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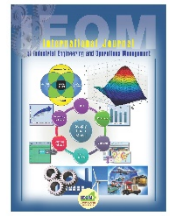

Predicting Average Wait-Time of COVID-19 Test Results and Efficacy Using Machine Learning Algorithms

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ABSTRACT

Due to the rising number of confirmed positive tests, the global impact of COVID-19 continues to grow. This can be attributed to the long wait times patients face to receive COVID-19 test results. During these lengthy waiting periods, people become anxious, especially those who are not experiencing early COVID-19 symptoms. This study

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aimed to develop models that predict waiting times for COVID-19 test results based on different factors such as testing facility, result interpretation, and date of test. Several machine learning algorithms were used to predict average waiting times for COVID-19 test results and to find the most accurate model. These algorithms include neural network, support vector regression, K-nearest neighbor regression, and more. COVID-19 test result waiting times were predicted for 54,730 patients recorded during the pandemic across 171 hospitals and 14 labs. To examine and evaluate the model's accuracy, different measurements were applied such as root mean squared and R-Squared. Among the eight proposed models, the results showed that decision tree regression performed the best for predicting COVID-19 test results waiting times. The proposed models could be used to prioritize testing for COVID-19 and provide decision makers with the proper prediction tools to prepare against possible threats and consequences of future COVID-19 waves.

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KEYWORDS
Machine Learning algorithms, Waiting time prediction, COVID-19 test results

1. Introduction

Since the novel COVID-19 virus was first identified in Wuhan, China on November 17, 2019, the disease has resulted in numerous infections worldwide and record-high mortalities (Helen 2020). Most countries have begun offering tests for those who are symptomatic and suspected to have COVID-19. According to consistent global reports, COVID-19 test results have routinely been delayed by at least a week, and sometimes much longer. Others are faced with longer waiting times at overwhelmed testing centers and cannot receive swabs at all (Jamie 202). Furthermore, some COVID-19 results require more than a week due to bottlenecks in testing supply chains (Conner 2020). One or more weeks is considered an unsafe waiting time because people may not seriously change their behavior, such as limiting exposure to others while waiting to receive their results. This may be contributing to why COVID-19 is continuing to spread very rapidly.

Due to the rate of spread, where an average infected person is capable of spreading it to more than three other people, COVID-19 has been considered highly communicable. Hence, it has an exponential rate of increase since its outbreak (Gates 2020). As noted by numerous governments worldwide, the disease poses a massive threat to humanity and it is only through early intervention and decisive action that nations can curtail it. However, this perception was not common among all governments. Some nations implemented early and effective control measures, whereas some countries overlooked the threat, thereby delaying control measure implementations.
One nation quick to execute containment measures was China. The government implemented unprecedented non-pharmaceutical interventions aimed at stopping the spread of the disease from its epicenter in Wuhan to other cities in the Hubei province through restrictions in travels in and out of the region. In addition, they closed all learning institutions and suspended air, road, and rail transport, and isolated the reported cases (Cyranoski 2020). Also, between February 2 and March 30, 2020, the government of Saudi Arabia announced precautionary measures by suspending flights, schools, public, private, and university education institutions and entry to individuals wishing to perform Umrah in Mecca or visit the Mosque in Medina (Komies et al. 2020).

Since the outbreak spread quickly, managing delays of COVID-19 test processes became an essential part of hospital management during the pandemic for several reasons. For example: (i) the long wait to get test results may have affected the healthcare system later by increasing the treatment demand and the capacity. For instance, cases were not adequately being controlled in the early stages. For asymptomatic people (those without symptoms), they take the test and wait for the results. In the interim, they may continue to have contact family and relatives, increasing the spread of the disease (Matt 2020), (ii) the delays of test results disproportionately affects people with adverse health conditions, such as older people or those suffering from chronic diseases (Garg and Wray 2020), (iii) long wait times for results disrupt life, such as school and work, and make it difficult for public health administrators to adapt their responses to the correct people (those who are infectious and people to whom they may have spread the disease). For example, in the United States, some schools and universities announced decisions for the Spring and Summer 2021 semesters, where students would continue with online education platforms (Wilmington University 2020; Khitam Al Amir 2020), (iv) due to a record high demand for the COVID-19 tests, labs continue to be overwhelmed. Testing centers in California and Texas were forced to close because of a surging demand (Kerry 2020).

