International Journal of Electrical and Computer Engineering (IJECE)
Vol. 13, No. 4, August 2023, pp. 4761~4776
ISSN: 2088-8708, DOI: 10.11591/ijece.v13i4.pp4761-4776

Susceptible exposed infectious recovered-machine learning for COVID-19 prediction in Saudi Arabia

Mutasem K. Alsmadi[1], Ghaith M. Jaradat[2], Sami A. Abahussain[3], Mohammed Fahed Tayfour[1], Usama A. Badawi[1], Hayat Alfagham[1], Muneerah Ebrahem Alshabanah[1], Daniah Abdulrahman Alrajhi[1], Hanouf Naif ALkhaldi[1], Njoud Ahmad Altuwaijri[1], Hany Answer ShoShan[4], Hayah Mohamed Abouelnaga[4], Ahmed Baz Mohamed Metwally[4]

[1]Department of Management Information Systems, College of Applied Studies and Community Service, Imam Abdulrahman Bin Faisal University, Dammam, Saudi Arabia
[2]Department of Computer Science and Information Systems, Faculty of Computer Sciences and Informatics, Amman Arab University, Amman, Jordan
[3]Department of Business Administration, College of Business Administration, Imam Abdulrahman Bin Faisal University, Dammam, Saudi Arabia
[4]Department of General courses, College of Applied Studies and Community Service, Imam Abdulrahman Bin Faisal University, Dammam, Saudi Arabia

Article Info

Article history:

Received Sep 29, 2020
Revised Jan 10, 2023
Accepted Jan 14, 2023

Keywords:

COVID-19
Deep neural network
Disease spread
Lockdowns
Machine learning
Saudi Arabia
Susceptible exposed infectious recovered model

ABSTRACT

Susceptible exposed infectious recovered (SEIR) is among the epidemiological models used in forecasting the spread of disease in large populations. SEIR is a fitting model for coronavirus disease (COVID-19) spread prediction. Somehow, in its original form, SEIR could not measure the impact of lockdowns. So, in the SEIR equations system utilized in this study, a variable was included to evaluate the impact of varying levels of social distance on the transmission of COVID-19. Additionally, we applied artificial intelligence utilizing the deep neural network machine learning (ML) technique. On the initial spread data for Saudi Arabia that were available up to June 25th, 2021, this improved SEIR model was used. The study shows possible infection to around 3.1 million persons without lockdown in Saudi Arabia at the peak of spread, which lasts for about 3 months beginning from the lockdown date (March 21st). On the other hand, the Kingdom's current partial lockdown policy was estimated to cut the estimated number of infections to 0.5 million over nine months. The data shows that stricter lockdowns may successfully flatten the COVID-19 graph curve in Saudi Arabia. We successfully predicted the COVID-19 epidemic's peaks and sizes using our modified deep neural network (DNN) and SEIR model.

Corresponding Author:

Mutasem K. Alsmadi
Department of Management Information Systems, College of Applied Studies and Community Service, Imam Abdulrahman Bin Faisal University
P.O. Box 1982, Dammam, Saudi Arabia
Email: mksalsmadi@iau.edu.sa

1. INTRODUCTION

As a result of several baffling instances of lower respiratory tract illnesses that were confirmed in China in December 2019, a coronavirus with a genetic relationship to the SARS virus (SARS-CoV-2) was discovered and named coronavirus disease (COVID-19) by the World Health Organization (WHO). The fundamental R0 (reproduction number) estimates for the epidemic's spread in mainland China range from 2.2

to 3.3, with a mortality rate of around 2.3 percent [1]–[8]. It was discovered that most COVID-19 patients in China were men who were older than 30. Fatigue, a fever, and dry cough are some of the basic COVID-19 symptoms. In addition, lymphopenia was the main type of laboratory abnormality [9]–[11]. In Singapore, a study of COVID-19 patients indicated that moderate respiratory tract infections were most common, with oxygen supplementation being rare [12]. To combat this illness, efficient SARSCoV-2 vaccinations and antibody-based medications are required. Currently, responsible bodies throughout the world have examined 90 vaccinations and more than 50 antibody methods [6], [13]–[15]. There are still questions since the virus is still not well known [16], [17], and because COVID-19 is spreading quickly, it is currently unable to create effective vaccinations or other treatment medicines [6], [18]. Lockdowns, along with other strict controls (such as curfews), have traditionally been used in many nations to ensure social distance [18]. The capacity of the current health systems in many nations has been exceeded by the rising number of COVID-19 patients [18], [19]. The only way to combat a pandemic without vaccination and the proper medical care is to flatten the pandemic curve.

