ruth-kitasi / **Seasonal-flu-vaccine**

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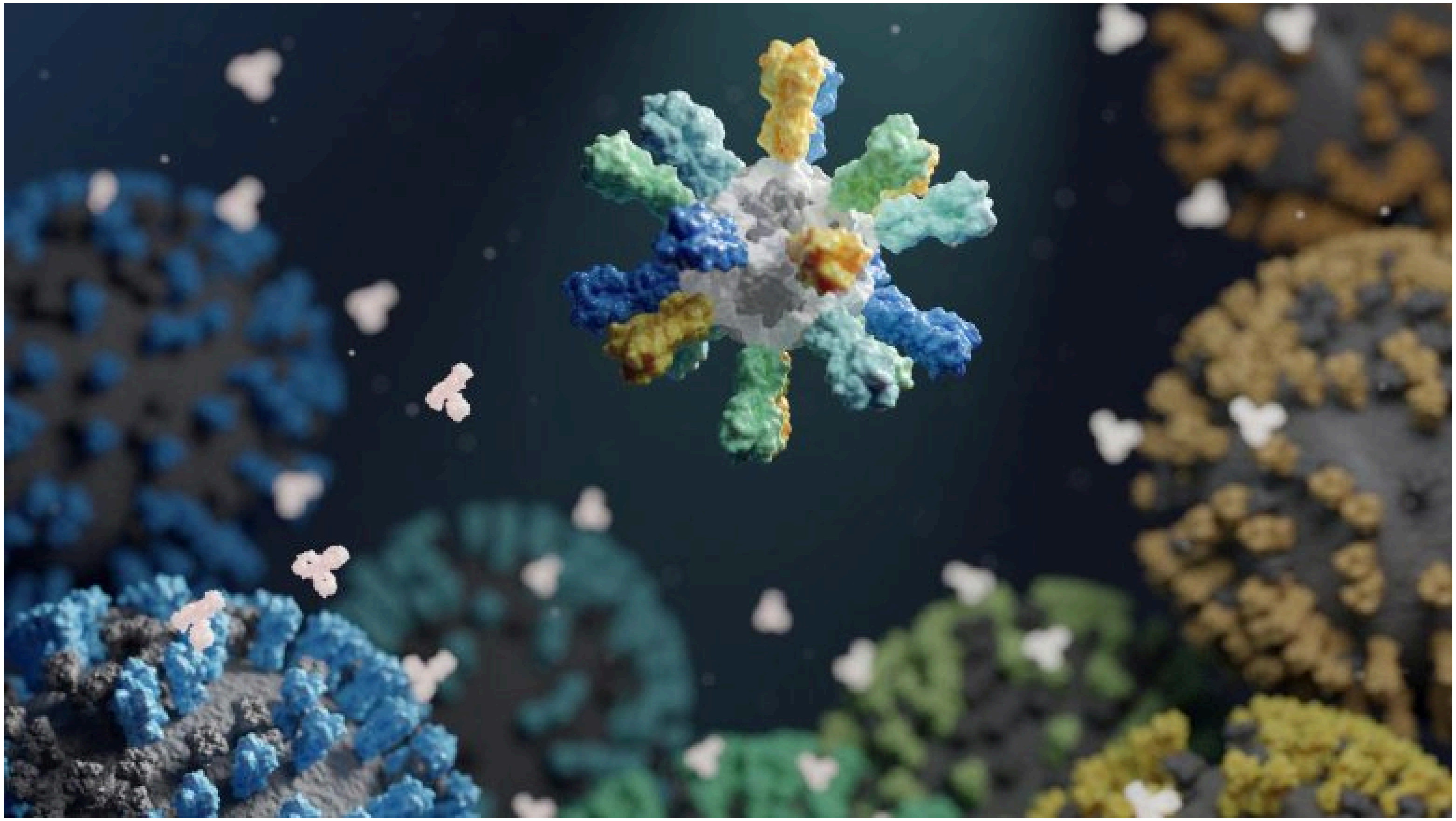
Seasonal-flu-vaccine / index.ipynb

ruth and ruth changing img 0b12d50 · 9 minutes ago

3913 lines (3913 loc) · 246 KB

Preview Code Blame Raw

SEASONAL FLU VACCINE UPTAKE PREDICTION



Problem statement

As a Data Analyst at a healthcare consulting firm in Nairobi, Kenya, whose vision is to be a leader in strengthening healthcare systems, I recognize the critical need to understand vaccine uptake behaviors.

The occurrence of the flu season repeats annually, and each year people make a choice to either receive the flu shot or not.

This attempts to develop a predictive model to forecast individuals' decision to receive the flu shot or not during the annual flu season.

The model should leverage historical data to identify patterns and factors that influence people's vaccination choices.

This predictive model aims to assist in public health planning and decision-making by providing insights into vaccination trends and helping allocate resources effectively to the United States government health Agencies

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Objective

- Create a model that can predict seasonal flu vaccine uptake based on a person's background and patterns of behavior
- Minimize False Positives and False Negatives to Enhance Model Reliability:
- Evaluate and compare various models to determine which one achieves the highest accuracy in predicting vaccination status.

Data understanding

Data Description

The datasets used for this project were downloaded from Kaggle. It contains information on the social,economic and demographic backgrounds of the respondents as well as their opinions on the H1N1 and seasonal flu vaccines. The training data has 26707 rows and 36 columns. The information contained with the columns is as follows as described by the data dictionary:

No.	Column	Description
1	`respondent_id`	Unique and random identifier for the respondents
2	`h1n1_concern`	Level of concern about H1N1 flu with 0 being not concerned at all and 3 being very concerned
3	`h1n1_knowledge`	Level of knowledge about H1N1 with 0 being no knowledge and 2 being a lot of knowledge
4	`behavioral_antiviral_meds`	Has taken any antiviral medication (0-no,1-yes)

5	`behavioral_avoidance`	Has avoided close contact with anyone with flu-like symptoms (0-no,1-yes)
6	`behavioral_face_mask`	Has bought a face mask (0-no,1-yes)
7	`behavioral_wash_hands`	Has frequently washed hands or used hand sanitizer (0-no,1-yes)
8	`behavioral_large_gatherings`	Has reduced time at large gatherings (0-no,1-yes)
9	`behavioral_outside_home`	Has reduced contact with people outside of own household (0-no,1-yes)
10	`behavioral_touch_face`	Has avoided touching eyes, nose or mouth (0-no,1-yes)
11	`doctor_recc_h1n1`	H1N1 flu vaccine was recommended by doctor (0-no,1-yes)
12	`doctor_recc_seasonal`	H1N1 flu vaccine was recommended by doctor (0-no,1-yes)
13	`chronic_med_condition`	Has any of the following chronic conditions: asthma or any lung condition, a heart condition, a kidney condition, sickle cell anaemia or any other anaemia, a neurological or neouromuscular condition, a liver condition, or a weakened immune system as a result of a chronic illness or medicines taken for a chronic illness (0-no,1-yes)
14	`child_under_6_months`	Has regular close contact with a child under the age of six months (0-no,1-yes)
15	`health_worker`	Is a healthcare worker (0-no,1-yes)
16	`health_insurance`	Has health insurance (0-no,1-yes)
17	`opinion_h1n1_vacc_effective`	Respondent's opinion on the efficacy of the vaccine with 1 being not at all effective and 5 being very effective
18	`opinion_h1n1_risk`	Respondent's opinion about risk of getting sick with H1N1 flu without vaccine with 1 being very low and 5 being very high
19	`opinion_h1n1_sick_from_vacc`	Respondent's worry of getting sick from H1N1 vaccine with 1 being not worried at all and 5 being very worried
20	`opinion_seas_vacc_effective`	Respondent's opinion about seasonal flu vaccine effectiveness with 1 being not effective at all and 5 being very effective

|21| `opinion_seas_risk` | Respondent's opinion about risk of getti |26| `sex` | Sex of respondent| |27| `income_poverty` | Household annual income of respondent with respect to 2008 Census poverty thresholds| |28| `marital status` | Marital status of respondent| |29| `rent_or_own` | Housing situation of respondent| |30| `employment_status` | Employment status of respondent| |31| `hhs_geo_region` | Respondent's residence using a 10-region geographic classification defined by the U.S. Dept. of Health and Human Services. Values are represented as short random character strings| |32| `census_msa` |

