



COVID-19 Prognosis AI: Enhancing Diagnosis, Reducing Burden

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Section 1: Questions to Answer

1. Why is your proposal important in today's world?

- In the midst of the ongoing COVID-19 pandemic, the importance of this proposal cannot be overstated. Accurate disease prediction is crucial to address the urgent need for effective screening and diagnosis. By harnessing the power of machine learning and data analytics, this project can play a pivotal role in saving lives and mitigating the social and economic impact of the virus. Furthermore, the knowledge gained from this project has broader implications for managing future disease outbreaks, making it highly relevant and timely.

2. How predicting a disease accurately can improve medical treatment?

- Accurate disease prediction is not just a matter of convenience but a matter of life and death. By predicting COVID-19 outcomes with precision, healthcare professionals can intervene early, administer appropriate treatments, and prevent severe complications. This can lead to reduced mortality rates, shorter hospital stays, and more efficient resource utilization, ultimately resulting in better healthcare outcomes.

3. How is it going to impact the medical field when it comes to effective screening and reducing healthcare burden?

- The impact of this project on the medical field is profound. Accurate prediction models can revolutionize the screening process, allowing for targeted testing of high-risk individuals. By identifying and isolating COVID-19-positive cases more efficiently, healthcare systems can reduce the burden of excessive testing and focus resources on those who need it most. This optimization not only conserves resources but also minimizes the risk of disease transmission within healthcare settings.

4. If any, what is the gap in the knowledge or how your proposed method can be helpful if required in the future for any other disease?

- Beyond its immediate relevance, this project addresses a broader knowledge gap in disease prediction and management. The methodologies and insights gained can be adapted for future infectious diseases, providing a valuable framework for early detection and intervention. This

project, therefore, serves as a blueprint for proactive healthcare strategies that can be deployed swiftly in the face of emerging diseases, strengthening global healthcare preparedness.

Section 2: Initial Hypothesis (or hypotheses)

Initial hypotheses may include:

- Patients with certain symptoms (e.g., shortness of breath, fever) are more likely to test positive for COVID-19.
- Elderly individuals (age ≥ 60) are at higher risk of testing positive.
- Known contact with COVID-19-positive individuals increases the likelihood of testing positive.
- Different machine learning models may perform differently in predicting COVID-19 outcomes, and we need to justify the choice of the best model.

Section 3: Data Analysis Approach

Data analysis approach:

- Perform exploratory data analysis (EDA) to identify data patterns, distributions, and outliers.
- Conduct feature engineering to create relevant features or transform existing ones.
- Visualize data to understand relationships between variables.
- Use statistical tests to validate hypotheses about the relationship between symptoms, age, contact history, and COVID-19 outcomes.

3.1 Business objective

1. Business objective

The project aims to develop an AI-driven predictive model, 'COVID-19 Prognosis AI: Enhancing Diagnosis, Reducing Burden,' to significantly improve the accuracy of COVID-19 diagnosis by leveraging patient symptoms, age, and contact history. This initiative seeks to enhance medical diagnosis, streamline resource allocation in healthcare, reduce the burden on healthcare systems, provide a scalable framework for future infectious diseases, and contribute valuable insights to ongoing research efforts in the field, ultimately improving public health outcomes and preparedness.

Data Preparation/Data preprocessing: Feature Engineering + Feature selection

3.2 Importing the required libraries

```
# Importing all required libraries:  
import pandas as pd  
import numpy as np  
import matplotlib.pyplot as plt  
import plotly.express as px  
import seaborn as sns
```

3.3 Importing the dataset

```
# Importing the collected dataset  
corona_db = pd.read_csv('corona_tested.csv')
```

3.4 A quick glance

```
# Quick glance  
corona_db.head()
```

	Ind_ID	Test_date	Cough_symptoms	Fever	Sore_throat	Shortness_of_breath	Headache	Corona	Age_60_above	Sex	Known_contact
0	1	11-03-2020	TRUE	FALSE	TRUE	FALSE	FALSE	negative	None	None	Abroad
1	2	11-03-2020	FALSE	TRUE	FALSE	FALSE	FALSE	positive	None	None	Abroad
2	3	11-03-2020	FALSE	TRUE	FALSE	FALSE	FALSE	positive	None	None	Abroad
3	4	11-03-2020	TRUE	FALSE	FALSE	FALSE	FALSE	negative	None	None	Abroad
4	5	11-03-2020	TRUE	FALSE	FALSE	FALSE	FALSE	negative	None	None	Contact with confirmed

3.5 Table info

```
corona_db.info()
```

```
<class 'pandas.core.frame.DataFrame'>  
RangeIndex: 278848 entries, 0 to 278847  
Data columns (total 11 columns):  
#   Column                Non-Null Count  Dtype  
---  -  
0   Ind_ID                278848 non-null  int64  
1   Test_date             278848 non-null  object  
2   Cough_symptoms        278848 non-null  object  
3   Fever                 278848 non-null  object  
4   Sore_throat           278848 non-null  object  
5   Shortness_of_breath   278848 non-null  object  
6   Headache              278848 non-null  object  
7   Corona                278848 non-null  object  
8   Age_60_above          278848 non-null  object  
9   Sex                   278848 non-null  object  
10  Known_contact          278848 non-null  object  
dtypes: int64(1), object(10)  
memory usage: 23.4+ MB
```

3.6 Table columns

```
corona_db.columns
```

```
Index(['Ind_ID', 'Test_date', 'Cough_symptoms', 'Fever', 'Sore_throat',  
      'Shortness_of_breath', 'Headache', 'Corona', 'Age_60_above', 'Sex',  
      'Known_contact'],  
      dtype='object')
```

3.7 Table data type

```
corona_db.dtypes
```

Ind_ID	int64
Test_date	object
Cough_symptoms	object
Fever	object
Sore_throat	object
Shortness_of_breath	object
Headache	object
Corona	object
Age_60_above	object
Sex	object
Known_contact	object
dtype:	object

3.8 Table Description

```
corona_db.describe(include='all')
```

	Ind_ID	Test_date	Cough_symptoms	Fever	Sore_throat	Shortness_of_breath	Headache	Corona	Age_60_above	Sex	Known_contact
count	278848.000000	278848	278848	278848	278848	278848	278848	278848	278848	278848	278848
unique	NaN	51	5	5	5	5	5	3	3	3	3
top	NaN	20-04-2020	False	False	False	False	False	negative	None	female	Other
freq	NaN	10921	127531	137774	212584	212842	212326	260227	127320	130158	242741
mean	139424.500000	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
std	80496.628269	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
min	1.000000	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
25%	69712.750000	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
50%	139424.500000	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
75%	209136.250000	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
max	278848.000000	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

3.9 Checking whether there is any wrong entries

```
corona_db["Cough_symptoms"].unique()
```

```
array(['TRUE', 'FALSE', 'None', False, True], dtype=object)
```

```
corona_db["Fever"].unique()
```

```
array(['FALSE', 'TRUE', 'None', False, True], dtype=object)
```

```
corona_db["Sore_throat"].unique()
```

```
array(['TRUE', 'FALSE', 'None', False, True], dtype=object)
```

```
corona_db["Headache"].unique()
```

```
array(['FALSE', 'TRUE', 'None', False, True], dtype=object)
```

```
corona_db["Corona"].unique()
```

```
array(['negative', 'positive', 'other'], dtype=object)
```

```
corona_db["Age_60_above"].unique()
```

```
array(['None', 'No', 'Yes'], dtype=object)
```

```
corona_db["Sex"].unique()
```

```
array(['None', 'male', 'female'], dtype=object)
```

```
corona_db["Known_contact"].unique()
```

```
array(['Abroad', 'Contact with confirmed', 'Other'], dtype=object)
```