The spread of COVID-19 might be predicted using a variety of techniques, such as data-driven analysis, soft computing techniques, and lately, numerical simulations [20]–[23]. The literature has extensively reported on the uses of the susceptible infectious removed (SIR) and susceptible exposed infectious recovered (SEIR) models in this context [19], [22]. Relevantly, using COVID-19 time series data, ensemble empirical mode decomposition (EEMD) and artificial neural network (ANN) based techniques are implemented in Hasan [23]. Additionally, Pinter *et al.* [24] in the context of Hungary showed the use of machine learning to estimate mortality rates and the number of affected individuals. Importantly, Bhardwaj and Bangia [25] used hybrid soft-computing techniques to calculate the spread hazards of COVID-19. Several reports have employed artificial intelligence methods to gather imaging data, segment it, and diagnose COVID-19 [26]. Where these methods have been used in the past to address different artificial intelligence issues and have shown promise [27]–[47]. Lockdowns are a useful tactic for reducing the spread of COVID-19. However, this aspect is ignored by the original SEIR epidemiological model. The current study, meantime, demonstrates how the COVID-19 lockout levels may prevent transmission in the Kingdom of Saudi Arabia. As shown, 3.1 million people might be impacted in the region without the use of lockdowns at the height of dissemination about two months after a lockdown (March 8^{th}). On the other hand, the estimated peak number of infections is roughly 320,000 in six months, starting on March 4^{th}, 2020, using the lockdown strategy used in the Kingdom of Saudi Arabia last year ($\rho=0.6$). The present investigation assessed the impact of the lockdown on the dissemination of COVID-19 by extending the conventional SEIR model. The influence of various lockdown levels on viral propagation was specifically introduced to the model in this research. As a result, the purpose of this research is to explain how lockdowns affect COVID-19 dissemination in the Kingdom of Saudi Arabia.

Alkhammash *et al.* [48] developed a fully connected deep neural network, long short-term memory (LSTM), and transformer model as the artificial intelligence (AI) models for the prediction of new COVID-19 cases to show the influence of different factors on the transmission of COVID-19 in Saudi cities. They claimed that LSTM model obtained the best prediction results with a reasonable computation time. In addition, Muniasamy *et al.* [49] showed that machine learning models can predict the significant information automatically for healthcare related problems. They focused on classification and prediction using standard machine learning techniques naive Bayes (NB) and support vector machine (SVM) when tested on cases from Kingdom of Saudi Arabia (KSA)-COVID-19 datasets. However, they mentioned that the predictive model performance may be improved by using more COVID-19 datasets.

A previous enhanced SEIR model was proposed in [50]. The SIR, SEIR, susceptible, exposed, infected, recovered, dan death (SEIRD), and susceptible, exposed, infected, recovered and vaccinated (SEIRV) models were explored in this paper as other pandemic models that fit the various types of diseases. Considering that contemporary models are one of the most reliable models for projecting the spread of a pandemic. The additional COVID-19 cases were anticipated to be predicted by an improved SEIR model. The model contains a separate vaccine compartment. Since it was discovered that vaccination was one of the greatest ways to reduce the spread of the COVID-19 pandemic, When the population is vaccinated, the SEIRV model predicts the severity of COVID-19. The SEIRV model took vaccination rates into account. Different compartments, including patient severity, vaccination rate, mortality rate, and birth rate, were included in that model [50]. The model's R0 value was 2.1619 without considering any social distance. The model was mathematically simulated and evaluated in various circumstances, including with and without social distance. According to the model, the number of affected people doubled every 10.7 days, and the epidemic grew at a pace of roughly 0.06 per day. The model's R0 value of 1.3 was obtained by adding social distance. Finally, vaccination and social distance standards were found crucial in countering COVID-19.

The remaining of the essay is arranged as follows: section 2 covers the past data for COVID-19 in the context of the Kingdom of Saudi Arabia, section 3 covers the materials and methods in this model, and section 4 discusses the results and discussions of the updated SEIR models application in predicting the spread of COVID-19 in the region. Section 5 of this paper provides a brief conclusion.