Respondent's residence within metropolitan statistical areas (MSA) as defined by the U.S. Census| |33| `household_adults` | Number of *other* adults in the household, top-coded to 3| |34| `household_children` | Number of children in the household, top-coded to 3| |35| `employment_industry` | Type of industry respondent is employed in. Values are represented as short random character strings| |36| `employment_occupation` | Type of occupation of respondent.Values are represented as short random character strings|

Data loading

This project provides 3 datasets as follows:-

- test_set_feature
- Training_set_features
- training_set_labels

Loading the traing_set feature an the trainin_set_labels

In [140…

```
#importing necessariy libraries to facilitate with data  loading
import pandas as pd
import numpy as np
```

In [141…

```
#loading the training_set_features to have an overview and look of the dataset
training_set_features = pd.read_csv(r'data_set\training_set_features.csv')
training_set_features.head()
```

Out[141…

	respondent_id	h1n1_concern	h1n1_knowledge	behavioral_antiviral_meds	behavioral_avoidance	behavioral_face_mask
0	0	1.0	0.0	0.0	0.0	0.0
1	1	3.0	2.0	0.0	1.0	0.0
2	2	1.0	1.0	0.0	1.0	0.0

3	3	1.0	1.0	0.0	1.0	0.0
4	4	2.0	1.0	0.0	1.0	0.0

5 rows × 36 columns

In [141…

```
#Loading the training_set_labels.
training_set_labels = pd.read_csv(r'data_set\training_set_labels.csv')
training_set_labels.head()
```

Out[141…

	respondent_id	h1n1_vaccine	seasonal_vaccine
0	0	0	0
1	1	0	1
2	2	0	0
3	3	0	1
4	4	0	0

Merging the train_set_features and the train_set_labels.

Merging the raining_set_features and the training_set_labels to ensures that the data is correctly aligned simplifying subsequent analysis and modeling processes.

In [141…

```
#merging the traing_set_features and the traing_set_labesl

train_f_train_l =pd.merge(training_set_features,training_set_labels, on="respondent_id", how="inner")
train_f_train_l.head()
```

Out[141…

	respondent_id	h1n1_concern	h1n1_knowledge	behavioral_antiviral_meds	behavioral_avoidance	behavioral_face_mask
0	0	1.0	0.0	0.0	0.0	0.0

0	0	1.0	0.0	0.0	0.0	0.0
1	1	3.0	2.0	0.0	1.0	0.0
2	2	1.0	1.0	0.0	1.0	0.0
3	3	1.0	1.0	0.0	1.0	0.0
4	4	2.0	1.0	0.0	1.0	0.0

5 rows × 38 columns

In [141…

```
#Inspecting the datatype after merging
train_f_train_l.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 26707 entries, 0 to 26706
Data columns (total 38 columns):
 #   Column                       Non-Null Count  Dtype
---  ------                       --------------  -----
 0   respondent_id                26707 non-null  int64
 1   h1n1_concern                 26615 non-null  float64
 2   h1n1_knowledge               26591 non-null  float64
 3   behavioral_antiviral_meds    26636 non-null  float64
 4   behavioral_avoidance         26499 non-null  float64
 5   behavioral_face_mask         26688 non-null  float64
 6   behavioral_wash_hands        26665 non-null  float64
 7   behavioral_large_gatherings  26620 non-null  float64
 8   behavioral_outside_home      26625 non-null  float64
 9   behavioral_touch_face        26579 non-null  float64
 10  doctor_recc_h1n1             24547 non-null  float64
 11  doctor_recc_seasonal         24547 non-null  float64
 12  chronic_med_condition        25736 non-null  float64
 13  child_under_6_months         25887 non-null  float64
 14  health_worker                25903 non-null  float64
```

```
 15  health_insurance             14433 non-null  float64
 16  opinion_h1n1_vacc_effective  26316 non-null  float64
 17  opinion_h1n1_risk            26319 non-null  float64
 18  opinion_h1n1_sick_from_vacc  26312 non-null  float64
 19  opinion_seas_vacc_effective  26245 non-null  float64
 20  opinion_seas_risk            26193 non-null  float64
 21  opinion_seas_sick_from_vacc  26170 non-null  float64
 22  age_group                    26707 non-null  object
 23  education                    25300 non-null  object
 24  race                         26707 non-null  object
 25  sex                          26707 non-null  object
 26  income_poverty               22284 non-null  object
 27  marital_status               25299 non-null  object
 28  rent_or_own                  24665 non-null  object
 29  employment_status            25244 non-null  object
 30  hhs_geo_region               26707 non-null  object
 31  census_msa                   26707 non-null  object
 32  household_adults             26458 non-null  float64
 33  household_children           26458 non-null  float64
 34  employment_industry          13377 non-null  object
 35  employment_occupation        13237 non-null  object
 36  h1n1_vaccine                 26707 non-null  int64
 37  seasonal_vaccine             26707 non-null  int64
dtypes: float64(23), int64(3), object(12)
memory usage: 7.9+ MB
```

The above output shows tht the merged files contains:-

- 23 floats64
- 3 Int64
- 12 Objects

Data Exploration

In [141…

```python
#loading the categorical colums
categorical_columns = train_f_train_l.select_dtypes(include=['object'])
categorical_columns.head(10)
```

Out[141…

	age_group	education	race	sex	income_poverty	marital_status	rent_or_own	employment_status	hhs_geo_region
0	55 - 64 Years	< 12 Years	White	Female	Below Poverty	Not Married	Own	Not in Labor Force	oxchjgsf

1	35 - 44 Years	12 Years	White	Male	Below Poverty	Not Married	Rent	Employed	bhuqouqj
2	18 - 34 Years	College Graduate	White	Male	<= $75,000, Above Poverty	Not Married	Own	Employed	qufhixun
3	65+ Years	12 Years	White	Female	Below Poverty	Not Married	Rent	Not in Labor Force	lrircsnp
4	45 - 54 Years	Some College	White	Female	<= $75,000, Above Poverty	Married	Own	Employed	qufhixun
5	65+ Years	12 Years	White	Male	<= $75,000, Above Poverty	Married	Own	Employed	atmpeygn
6	55 - 64 Years	< 12 Years	White	Male	<= $75,000, Above Poverty	Not Married	Own	Employed	qufhixun
7	45 - 54 Years	Some College	White	Female	<= $75,000, Above Poverty	Married	Own	Employed	bhuqouqj
8	45 - 54 Years	College Graduate	White	Male	> $75,000	Married	Own	Employed	bhuqouqj
9	55 - 64 Years	12 Years	White	Male	<= $75,000, Above Poverty	Not Married	Own	Not in Labor Force	qufhixun

Apon investigation of the categorical columns, following were deem unusable hence need to drop them.