The ability to accurately predict the waiting time for COVID-19 test results may increase patient satisfaction and effectively improve the healthcare system (Conner 2020). This improvement will be accomplished by predicting the waiting times for COVID-19 test results based on predictive factors such as test location and labs where patients took the COVID-19 test (as queues or lines for patients). Even though the patients are not in a physical line, they still count as people waiting for service to be finished. Therefore, when patients (e.g., 200 patients) send their tests to facility 1 (queue1), and the next group of patients (e.g., 200 patients) goes to the second facility (queue2), when the third group of patients has to do a test, decision makers can determine how much waiting time is left in facility 1 versus facility 2 using a prediction. If facility 2 shows a lower waiting time, the third group can be assigned to facility 1. This process is repeated for a number of facilities (queues) and a number of patients. This example shows how patient waiting time analysis is essential based on the predictive factors including the sending facility (location where the patient took the exam, such as hospitals).

Predicting COVID-19 test result waiting time can enable healthcare management and governments to respond to pandemics more accurately. In this research, multiple machine learning (ML) algorithms were leveraged to forecast COVID-19 test result waiting times based on different factors to support healthcare management using real-life data from *HESN* system in Saudi Arabia. Also, these predictions allow for informed decisions during the pandemic, which may motivate other researchers to conduct additional work by applying models to the other areas in the Middle East, Africa, and other areas with similar populations. Furthermore, this study's novelty lies in a huge amount of analyzed data which has been recorded throughout the pandemic. Moreover, multiple machine learning algorithms are implemented which will add to the current literature and may be used to anticipate and better optimize risk management, such as managing situations where the ICU capacity is exceeded.

This paper is organized for the remaining sections as follows: Section 2 introduces the related work presented in the current literature. Section 3 describes the proposed methodology with subsections inducing preparation of data and preprocessing procedures then using machine learning algorithms, evaluation and prediction. The results present in Section 4 and a discussion can be found in Section 5. Finally, the conclusions and future work of this research are provided in Section 6.

2. Literature Review

Several studies have attempted to propose models for COVID-19 prediction using different methodologies. For example, classification models and mathematical approaches have been implemented to predict COVID-19 symptoms based on patient hospitalization, death, and ICU beds (Manca et al. 2020; Wollenstein et al. 2020). They have also been used to predict positive COVID-19 cases reported and the spread of the virus (Arora et al. 2020). Similarly, Zivkovic et al. proposed hybrid machine learning algorithms method to predict new COVID-19 cases. They improved the current time-series forecasting of beetle antennae search (BAS) algorithm and the adaptive neuro-fuzzy inference system (ANFIS) machine learning method (Zivkovic et al. 2021). Moreover, a machine learning model proposed by (Zoabi et al. 2021) to predict COVID-19 diagnosis based on symptoms using data from Israel. Several features were used in this study to estimate the risk of infection such as sex, age and symptoms (Cough, Fever, Sore throat etc.)

A survey conducted for COVID-19 diagnostic test results across 50 states between July 10 and 26, 2020 found that the United States was not performing testing with nearly enough speed. The study results reported the mean waiting time of COVID-19 test results to be 4.1 days, with a median waiting time of about 3 days. Only 21% of sample people waited more than five days and 37% waited for within 2 days (Lazer et al. 2020). The average waiting time was 2.5 days per the data used in this research. Only 0.7% of the sample people waited for more than five days, and 74.4% waited for within 2.5 days. According to the authors in (Lazer et al. 2020) the ideal time for test results should be returned within the same day.

Predictive models have long been used to understand and predict how diseases spread in populations (Cleveland Clinic 2020; DAS 2020). Machine learning (ML) techniques play a very critical role in yielding accurate predictions (Shinde et al. 2020). Aspects such as ML, reasoning, planning, and memory, among others, are part of the concept of Artificial Intelligence (Brownlee 2018). Predictive modeling, or predictive analytics, involves studying the creation of computer programs that learn and adapt when exposed to new data (Mitchell 1997). Observation or statistical data, for instance, is used to induce the algorithms, and subsequent optimization of their performance is the most common type of learning in ML.

Other examples of studies using ML approaches in the literature include predicting patient hospital admission (Parker et al. 2019), waiting time prediction and patient delay (Curtis et al. 2018), predicting patient waiting time to be seen by doctor (Pak et al. 2020), predicting the mortality of patients diagnosed based on their sociodemographic and health information (An et al. 2020), and patient discharge time from hospital (Nemati et al. 2020).

In other ML algorithm application areas, Artificial neural network (ANN) plays a critical role in the dynamic characteristics prediction, (Arun and Mallikarjuna 2020b), studded the effect of delamination in laminated composite plate structures where the algorithms used to minimize the complex mathematical model and computational time. Similarity, Masanobu (2019) used artificial neural network and support vector machines to predict the risk of bankruptcy for Japanese stock companies, including both the entire industry and individual accounts. Applying advanced ML and data driven techniques, Arun and Mallikarjuna (2020a) studied damage detection using a simple beam model to identify multiple structural damages using the signal or shape of the same damaged beam. The damaged procedure was identified using Wavelets and Local Regularity algorithms. Similarly, Mallikarjuna et al. (2015), proposed a new method to explain detecting structural damage for the beam and bridge modes of the spatial signals using empirical mode decomposition.