3.10 Standardizing the entries (Data cleaning)

- As we can see there are some columns with various representations of boolean values, including strings ('TRUE' and 'FALSE') as well as Python's boolean values (True and False).
- The presence of multiple representations of the same information (e.g., 'TRUE', 'FALSE', True, False) can affect the nominal encoding of categorical data in a machine learning context. To effectively encode such data, you should ensure that the values are consistent and properly converted to a single data type.

```
# Standardizing the entries in the column Cough_symptoms  
corona_db['Cough_symptoms'] = corona_db['Cough_symptoms'].replace({'TRUE': True, 'FALSE': False})
```

```
corona_db["Cough_symptoms"].unique()
```

```
array([True, False, 'None'], dtype=object)
```

```
# Standardizing the entries in the column Fever  
corona_db['Fever'] = corona_db['Fever'].replace({'TRUE': True, 'FALSE': False})
```

```
corona_db['Fever'].unique()
```

```
array([False, True, 'None'], dtype=object)
```

```
# Standardizing the entries in the column Sore_throat  
corona_db['Sore_throat'] = corona_db['Sore_throat'].replace({'TRUE': True, 'FALSE': False})
```

```
corona_db['Sore_throat'].unique()
```

```
array([True, False, 'None'], dtype=object)
```

```
# Standardizing the entries in the column Sore_throat  
corona_db['Headache'] = corona_db['Headache'].replace({'TRUE': True, 'FALSE': False})
```

```
corona_db['Headache'].unique()
```

```
array([False, True, 'None'], dtype=object)
```


3.11 Checking for null values

```
corona_db.isnull().sum()
```

```
Ind_ID          0
Test_date       0
Cough_symptoms  0
Fever           0
Sore_throat     0
Shortness_of_breath  0
Headache        0
Corona          0
Age_60_above    0
Sex             0
Known_contact   0
dtype: int64
```

3.12 Checking for duplicates

```
corona_db.duplicated()
```

```
0      False
1      False
2      False
3      False
4      False
...
278843  False
278844  False
278845  False
278846  False
278847  False
Length: 278848, dtype: bool
```

```
corona_db.duplicated().sum()
```

```
0
```

3.13 Renaming the columns properly (Data cleaning)

```
# Renaming columns properly:  
corona_db.rename(columns = {  
    'Ind_ID':'Id',  
    'Cough_symptoms':'Cough',  
    'Corona':'Test_results'  
}, inplace = True)
```

3.14 Rearranging the columns (Data cleaning)

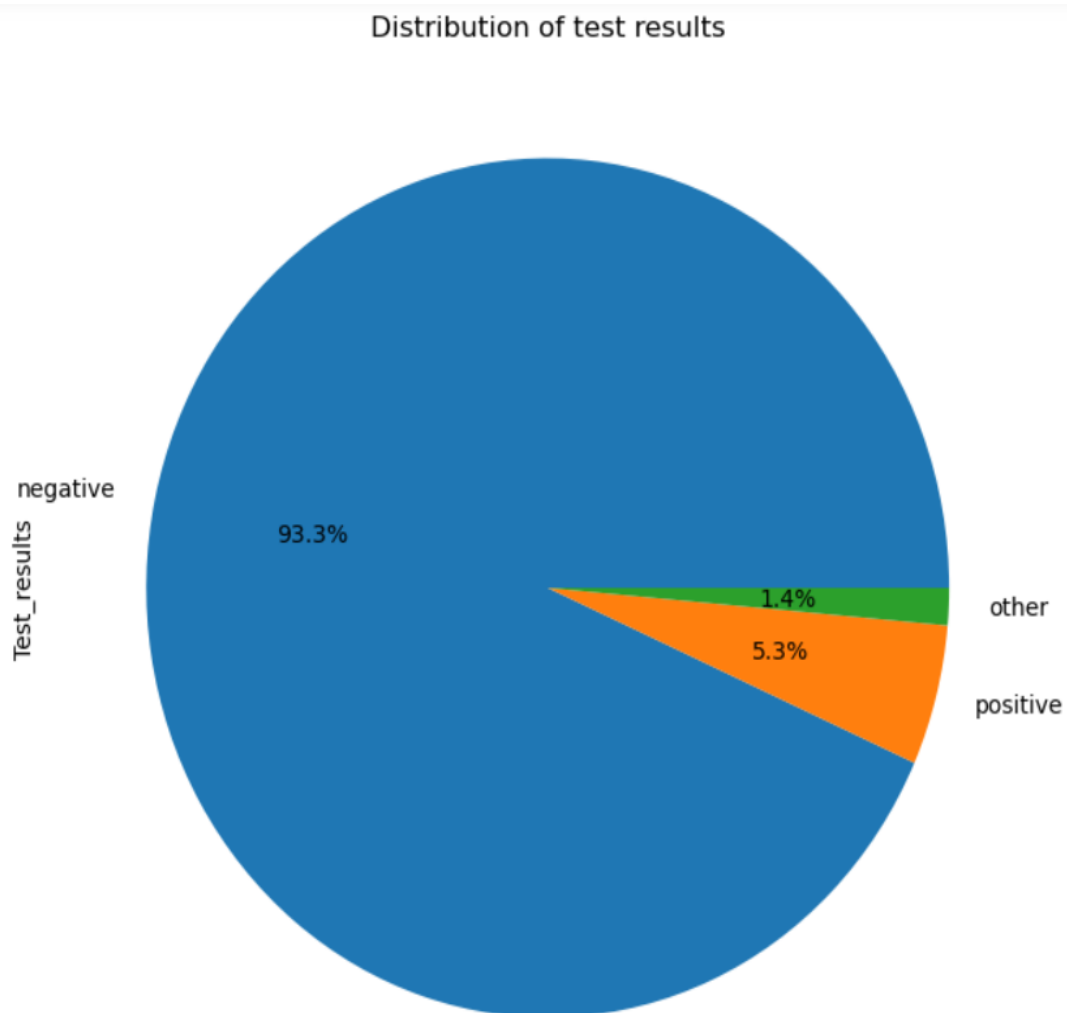
```
columns=["Id", "Test_date", "Cough", "Fever", "Sore_throat", "Shortness_of_breath", "Headache",  
        "Age_60_above", "Sex", "Known_contact", "Test_results"]  
corona_df = corona_db[columns]
```

