRESSION INDICATOR					
VARIABLE	CODE	P- VALUE	CRITICAL	STATIC	REJECT NULL
Age	AGE	0.00000	96.217	198.706	YES
Gender	SEXML	0.00004	3.841	16.681	YES
White	RACEWH	0.04018	3.841	4.21	YES
Black	RACEBL	0.11329	3.841	2.508	NO
Other	RACEOT	0.25653	3.841	1.287	NO
Provider-withheld	NOPROVID	0.41137	3.841	0.675	NO
MD/DO	PHYS	0.00000	3.841	184.963	YES
PA	PHYSASST	0.00001	3.841	20.164	YES
NPNMW	NPNMW	0.33057	3.841	0.947	NO
Nurse	RNLPN	0.09016	3.841	2.871	NO
MHP	MHP	0.00000	3.841	442.487	YES
Other Provider	OTHPROV	0.00005	3.841	16.417	YES
No provider	PROVNONE	0.22218	3.841	1.49	NO
Medicare	INSMCARE	0.00000	3.841	27.031	YES
State-funded	INSSTATE	0.00475	3.841	7.972	YES
Uninsured	INSNOCH	0.11259	3.841	2.517	NO
Commercial	INSPRVT	0.02384	3.841	5.106	YES
Primary Care	SPPRC	0.00085	3.841	11.126	YES
Surgery Care	SPSUR	0.00000	3.841	365.775	YES
Speciality Care	SPMEC	0.00000	3.841	298.753	YES
Owner-withheld	OWNUNKN	0.00448	3.841	8.08	YES
Phy.Owner	OWNPHYS	0.00000	3.841	35.709	YES
Hospital Owner	OWNHOSP	0.00000	3.841	21.41	YES
Insurance Owner	OWNINSR	0.00000	3.841	24.63	YES
No illness	NOCHRON	0.00000	3.841	373.763	YES
Infection	DGRP1	0.50118	3.841	0.452	NO
Cancer/Blood	DGRP2	0.00000	3.841	27.45	YES
Metabolic	DGRP3	0.01191	3.841	6.325	YES
Neurologic	DGRP4	0.02569	3.841	4.977	YES
Eyes/Ears	DGRP5	0.00000	3.841	148.936	YES
Heart/Lung	DGRP6	0.03875	3.841	4.272	YES
Digestive	DGRP7	0.01181	3.841	6.34	YES
Skin	DGRP8	0.00191	3.841	9.631	YES
Bones	DGRP9	0.27198	3.841	1.207	NO
Urinary	DGRP10	0.01331	3.841	6.127	YES
Women's Health	DGRP11	0.00273	3.841	8.983	YES
Genetic	DGRP12	1.00000	3.841	0	NO
Other Disorder	DGRP13	0.16058	3.841	1.969	NO
Injury	DGRP14	0.02574	3.841	4.973	YES
Public Health	DGRP16	0.00000	3.841	40.53	YES

Figure 11. Chi-Square Testing Results NAMCS

The proportion of the DI between NHANES (Figure) and NAMCS (Error! Reference source not found.**)** was also used as a measure of hypothesis testing. The percentage of positive DI per dataset was compared. If the NHANES proportion of DI was higher than the NAMCS proportion, the null hypothesis would be rejected.

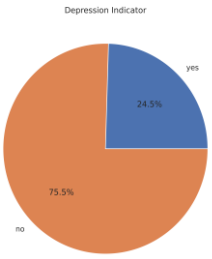


Figure 12. Proportion of DI in NHANES

4.2 Machine Learning and Model Testing.

Binary classification model. XGBoost and Random Tree Forest
With the significant features determined for each dataset, the datasets, a model was be built for future predictions about the risk of depression and depression underreporting will be used as a supervised machine learning model to predict between the classification of depression diagnosis or no depression diagnosis. Scikit-Learn in Python will be used to build and test the model.

4.3 *Performance Analysis*. Python scikit-learn and a Precision-Recall (PR) Curve [14] will be used to evaluate the model's performance. The PR Curve will produce precision and recall values for probabilities at set thresholds. The PR area under the curve (AUC) will be the metric for evaluating the model's performance.

Binary Classification Models:

With the significant variables from both the datasets we build two models for the diagnosis of depression among the two datasets. The models that we employed for the diagnosis of depression for the two datasets are

- XGBOOST CLASSIFIER
- RANDOM FOREST CLASSIFIER

The two machine learning algorithms were performed on both the datasets. We used different functions for Cross-Validation, Determining Model Metrics, Feature importance, Confusion Matrix, PR-Curves, and ROC curves of the models for comparison and performance analysis between the models.

XGBOOST CLASSIFIER

NAMCS DATASET

As 70% of the data contains information for the N Depression reported and 30% for the Depression reported, we performed a function called **SMOTE** (Synthetic Minority Oversampling Technique) for the balancing of the data we have among the two datasets. Then we performed the testing and training of the NAMCS data set.

The cross-validation score of the NAMCS dataset after SMOTE with XGBOOST classifier using F1 macro is 0.89 with a standard deviation of 0.1. we can see the significant difference for score before and after using the SMOTE.