3. Methodology

In this section, ML algorithms were applied to predict the waiting times for COVID-19 test results based on predictive factors such as receiving lab and sending facility. Different algorithms were trained, including network (NN), support vector regression (SVR), linear regression (LR), K-nearest neighbor regression (KNN), gradient boosting regression (GBRT), extra trees regression (ET), decision tree (DT), and random forest (RF). Also, different performance measures (metrics) were used to evaluate the models, such as mean square error (MSE), mean absolute error (MAE), root mean square (RMSE) and R-Squared to estimate and evaluate the model performance. Finally, the proposed models were compared to determine which one works best across all predictive factors using the lowest measures indicated by evaluation metrics. The proposed methodology stages are presented, and a flowchart is shown in Figure 1. Each step is illustrated in the following subsections.

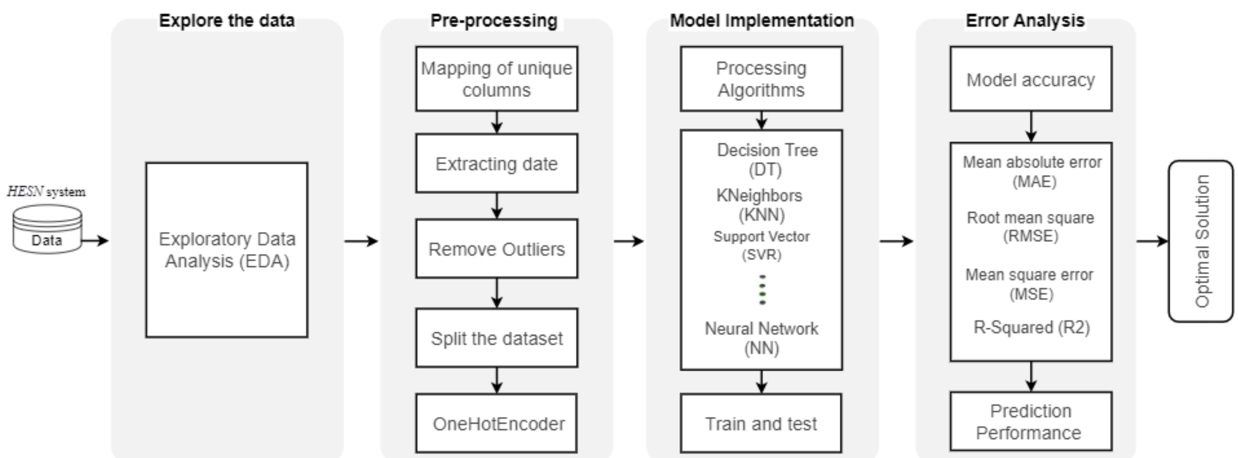

Figure 1. A framework of proposed methodology

3.1 Data preparation

Data were used from the Saudi Arabian Ministry of Health's *HESN* system. Data were obtained between March and July of 2020 and comprised 54,730 patients (around 70.8% were negative cases and around 23.3% were positive cases) as shown in Table 1. *HESN* is an online platform that monitors disease management and offers health professionals and decision-makers accurate information (MOH 2020). Data demographics included patient age, gender, and nationality, as well as test status, result status (complete and rejected), receiving lab, result interpretation (positive and negative), date time required (the date that patient took the test), and result date time (the date of receiving the results). Also, the data included results from COVID-19 testing in multiple departments within one hospital, including an emergency room. From the required date and result date, waiting time was calculated, which is the difference between the date and time the test was requested, and the date and time results were received. Some of the required date-time categories came without time of test taken in the dataset but these still had dates provided. For this data, we assigned a time placeholder of 00:00:00.

3.2 Data analysis

As an initial step of this project, different tables and plots were derived from the data and explored to understand the trends therein to achieve the best outcomes. First, the dataset was summarized based on the input's factors such as gender, result status, and result interpretation, as shown in Table 1. A total of 54,730 patients were recorded in the dataset, which was 31.3% female and 68.7% male. A total of 54,730 tests were conducted; 53,016 tests were completed (around 96.8% of total data); three were preliminary and around 1,709 were rejected (around 3.2% of total data). In result interpretation, the negative results of the dataset totaled 38,750 (around 70.8% of total data) and 12,763 positives (around 23.3% of total data). As expressed in the table, a massive number of cases were negative. The large negative rate reflects the expanded testing conducted by the Ministry of Health in Saudi Arabia. According to the Division of Public Health, "Expanded Testing is considered one of the initiatives carried out by the government to respond to COVID-19 outbreak, which has been launched through a few stages. It aims to benefit both citizens and residents by expanded testing to evaluate the COVID-19 spread"(Public Health - Expanded Testing 2020).

