Machine Learning-based Quarantine Recommendations to Reduce COVID-19 Misclassification

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***Abstract*—The COVID-19, caused by the SARS-CoV-2 virus, emerged in Wuhan, China, in December 2019. Our study aims to create a machine learning model using data from the Israeli Ministry of Health to identify individuals requiring quarantine based on common symptoms, offering a more accessible alternative to traditional testing and reducing false positives.**

Keywords*—*SARS-CoV-2, isolation, machine learning, symptom classification, healthcare

I. Introduction

The coronavirus disease (COVID-19) is an infectious disease caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), which was originally called novel coronavirus in 2019. The COVID-19 had a widespread appearance in Wuhan, China, in December 2019. The worldwide transmission caused a pandemic declared on March 11, 2020, by the World Health Organization (WHO) [1]. It has caused nationwide lockdowns, impact on our health, society, and economy. The impact on public health management has presented us with difficulties in mitigating the spread of the virus, even with quarantine restrictions being implemented to halt the spread.

During the pandemic, different kinds of lockdown strategies were implemented in different countries, and each had their own effects in the long run [2], like psychological effects as it is strongly associated with symptoms of depression, anxiety, and insomnia [3], it also brought the economy to a halt which caused an immense economic losses for different industries, but lockdowns also gave time for environmental and natural resources to recuperate [4].

This study aims to develop a machine learning model to aid in identifying individuals that need to follow normal quarantine procedures based on the most common COVID-19 symptoms in [5]. Most of COVID-19 related models used in healthcare require laboratory tests [6], but our model can be used by individuals as a quarantine recommendation, thus, reducing potential risks involved in having tested in testing facilities.

II. Methods

A. Data Collection

We collected the COVID-19 Dataset from the Israeli Government website published by the Israeli Ministry of Health; it contains records of individuals who were tested for the first time from 2020 March to 2022 March.

TABLE I. Dataset Important Features

Testing Date
cough
fever
Sore Throat
Shortness of Breath
Headache
Laboratory Result
Age
Gender
Abroad
Contact with Confirmed Patient

B. Data Preprocessing

The dataset was first translated from Hebrew to English, and records containing empty values and records with non-binary features were removed. Since the dataset does not contain any numerical values, we decided to perform one-hot encoding to gender and test indication, after cleaning, it still had over 9,000,000 records of data.

The training-validation set that we used was based on testing date from 1st of January up until 10th of January 2022, it contains an imbalanced data with positive results being extremely small compared to negative results as shown in Table 1, this caused the model to us to perform resampling on the majority class to balance both classes. The testing data was from the 11th of March up until 31st of Match 2020, and resampling was also done to balance the data.

TABLE II. DATASET VALUE COUNT

Balanced Resampling Result				
Subset name	***Before***		***After***	
	Negative	Positive	Negative	Positive
Training-validation set	1,725,729	135,283	135,283	135,283
Testing set	100,431	27,400	27,400	27,400

C. Machine Learning Algorithms

The machine learning algorithm that we use was mostly derived from ensemble learning.

1) *Naive Bayes Classifier*
2) *Random Forest Classifier*
3) *Bagging Classifier*
4) *eXtreme Gradient Boosting Classifier*
5) *Stacking*

D. Metrics and Evaluation

The metrics and evaluation not only relied on the accuracy of the model but also recall and precision.

1) *Accuracy Score*
2) *F1-Score*
3) *area under Receiver Operating Characteristic (auROC) Score*
4) *ROC Curve*
5) *Precision-Recall Curve*
6) *Feature Importance*