3.15 Saving the cleaned data as a csv file to be used in sql queries

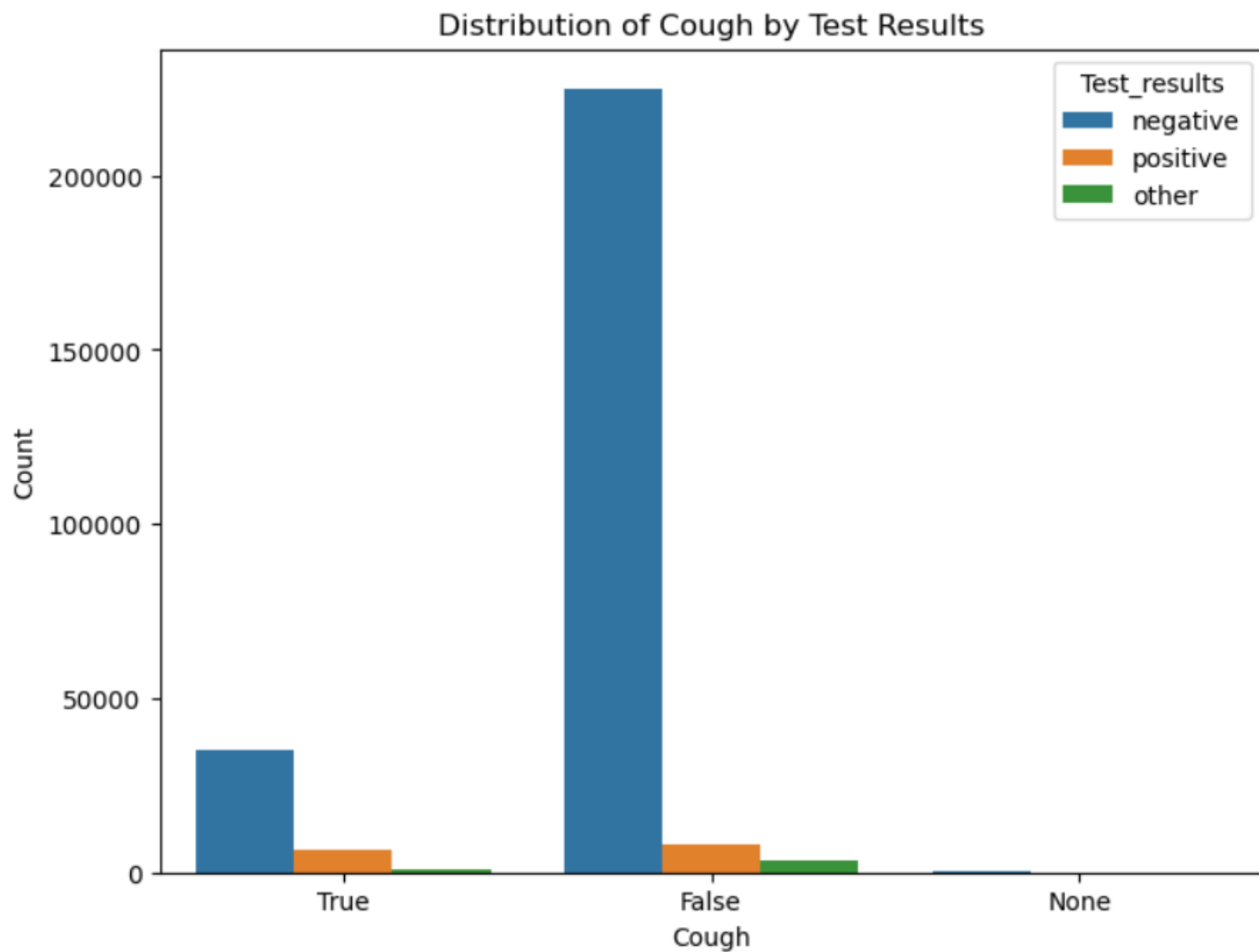
```
# Saving the cleaned data as a csv file to be used in sql queries  
corona_df.to_csv('corona.csv', index=False)
```

3.16 Data exploration using plots

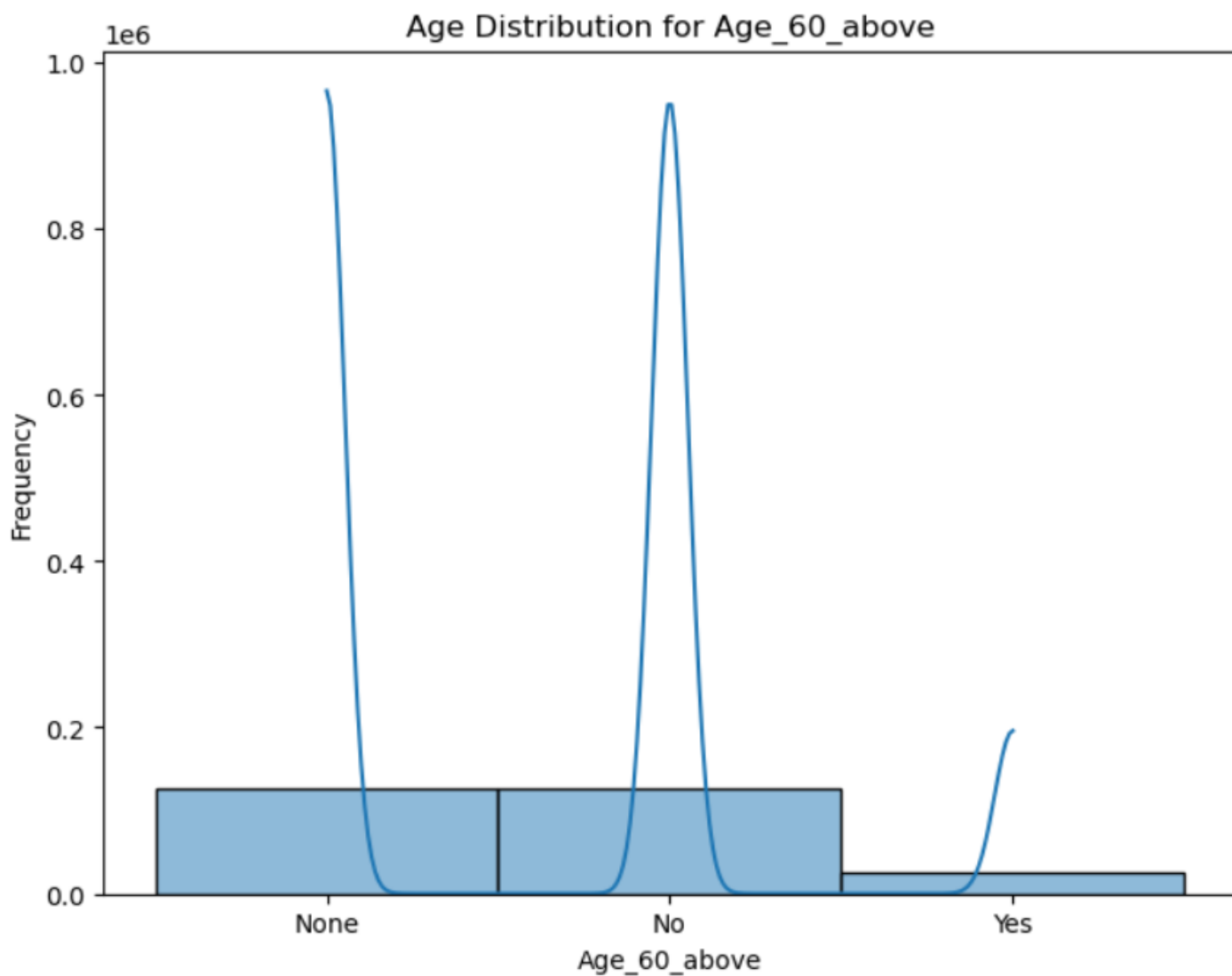
```
# Pie Chart-Sex
plt.figure(figsize=(8, 8))
corona_df['Test_results'].value_counts().plot(kind='pie', autopct='%1.1f%%')
plt.title('Distribution of test results')
plt.show()
```