- employment_industry
- employment_occupation
- hhs_geo_region

In [141…

```
##Numerical columns
numerical_columns = train_f_train_l.select_dtypes(include=['float64'])
numerical_columns.head(10)
```

Out[141…

	h1n1_concern	h1n1_knowledge	behavioral_antiviral_meds	behavioral_avoidance	behavioral_face_mask	behavioral_wash_
0	1.0	0.0	0.0	0.0	0.0	
1	3.0	2.0	0.0	1.0	0.0	
2	1.0	1.0	0.0	1.0	0.0	
3	1.0	1.0	0.0	1.0	0.0	
4	2.0	1.0	0.0	1.0	0.0	
5	3.0	1.0	0.0	1.0	0.0	
6	0.0	0.0	0.0	0.0	0.0	
7	1.0	0.0	0.0	1.0	0.0	
8	0.0	2.0	0.0	1.0	0.0	
9	2.0	1.0	0.0	1.0	0.0	

10 rows × 23 columns

Dropping unneccesary categorical columns and ny other column associated with the HINI vaccine since our focus is on the seasonal flu vaccine

In [141…

```
#dropping colmuns directly assocaited with the H1N1 vaccine under the train set
train_f_train_l.drop(columns={'respondent_id','hhs_geo_region','employment_occupation','employment_industry','h
```

In [141…

```
#inspectig the data to ensure neccessary col have been dropped
train_f_train_l.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 26707 entries, 0 to 26706
Data columns (total 27 columns):
```

```
Data columns (total 27 columns):
 #   Column                       Non-Null Count  Dtype  
---  ------                       --------------  -----  
 0   behavioral_antiviral_meds    26636 non-null  float64
 1   behavioral_avoidance         26499 non-null  float64
 2   behavioral_face_mask         26688 non-null  float64
 3   behavioral_wash_hands        26665 non-null  float64
 4   behavioral_large_gatherings  26620 non-null  float64
 5   behavioral_outside_home      26625 non-null  float64
 6   behavioral_touch_face        26579 non-null  float64
 7   doctor_recc_seasonal         24547 non-null  float64
 8   chronic_med_condition        25736 non-null  float64
 9   child_under_6_months         25887 non-null  float64
 10  health_worker                25903 non-null  float64
 11  health_insurance             14433 non-null  float64
 12  opinion_seas_vacc_effective  26245 non-null  float64
 13  opinion_seas_risk            26193 non-null  float64
 14  opinion_seas_sick_from_vacc  26170 non-null  float64
 15  age_group                    26707 non-null  object 
 16  education                    25300 non-null  object 
 17  race                         26707 non-null  object 
 18  sex                          26707 non-null  object 
 19  income_poverty               22284 non-null  object 
 20  marital_status               25299 non-null  object 
 21  rent_or_own                  24665 non-null  object 
 22  employment_status            25244 non-null  object 
 23  census_msa                   26707 non-null  object 
 24  household_adults             26458 non-null  float64
 25  household_children           26458 non-null  float64
 26  seasonal_vaccine             26707 non-null  int64  
dtypes: float64(17), int64(1), object(9)
memory usage: 5.7+ MB
```

Handing missing values

Investigating missing values in the merged dataset

In [141…

```python
#checking the percentage of null values on the categoricla colums
missing_values_percentage = (train_f_train_l.isnull().sum() / len(train_f_train_l)) * 100
missing_values_percentage_sorted =missing_values_percentage .sort_values(ascending=False)
# missing_values_percentage_sorted
missing_values_percentage_sorted
```

Out[141… health_insurance 45.957989

```
health_insurance              [illegible]
income_poverty                16.561201
doctor_recc_seasonal           8.087767
rent_or_own                    7.645936
employment_status              5.477965
marital_status                 5.272026
education                      5.268282
chronic_med_condition          3.635751
child_under_6_months           3.070356
health_worker                  3.010447
opinion_seas_sick_from_vacc    2.010709
opinion_seas_risk              1.924589
opinion_seas_vacc_effective    1.729884
household_children             0.932340
household_adults               0.932340
behavioral_avoidance           0.778822
behavioral_touch_face          0.479275
behavioral_large_gatherings    0.325757
behavioral_outside_home        0.307036
behavioral_antiviral_meds      0.265848
behavioral_wash_hands          0.157262
behavioral_face_mask           0.071142
age_group                      0.000000
race                           0.000000
sex                            0.000000
census_msa                     0.000000
seasonal_vaccine               0.000000
dtype: float64
```

Heath Insurance followed by poverty_income exhibits the most null values

In [141…

```python
#dropping the health insurance and the poverty_income level
train_f_train_l.drop(columns={'health_insurance','income_poverty'}, inplace=True)
```

Filling the missing values

In [142…

```python
#filling in the missing values.

train_df = train_f_train_l

# Fill 'object' type columns with the word 'unknown'
train_df.fillna({col: 'unknown' for col in train_df.select_dtypes(include='object').columns}, inplace=True)
```

```
# Fill 'int' and 'float' type columns with the mean of the column
train_df.fillna(train_df.select_dtypes(include=['int64','float64']).mean(), inplace=True)
```

In [142…

```
##Invenstigating the dataset after filling in the missing values
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 26707 entries, 0 to 26706
Data columns (total 25 columns):
 #   Column                       Non-Null Count  Dtype  
---  ------                       --------------  -----  
 0   behavioral_antiviral_meds    26707 non-null  float64
 1   behavioral_avoidance         26707 non-null  float64
 2   behavioral_face_mask         26707 non-null  float64
 3   behavioral_wash_hands        26707 non-null  float64
 4   behavioral_large_gatherings  26707 non-null  float64
 5   behavioral_outside_home      26707 non-null  float64
 6   behavioral_touch_face        26707 non-null  float64
 7   doctor_recc_seasonal         26707 non-null  float64
 8   chronic_med_condition        26707 non-null  float64
 9   child_under_6_months         26707 non-null  float64
 10  health_worker                26707 non-null  float64
 11  opinion_seas_vacc_effective  26707 non-null  float64
 12  opinion_seas_risk            26707 non-null  float64
 13  opinion_seas_sick_from_vacc  26707 non-null  float64
 14  age_group                    26707 non-null  object 
 15  education                    26707 non-null  object 
 16  race                         26707 non-null  object 
 17  sex                          26707 non-null  object 
 18  marital_status               26707 non-null  object 
 19  rent_or_own                  26707 non-null  object 
 20  employment_status            26707 non-null  object 
 21  census_msa                   26707 non-null  object 
 22  household_adults             26707 non-null  float64
 23  household_children           26707 non-null  float64
 24  seasonal_vaccine             26707 non-null  int64  
dtypes: float64(16), int64(1), object(8)
memory usage: 5.3+ MB
```