Cross Validation Score for namcs before smote

```
cross(xgb_cl, Xnam_train, ynam_train,'f1_macro')
```

```
Mean f1_macro of 0.68 with a standard deviation of 0.02
```

Cross Validation Score for namcs after smote

```
cross(xgb_cl, Xnam_train, ynam_train,'f1_macro')
```

```
Mean f1_macro of 0.89 with a standard deviation of 0.10
```

Figure 13 Cross Validation Score before smote NAMCS

The model Performance Scores for the NAMCS after SMOTE are

Accuracy: 85%
Precision: 54.9%
Sensitivity recall: 51%
Specificity: 91.8%
F1_score: 0.5292

Model scores for namcs after smote

```
In [29]: skmets(ynam_test, prednam)

Out[29]: {'Accuracy': 0.851809304997128,
          'Precision': 0.5492424242424242,
          'Sensitivity_recall': 0.5105633802816901,
          'Specificity': 0.9183253260123542,
          'F1_score': 0.5291970802919708}
```

Figure 14 Model Scores for NAMCS after smote

After using the function SMOTE the top three features that contributed for the reporting of the depression are: No Chronic Conditions, patients with diagnosis of heart or lung diseases, and patients with diagnosis of cancer or blood related diseases.

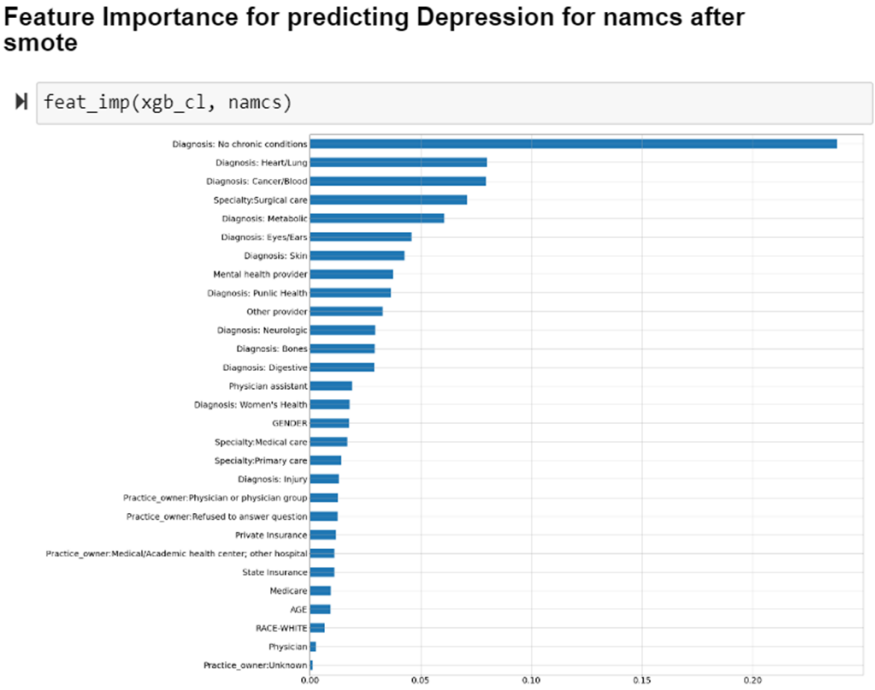


Figure 15 Feature Importance for NAMCS

Confusion Matrix of XGBOOST classifier for NAMCS dataset: The confusion matrix for the XGBOOST classifier after using the SMOTE, we can see that model predictions. Of all the positive cases form the dataset, the model predicted 51% of them as True positives and 49% as False Negatives. But, of all the negative cases from the dataset, the model predicted 91.8% of them as True Negative and 8.2% as False Positives. The model has high accuracy for the prediction of patients with no depression.

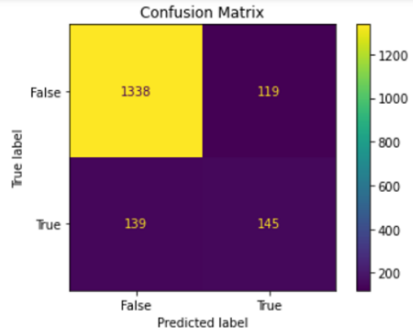


Figure 16 Confusion Matrix of NAMCS

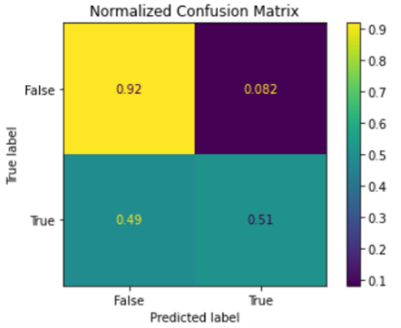


Figure 17 Normalizaed Confusion Matrix NAMCS

PR curve:

The precision- recall curve for the NAMCS dataset after applying SMOTE, AUC is 0.5698

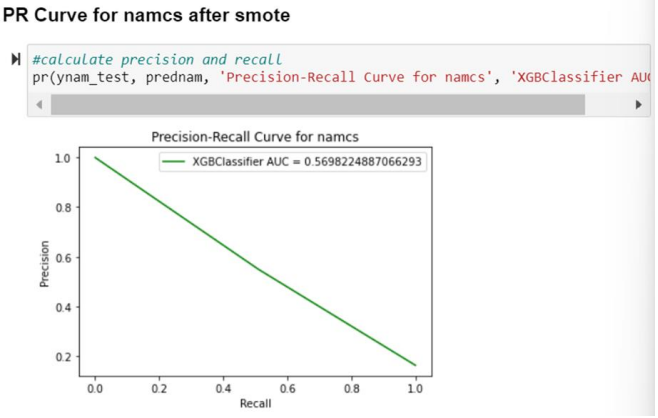


Figure 18 PR Curve NAMCS after Smote

ROC Curve:

The ROC curve for the XGBOOST classifier performed on the NAMCS dataset after SMOTE, AUC is 0.83

ROC Curve for namcs after smote

```
roc(xgb_cl, Xnam_test, ynam_test)
```

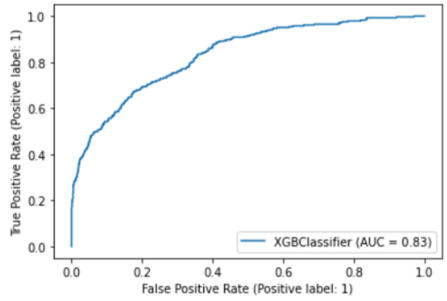


Figure 19 ROC Curve XBBOOST

NHANES DATASET

After performing the XGBOOST classifier on the NAMCS dataset, we performed the same on the NHANES dataset. The SMOTE function is applied to the NHANES dataset for the balancing of the data. The XGBOOST classifier is performed on the NHANES dataset by splitting the data into training and testing data. The cross-validation score(f1_macro) for the NHANES after SMOTE is 0.79 with a standard deviation of 0.17.

Cross Validation Score for nhanes before smote

```
cross(xgb_cl, Xnh_train, ynh_train,'f1_macro')
```

```
Mean f1_macro of 0.59 with a standard deviation of 0.02
```

Cross Validation Score for nhanes after smote

```
cross(xgb_cl, Xnh_train, ynh_train,'f1_macro')
```

```
Mean f1_macro of 0.79 with a standard deviation of 0.17
```

The model performance scores for NHANES are:

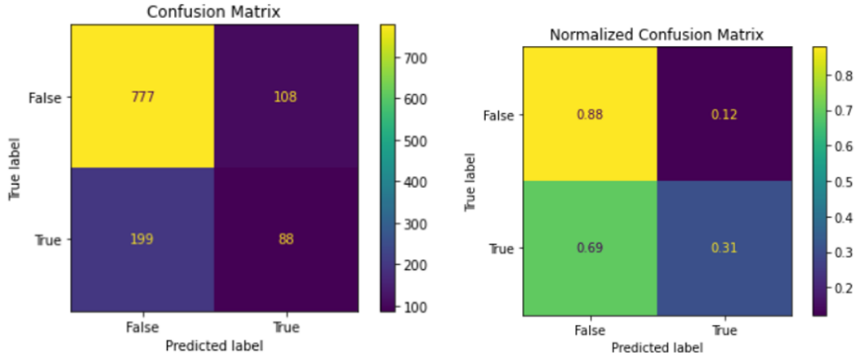
Accuracy: 73.8%
Precision: 44.9%
Sensitivity recall: 30.66%
Specificity: 87.8%
F1_score: 0.3644

Model scores for nhanes after smote

```
In [46]: skmets(ynh_test, prednh)
Out[46]: {'Accuracy': 0.7380546075085325,
          'Precision': 0.4489795918367347,
          'Sensitivity_recall': 0.30662020905923343,
          'Specificity': 0.8779661016949153,
          'F1_score': 0.36438923395445133}
```

Confusion Matrix of XGBOOST classifier for NHANES dataset:

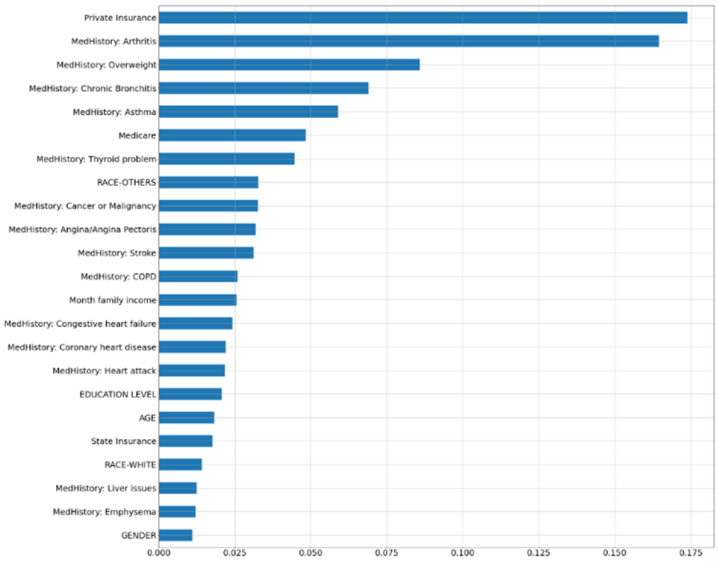
From the confusion matrix, we can see the model predictions. Of all the positive cases from the dataset, the classifier predicted 31% of them as True Positives and 69% of them as False Negatives. Of all the negatives for the Depression from the dataset, the classifier predicted 88% of them as True Negatives and with 12% as False Positives.



After performing the Feature importance function on the NHANES dataset, the top three factors that contributed for the diagnosis of depression are Private Insurance, people suffering from arthritis, and people with overweight in medical history.

