

# Risk Factors for Hospitalization and Death from COVID-19 in Humanitarian Settings

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Introduction to Data Mining Final Project Presentation

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# Risk Factors for Hospitalization and Death from COVID-19 in Humanitarian Settings

- Dataset source: Google data search
  - [Risk Factors for Hospitalization and Death from COVID-19 in Humanitarian Settings - Humanitarian Data Exchange \(humdata.org\)](https://humdata.org/)
- Data set provided by: [Johns Hopkins Bloomberg School of Public Health](https://www.jhu.edu/)
  - csv(275777)
  - Dataset updated  
Apr 12, 2022
- Data description
  - Deidentified dataset used for analysis presented in *"Risk Factors for Hospitalization and Death from COVID-19: A Prospective Cohort Study in South Sudan and Eastern Democratic Republic of the Congo"* by Leidman et al.

# Data processing tools

- Python packages, and
- sklearn

## Data preprocessing

- Get the data
  - `pd.read_csv('covid_risk_factors.csv')`
- look at first few rows
  - `print(df.head())`

```
      Unnamed: 0  age_categories  ...  test_reason  uncontrolled_diabetes8
0              1      18-44      ...      Travel                      NaN
1              2      18-44      ...      Travel                      NaN
2              3      18-44      ...      Travel                      NaN
3              4      18-44      ...      Travel                      NaN
4              5      45-64      ...      Travel                      NaN
```

```
[5 rows x 57 columns]
```

- (Data frame shape: 519, 57)

# EDA

- Columns

```
'covidcasestatus_new', 'deceased', 'ever_hospitalized',  
'exposure_carecovidpatient', 'exposure_contactcovidcase',  
'exposure_hcw', 'exposure_visithcf', 'exposure_workingoutsidehome',  
'fever', 'highbloodpressure_enrollment_13080', 'history_asthma',  
'history_cardiac', 'history_chronic_cat', 'history_diabetes',  
'history_hiv', 'history_hypertension', 'history_pulmonary',  
'history_tb', 'hypothermia_enrollment', 'form.case..case_id',  
'low_oxygen94_enrollment', 'obs_appearance', 'Region_collapsed',  
'Region_manuscript', 'respiratorydistress', 'sex', 'smoke',  
'Studysite_manuscript', 'suspected_malaria', 'symptoms_abdominalpain.x',  
'symptoms_any', 'symptoms_appetite', 'symptoms_chestpain.x',  
'symptoms_chills.x', 'symptoms_cough.x', 'symptoms_diarrhea.x',  
'symptoms_fatigue.x', 'symptoms_headache.x', 'symptoms_jointpain.x',  
'symptoms_nausea.x', 'symptoms_runnynose.x', 'symptoms_sob.x',  
'symptoms_sorethroat.x', 'symptoms_tasteorsmell', 'symptoms_wheezing.x',  
'test_reason', 'uncontrolled_diabetes8'],  
dtype='object')
```

# EDA

- check the structure of data  
`print(df.info())`
- check the summary of the data  
`print(df.describe(include='all'))`

```
dtypes: float64(1), int64(2), object(54)
```

```
memory usage: 231.2+ KB
```

```
None
```

	Unnamed: 0	age_categories	...	test_reason	uncontrolled_diabetes8
count	519.000000	519	...	491	28
unique	NaN	4	...	4	2
top	NaN	18-44	...	Travel	no
freq	NaN	308	...	211	19
mean	260.000000	NaN	...	NaN	NaN
std	149.966663	NaN	...	NaN	NaN
min	1.000000	NaN	...	NaN	NaN
25%	130.500000	NaN	...	NaN	NaN
50%	260.000000	NaN	...	NaN	NaN
75%	389.500000	NaN	...	NaN	NaN
max	519.000000	NaN	...	NaN	NaN

```
[11 rows x 57 columns]
```

# EDA

- Select important features that have potential effect on the outcome (risk factors that potentially affect the outcome of covid infection)
- Select columns by index;

```
df1 = df.iloc[:, [1, 5, 7, 18, 19, 22, 30, 35, 36, 37, 40, 55, 12, 11]].copy()
print(df.columns)
```