Apon deleting of unneccesary collumns the dataset now has

- 17 floats64
- 1 Int64
- 9 Objects

- 9 Objects

Confirming that the dataset now has no missing values

In [142...

```
# confirming that there are no missing values in our categorical columns.
if train_df.isnull().values.any():
    print("Contains null values")
else:
    print("No null values")
```

```
No null values
```

In [142...

```
train_df.isnull().sum()/len(train_df)*100
```

Out[142...

```
behavioral_antiviral_meds      0.0
behavioral_avoidance           0.0
behavioral_face_mask           0.0
behavioral_wash_hands          0.0
behavioral_large_gatherings    0.0
behavioral_outside_home        0.0
behavioral_touch_face          0.0
doctor_recc_seasonal           0.0
chronic_med_condition          0.0
child_under_6_months           0.0
health_worker                  0.0
opinion_seas_vacc_effective    0.0
opinion_seas_risk              0.0
opinion_seas_sick_from_vacc    0.0
age_group                      0.0
education                      0.0
race                           0.0
sex                            0.0
marital_status                 0.0
rent_or_own                    0.0
employment_status              0.0
census_msa                     0.0
household_adults               0.0
household_children             0.0
seasonal_vaccine               0.0
dtype: float64
```

Performing Ordinal encoding on my categorical dataset of the train_df

In [142…

```
#importing necessary library.

from sklearn.preprocessing import OrdinalEncoder

# Select columns of object type
object_columns = train_df.select_dtypes(include='object').columns

# Initializing OrdinalEncoder
ordinal_encoder = OrdinalEncoder()

# Applyng  Ordinal Encoding to the object columns
train_df[object_columns] = ordinal_encoder.fit_transform(train_df[object_columns])

# View the updated DataFrame
train_df.head()
```

Out[142…

	behavioral_antiviral_meds	behavioral_avoidance	behavioral_face_mask	behavioral_wash_hands	behavioral_large_gatherin
0	0.0	0.0	0.0	0.0	C
1	0.0	1.0	0.0	1.0	C
2	0.0	1.0	0.0	0.0	C
3	0.0	1.0	0.0	1.0	1
4	0.0	1.0	0.0	1.0	1

5 rows × 25 columns

The encoding transforms categorical values into numerical values while preserving their order, improving model interpretability, performance, and reducing dimensionality, making it an essential step in the preprocessing pipeline when dealing with ordered categories.

In [142…

```
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 26707 entries, 0 to 26706
Data columns (total 25 columns):
 #   Column                       Non-Null Count  Dtype
```

```
---  ------                        --------------  -----
 0   behavioral_antiviral_meds     26707 non-null  float64
 1   behavioral_avoidance          26707 non-null  float64
 2   behavioral_face_mask          26707 non-null  float64
 3   behavioral_wash_hands         26707 non-null  float64
 4   behavioral_large_gatherings   26707 non-null  float64
 5   behavioral_outside_home       26707 non-null  float64
 6   behavioral_touch_face         26707 non-null  float64
 7   doctor_recc_seasonal          26707 non-null  float64
 8   chronic_med_condition         26707 non-null  float64
 9   child_under_6_months          26707 non-null  float64
 10  health_worker                 26707 non-null  float64
 11  opinion_seas_vacc_effective   26707 non-null  float64
 12  opinion_seas_risk             26707 non-null  float64
 13  opinion_seas_sick_from_vacc   26707 non-null  float64
 14  age_group                     26707 non-null  float64
 15  education                     26707 non-null  float64
 16  race                          26707 non-null  float64
 17  sex                           26707 non-null  float64
 18  marital_status                26707 non-null  float64
 19  rent_or_own                   26707 non-null  float64
 20  employment_status             26707 non-null  float64
 21  census_msa                    26707 non-null  float64
 22  household_adults              26707 non-null  float64
 23  household_children            26707 non-null  float64
 24  seasonal_vaccine              26707 non-null  int64
dtypes: float64(24), int64(1)
memory usage: 5.3 MB
```

The above output sows that all the categorical columns have been transformed to numerical indicating a successful encoding process

---

Feature Scaling on the train_df

In [142…

```
from sklearn.preprocessing import MinMaxScaler

# Initialize the MinMaxScaler
scaler = MinMaxScaler()

# Select only numerical columns for scaling
numerical_cols = train_df.select_dtypes(include=['int64', 'float64']).columns
```

```
# Fit and transform the numerical columns with MinMaxScaler
train_df[numerical_cols] = scaler.fit_transform(train_df[numerical_cols])

# Display the first few rows to verify the scaling
train_df.head()
```

Out[142…

	behavioral_antiviral_meds	behavioral_avoidance	behavioral_face_mask	behavioral_wash_hands	behavioral_large_gathering
0	0.0	0.0	0.0	0.0	C
1	0.0	1.0	0.0	1.0	C
2	0.0	1.0	0.0	0.0	C
3	0.0	1.0	0.0	1.0	1
4	0.0	1.0	0.0	1.0	1

5 rows × 25 columns

By scaling features to the same range, the model treats all features equally, preventing some features from dominating the learning process just because of their larger scale.

2.Loading the test_set_features dataset

In [142…

```
#loading the test_set_features.
test_set_features = pd.read_csv(r'data_set\test_set_features.csv')
test_set_features.head()
```

Out[142…

	respondent_id	h1n1_concern	h1n1_knowledge	behavioral_antiviral_meds	behavioral_avoidance	behavioral_face_mask	I
0	26707	2.0	2.0	0.0	1.0	0.0	
1	26708	1.0	1.0	0.0	0.0	0.0	
2	26709	2.0	2.0	0.0	0.0	1.0	

3	26710	1.0	1.0	0.0	0.0	0.0
4	26711	3.0	1.0	1.0	1.0	0.0

5 rows × 36 columns

In [142…

```
#checking for the structure of the dataset
test_set_features.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 26708 entries, 0 to 26707
Data columns (total 36 columns):
 #   Column                       Non-Null Count  Dtype
---  ------                       --------------  -----
 0   respondent_id                26708 non-null  int64
 1   h1n1_concern                 26623 non-null  float64
 2   h1n1_knowledge               26586 non-null  float64
 3   behavioral_antiviral_meds    26629 non-null  float64
 4   behavioral_avoidance         26495 non-null  float64
 5   behavioral_face_mask         26689 non-null  float64
 6   behavioral_wash_hands        26668 non-null  float64
 7   behavioral_large_gatherings  26636 non-null  float64
 8   behavioral_outside_home      26626 non-null  float64
 9   behavioral_touch_face        26580 non-null  float64
 10  doctor_recc_h1n1             24548 non-null  float64
 11  doctor_recc_seasonal         24548 non-null  float64
 12  chronic_med_condition        25776 non-null  float64
 13  child_under_6_months         25895 non-null  float64
 14  health_worker                25919 non-null  float64
 15  health_insurance             14480 non-null  float64
 16  opinion_h1n1_vacc_effective  26310 non-null  float64
 17  opinion_h1n1_risk            26328 non-null  float64
 18  opinion_h1n1_sick_from_vacc  26333 non-null  float64
 19  opinion_seas_vacc_effective  26256 non-null  float64
 20  opinion_seas_risk            26209 non-null  float64
 21  opinion_seas_sick_from_vacc  26187 non-null  float64
 22  age_group                    26708 non-null  object
 23  education                    25301 non-null  object
 24  race                         26708 non-null  object
```

```
 25  sex                          26708 non-null  object
 26  income_poverty               22211 non-null  object
 27  marital_status               25266 non-null  object
 28  rent_or_own                  24672 non-null  object
 29  employment_status            25237 non-null  object
 30  hhs_geo_region               26708 non-null  object
 31  census_msa                   26708 non-null  object
 32  household_adults             26483 non-null  float64
 33  household_children           26483 non-null  float64
 34  employment_industry          13433 non-null  object
 35  employment_occupation        13282 non-null  object
dtypes: float64(23), int64(1), object(12)
memory usage: 7.3+ MB
```