Feature Importance for predicting Depression for nhanes after smote

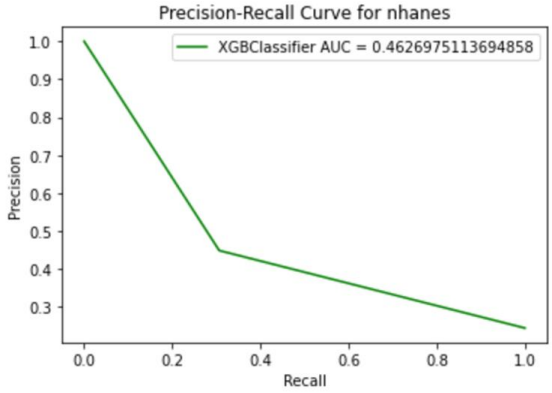
```
feat_imp(xgb_cl, nhanes)
```



PR curve:
The precision- recall curve for the XGBOOST classifier performed on the NHANES dataset after applying SMOTE, AUC is 0.4627

PR Curve for nhanes after smote

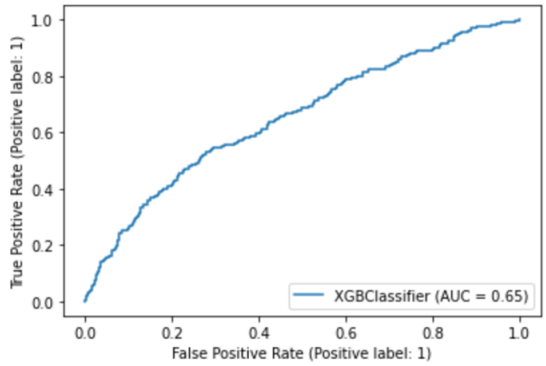
```
#calculate precision and recall
pr(ynh_test, prednh, 'Precision-Recall Curve for nhanes', 'XGBClassif
```



ROC Curve:
The ROC curve for the XGBOOST classifier performed on the NHANES dataset after SMOTE, AUC is 0.65

ROC Curve for nhanes after smote

```
roc(xgb_cl, Xnh_test, ynh_test)
```



RANDOM FOREST CLASSIFIER

After performing the XGBOOST classifier on both datasets, we employed the Random Forest Classifier to classification on both datasets. We fine-tuned the hyperparameters of the Random Forest Classifier using the the RandomizedSearchCV and found that the optimal parameters were:

n_estimators = 89,
min_samples_split = 12,

min_samples_leaf = 4,
max_features = 'auto',
max_depth = 28,
bootstrap = True

NAMCS DATASET

The Random Forest Classifier was performed on the NAMCS dataset by dividing it into train and test data. The SMOTE function was applied to this classifier for balancing the data. The cross-validation score (f1_macro) of Random Forest Classifier for the NAMCS dataset is 0.87 with a standard deviation of 0.08.

```
Mean f1_macro of 0.63 with a standard deviation of 0.02

Mean f1_macro of 0.87 with a standard deviation of 0.08
```

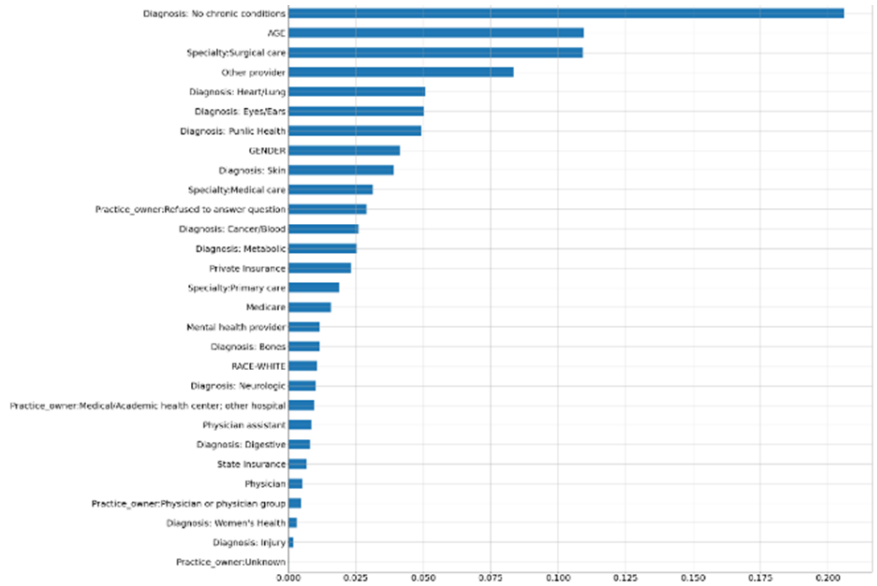
The model performance score of Random Forest Classifier for NAMCS dataset are:
Accuracy: 84.55%
Precision: 52.59%
Sensitivity recall: 53.52%
Specificity: 90.6%
F1_score: 0.53