Table 1. Summary statistics of dataset between March and July 2020

	Statistical Summary		
	Frequency	Percent	Cumulative Percent
Gender			
Female	17,135	31.3	31.3
Male	37,595	68.7	100.0
Result Status			
Complete	53,016	96.8	96.8
Pending	2	.0	.0
Preliminary	3	.0	.0
Rejected	1709	3.2	100.0
Result Interpretation			
Negative	38,750	70.8	70.8
Positive	12,763	23.3	94.1
Rejected	1939	3.5	97.6
Repeat Sample	1,278	2.4	100.0
Total	54,730	100.0	

Second, the waiting times for COVID-19 test results were analyzed within one week of wait time using the dataset because the literature noted complaints that the waiting time of test results are delayed by more than one week (Jamie 2020). Table 2 shows how many patients waited between less than 1 day to more than 5 days. The waiting times were divided into groups (waiting time <1 day, between 1 and 2.5 days, between 2.5 and 5 days, and more than 5 days). As shown below, 5.1% of patients waited for less than 1 day, 74.4% waited for their results between 1 and 2.5 days, and 19.8.% incurred a waiting time between 2.5 and 5 days. Only 0.7% had waiting times of more than 5 days.

Table 2. Waiting times analysis between less than 1 day to more than 5 days

	Waiting Time Grouped		
	Frequency	Percent	Cumulative Percent
Less than 1 day	2,785	5.1	5.1
Between 1 and 2.5 days	40,688	74.4	79.5
Between 2.5 and 5 days	10,885	19.8	99.3
More than 5 days	372	0.7	100.0
Total	54,730	100.0	

Third, waiting times based on other factors were analyzed including patient gender, result status, and result interpretation, as shown in Table 3. Based on the initial results, there was no statistical significance based on gender difference for the wait time; the average waiting time for both genders was roughly the same at approximately 2.4 days each. Around 51,005 patients who completed test results waited for 2.4 days, and for two patients, the result status was pending for 2.9 days. Around 38,254 patients waited 2.4 days for negative results and 12,101 patients with positive results waited for 2.3 days.

Table 3. Summary for Mean waiting time based on selected factors

	Statistical Summary		
	Mean	**N**	**Std. Deviation**
Gender			
Female	2.398	15,944	0.887
Male	2.405	36,299	0.887
Result Status			
Complete	2.496	51005	0.891
Pending	2.954	2	2.011
Preliminary	2.273	3	0.951
Rejected	2.408	1,233	0.891
Result interpretation			
Negative	2.403	38,254	0.890
Positive	2.399	12,101	0.893
Rejected	2.375	597	0.905
Repeat Sample	2.370	1,291	0.918

Then, the average waiting time per lab was analyzed, as shown in Table 4. There were 14 labs in the dataset. Only 5 labs were used in the training process and these labs had more than 50 recorded cases. The names of the labs were coded by numerals, e.g., lab 1 to lab 5. This was done to simplify the analysis. Most labs' mean waiting time was approximately 2.0 to 2.5 days. The highest mean waiting time by receiving lab was recorded for Lab 1, who had a 2.5-days average turnaround time, as compared to the lowest waiting time of 2.0 days at Lab 2.

Table 4. Summary of Mean waiting time based on receiving labs

	Statistical Summary (receiving labs)		
	Mean	**N**	**Std. Deviation**
Lab 1	2.499	13,958	0.879
Lab 2	2.063	108	2.602
Lab 3	2.305	368	2.344
Lab 4	2.426	1,168	0.861
Lab 5	2.396	39,128	0.889

An extra regressor was used to calculate feature importance, as shown in Figure 2. The input features were placed on the y axis. On the x axis, an impotence score was placed, which is also illustrated in the score figure below. The receiving lab and sending facility had the most contribution toward the output prediction.