In [142…

```
#dropping colmuns directly assocaited with the H1N1 vaccine under the train set
test_set_features.drop(columns={'respondent_id','hhs_geo_region','employment_occupation','employment_industry',
```

In [143…

```
#checking datastructure after dropping collumns
test_set_features.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 26708 entries, 0 to 26707
Data columns (total 26 columns):
 #   Column                       Non-Null Count  Dtype
---  ------                       --------------  -----
 0   behavioral_antiviral_meds    26629 non-null  float64
 1   behavioral_avoidance         26495 non-null  float64
 2   behavioral_face_mask         26689 non-null  float64
 3   behavioral_wash_hands        26668 non-null  float64
 4   behavioral_large_gatherings  26636 non-null  float64
 5   behavioral_outside_home      26626 non-null  float64
 6   behavioral_touch_face        26580 non-null  float64
 7   doctor_recc_seasonal         24548 non-null  float64
 8   chronic_med_condition        25776 non-null  float64
 9   child_under_6_months         25895 non-null  float64
 10  health_worker                25919 non-null  float64
 11  health_insurance             14480 non-null  float64
 12  opinion_seas_vacc_effective  26256 non-null  float64
 13  opinion_seas_risk            26209 non-null  float64
 14  opinion_seas_sick_from_vacc  26187 non-null  float64
 15  age_group                    26708 non-null  object
 16  education                    25301 non-null  object
```

```
 17  race                         26708 non-null  object
 18  sex                          26708 non-null  object
 19  income_poverty               22211 non-null  object
 20  marital_status               25266 non-null  object
 21  rent_or_own                  24672 non-null  object
 22  employment_status            25237 non-null  object
 23  census_msa                   26708 non-null  object
 24  household_adults             26483 non-null  float64
 25  household_children           26483 non-null  float64
dtypes: float64(17), object(9)
memory usage: 5.3+ MB
```

Handling missing values of the test_set_feature

In [143…

```
#checking the percentage of null values on the categoricla colums
missing_values_test_df = (test_set_features.isnull().sum() / len(train_f_train_l)) * 100
missing_values_test_df_sorted = missing_values_test_df.sort_values(ascending=False)
# missing_values_percentage_sorted
missing_values_test_df_sorted
```

Out[143…

```
health_insurance               45.785749
income_poverty                 16.838282
doctor_recc_seasonal            8.087767
rent_or_own                     7.623470
employment_status               5.507919
marital_status                  5.399334
education                       5.268282
chronic_med_condition           3.489722
child_under_6_months            3.044146
health_worker                   2.954282
opinion_seas_sick_from_vacc     1.950799
opinion_seas_risk               1.868424
opinion_seas_vacc_effective     1.692440
household_children              0.842476
household_adults                0.842476
behavioral_avoidance            0.797544
behavioral_touch_face           0.479275
behavioral_outside_home         0.307036
behavioral_antiviral_meds       0.295803
behavioral_large_gatherings     0.269592
behavioral_wash_hands           0.149773
behavioral_face_mask            0.071142
age_group                       0.000000
race                            0.000000
```

```
sex                           0.000000
census_msa                    0.000000
dtype: float64
```

In [143…

```
#dropping the health insurance and the poverty_income level
test_set_features.drop(columns={'health_insurance','income_poverty'}, inplace=True)
```

Filling in the missing values on the test_set_feature

In [ ]:

```
#filling in the missing values.

test_df = test_set_features

# Fill 'object' type columns with the word 'unknown'
test_df.fillna({col: 'unknown' for col in test_df.select_dtypes(include='object').columns}, inplace=True)

# Fill 'int' and 'float' type columns with the mean of the column
test_df.fillna(test_df.select_dtypes(include=['int64', 'float64']).mean(), inplace=True)
```

Confirming that there are no missing values in our categorical columns

In [ ]:

```
# confirming that there are no missing values
if test_df.isnull().values.any():
    print("Contains null values")
else:
    print("No null values")
```

```
No null values
```

Performing Ordinal encoding on my categorical dataset of the train_df

In [143…

```
#importing necessary library.

from sklearn.preprocessing import OrdinalEncoder

# Select columns of object type
object_columns_test = test_df.select_dtypes(include='object').columns

# Initializing OrdinalEncoder
```

```
ordinal_encoder = OrdinalEncoder()

# Applyng  Ordinal Encoding to the object columns
test_df[object_columns_test] = ordinal_encoder.fit_transform(test_df[object_columns_test])

# View the updated DataFrame
test_df.head()
```

Out[143...

	behavioral_antiviral_meds	behavioral_avoidance	behavioral_face_mask	behavioral_wash_hands	behavioral_large_gatherin
0	0.0	1.0	0.0	1.0	1
1	0.0	0.0	0.0	0.0	C
2	0.0	0.0	1.0	1.0	1
3	0.0	0.0	0.0	0.0	C
4	1.0	1.0	0.0	1.0	1

5 rows × 29 columns

Feature Scaling on the test_df

In [143...

```
from sklearn.preprocessing import MinMaxScaler

# Initialize the MinMaxScaler
scaler = MinMaxScaler()

# Select only numerical columns for scaling
numerical_cols = test_df.select_dtypes(include=['int64', 'float64']).columns

# Fit and transform the numerical columns with MinMaxScaler
test_df[numerical_cols] = scaler.fit_transform(test_df[numerical_cols])

# Display the first few rows to verify the scaling
test_df.head()
```

Out[143...

	behavioral_antiviral_meds	behavioral_avoidance	behavioral_face_mask	behavioral_wash_hands	behavioral_large_gatherin

0	0.0	1.0	0.0	1.0	1
1	0.0	0.0	0.0	0.0	C
2	0.0	0.0	1.0	1.0	1
3	0.0	0.0	0.0	0.0	C
4	1.0	1.0	0.0	1.0	1

5 rows × 29 columns

Feature Selection

In [144…

```
from sklearn.ensemble import RandomForestClassifier

X = train_df.drop(columns='seasonal_vaccine')
y = train_df['seasonal_vaccine']
model = RandomForestClassifier()
model.fit(X, y)

# Get feature importances
importances = model.feature_importances_
feature_importances = pd.DataFrame({'Feature': X.columns, 'Importance': importances})
feature_importances = feature_importances.sort_values(by='Importance', ascending=False)
print(feature_importances)
```

```
                        Feature  Importance
11  opinion_seas_vacc_effective    0.119193
12            opinion_seas_risk    0.118285
7           doctor_recc_seasonal    0.095059
14                    age_group    0.086962
15                    education    0.057759
13  opinion_seas_sick_from_vacc    0.054497
21                   census_msa    0.050836
22             household_adults    0.042868
23           household_children    0.034322
20            employment_status    0.033522
16                         race    0.030324
```

```
17                          sex    0.028599
8         chronic_med_condition    0.026950
18               marital_status    0.025437
4   behavioral_large_gatherings    0.025384
19                  rent_or_own    0.025148
5       behavioral_outside_home    0.025063
1           behavioral_avoidance   0.024475
6         behavioral_touch_face    0.023039
10                health_worker    0.020448
3         behavioral_wash_hands    0.016403
9           child_under_6_months   0.014065
2           behavioral_face_mask   0.011665
0      behavioral_antiviral_meds   0.009697
```