Model scores for namcs after smote

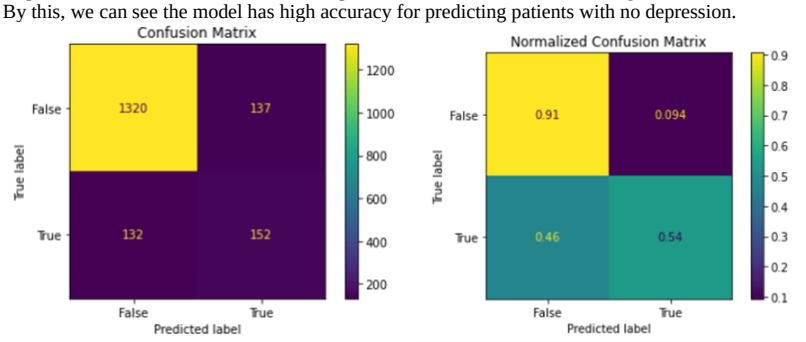
```
skmets(ynam_test, prednam)
```

```
9]: {'Accuracy': 0.8454910970706491,
     'Precision': 0.5259515570934256,
     'Sensitivity_recall': 0.5352112676056338,
     'Specificity': 0.905971173644475,
     'F1_score': 0.5305410122164049}
```

After performing the Feature importance function on the NAMCS dataset, the top three features that contributed for the reporting of the depression are No Chronic Conditions, Age and Specialty: Surgical Care.



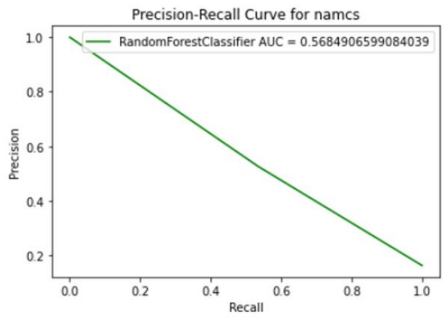
Confusion Matrix of Random Forest Classifier for NAMCS dataset:
From the confusion matrix, we can see the model predictions. Of all the positive cases from the dataset, the classifier predicted 54% of them as True Positives and 46% as False Negatives. Of all the negatives for the Depression from the dataset, the classifier predicted 90.6% of them as True Negatives and 9.4% as False Positives. By this, we can see the model has high accuracy for predicting patients with no depression.



PR curve:
The precision- recall curve for the Random Forest classifier performed on the NAMCS dataset after applying SMOTE, AUC is 0.5685

PR Curve for namcs after smote

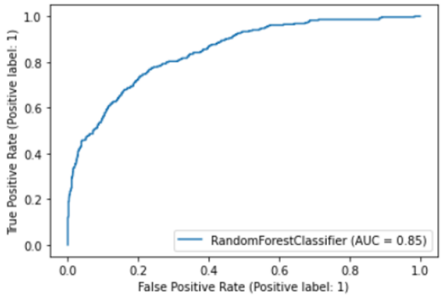
```
#calculate precision and recall
pr(ynam_test, prednam, 'Precision-Recall Curve for namcs', 'RandomForestClas
```



ROC Curve:
The ROC curve for the Random Forest classifier performed on the NAMCS dataset after SMOTE, AUC is 0.85

ROC Curve for namcs after smote

```
roc(clf, Xnam_test, ynam_test)
```



NHANES DATASET

Here, we performed the Random Forest Classifier on the NHANES dataset by splitting the data into training and testing data. Even here, we used the SMOTE function for balancing the data from the datasets. The cross-validation score (f1_score) of the Random Forest Classifier for the NHANES dataset is 0.79 with a standard deviation of 0.15.

```
Mean f1_macro of 0.54 with a standard deviation of 0.00

Mean f1_macro of 0.79 with a standard deviation of 0.15
```

The model performance score of Random Forest Classifier for NHANES dataset are:

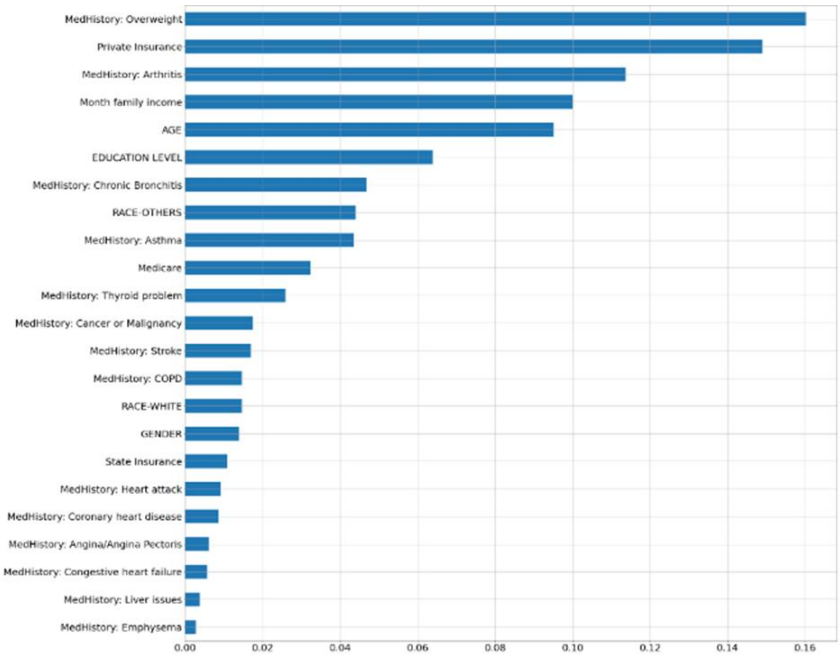
Accuracy: 72.87%
Precision: 42.36%
Sensitivity recall: 29.97%
Specificity: 86.78%
F1_score: 0.3510