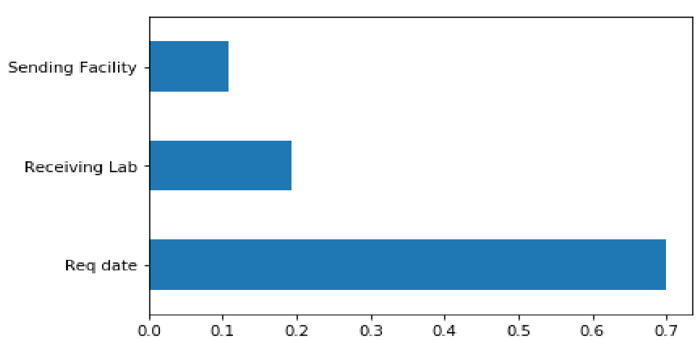

Figure 2. Features importance tests for retained features

Finally, the basic process of analyzing the dataset helped us choose the best features to apply in training models. Moreover, to maximize the best outcomes of the prediction models, at the end of the study, the actual and predicted results based on those input factors were compared.

3.3 Preprocessing

Data preprocessing is a necessary step in ML problems. Different basic programs were developed in Python to explore the data and identify missing value and outliers, encode string value, split dataset and feature scaling. All the rows with missing values were deleted from the dataset, and the outlier values were analyzed by removing them from the dataset before training. Also, irrelevant features such as patient IDs and names were removed from the dataset. One-hot encoding was used to encode all the categorical data into binary. Feature selection is an essential part of the ML model structure that determines the model performance and was therefore incorporated into our process as well. Also, the input factors were checked to ensure they positively correlated with outputs. Variables with similar information were deleted to improve the performance of the models, which allowed the algorithms to learn faster and decreased overall bias. Similarly, we checked the input factors that had an effect on the waiting and later in the training process, the factors that were not directly related to waiting time were removed.

3.4 Prediction and evaluation

In this stage, two techniques were used. The data was first split into Train and Test Sets. Next, K-fold Cross-Validation was implemented for the machine learning algorithms to evaluate all models and to split up the training dataset. Initially, the data was split into two datasets (20% and 80%): the first set was used to test the model and consisted of data that the model had not encountered prior. The second dataset was used to train the K-fold cross validation model. Once that was finished, the model checked its validity with the hidden dataset. Then for more accuracy, Cross-Validation was used again to estimate the performance of machine learning regression algorithms with less variance than a single train-test set split (Moss et al. 2018). The dataset was split into k-parts (K being equal to 5). Also, it was essential to use metrics in machine learning applications to evaluate the algorithms. The four standard metrics used in this research to evaluate the prediction on regression models were MSR, MAE, RMSE, and R-Squared (Kyritsis and Deriaz 2019).

All the modeling steps, including data preparation, preprocessing, training and testing, and parameter tuning, were achieved using Python 3.7. In the regression models, 8 regression algorithms were used to spot check and train the dataset. First, we applied linear algorithms, such as multiple linear regression (LR). Then, nonlinear algorithms, such as support vector (SVR), and K-nearest neighbors' regression (KNN), were applied. Also, fully connected neural network models were trained with two hidden layers (the first layers = 6 neurons and the second hidden layers = 4 neurons). Finally, the results for different algorithms were compared to determine the best choice from the prediction model. This is indicated by different metrics versus applied algorithms in the results section, as presented in Table 5.

4. Results

Several models were evaluated by visualizing their actual and predicted waiting times for COVID-19 test results based on sending facility and receiving lab, as shown in Figures 3 and 4 below. COVID-19 test result waiting times were predicted for 54,730 patients recorded across four facilities and 5 testing labs. DT, ET and RF reported as the best performing algorithms among all models indicated by R-Squared and RMSE metrics, as shown in Figure 5.

Sending facility is the place where patients must go to receive a COVID-19 test. These facilities include hospitals, clinics, or testing centers. There were 171 facilities in the dataset and the waiting time per facility was predicted using multiple regression (linear and nonlinear) and neural networks. Sending facilities were mapped based on geographical location, for example middle centers, northern centers, southern centers, and northwest centers. All centers in the southern area were grouped under one area called "southern centers." Figure 3 (a and b) shows the predicted waiting times for COVID-19 test results and actual versus sending facility. The red dots in Figure 3(a) represent the actual waiting time for patients' test results, and the blue dots in Figure 3(b) represent the predicted waiting times. As shown, the most waiting time occurred between less than 1 day to 6 days, with a mean waiting time of around 2.5 days.