I have used the random forest classifer to perform feature selection. The output shows the features with the hightest impotance to my y which is the seasonal flu vaccine

---

Display the top 10 features

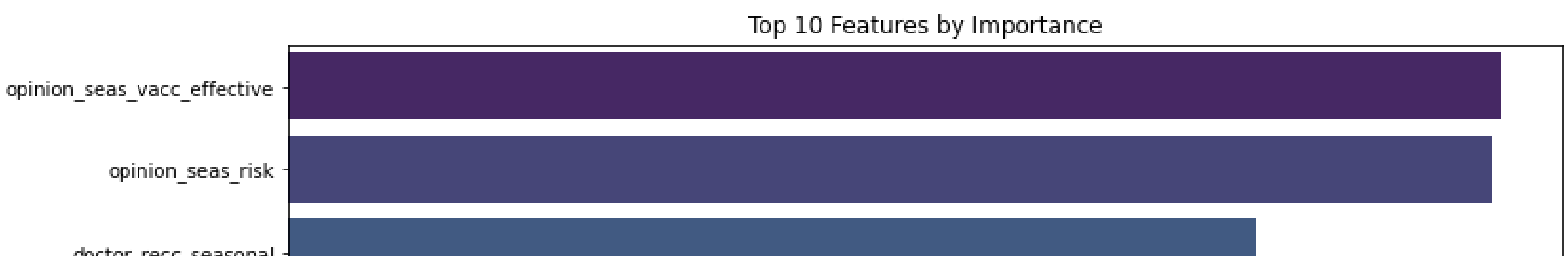
In [144…

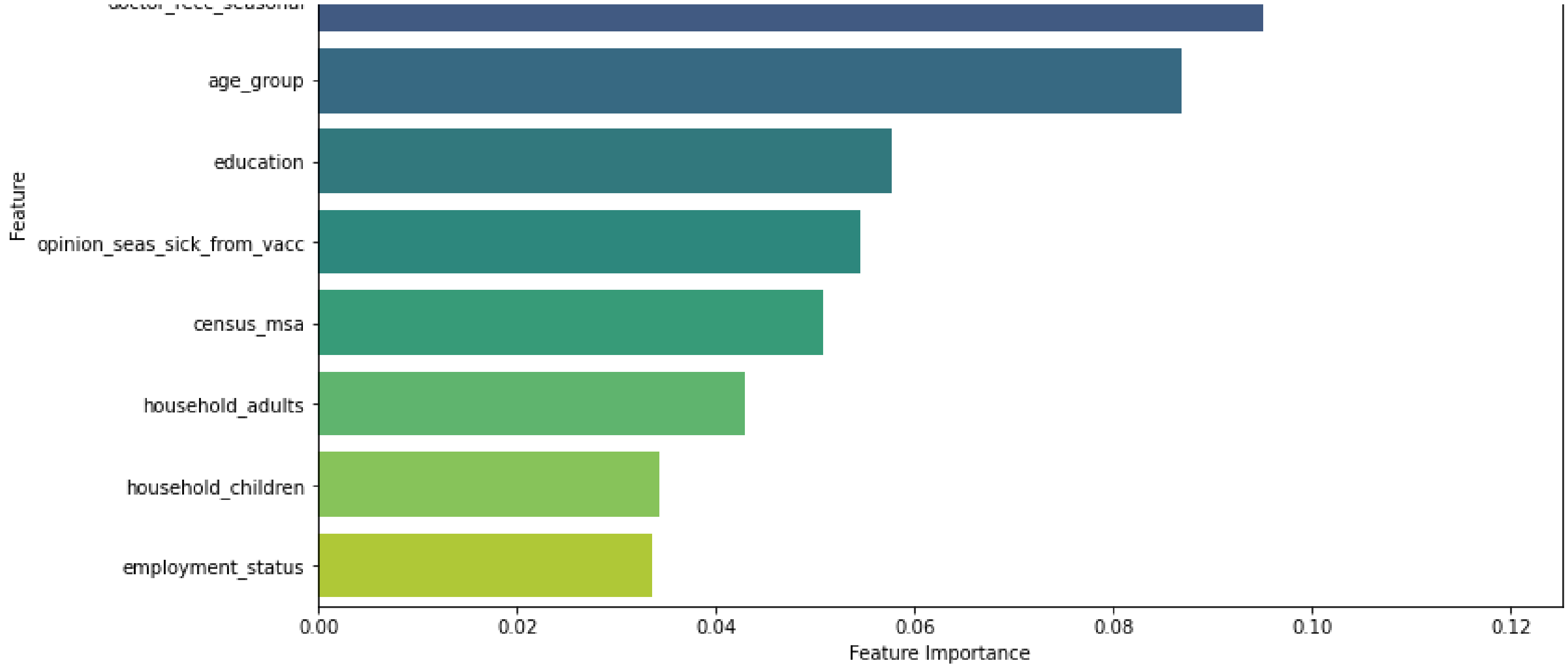
```python
# Display the top 10 features
top_10_features = feature_importances.head(10)

# Plotting the feature importance
plt.figure(figsize=(12, 8))
sns.barplot(x='Importance', y='Feature', data=top_10_features, palette='viridis')

# Set labels and title
plt.xlabel('Feature Importance')
plt.ylabel('Feature')
plt.title('Top 10 Features by Importance')

# Show plot
plt.show()
```





Modeling

1.Logical Reggression model

In [144…

```
#importing necessary libraries
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report

# Step 1: Train a Random Forest to get feature importances
X = train_df.drop(columns='seasonal_vaccine')
y = train_df['seasonal_vaccine']

model = RandomForestClassifier()
model.fit(X, y)

# Get feature importances
importances = model.feature_importances_
feature_importances = pd.DataFrame({'Feature': X.columns, 'Importance': importances})
```

```python
feature_importances = feature_importances.sort_values(by='Importance', ascending=False)

# Step 2: Select the top 10 features
top_10_features = feature_importances.head(10)['Feature']
X_top_10 = X[top_10_features]

# Step 3: Split the data
X_train, X_val, y_train, y_val = train_test_split(X_top_10, y, test_size=0.2, random_state=42)

# Step 4: Create and train the baseline model
baseline_model = LogisticRegression(max_iter=1000, random_state=42)
baseline_model.fit(X_train, y_train)

# Step 5: Make predictions and evaluate
y_pred = baseline_model.predict(X_val)

# Evaluate model performance
accuracy = accuracy_score(y_val, y_pred)
print(f'Baseline Model Accuracy: {accuracy:.2f}')

# Detailed classification report
report = classification_report(y_val, y_pred)
print('Classification Report:')
print(report)
```

```
Baseline Model Accuracy: 0.77
Classification Report:
              precision    recall  f1-score   support

         0.0       0.78      0.81      0.79      2891
         1.0       0.76      0.73      0.74      2451

    accuracy                           0.77      5342
   macro avg       0.77      0.77      0.77      5342
weighted avg       0.77      0.77      0.77      5342
```

- The Logistic Regression model shows a balanced performance with a slightly better recall for class 0.0 and slightly higher precision for class 1.0.
- It performs well overall, with an accuracy of 77%, indicating that it is a reliable model for predicting vaccination status.
- Both classes are relatively well-predicted, though there's room for improvement, especially in recall for class 1.0.