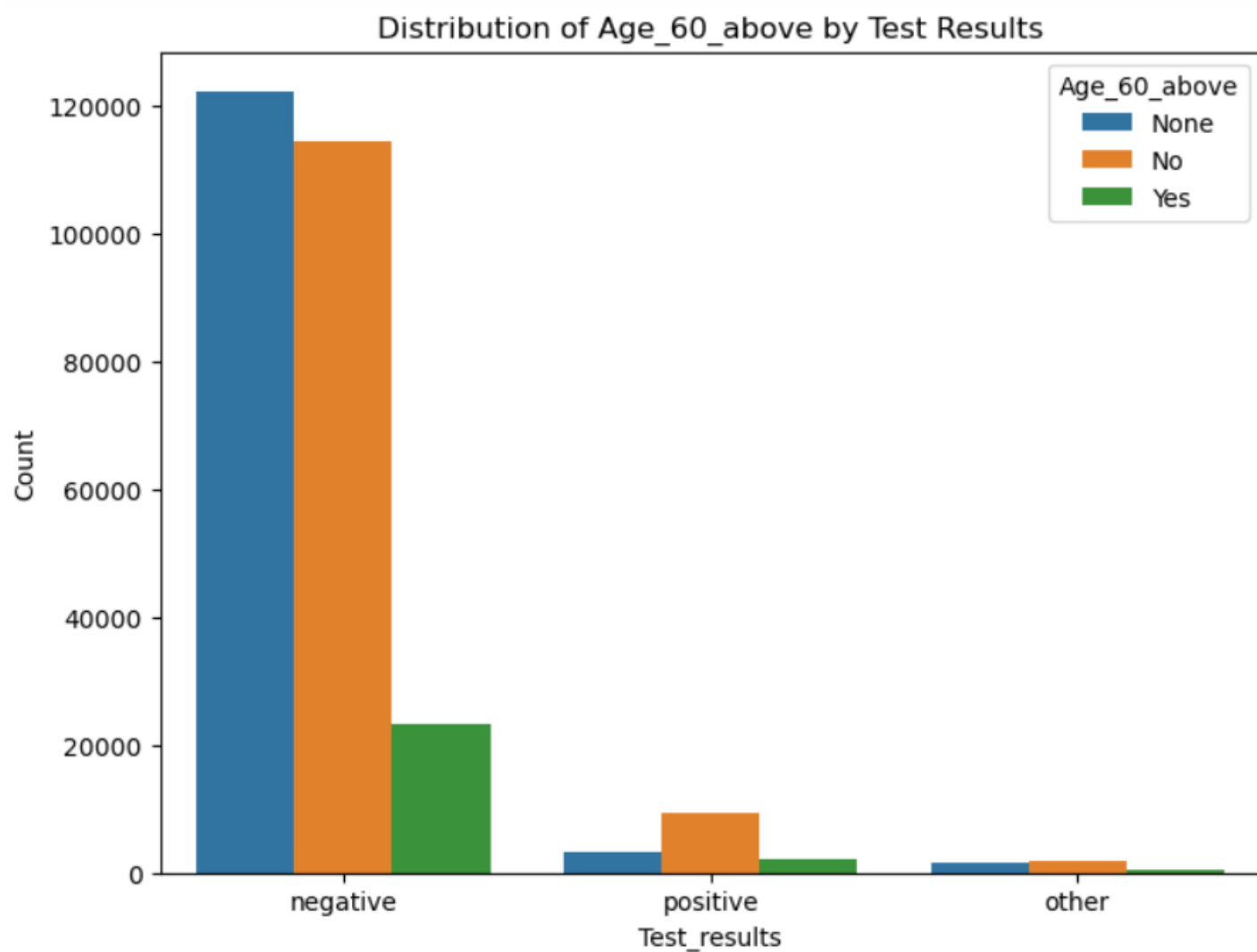
```
# Count plot-Distribution of Cough by Test Results
plt.figure(figsize=(8, 6))
sns.countplot(data=corona_df, x='Cough', hue='Test_results')
plt.title('Distribution of Cough by Test Results')
plt.xlabel('Cough')
plt.ylabel('Count')
plt.show()
```



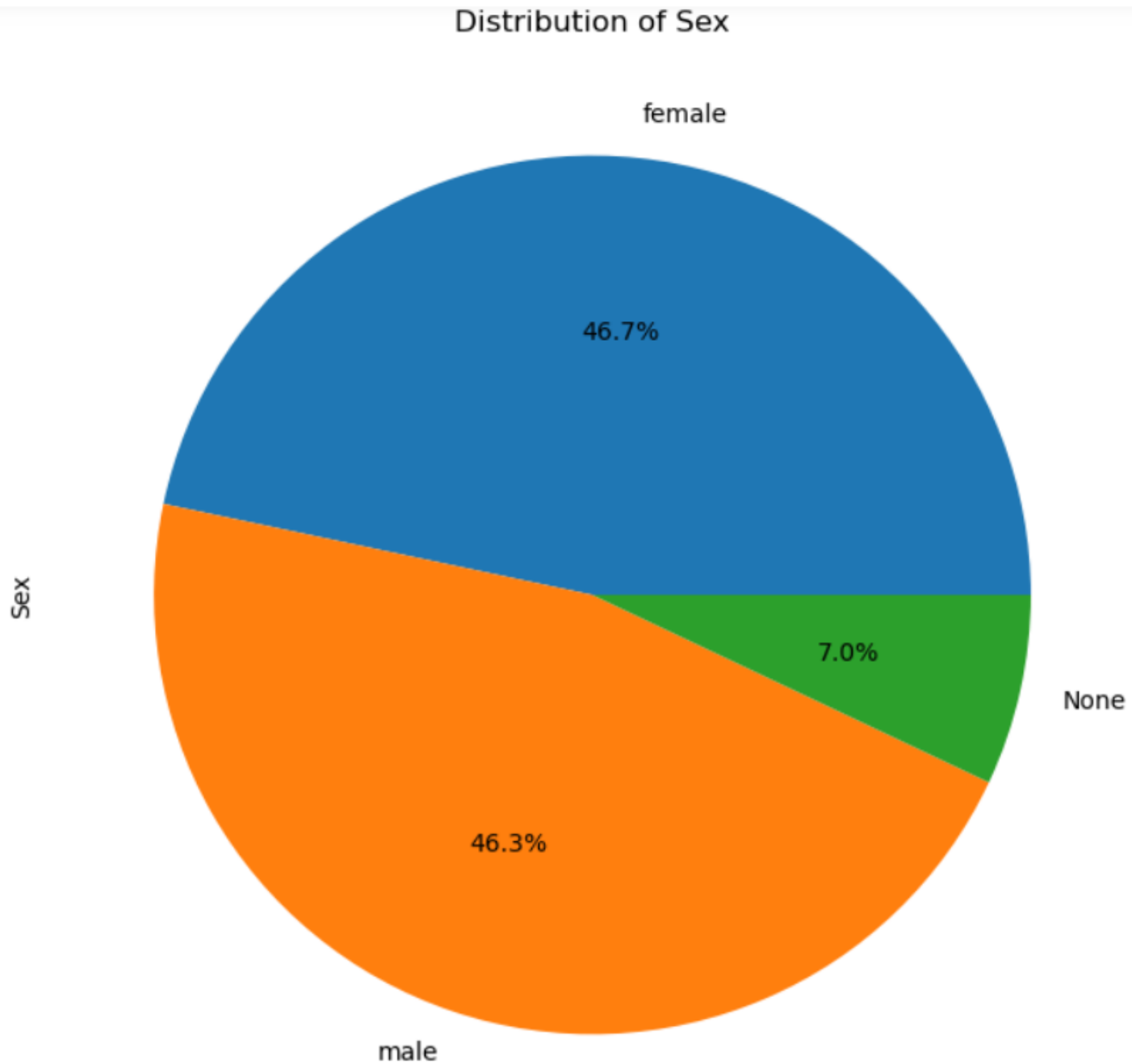
```
# Hist plot-Age Distribution for Age_60_above
plt.figure(figsize=(8, 6))
sns.histplot(data=corona_df, x='Age_60_above', bins=10, kde=True)
plt.title('Age Distribution for Age_60_above')
plt.xlabel('Age_60_above')
plt.ylabel('Frequency')
plt.show()
```