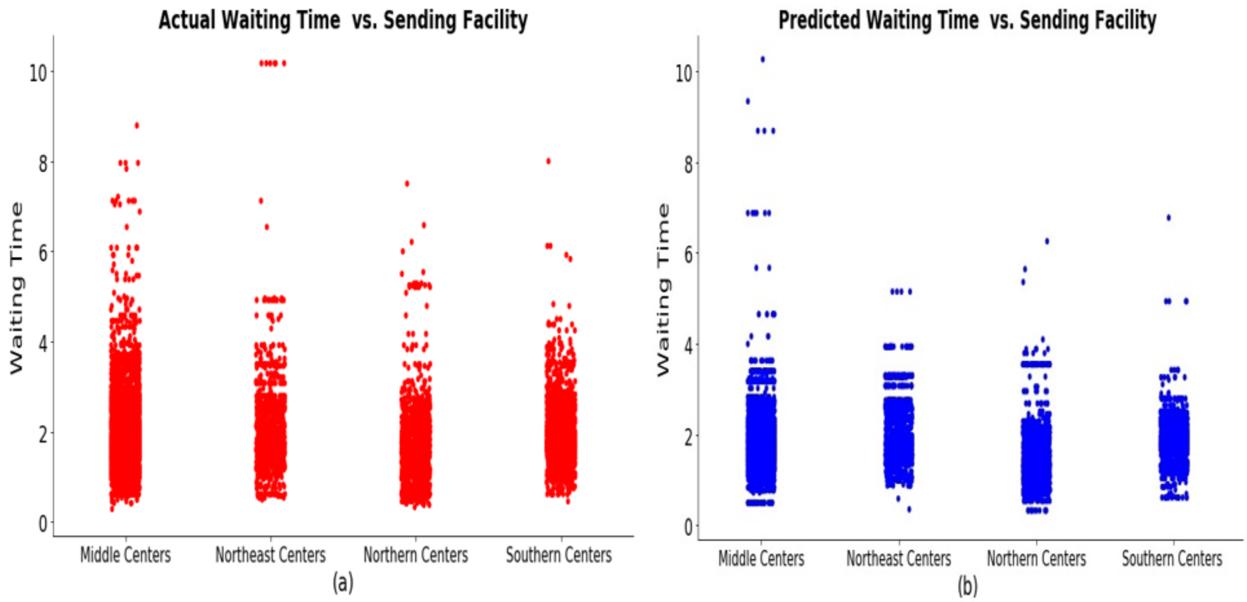

Figure 3. The waiting time of COVID-19 test results (actual and predicted based on facilities)

The models predicted the waiting times for COVID-19 test results based on receiving labs, Figure 4 (a and b) shows predicted and actual versus receiving labs. Receiving labs are where the COVID-19 tests are sent for analysis. The number of test cases were in each lab, and how long the waiting times were during the lab process, are illustrated in Figure 4(a). Also, receiving labs were mapped from real lab names to be Lab 1, Lab 2, Lab 3 and so on. As shown in Figure 4, Lab 1 and Lab 4 had the highest waiting times; each passed seven days with a few cases, whereas the majority of other labs (2, 3 and 5) were between 1 to 5 days wait time.

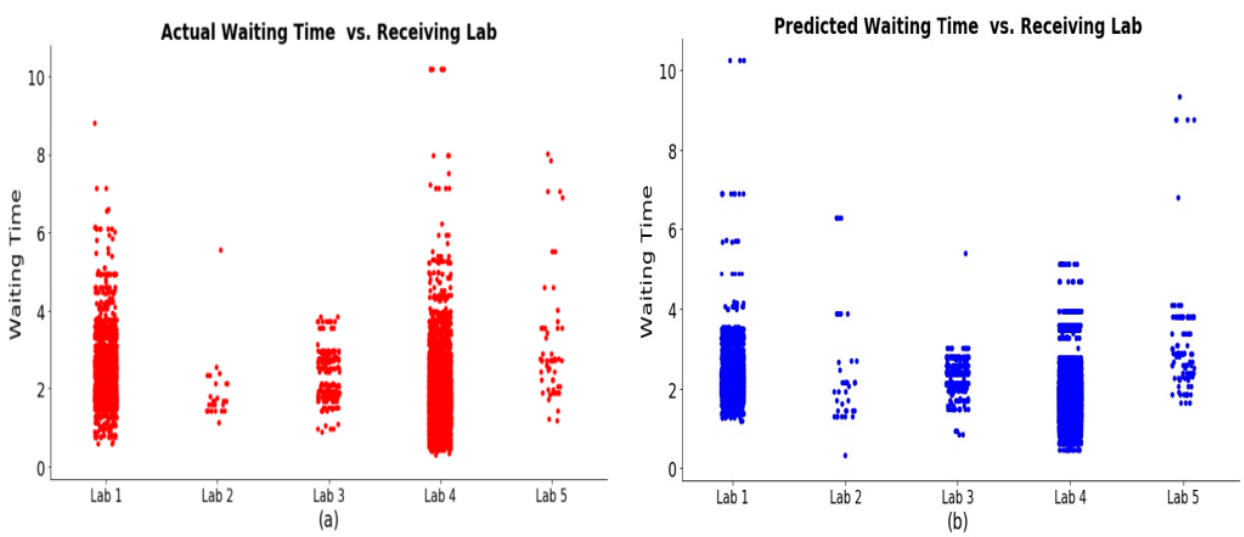

Figure 4. The waiting time of COVID-19 test results (actual and predicted based on labs)