Plotting the presicion and recall for each class

In [144…

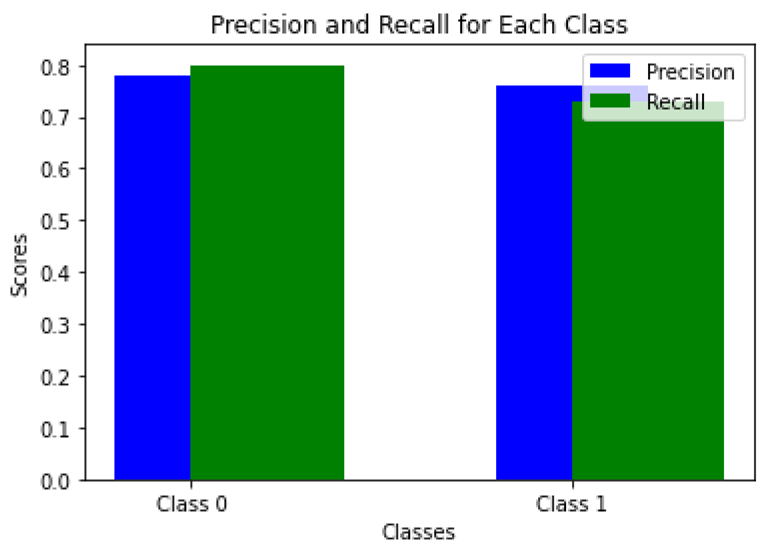
```
# Data from your classification report
classes = ['Class 0', 'Class 1']
precision = [0.78, 0.76]
recall = [0.80, 0.73]

# Creating the plot
x = range(len(classes))

plt.bar(x, precision, width=0.4, label='Precision', color='blue', align='center')
plt.bar(x, recall, width=0.4, label='Recall', color='green', align='edge')

# Adding title and labels
plt.xlabel('Classes')
plt.ylabel('Scores')
plt.title('Precision and Recall for Each Class')
plt.xticks(x, classes)
plt.legend()

# Show plot
plt.show()
```



- The above graph shows that the model performed fairly well across both classes, with all metrics hovering around 0.75 to

0.80. This indicates a balanced model, although it is slightly better at identifying people who did not receive the vaccine (Class 0) than those who did (Class 1).

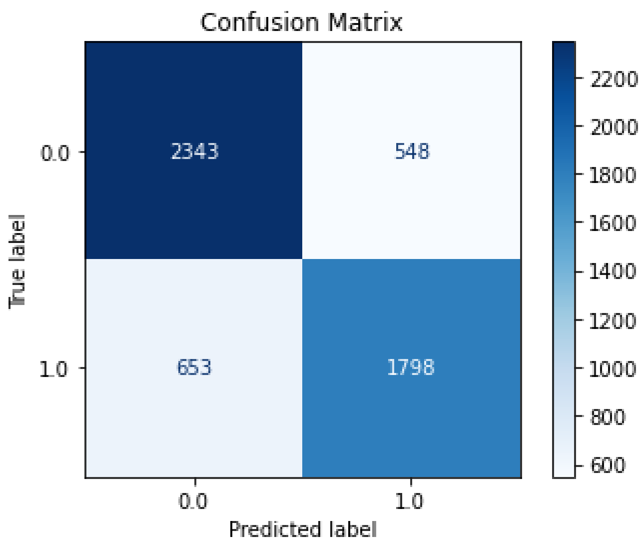
Logical regression Model Evluation

1.Confusion matrix

In [ ]:
```
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay

# Generate the confusion matrix
cm = confusion_matrix(y_val, y_pred)

# Display the confusion matrix
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=baseline_model.classes_)
disp.plot(cmap='Blues')
plt.title('Confusion Matrix')
plt.show()
```



- The proportion of correctly predicted samples (both true positives and true negatives) out of all predictions ligns with the accuracy of around 77%.
- There is a noticeable amount of False Positives (543) and False Negatives (653), meaning the model struggles with

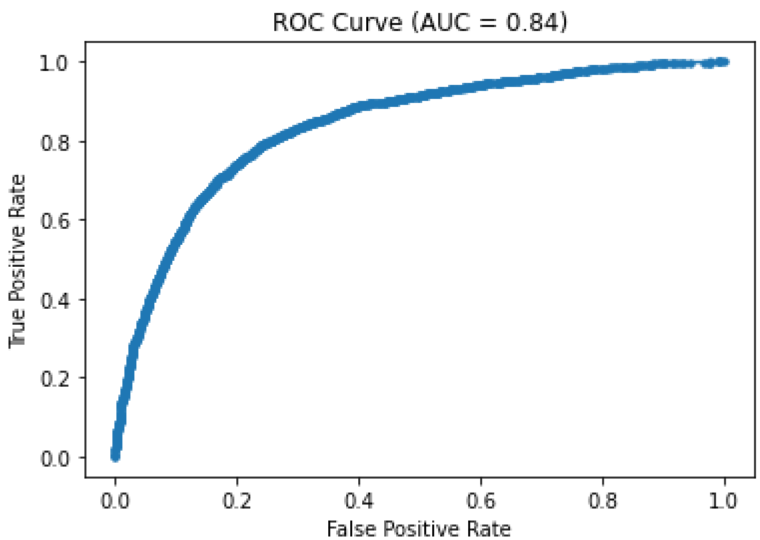
correctly identifying some of the positive and negative classes.

In [144…

```
from sklearn.metrics import roc_curve, roc_auc_score

y_proba = baseline_model.predict_proba(X_val)[:, 1]
fpr, tpr, _ = roc_curve(y_val, y_proba)
auc = roc_auc_score(y_val, y_proba)

plt.plot(fpr, tpr, marker='.')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title(f'ROC Curve (AUC = {auc:.2f})')
plt.show()
```



The ROC curve and the AUC value indicate that the baseline model performs well in predicting the outcome.