III. RESULTS

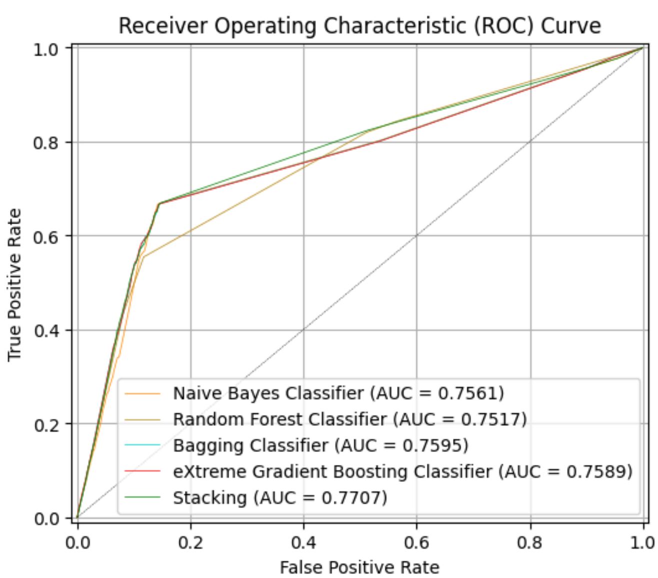

Fig. 1. ROC Curve of Classifiers

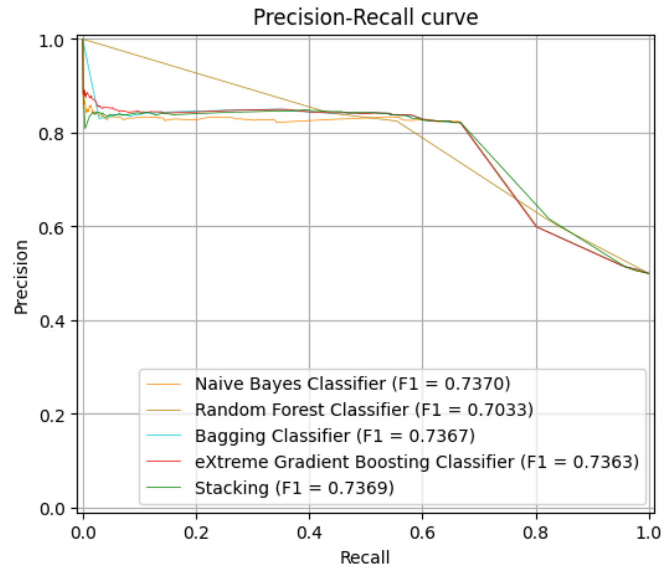

Fig. 2. Precision-Recall Curve of Classifiers

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Classification Report
              precision    recall  f1-score   support

           0       0.72      0.85      0.78    135283
           1       0.82      0.67      0.74    135283

    accuracy                           0.76    270566
   macro avg       0.77      0.76      0.76    270566
weighted avg       0.77      0.76      0.76    270566
```

Fig. 3. Naive Bayes Classifier Classification Report

```
Classification Report
              precision    recall  f1-score   support

           0       0.72      0.85      0.78    135283
           1       0.82      0.67      0.74    135283

    accuracy                           0.76    270566
   macro avg       0.77      0.76      0.76    270566
weighted avg       0.77      0.76      0.76    270566
```

Fig. 4. Random Forest Classifier Classification Report

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Classification Report
              precision    recall  f1-score   support

           0       0.72      0.85      0.78    135283
           1       0.82      0.67      0.74    135283

    accuracy                           0.76    270566
   macro avg       0.77      0.76      0.76    270566
weighted avg       0.77      0.76      0.76    270566
```

Fig. 5. Bagging Classifier Classification Report

```
Classification Report
              precision    recall  f1-score   support

           0       0.72      0.85      0.78    135283
           1       0.82      0.67      0.74    135283

    accuracy                           0.76    270566
   macro avg       0.77      0.76      0.76    270566
weighted avg       0.77      0.76      0.76    270566
```

Fig. 6. eXtreme Gradient Boosting Classification Report

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Classification Report
              precision    recall  f1-score   support

           0       0.72      0.85      0.78    135283
           1       0.82      0.67      0.74    135283

    accuracy                           0.76    270566
   macro avg       0.77      0.76      0.76    270566
weighted avg       0.77      0.76      0.76    270566
```

Fig. 7. Stacking Classification Report

IV. Discussion

The pandemic presented previously unheard-of difficulties for public health management. It was challenging to contain the virus even with strict quarantine protocols. The psychological toll on society made clear the necessity of all-encompassing plans that address mental health during times of crisis.

The lockdowns brought by the pandemic stopped economic activity and resulted in significant losses for all industries of the economy. In the face of a health crisis, job losses, company closures and interruptions in supply lines highlighted how fragile the economy was. This study aims to create a machine learning model for identifying individuals requiring standard quarantine based on common COVID-19 symptoms.

In Table III, we can see that the results of all classifiers used almost had no change, performing Stacking on all the models, we managed to achieve an auROC score of 77.07%, which is comparably higher than the average auROC score of all the classifiers.

TABLE III. Models Evaluation Scores

Evaluation Scores			
Classifiers	***Accuracy Score***	***F1 Score***	***auROC Score***
Naive Bayes	76.10%	73.69%	75.61%
Random Forest	76.08%	73.59%	75.88%
Bagging using Random Forest	76.10%	73.66%	75.94%
eXtreme Gradient Boosting	76.10%	73.62%	75.89%
Stacking	76.10%	73.69%	**77.07%**

Despite its potential, the model has its limitations. Identifying patients based only on symptoms may not yield to conclusive diagnosis, which could result in incorrect suggestions.

Following studies need to focus on enhancing the model's precision by integrating more extensive datasets and advanced machine learning procedures. In addition, the effectiveness of the model in public health campaigns can be increased by addressing its use in a variety of populations to its interactions with healthcare systems.

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