- Index(['age\_categories', 'anyinfectious', 'bmi\_cat', 'fever',  
# 'highbloodpressure\_enrollment\_13080', 'history\_chronic\_cat',  
# 'low\_oxygen94\_enrollment', 'sex', 'smoke', 'Studysite\_manuscript',  
# 'symptoms\_any', 'test\_reason', 'ever\_hospitalized', 'deceased'], dtype='object')
- Df1 shape = (519, 11)

# Data cleaning

- Identify unique values of each column

```
print(df1['column_name'].unique())
```

- Change longer column names to shorter (easier to use)

```
df1.rename(columns= {'highbloodpressure_enrollment_13080': 'highbloodpressure',  
                    'low_oxygen94_enrollment': 'low oxygen',  
                    'ever_hospitalized': 'hospitalized'}, inplace=True)
```

- check the null values in each column

```
print(df1.isnull().sum())
```

- drop columns with significant number of Nan

```
df1=df1.drop('anyinfectious'), axis=1).# 'anyinfectious' has #223/519 null
```

- replace categorical data with the most frequent value in that column

```
df1 = df1.apply(lambda x: x.fillna(x.value_counts().index[0]))
```

- check the null values again in each column

```
print(df1.isnull().sum())
```



# Data cleaning

- Replace string values with numerical values;
  - Create a dictionary of categorical values and numeric values to replace the categorical values by number.

```
age_cat=df1['age_categories'].unique()
age_num= np.arange(4)
dict_age=dict(zip(age_cat, age_num))
df1['age_categories'] = df1['age_categories'].replace(dict_age)
```

- Feature selection

```
from sklearn.feature_selection import VarianceThreshold
df1 = df1.drop('hospitalized', axis=1)
sel = VarianceThreshold(threshold=(.8 * (1 - .8)))
sel.fit_transform(dfX)
print(df1.head)
```

- No feature dropped by using the variance threshold feature selection

# *Use the Data mining models*

- *split the dataset*

```
X= df1.drop(['hospitalized'],axis=1)  
y= df1['hospitalized']
```

- *Splitting the dataset into train and test*

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,  
random_state=100)
```

- *Standardize the Variables*

```
stdsc = StandardScaler()  
stdsc.fit(X_train)  
X_train = stdsc.transform(X_train)  
X_test= stdsc.transform(X_test)
```

- *Train the model*
- *perform prediction*
- *Metrix Evaluations: Confusion matrix, accuracy*

# Matrix evaluation of different models

		True value	
		0	1
Pred value	0	109	2
	1	27	18
Accuracy = 0.81			

		True value	
		0	1
Pred value	0	97	14
	1	26	19
Accuracy = 0.74			

		True value	
		0	1
Pred value	0	108	3
	1	26	19
Accuracy = 0.81			

		True value	
		0	1
Pred value	0	93	18
	1	24	21
Accuracy = 0.73			

		True value	
		0	1
Pred value	0	99	12
	1	22	23
Accuracy = 0.78			

		True value	
		0	1
Pred value	0	99	12
	1	22	23
Accuracy = 0.81			

# Apply voting classifier

```
voting_clf= VotingClassifier(estimators=[('knn', knn),  
                                         ('svm', svm),  
                                         ('lm', lm),  
                                         ('dtmodel', dtmodel),  
                                         ('rfclf', rfclf),  
                                         ('NBclf', NBclf)])
```

Accuracy = 0.79

```
voting_clf.fit(X_train, y_train)
```

```
voting_clf.score(X_test,y_test)
```

```
# ---Hard Voting from three three models ---
```

```
voting_clf1= VotingClassifier(estimators=[('svm', svm),  
                                           ('logitreg', lm),  
                                           ('NBclf', NBclf)])
```

```
voting_clf1.fit(X_train, y_train)
```

```
voting_clf1.score(X_test,y_test)
```

```
votclfpred1=voting_clf1.predict(X_test)
```

```
accuracy1 = accuracy_score(y_test,votclfpred1)
```

```
print("Accuracy1 = {} %".format(accuracy*100))
```

```
print(confusion_matrix(y_test, votclfpred1))
```

Accuracy 1= 0.78

# Apply K-fold cross validation