2.Desicion Tree Model

In [144…

```
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score

# Step 4: Create and train the Decision Tree model
decision_tree_model = DecisionTreeClassifier(random_state=42)
```

```python
decision_tree_model.fit(X_train, y_train)

# Step 5: Make predictions and evaluate
y_pred_dt = decision_tree_model.predict(X_val)

# Evaluate model performance
accuracy_dt = accuracy_score(y_val, y_pred_dt)
print(f'Decision Tree Model Accuracy: {accuracy_dt:.2f}')
print(report)
```

```
Decision Tree Model Accuracy: 0.68
              precision    recall  f1-score   support

         0.0       0.78      0.81      0.79      2891
         1.0       0.76      0.73      0.74      2451

    accuracy                           0.77      5342
   macro avg       0.77      0.77      0.77      5342
weighted avg       0.77      0.77      0.77      5342
```

The desicion tree model shows a lower accuracy of 68% compared to that of the logical regresion whichis 77%

Decision tree model evaluation

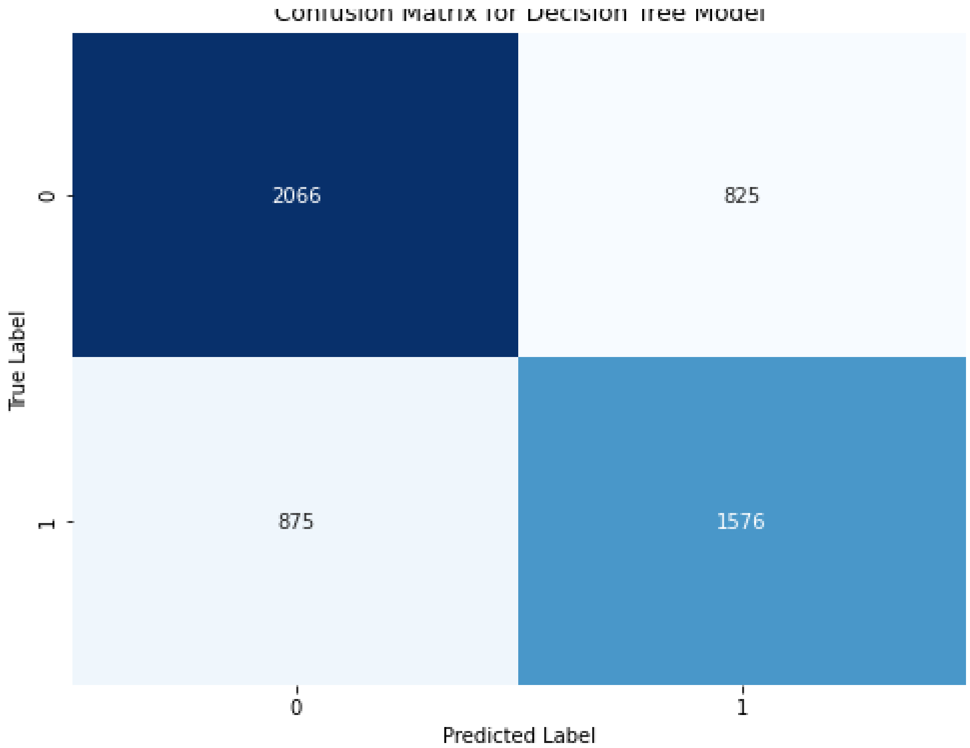
- Confusion Matrix

In [ ]:

```python
from sklearn.metrics import confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt

# Step 6: Generate the confusion matrix
conf_matrix = confusion_matrix(y_val, y_pred_dt)

# Step 7: Plot the confusion matrix
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt="d", cmap="Blues", cbar=False)
plt.title("Confusion Matrix for Decision Tree Model")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
```



ROC Evaluation

In [ ]:

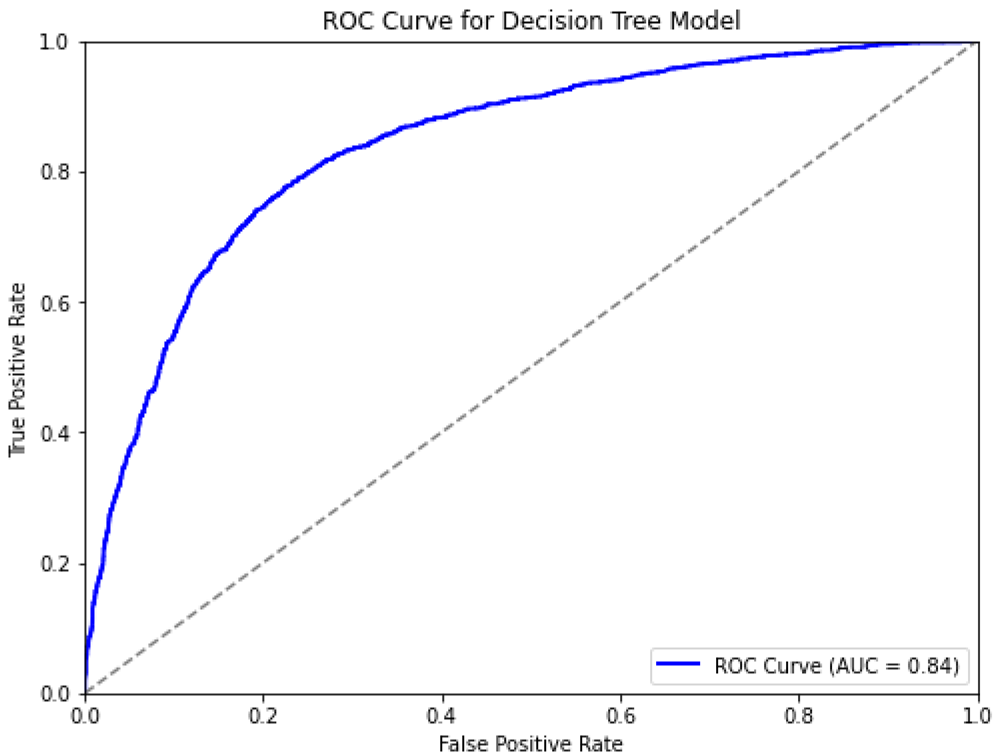
```
from sklearn.metrics import roc_curve, auc, RocCurveDisplay

# Step 6: Calculate probabilities
y_prob_dt = baseline_model.predict_proba(X_val)[:, 1]

# Step 7: Compute the ROC curve and AUC
fpr, tpr, _ = roc_curve(y_val, y_prob_dt)
roc_auc = auc(fpr, tpr)

# Step 8: Plot the ROC curve
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='blue', lw=2, label=f'ROC Curve (AUC = {roc_auc:.2f})')
plt.plot([0, 1], [0, 1], color='grey', linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.0])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve for Decision Tree Model')
```

```
plt.legend(loc="lower right")
plt.show()
```



Conclusions

1. Objective: Build a Model to Identify Key Features Influencing Vaccination Status

The analysis successfully identified the top 10 features most critical for predicting seasonal flu vaccination status. The correlation matrix highlights that the two most significant features are related to personal opinions about the vaccine, each with an importance score of approximately 0.11. This underscores that individuals' perceptions of the vaccine's risk and effectiveness are major factors influencing their decision to get vaccinated. These insights are crucial for understanding the key drivers behind vaccination decisions.

2. Objective: Minimize False Positives and False Negatives to Enhance Model Reliability

The logical regression model significantly outperforms decision tree model in minimizing prediction errors. The logical regression model achieved 222 more true negatives (TN) and 277 more true positives (TP) compared desicion tree model. This indicates that logical regression is more effective at accurately identifying both individuals who did and did not receive the vaccine. By reducing false positives and false negatives, GBM enhances the overall reliability of vaccination status predictions.

3. Objective: Evaluate and Compare Models to Determine the Highest Accuracy

The logical regression model demonstrates superior performance over decision tree based on accuracy metrics. With and accuracy level of 77% and an ROC AUC score of 86 compared to 68% and 84 of the decsion tree,

Recommenations

- Careful examination of the significance of identified predictors, such as opinion_seas_risk, will help understand underlying