Model scores for nhanes after smote

```
skmets(ynh_test, predh)
```

```
1]: {'Accuracy': 0.7286689419795221,
     'Precision': 0.4236453201970443,
     'Sensitivity_recall': 0.29965156794425085,
     'Specificity': 0.8677966101694915,
     'F1_score': 0.3510204081632653}
```

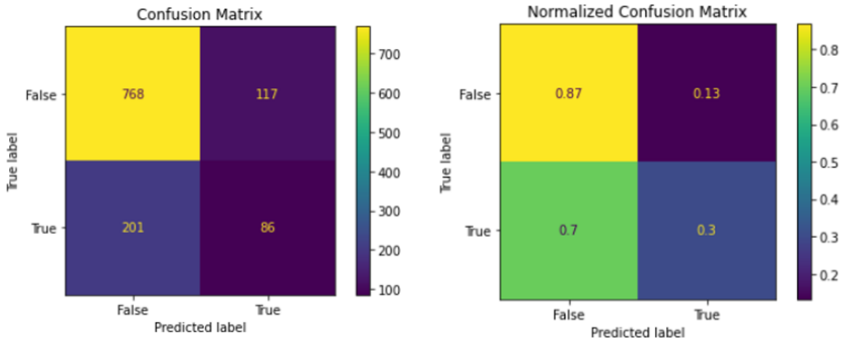
After performing the Feature importance function on the NHANES dataset, the top three features that contributed for the reporting of depression are Medical History of Overweight, Private Insurance and Medical History of Arthritis.



Confusion Matrix of Random Forest Classifier for NHANES dataset:

From the confusion matrix, we can see the model predictions. Of all the positive cases from the dataset, the classifier predicted 30% of them as True Positives and 70% of them as False Negatives. Of all the negatives for the Depression from the dataset, the classifier predicted 87% of them as True Negatives and with 13% as False Positives.

The model has high accuracy for predicting patients with no depression.

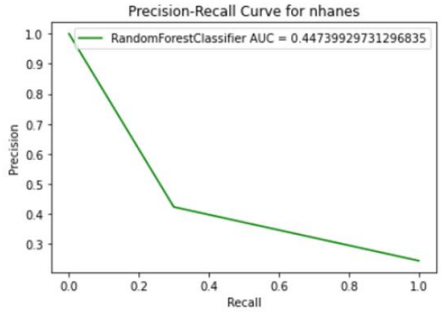


PR curve:

The precision- recall curve for the Random Forest classifier performed on the NHANES dataset after applying SMOTE, AUC is 0.4474

PR Curve for nhanes after smote

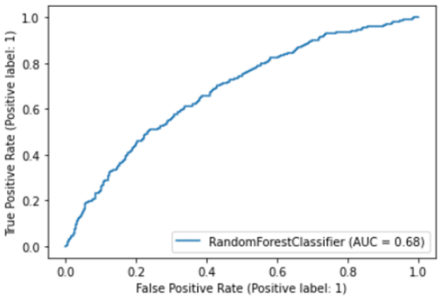
```
#calculate precision and recall
pr(ynh_test, prednh, 'Precision-Recall Curve for nhanes', 'RandomForestClass
```



ROC Curve:
The ROC curve for the Random Forest classifier performed on the NHANES dataset after SMOTE, AUC is 0.68

ROC Curve for nhanes after smote

```
roc(clf, Xnh_test, ynh_test)
```



5 Results

Future research should investigate the consequences of depression reporting patterns for provider-reported outcomes. A surprising finding of this study was the higher prevalence of depression reported by healthcare providers compared to self-reporting. Although there were discrepancies in depression reporting, additional research is required to investigate the influence of this reporting on adults and the steps that should be taken on a specific age group for better screening and diagnosis. More research is also required to determine how providers, patients, and members of various health professions report depression.

5.1 Hypothesis Testing

- The chi-square test was utilized for hypothesis testing because both of the data sets contained categorical data.
- Even though we mentioned in the draft proposal using a two-sample t test, we employed the chi square test because the data we had was categorical. So we chose Chi Square over the two sample tests.

- With the use of the chi-square contingency test, we identified the significant factors from both datasets have an association with the depression indicator.
- The significant factors for the depression indicator for both datasets was used to forecast depression using XGBoost, Random Forest and SVM models.

Both models were able to provide good classification for the NHANES and namcs datasets. The namcs data was able to provide better classification for the Depression as compared to NHANES survey data. The diagnosis codes were able to provide a good deal of information to the model to enable the Depression Indicator. There was found to be a increase in the depression proportion in the NHANES dataset as compared to namcs dataset and significant associations between the depression indicator and multiple factors that were also found to predict depression. Hence, we reject the null hypothesis as there is substantiating evidence to do so. The predictive model found that a person in the NAMCS dataset has a higher chance of being detected for depression compared to a person who was surveyed in NHANES. The analysis provided information for the specific groups most in need of screening for depression and for those providers and can be used in future study to develop a more precise depression screening tool for adults.