```
# ----- Apply K-fold methods to optimize models -----  
  
kf = KFold(n_splits=10, random_state=1, shuffle=True)  
kfmodel = voting_clf2  
# evaluate model  
scores = cross_val_score(kfmodel, X, y, scoring='accuracy', cv=kf, n_jobs=-1)  
# report performance  
print('Accuracy: %.3f (%.3f)' % (mean(scores), std(scores)))
```

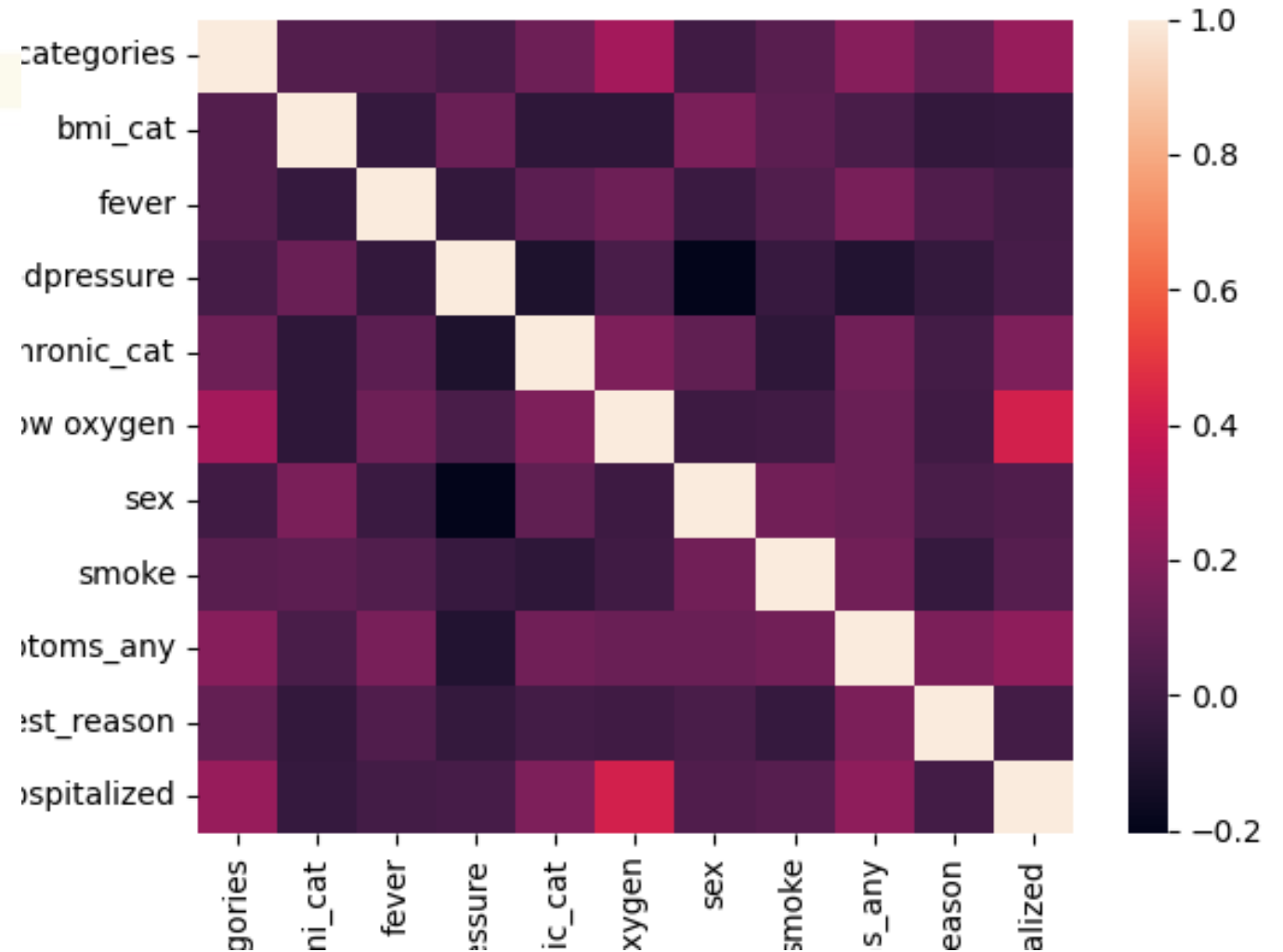
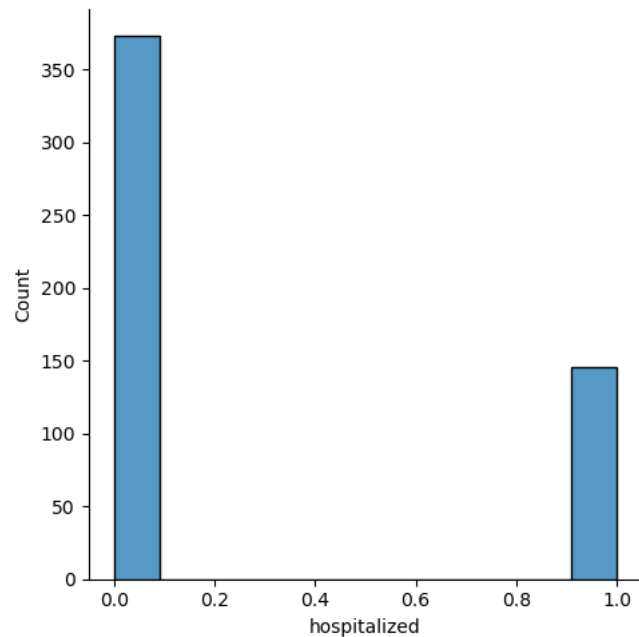
K=10, Accuracy: 0.78 (0.056)

K=5, Accuracy: 0.777 (0.055)

## Distribution of the data