The overall results of all models' predictions performance were investigated using evaluation metrics, as shown in Table 5. As shown below, the results of model performance varied across all algorithms. For example, out of all the algorithms, the lowest performance with MAE was about 0.40 to 0.53, around 0.38 to 0.54 with MSE, and around 0.62 to 0.74 with RMSE. It is worth noting an interesting result: of the models that applied R-Squared, only three algorithms performed highly. These models were decision tree regression (DT), extra tree regression (ET) and random forest regression (RF). The results are summarized in Table 5 below.

Table 5. Summary of models' algorithms using evaluation metrics

Algorithms	**Models**			
	MAE	MSE	RMSE	R-Squared
Decision Tree Regression (DT)	0.424	0.388	0.623	0.365
Extra Tree Regression (ET)	0.423	0.389	0.623	0.366
Gradient Boosting Regression (GBRT)	0.464	0.442	0.665	0.276
K-Neighbors Regression (KNN)	0.449	0.459	0.677	0.249
Linear Regression (LR)	0.534	0.574	0.757	0.062
Random Forest Regression (RF)	0.423	0.388	0.623	0.366
Support Vector Regression (SVR)	0.401	0.428	0.654	0.300
Neural Network (NN)	0.498	0.547	0.739	0.105

Note: mean square error (MSE), mean absolute error (MAE), and root mean square error (RMSE)

The algorithms were ranked based on performance using a combination of matrices. The prediction performance was compared using R-Squared versus RMSE across all models, as shown in Figure 5. The highest performing model found to predict the waiting time for COVID-19 test results was DT, followed by ET and RF, as shown in the top left corners of the figure. These models resulted in the lowest RMSE and highest R-Squared performance among all algorithms. As revealed in the figure, DT performance results were not far from ET and RF; in fact, they were almost the same. This makes sense because ET and RF are also tree algorithms; however, DT is the simplest regarding overall usability.

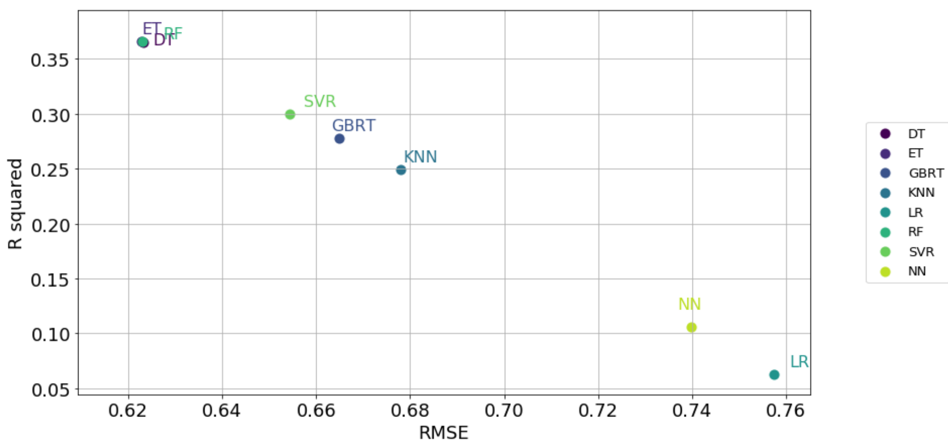

Figure 5. Comparison of prediction models (RMSE Vs. R-Squared)

5. Discussion

COVID-19 test results sometimes require more than a week due to bottlenecks in testing supply chains. This is considered an unsafe waiting time, which may be why the COVID-19 is continuing to spread so rapidly. Furthermore, the delay of test results disproportionately affects people with adverse health conditions, such as older people or those suffering from chronic diseases. Managing delays of the COVID-19 tests process became an essential part of hospital management during the preparation and planning of increased medical needs overcoming the uncertainty time of pandemic (Garg and Wray 2020).