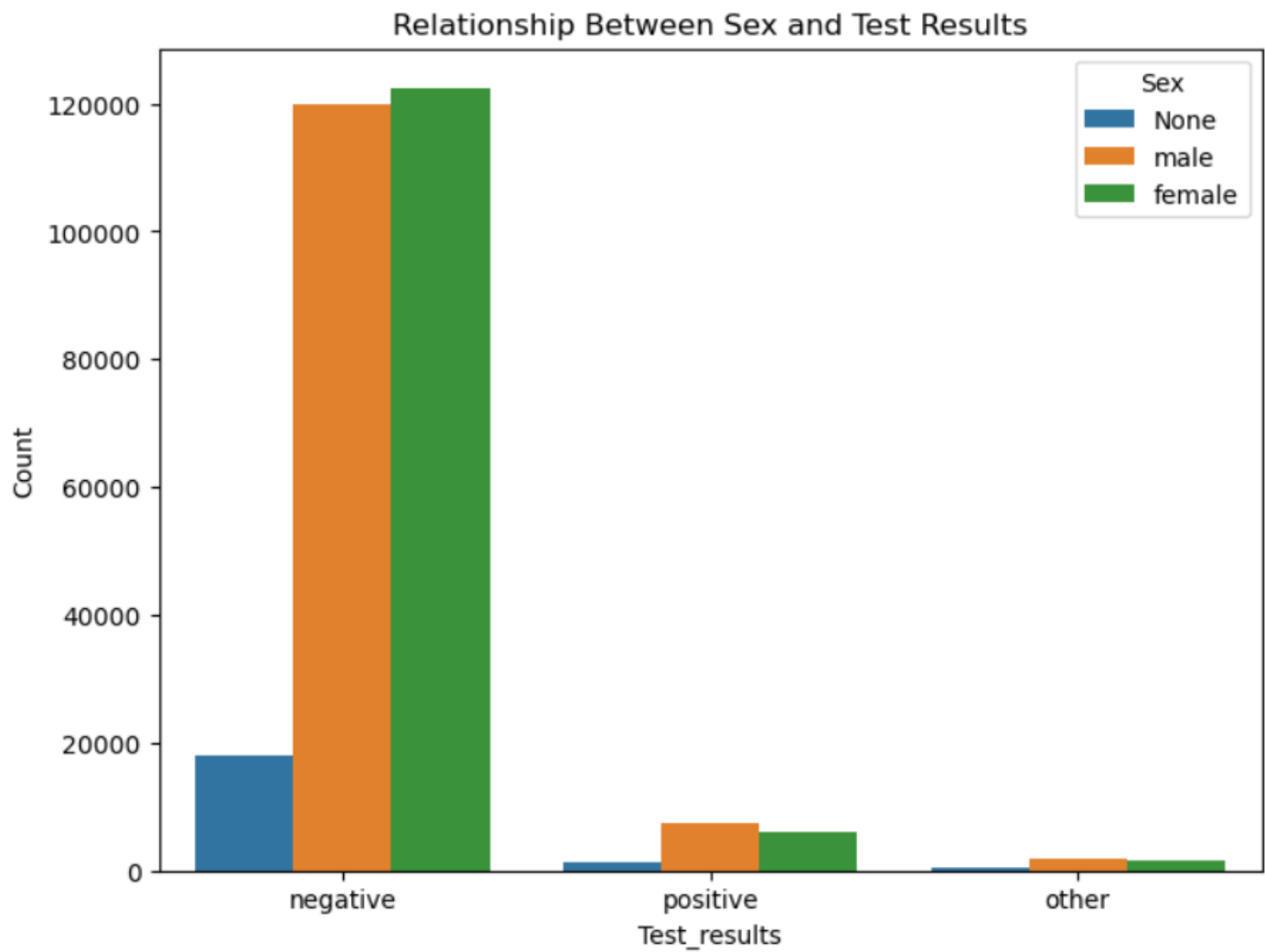
```
# Count Plot-Age_60_above by Test_results
plt.figure(figsize=(8, 6))
sns.countplot(data=corona_df, x='Test_results', hue='Age_60_above')
plt.title('Distribution of Age_60_above by Test Results')
plt.xlabel('Test_results')
plt.ylabel('Count')
plt.show()
```



```
# Pie Chart-Sex
plt.figure(figsize=(8, 8))
corona_df['Sex'].value_counts().plot(kind='pie', autopct='%1.1f%%')
plt.title('Distribution of Sex')
plt.show()
```



```
# Stacked Bar Chart-Sex and Test_results
plt.figure(figsize=(8, 6))
sns.countplot(data=corona_df, x='Test_results', hue='Sex')
plt.title('Relationship Between Sex and Test Results')
plt.xlabel('Test_results')
plt.ylabel('Count')
plt.legend(title='Sex', loc='upper right')
plt.show()
```




```
# Line Chart-Test_date against Test_results
plt.figure(figsize=(10, 6))
sns.lineplot(data=corona_df, x='Test_date', y='Test_results')
plt.title('Trend of Test Results Over Time')
plt.xlabel('Test Date')
plt.ylabel('Test Results')
plt.xticks(rotation=45)
plt.show()
```



3.17 Dropping unwanted rows (Data cleaning)

```
x = corona_df['Test_results'] != 'other'
corona_df = corona_df[x]
```

```
corona_df['Test_results'].value_counts()
```

```
negative    260227
positive     14729
Name: Test_results, dtype: int64
```

```
corona_df['Test_results'] = corona_df['Test_results'].replace({'negative': 0, 'positive': 1})
```

Data transformation or Data Wrangling

3.18 Encoding (Dummy encoding)

```
# Dummy encoding
```

```
covid_df = pd.get_dummies(corona_df, columns=['Cough', 'Fever', 'Sore_throat', 'Shortness_of_breath', 'Headache',
                                             'Age_60_above', 'Sex', 'Known_contact'], drop_first=True)
```

3.19 Train Test Split

```
# Separating Independent and dependent variables
```

```
x = covid_df.iloc[:, :-1]
y = covid_df.iloc[:, -1]
```

```
x.head()
```

	Test_results	Cough_True	Cough_None	Fever_True	Fever_None	Sore_throat_True	Sore_throat_None	Shortness_of_breath_True
0	0	1	0	0	0	1	0	0
1	1	0	0	1	0	0	0	0
2	1	0	0	1	0	0	0	0
3	0	1	0	0	0	0	0	0

```
# Train Test Split

from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.15, random_state = 16)
```

3.20 Standardization / Feature scaling

```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()

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

Section 4: Machine Learning Approach

1. **Machine Learning Method:** Use various machine learning models such as logistic regression, decision trees, random forests, and support vector machines to predict COVID-19 outcomes.
2. **Justification for Model Choice:** Compare models based on metrics like accuracy, precision, recall, and F1-score. Choose the model that provides the best overall performance.
3. **Model Improvement:** Implement techniques like hyperparameter tuning, cross-validation, and feature selection to improve model accuracy.
4. **Model Comparison:** Compare at least four machine learning models and justify their selection based on cost functions and performance metrics.

4.1 Logistic Regression

```
# Modeling
from sklearn.linear_model import LogisticRegression
logistic_reg = LogisticRegression(random_state = 0, max_iter=1000)
logistic_reg.fit(x_train, y_train)

# Predictions
ypred_train = logistic_reg.predict(x_train)
ypred_test = logistic_reg.predict(x_test)

# Evaluation
from sklearn.metrics import accuracy_score
print("Train Accuracy: ", accuracy_score(y_train, ypred_train))
print("Test Accuracy: ", accuracy_score(y_test, ypred_test))

# Calculation of cross validation score:
from sklearn.model_selection import cross_val_score
print("Cross validation score: ", cross_val_score(logistic_reg, x,y, cv=5, scoring="accuracy").mean())
```

Train Accuracy: 0.9160804751146711
Test Accuracy: 0.9158907962370284
Cross validation score: 0.9082434280369215

4.2 KNN

```
# K-Nearest Neighbors with default parameters

# Modeling
from sklearn.neighbors import KNeighborsClassifier
model = KNeighborsClassifier()
model.fit(x_train, y_train)

# Prediction
ypred_train = model.predict(x_train)
ypred_test = model.predict(x_test)

# Evaluation
from sklearn.metrics import accuracy_score
print("Train Accuracy: ", accuracy_score(y_train, ypred_train))
print("Test Accuracy: ", accuracy_score(y_test, ypred_test))

from sklearn.model_selection import cross_val_score
print("Cross validation score: ", cross_val_score(model,x,y, cv=5, scoring="accuracy").mean())
```

Train Accuracy: 0.9149423221742999
Test Accuracy: 0.9134419551934827
Cross validation score: 0.9078979076280935

4.2.2 Using Hyper parameter tuning to improve the model performance