The team was meticulous about details and had to rerun the codes several times to attain the required results. After cleaning and running the codes, we saw anomalies in our methods and considered several approaches to ensure we were doing the project correctly and on time. It would have been far better if we had chosen a dataset from the same population that self-reported depression and where providers reported depression, which would have provided more accurate results about depression reporting.

6 Conclusions

- This project was able to demonstrate multiple factors impacting depression and the providers who report depression.
- Hypothesis testing supported the rejection of the null hypothesis. Depression cases were observed to be lower in the NHANES dataset compared to the NAMCS dataset. As a result, we reject the null hypothesis since there is sufficient evidence to support it.
- A person in the NAMCS dataset has a higher chance of being detected for depression compared to a person who was surveyed in NHANES.
- A model was established to support the further development of a survey that can be used to further develop a depression indicator.
- Both models were able to provide good classification for the NHANES and NAMCS datasets. The NAMCS data was able to provide better classification for the Depression as compared to NHANES survey data.
- We conclude that a person in the NAMCS dataset has a higher chance of being detected for depression compared to a person who was surveyed in NHANES.

7 Limitations

Although we made every effort to minimize limitations, there inevitably are limitations in any research study. The use of 2018 survey data for both datasets due to constraints from the Covid pandemic's ban on in-person contact limits the possible relevancy of the data. The data is recent data, however data changes rapidly in all data science, especially medical data. There is a chance that depression rates and factors leading to depression have been altered from the compounding effect of the Covid pandemic on depression.

Findings from the models related to direct comparisons of the two datasets are limited because the two samples are from two separate populations. To compare the datasets, we ran the model predictions for the diagnosis of depression on the two datasets.

8 Project Challenges and Successes

Initially, the team was meant to do a comparative analysis by identifying the common variables in both datasets and analyze the mean differences in depression reporting by providers compared to the lay public. The project intended to identify any discrepancies in identification of patients with depression by providers. Nonetheless, after consultation with our advisor and further investigation into the data, the populations are not the same and cannot be compared directly. Also, after getting full access to the data, the team realized that most of the variables were categorical, and t-testing was not appropriate for hypothesis testing. To obtain pertinent findings, chi-square analyses were required to identify significant variables, and the modeling was possible to conclude the hypothesis testing.

9 Appendix

(Figure)

CONTINUOUS DATA										
DATASET	n	VARIABLE	MEAN	MEDIAN	MODE	STD	VARIANCE	IQR	SKEWNESS	KURTOSIS
NAMCS	8701	Age	58	61	71	18.44	340.1	27	0	-0.74
NHANES	5856	Age	50	51	80	18.78	352.54	32	-0.06	-1.17
NHANES	5856	PHQ Score	2.82	1	0	4.11	16.89	4	2.08	4.67

Figure 20. Descriptive Statistics-Continuous Variables

(Figure)