This study aimed to provide the healthcare division with more accurate models to predict the waiting times for COVID-19 test results based on selected factors using machine learning algorithms. The models are an essential tool for responsive and proactive action during the pandemic. If healthcare providers and authorities have prior knowledge of average waiting times for labs using prediction, it can greatly improve the healthcare system. For example, they can reduce waiting times of longer than 2.5 days by improving the services through sending test samples to labs with fewer tests, as predicted in Figure 4 in the results section. Similarly, as shown in Figure 3, it is easy to identify which center is struggling with immense numbers of tests and long waiting times. Also, as noted in the literature, there are complaints that the waiting time for test results have been delayed in some cases by more than one week (Jamie 202; Matt Berger 2020). The results of this study show waiting times based on patient testing centers and labs, within ten days. However, the findings show that the average waiting time in the prediction within one week is 2.5-days as compared with complaints in the literature.

Some studies in the literature have attempted to propose models for COVID-19 prediction using different methodologies. For example, classifier models and mathematical approaches to predict the COVID-19 symptoms based on patient hospitalization, death, and ICU beds needed as suggested in (Manca et al. 2020; Wollenstein-Betech et al. 2020). Also, Zoabi and Shomron proposed machine learning models to predict COVID-19 diagnosis based on symptoms using Several features such sex, and age (Zoabi et al. 2021). These studies are limited by instigating local data of COVID-19 cases prediction. Also, there is no study in literature attempting to predict COVID-19 symptoms considering the waiting time of test results using multiple machine learning algorithms, such as a regression and Neural Network as presented in this research. Moreover, recent research in the literature reported small sample sizes and model accuracy as limitations in proposed models' prediction for diagnosis and prognosis of COVID-19 (Wollenstein et al. 2020). The current study provided a novel model focused on predicting COVID-19 symptoms, considering the waiting time of test results with appropriate sample size and more accurate prediction performance. This was motivated by small sample sizes and locality data collection in previous studies (Wynants et al. 2020). Furthermore, this work compared the best model performed with the previous study model performance indicated by RMSE for prediction error (Curtis et al. 2018). Moreover, the proposed method in this work could benefit both practitioners and researchers who work on similar problems in different fields such as waiting time for services and customer queueing.

There were some limitations in this research. It is necessary to clarify that the dataset used in this research did not include certain information that may affect the waiting times, such as how long the test samples took to transfer from testing centers to receiving labs. The reader should be aware that COVID-19 policies and restrictions vary by jurisdiction, which could affect the model's stability. For example, the supply of detection kits, mask-wearing, or isolation policies may differ in different countries or provinces. Also, this study investigated the COVID-19 test result waiting time issue in only one particular jurisdiction, (i.e., Saudi Arabia), which may have an impact on the global generalizability of the findings.

6. Conclusion

This study's novelty lies on a huge amount of data analyzed which is recorded during the pandemic and it contributes to machine learning literature by implement multi-algorithms (such as NN, SVR, LR, KNN, GBRT, ET, DT, and RF) to predict waiting times for COVID-19 test results. A significant improvement was achieved in model performance using different metrics including MSR, MAE, RMSE, and R-Squared. The most accurate model was DT, followed by ET and RF. These models resulted in nearly identical performance ratings, though DT outperformed other ML algorithms in prediction accuracy, simplicity and explainability than ET and RF.

Research in the literature reported that the mean waiting time of COVID-19 test results was delayed by at least a week, and sometimes much longer, which motivated this study for further analysis. On the other hand, the models presented in the literature have small sample sizes and limited accuracy. This research provided an essential tool to predict waiting times for COVID-19 test results using multi machine learning algorithms. The model can reduce error prediction and achieve better accuracy, when compared with studies in literature. Moreover, the proposed models can help medical decision-makers prepare for future demands. It gives the healthcare providers an initial measurement of the COVID-19 test process and the action needed to improve the service (e.g., increases in the centers or speed up the process). Furthermore, the models can provide data to inform guidelines and provide decision makers with the proper prediction tools to prepare against possible threats and consequences for future waves of COVID-19. The theoretical contribution of this paper is to predict average waiting times of COVID-19 test results with multi machine learning algorithms and achieve the best performing model. Also, a practical contribution was offered in this study by using real-life data from *HESN* system, Saudi Arabia recorded during the pandemic.

Only the waiting time was used in this work. To extend the work of this research, perhaps the average time per lab could be used to compare results. Also, variables such as result status (rejected or repeat sample) could be used to analyze waiting time of COVID-19 test results. Other factors could be included to analysis the waiting time in extended work such as how long the test samples take to transfer from testing centers to receiving labs. Moreover, the impact of the current model could be studied by comparing it with more data collection globally. Also, the models could be implemented on similar problems in different fields, including waiting time for services and customer queueing problems. In future iterations and to translate this work into practice, we plan to deploy the DT model as a web application to predict waiting time for COVID-19 test results with ease. Also, apply the model in a different area, compare it with current work and incorporate other variables.

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