```
# check the distribution of the target
sns.displot(df1['hospitalized'])
plt.savefig('plot.png', dpi=300, bbox_inches='tight')
plt.show()
```

```
# check correlation between the variables
sns.heatmap(df1.corr())
plt.show()
```



# Drop features with low correlation

```
|  
# ----- drop the features with low corellation, creat new data frame2 ---  
df2=df1.drop(['highbloodpressure', 'bmi_cat'], axis=1)  
print(df2.columns)  
  
# split the dataset and encode the variables  
X2= df2.drop(['hospitalized'],axis=1)  
y2=df2['hospitalized']
```

Accuracy2 = 78.8

```
|  
# ----- run voting classifier model on df2 -----
```

```
|  
voting_clf2= VotingClassifier(estimators=[('lm', LogisticRegression()),  
                                         ('dtmodel', DecisionTreeClassifier()),  
                                         ('rfclf', RandomForestClassifier())])
```

```
voting_clf2.fit(X_train2, y_train2)  
pred2=voting_clf2.predict(X_test2)
```

# Optimize RF

```
#----- Random Forest -----  
#increase the n_estimator to 200  
rfclf2 = RandomForestClassifier(n_estimators=200)  
rfclf2.fit(X_train, y_train)  
rfpred2 = rfclf.predict(X_test)
```

#metrix

```
print("rf2 confusion matrix: ")  
print(confusion_matrix(y_test, rfpred))  
print("rf2 Classification Report: ")  
print(classification_report(y_test, rfpred))  
print("rf2 Accuracy : ", accuracy_score(y_test, rfpred2) * 100)
```

Accuracy 78.8



# Summary

- these three models have better accuracy in predicting the outcome

<i>Logit reg</i>		<i>True value</i>	
		0	1
Pred value	0	109	2
	1	27	18
Accuracy = 0.81			

<i>SVM</i>		<i>True value</i>	
		0	1
Pred value	0	108	3
	1	26	19
Accuracy = 0.81			

<i>NB</i>		<i>True value</i>	
		0	1
Pred value	0	99	12
	1	22	23
Accuracy = 0.81			

**Thank you!**

**Questions**