CATEGORICAL DATA																
	NHANES						NAMCS									
VARIABLE	MODE	STD	VARI	IQR	SKEWNESS	KURTOSIS	VARIABLE	MODE	STD	VARIANCE	IQR	SKEWNESS	KURTOSIS
Gender	1	0.50	0.25	1	-0.06	-2.00	Gender	0	0.49	0.24	1	0.31	-1.90
Black	0	0.42	0.18	0	1.29	-0.34	Black	0	0.26	0.07	0	3.25	8.60
Other Race	0	0.49	0.24	1	0.31	-1.91	Other Race	0	0.23	0.05	0	3.77	12.20
White	0	0.48	0.23	1	0.64	-1.59	White	1	0.34	0.11	0	-2.17	2.71
Education	4	1.55	2.40	3	-0.44	-1.33	Speciality Care	0	0.46	0.21	1	0.84	-1.29
Income	15	4.98	24.81	10	0.04	-1.17	Primary Care	0	0.44	0.20	1	1.05	-0.91
Medicare	0	0.44	0.20	1	1.04	-0.91	Surgery Care	0	0.49	0.24	1	0.30	-1.91
Uninsured	0	0.01	0.00	0	76.52	5856.00	Nurse	0	0.30	0.09	0	2.65	5.05
Commercial	0	0.50	0.25	1	0.05	-2.00	Provider-withheld	0	0.03	0.00	0	31.05	962.33
State-funded	0	0.38	0.14	0	1.71	0.93	NPNMW	0	0.11	0.01	0	8.98	78.72
Asthma	0	0.36	0.13	0	1.95	1.79	MHP	0	0.11	0.01	0	9.22	82.95
Overweight	0	0.49	0.24	1	0.49	-1.76	Other provider	0	0.46	0.21	1	0.83	-1.31
Arthritis	0	0.45	0.21	1	0.93	-1.14	MD/DO	1	0.11	0.01	0	-8.49	70.06
CHF	0	0.18	0.03	0	5.12	24.19	PA	0	0.18	0.03	0	5.12	24.25
Vascular	0	0.21	0.04	0	4.38	17.16	No provider	0	0.02	0.00	0	46.62	2171.50
Chest Pain	0	0.16	0.03	0	5.78	31.43	Hospital Owner	0	0.21	0.05	0	4.21	15.73
Heart attack	0	0.21	0.04	0	4.33	16.75	Insurance Owner	0	0.32	0.10	0	2.36	3.57
Stroke	0	0.21	0.04	0	4.30	16.51	Phys.Owner	1	0.41	0.17	0	-1.41	-0.02
Emphysema	0	0.13	0.02	0	7.23	50.31	Owner-withheld	0	0.06	0.00	0	17.87	317.45
Bronchitis	0	0.25	0.06	0	3.45	9.91	Medicare	0	0.48	0.23	1	0.60	-1.64
Thyroid	0	0.32	0.10	0	2.46	4.07	Uninsured	0	0.15	0.02	0	6.17	36.09
COPD	0	0.22	0.05	0	4.13	15.05	Commercial	0	0.50	0.25	1	0.26	-1.93
Cancer	0	0.30	0.09	0	2.66	5.08	State-funded	0	0.27	0.07	0	3.09	7.58
Liver	0	0.22	0.05	0	4.12	14.99	Infection	0	0.04	0.00	0	23.26	539.12
DPQ1	0	0.72	0.52	0	2.31	4.74	Urinary	0	0.23	0.05	0	3.88	13.08
DPQ2	0	0.68	0.46	0	2.48	5.84	Womens Health	0	0.12	0.01	0	8.10	63.56
DPQ3	0	0.91	0.83	1	1.60	1.44	Genetic	0	0.05	0.00	0	19.82	390.73
DPQ4	0	0.91	0.83	1	1.33	0.83	Other Disorder	0	0.28	0.08	0	3.01	7.03
DPQ5	0	0.74	0.55	0	2.32	4.68	Injury	0	0.15	0.02	0	6.38	38.77
DPQ6	0	0.59	0.34	0	3.18	10.30	Morbidity	0	0.00	0.00	0	0.00	0.00
DPQ7	0	0.64	0.41	0	3.10	9.27	Public health	0	0.37	0.13	0	1.87	1.50
DPQ8	0	0.51	0.26	0	4.01	16.56	Cancer/Blood	0	0.18	0.03	0	5.16	24.65
DPQ9	0	0.28	0.08	0	7.38	61.53	Metabolic	0	0.21	0.05	0	4.27	16.23
PHQ Score	0	4.11	16.89	4	2.08	4.67	Neurologic	0	0.17	0.03	0	5.49	28.13
Feels DPRN	5	1.27	1.61	1	-1.40	1.19	Eyes/Ears	0	0.35	0.12	0	2.07	2.30
DPRN Meds	2	0.39	0.15	0	-2.99	8.73	Heart/Lung	0	0.26	0.07	0	3.20	8.27
DPRN Level	0	1.15	1.31	2	0.80	-0.86	Digestive	0	0.17	0.03	0	5.37	26.80
DI	0	0.43	0.19	0	1.18	-0.60	Skin	0	0.28	0.08	0	2.89	6.37
							Bones	0	0.25	0.06	0	3.47	10.05
							No illness	0	0.47	0.22	1	0.70	-1.50
							Chronic DPRN	0	0.30	0.09	0	2.61	4.81
							Therapy Referral	0	0.14	0.02	0	6.97	46.53
							MHP Referral	0	0.14	0.02	0	6.76	43.66
							DPRN Screen	0	0.20	0.04	0	4.58	19.02
							DI	0	0.36	0.13	0	1.91	1.66

Figure 21. Descriptive Statistics-Categorical Variables

10 References

2. World Health Organization: Mental Health and COVID-19: Early evidence of the pandemic's impact (2022)
3.
4. Knaak, S., Mantler, E., Szeto, A.: Mental illness-related stigma in healthcare. Healthcare Management Forum 30, 111-116 (2017)
5. Hansson, L., Jormfeldt, H., Svedberg, P., Svensson, B.: Mental health professionals' attitudes towards people with mental illness: do they differ from attitudes held by people with mental illness? Int J Soc Psychiatry 59, 48-54 (2013)
6. Garcia, M.E., Hinton, L., Neuhaus, J., Feldman, M., Livaudais-Toman, J., Karliner, L.S.: Equitability of Depression Screening After Implementation of General Adult Screening in Primary Care. JAMA Network Open 5, e2227658-e2227658 (2022)
7. National Center for Health Statistics: Summary of Current Surveys and Data Collection Systems. factsheet, Centers for Disease Control and Prevention (2020)
8. National Center for Health Statistics (NCHS): National Health and Nutrition Examination Survey. In: Centers for Disease Control and Prevention (CDC) (ed.). U.S. Department of Health and Human Services, Centers for Disease Control and Prevention,, Hyattsville, MD (2018)
9. National Center for Health Statistics: Unweighted Response Rates for NHANES 2017-2018 by Age and Gender. In: NHANES-2017-2018-Response-Rates-508 (ed.).
10. National Center for Health Statistics: National Ambulatory Medical Care Survey. Center for Disease Control, (2018)
11. National Center for Health Statistics: National Ambulatory Medical Care Survey: 2018 National Summary Tables. Centers for Disease Control and Prevention, (2018)
12. National Center for Health Statistics (NCHS): 2018 NAMCS Micro-Data File Documentation. In: Ambulatory and Hospital Care Statistics (ed.), pp. 155. Division of Health Care Statistics, (2018)
13.
14. Boyd, K., Eng, K.H., Page, C.D.: Area under the Precision-Recall Curve: Point Estimates and Confidence Intervals. In: Machine Learning and Knowledge Discovery in Databases, pp. 451-466. Springer Berlin Heidelberg, (Year)

Commented [TAD1]: Monitor for updates