```
# Hyper Parameter Tuning to improve the model's performance with best combination of hyperparameters
from sklearn.model_selection import GridSearchCV

estimator = KNeighborsClassifier()

param_grid = {'n_neighbors': list(range(1,11))}

cv_classifier = GridSearchCV(estimator, param_grid, cv=5, scoring='accuracy')

cv_classifier.fit(x_train, y_train)

cv_classifier.best_params_

{'n_neighbors': 9}
```

4.2.3 Applying the k value obtained from Hyper parameter tuning

```
# KNN with the best combinations
# Applying the k value obtained from Hyper parameter tuning to the KNN to get the best accuracy & CVS

# Modeling
from sklearn.neighbors import KNeighborsClassifier
model = KNeighborsClassifier(n_neighbors = 9)      # Changed the default K value to the value obtained from HPT
model.fit(x_train, y_train)

# Prediction
ypred = model.predict(x_test)
ypred_train = model.predict(x_train)
ypred_test = model.predict(x_test)

# Evaluation
from sklearn.metrics import accuracy_score
print("Train Accuracy: ", accuracy_score(y_train, ypred_train))
print("Test Accuracy: ", accuracy_score(y_test, ypred_test))

from sklearn.model_selection import cross_val_score
print("Cross validation score: ", cross_val_score(model,x,y, cv=5, scoring="accuracy").mean())

Train Accuracy:  0.9178176559183953
Test Accuracy:   0.9159150421879546
Cross validation score:  0.9073632755479277
```

4.3 SVM

```
# Modeling
from sklearn.svm import SVC
svm_model = SVC()
svm_model.fit(x_train, y_train)

# Prediction
ypred_train = svm_model.predict(x_train)
ypred_test = svm_model.predict(x_test)

# Evaluation
from sklearn.metrics import accuracy_score
print("Train Accuracy: ", accuracy_score(y_train, ypred_train))
print("Test Accuracy: ", accuracy_score(y_test, ypred_test))

from sklearn.model_selection import cross_val_score
print("cross validation score: ", cross_val_score(model, x, y, cv=5, scoring="accuracy").mean())
```

Train Accuracy: 0.9220279660436776
Test Accuracy: 0.9206430026185627
cross validation score: 0.9073632755479277

4.4 Decision Tree

```
from sklearn.tree import DecisionTreeClassifier
dt_model = DecisionTreeClassifier()

dt_model.fit(x_train, y_train)
```

DecisionTreeClassifier()

**In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.**

```
# Modeling
from sklearn.tree import DecisionTreeClassifier
dt_model = DecisionTreeClassifier(random_state=16)
dt_model.fit(x_train, y_train)

# Prediction
ypred_train = dt_model.predict(x_train)
ypred_test = dt_model.predict(x_test)

# Evaluation
from sklearn.metrics import accuracy_score
print("Train Accuracy: ", accuracy_score(y_train, ypred_train))
print("Test Accuracy: ", accuracy_score(y_test, ypred_test))

from sklearn.model_selection import cross_val_score
print("cross validation score: ", cross_val_score(model, x, y, cv=5, scoring="accuracy").mean())
```

Train Accuracy: 0.9223274799753542
Test Accuracy: 0.9202793133546697
cross validation score: 0.9073632755479277

4.5 Random Forest

```
# Random forest with default parameters

# Modeling
from sklearn.ensemble import RandomForestClassifier
model = RandomForestClassifier(random_state=16)
model.fit(x_train, y_train)

# Prediction
ypred_train = model.predict(x_train)
ypred_test  = model.predict(x_test)

# Evaluation
from sklearn.metrics import accuracy_score
print("Train Accuracy: ", accuracy_score(y_train, ypred_train))
print("Test Accuracy:  ", accuracy_score(y_test, ypred_test))

from sklearn.model_selection import cross_val_score
print("cross validation score: ", cross_val_score(model, x, y, cv=5, scoring="accuracy").mean())
```

Train Accuracy: 0.9223274799753542
Test Accuracy: 0.9204005431093008
cross validation score: 0.9089199019722681

4.5.2 Measuring the importance of each feature in this model

```
# Measuring the importance of each feature in this model
model.feature_importances_
```

array([7.75637861e-02, 4.48771550e-01, 6.37197422e-05, 1.04966066e-01,
5.67602277e-05, 7.66291430e-03, 3.41449641e-07, 1.20679377e-03,
1.09050986e-02, 9.39656730e-07, 3.92016700e-03, 9.96012422e-03,
1.46618080e-06, 6.30776205e-03, 4.03184438e-03, 2.64083960e-03,
3.05158359e-03, 3.18888243e-01])

- - - - -

4.6 XG Boost

```
# Modeling
from xgboost import XGBClassifier
xgb_model = XGBClassifier()
xgb_model.fit(x_train, y_train)

# Prediction
ypred_train = xgb_model.predict(x_train)
ypred_test = xgb_model.predict(x_test)

# Evaluation
from sklearn.metrics import accuracy_score
print("Train Accuracy: ", accuracy_score(y_train, ypred_train))
print("Test Accuracy: ", accuracy_score(y_test, ypred_test))

from sklearn.model_selection import cross_val_score
print("cross validation score: ", cross_val_score(model, x, y, cv=5, scoring="accuracy").mean())

Train Accuracy:  0.9221477716163483
Test Accuracy:  0.9204975269130056
cross validation score:  0.9089199019722681
```

Model Selection

Selecting the best model on the basis of:

(a) Condition1: Test accuracy = Train accuracy = Cross validation score (+/- 5 is acceptable)

(b) Condition2: If the more than one model is satisfying the 1st condition go for the model having the highest CV

- While examining all the models Random forest and XGBoost appears to be almost equal giving high train accuracy, test accuracy and cross validation score.
- But Random forest gives little more train accuracy.
- So I opt for Random forest as the best model.

Checking for confusion metrix and Classification report for the final model

```
from sklearn.metrics import confusion_matrix  
print(confusion_matrix(y_test, ypred_test))
```

```
[[ 3602  1771]  
 [ 1512 34359]]
```

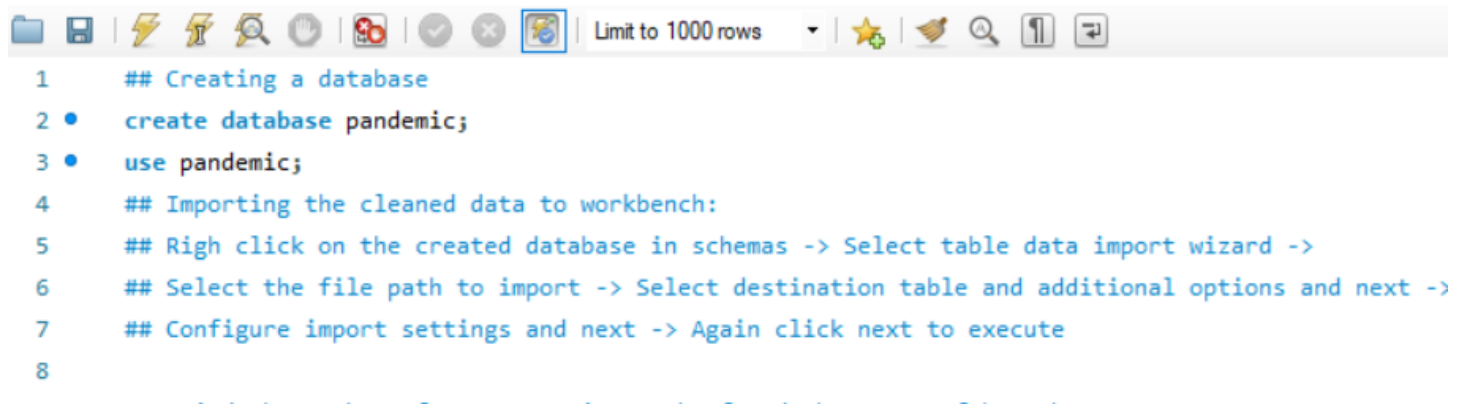
```
from sklearn.metrics import classification_report  
print(classification_report(y_test, ypred_test))
```

	precision	recall	f1-score	support
0	0.70	0.67	0.69	5373
1	0.95	0.96	0.95	35871
accuracy			0.92	41244
macro avg	0.83	0.81	0.82	41244
weighted avg	0.92	0.92	0.92	41244

SQL Part of the Project

Used MySQL to perform the following queries on the cleaned data:

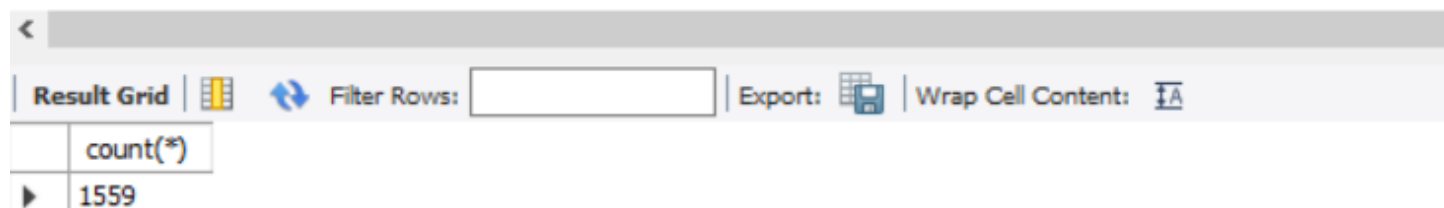
Creating the database and importing the dataset:



```
1  ## Creating a database
2  • create database pandemic;
3  • use pandemic;
4  ## Importing the cleaned data to workbench:
5  ## Right click on the created database in schemas -> Select table data import wizard ->
6  ## Select the file path to import -> Select destination table and additional options and next ->
7  ## Configure import settings and next -> Again click next to execute
8
```

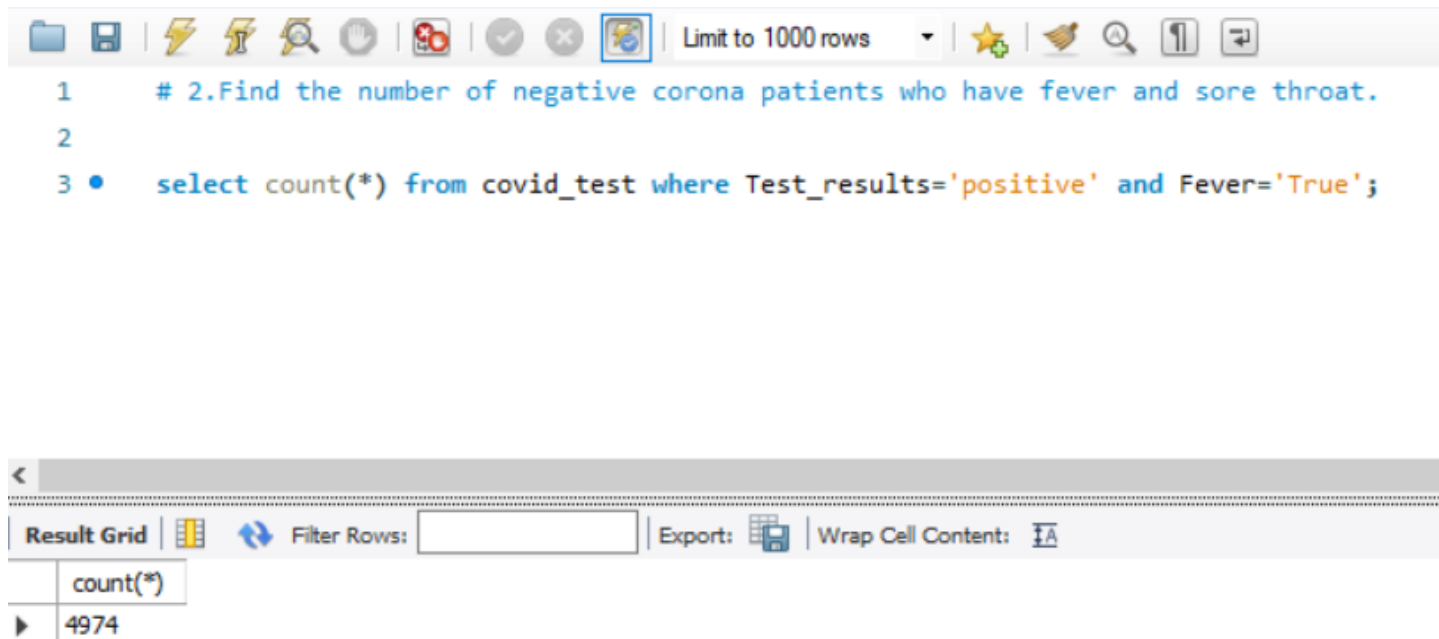
1. Find the number of corona patients who faced shortness of breath.

```
9  # 1.Find the number of corona patients who faced shortness of breath.
10 • select count(*) from covid_test where Shortness_of_breath = 'True';
```



Result Grid		Filter Rows:	Export:	Wrap Cell Content:
	count(*)			
▶	1559			

2. Find the number of negative corona patients who have fever and sore throat.



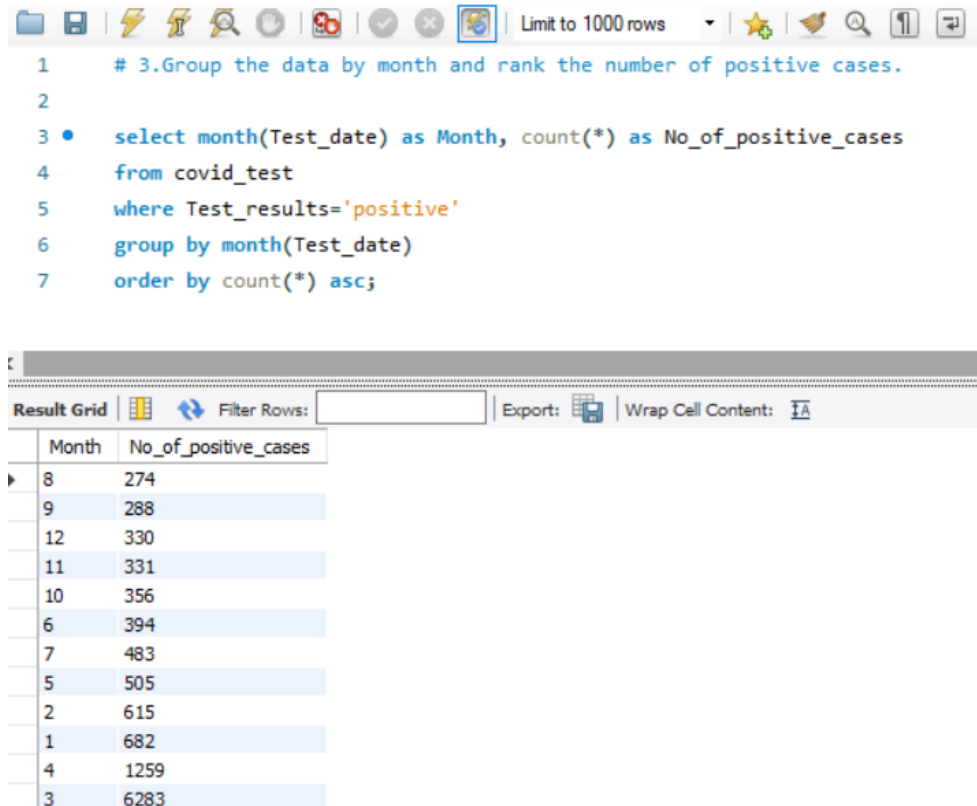
The screenshot shows a SQL query editor with a toolbar at the top. The query is as follows:

```
1 # 2.Find the number of negative corona patients who have fever and sore throat.
2
3 • select count(*) from covid_test where Test_results='positive' and Fever='True';
```

Below the query editor, the "Result Grid" is displayed, showing the result of the query:

count(*)
4974

3. Group the data by month and rank the number of positive cases.



The screenshot shows a SQL query editor with a toolbar at the top. The query is as follows:

```
1 # 3.Group the data by month and rank the number of positive cases.
2
3 • select month(Test_date) as Month, count(*) as No_of_positive_cases
4 from covid_test
5 where Test_results='positive'
6 group by month(Test_date)
7 order by count(*) asc;
```

Below the query editor, the "Result Grid" is displayed, showing the results of the query:

Month	No_of_positive_cases
8	274
9	288
12	330
11	331
10	356
6	394
7	483
5	505
2	615
1	682
4	1259
3	6283

4. Find the female negative corona patients who faced cough and headache.

Limit to 1000 rows

```
1 # 4.Find the female negative corona patients who faced cough and headache.
2
3 • select * from covid_test where Sex='female' and Cough='True' and Headache='True' and Test_results='negative';
```

Result Grid

	Id	Test_date	Cough	Fever	Sore_throat	Shortness_of_breath	Headache	Age_60_above	Sex	Known_contact	Test_results
▶	13756	2020-03-22	True	True	True	FALSE	True	No	female	Abroad	negative
	17289	2020-03-22	True	True	True	FALSE	True	No	female	Abroad	negative
	17657	2020-03-23	True	False	True	FALSE	True	No	female	Abroad	negative
	19554	2020-03-23	True	True	False	FALSE	True	No	female	Other	negative
	19615	2020-03-23	True	False	True	TRUE	True	No	female	Contact with confirmed	negative
	20248	2020-03-23	True	True	False	FALSE	True	Yes	female	Abroad	negative
	20253	2020-03-23	True	True	False	FALSE	True	No	female	Contact with confirmed	negative
	37904	2020-03-27	True	True	True	TRUE	True	No	female	Contact with confirmed	negative
	40616	2020-03-27	True	False	False	TRUE	True	No	female	Contact with confirmed	negative
	40752	2020-03-27	True	True	False	FALSE	True	No	female	Contact with confirmed	negative
	43650	2020-03-28	True	False	True	TRUE	True	No	female	Contact with confirmed	negative
	49678	2020-03-29	True	True	False	FALSE	True	No	female	Contact with confirmed	negative
	51034	2020-03-29	True	False	False	FALSE	True	Yes	female	Contact with confirmed	negative
	52740	2020-03-29	True	True	True	FALSE	True	No	female	Contact with confirmed	negative

5. How many elderly corona patients have faced breathing problems?

Limit to 1000 rows

```
1 # 5.How many elderly corona patients have faced breathing problems?
2
3 • select count(*) from covid_test where Age_60_above='Yes' and Shortness_of_breath='True';
```

Result Grid

	count(*)
▶	292

6. Which three symptoms were more common among COVID positive patients?

The screenshot shows a SQL IDE interface with multiple tabs labeled 'SQL File 1*' through 'SQL File 8*'. The active tab is 'SQL File 6*'. The query editor contains the following SQL code:

```
3 • select 'Cough' as Symptom,
4     sum(case when Test_results = 'positive' and Cough = 'True' then 1 else 0 end) as Positive_Count
5     from covid_test
6     union
7     select 'Fever' as Symptom,
8     sum(case when Test_results = 'positive' and Fever = 'True' then 1 else 0 end) as Positive_Count
9     from covid_test
10    union
11    select 'Sore_throat' as Symptom,
12    sum(case when Test_results = 'positive' and Sore_throat = 'True' then 1 else 0 end) as Positive_Count
13    from covid_test
14    union
15    select 'Shortness_of_breath' as Symptom,
16    sum(case when Test_results = 'positive' and Shortness_of_breath = 'True' then 1 else 0 end) as Positive_Count
17    from covid_test
18    union
19    select 'Headache' as Symptom,
20    sum(case when Test_results = 'positive' and Headache = 'True' then 1 else 0 end) as Positive_Count
```

Below the query editor, the 'Result Grid' is displayed with the following data:

Symptom	Positive_Count
Cough	5604
Fever	4974
Headache	2224

At the bottom, the 'Output' pane shows the execution log for 'Result 3':

#	Time	Action	Message
✓ 46	07:51:39	select * from covid_test LIMIT 0, 1000	1000 row(s) returned
✓ 47	07:55:34	select 'Cough' as Symptom, sum(case when Test_results = 'positive' and Cough = 'True' then 1 else 0 end)...	3 row(s) returned

7. Which symptom was less common among COVID negative people?

The screenshot shows a SQL IDE interface with multiple tabs labeled 'SQL File 1*' through 'SQL File 8*'. The active tab is 'SQL File 7*'. The query editor contains a SQL query that counts the number of negative COVID test results for four symptoms: Cough, Fever, Sore_throat, and Shortness_of_breath. The query uses a union of four SELECT statements, each with a CASE WHEN clause to filter for 'negative' test results and a specific symptom. The results are displayed in a 'Result Grid' below the query editor. The grid shows the following data:

Symptom	Negative_Count
Headache	131
Sore_throat	345
Shortness_of_breath	371

Below the Result Grid, there is a 'Result 2' tab and an 'Output' section. The 'Output' section shows a table with columns '#', 'Time', 'Action', and 'Message'. It contains two entries:

#	Time	Action	Message
46	07:51:39	select * from covid_test LIMIT 0, 1000	1000 row(s) returned
47	07:55:34	select 'Cough' as Symptom, sum(case when Test_results = 'positive' and Cough = 'True' then 1 else 0 end) as Negative_Count	3 row(s) returned

8. What are the most common symptoms among COVID positive males whose known contact was abroad?

The screenshot shows a SQL IDE interface with multiple tabs labeled 'SQL File 1*' through 'SQL File 8*'. The active tab is 'SQL File 8*'. The query editor contains a SQL query that counts the number of positive COVID test results for males with known contact abroad, categorized by symptom: Cough, Fever, Sore_throat, Shortness_of_breath, and Headache. The query uses a series of UNIONs to combine the results for each symptom.

```
3 • select 'Cough' as Symptom,
4     sum(case when Test_results = 'positive' and Cough = 'True' then 1 else 0 end) as Positive_Count
5     from covid_test where Sex = 'male' and Known_contact = 'abroad'
6     union
7     select 'Fever' as Symptom,
8     sum(case when Test_results = 'positive' and Fever = 'True' then 1 else 0 end) as Positive_Count
9     from covid_test where Sex = 'male' and Known_contact = 'abroad'
10    union
11    select 'Sore_throat' as Symptom,
12    sum(case when Test_results = 'positive' and Sore_throat = 'True' then 1 else 0 end) as Positive_Count
13    from covid_test where Sex = 'male' and Known_contact = 'abroad'
14    union
15    select 'Shortness_of_breath' as Symptom,
16    sum(case when Test_results = 'positive' and Shortness_of_breath = 'True' then 1 else 0 end) as Positive_Count
17    from covid_test where Sex = 'male' and Known_contact = 'abroad'
18    union
19    select 'Headache' as Symptom,
20    sum(case when Test_results = 'positive' and Headache = 'True' then 1 else 0 end) as Positive_Count
```

Below the query editor, the 'Result Grid' tab is active, displaying the results of the query. The results are as follows:

Symptom	Positive_Count
Cough	508
Fever	390
Headache	129

Below the result grid, the 'Output' tab is active, showing the execution log. The log contains two entries:

#	Time	Action	Message
✓ 46	07:51:39	select * from covid_test LIMIT 0, 1000	1000 row(s) returned
✓ 47	07:55:34	select 'Cough' as Symptom, sum(case when Test_results = 'positive' and Cough = 'True' then 1 else 0 end)...	3 row(s) returned