2. COVID-19 SPREAD IN THE KINGDOM OF SAUDI ARABIA

The Kingdom of Saudi Arabia is a nation located in the Middle East. 35 million people are living there. The Saudi Ministry of Health issued a health warning after WHO declared COVID-19 to be a pandemic, requiring those with viral-like signs and those who had recently traveled to outbreak areas to be tested for SARS-CoV-2 exposure [51]. On March 2nd, 2020, the Kingdom of Saudi Arabia reported its first COVID-19 case [6]. After that, symptomatic contact screening, stringent contact tracking policies, quarantine for asymptomatic contacts, and hospital isolation were implemented. Additional steps included the imposition of a midnight curfew and a nationwide strict lockdown. Additionally, starting on March 8th, 2020, the Kingdom of Saudi Arabia closed its borders and forbade all outdoor and indoor travel. By using these techniques, the curve might be flattened and the disease's detrimental impact on public health could be reduced because of their resilience. Mankind has learned from history that pandemics often reach their height and then dissipate. Given that the human population has doubled in size over the last five decades, COVID-19 may perhaps represent an exception. Therefore, COVID-19 has a greater potential for spreading from person to person and may generate an early peak impact that many countries' present health systems cannot manage [6], [52]–[54], and 3/4th of the world's population lives in urban areas, which adds to the problem's severity and makes the population they are more susceptible to pandemics [55], [56]. Future infrastructure improvements must be more effective in identifying, reporting, and analyzing a variety of signs of the illness to effectively control its spread and avoid spreads inside buildings [6]. COVID-19 has tremendously affected all fields in Saudi Arabia, especially the field of education and resulted in most institutions embracing online exams [57]. Moreover, the COVID-19 pandemic has led to a resistance to change from traditional models of conducting tests to new ways because of their reliability, accessibility, and availability [58]. Not all students and tutors have access to the essential digital tools required to conduct online tests, including Wi-Fi, internet, and other devices. In addition; there is a massive rigor and imagination required to design online tests compared to conventional assessment forms, preventing faculty members from adopting the digital tool.

The COVID-19 pandemic has changed the entire world. It has changed communication, education, shopping and working and more. With the implementation of COVID-19 restriction rules in Saudi Arabia, the technology and software solutions have authorized the provision of fundamental services [59]. The use of variety software solutions was assured successful in fighting the pandemic in addition to continuing the live safely in Saudi Arabia [60]. According to Alammary *et al.* [61], The compulsory and unexpected transition to e-learning due to the COVID-19 pandemic has raised many challenges that require highlighting. This includes the challenges facing education in Saudi universities. For instance, the usability, suitability, and reliability of the solutions used in e-learning, the technical skills of academics, the efficiency and suitability of technical support available to academics as well as the awareness of academics in terms of cybersecurity risks. In contrast, Alqahtani and Rajkhan [62] indicate that one of the main factors for the success of the transformation process during the COVID-19 pandemic is the information technology infrastructure in Saudi Arabia universities. Noting that some Saudi universities faced difficulties in their ability to transform flexibly, due to the limited awareness about using e-learning solutions before the COVID-19 pandemic.

Population density, local COVID-19 advancement, societal lifestyle, and other variables are the main causes of COVID-19 dissemination. For instance, of the 35 million inhabitants in the Kingdom of Saudi Arabia, 84 percent [63], resided in metropolitan areas. On the other side, Japan had 126.4 million residents, with 92 percent of them living in cities [6]. These findings suggest that the disease might spread more quickly in Japan than in the Kingdom of Saudi Arabia. In Jordan, 91.5 percent of the 11 million residents reside in metropolitan areas. Accordingly, 76% of Iran's 83.9 million residents were urbanites, compared to 84.3 million urban residents in Turkey [64]. Since COVID-19 spreads at varying rates in various geographical locations, it is challenging to identify the precise rate [19], [65]. Hospitals in the Kingdom of Saudi Arabia may experience extreme pressure due to peak cases given that the illness spreads from person to person on average by a factor of 1.5 to 3.5 [6], [19], [66] and that it is assumed that case numbers will continue to rise at the rate seen in June 2020. Kingdom of Saudi Arabia recorded its first COVID-19 case on March 2nd, 2020 [67], and by April 3rd, 2020, there were 154 instances [63]. However, the pace of transmission was far slower in Japan, where it took 71 days as compared to 34 days for the Kingdom of Saudi Arabia to register 2400 verified cases. On January 16, 2020, Japan announced the first verified COVID-19 case [6]. Jordan also noted 2400 cases in only 31 days. Iran and Turkey saw a far higher rate of illness transmission than the Kingdom of Saudi Arabia, Jordan, or Japan, with both nations recording 2,400 verified cases in only 14 days. 36 countries have recorded at least 2,400 cases by April 5th, 2020, with an average of around 39.1 days for these nations [6]. The current statistics, however, could not accurately represent the true number of instances that these countries have given the differing testing and reporting practices of the various nations.

To prevent the spread of COVID-19, the Kingdom of Saudi Arabia has implemented strict restraining regulations. The distribution of COVID-19 is documented in this research using the information given by John Hopkins University [67]. Although no model can reliably forecast how it would spread, this study's simulations indicate that even partial lockdowns in Saudi Arabia might cause the expected 3-month period without a lockdown to be delayed by 5 to 6 months. Moreover, this model demonstrates that efficient lockdowns may lower Saudi Arabia's infection rate to fewer than 0.5 million instances. The study's limitation is that real instances may drastically deviate from the forecast when the authority enforces social distancing to stop the spread. Notably, the quickly spreading COVID-19 has placed a heavy load on many countries' present health infrastructure, leaving the system unable to manage the rising number of people who have been verified to have COVID-19. While preparing for the outbreak, cities try to shorten the pandemic curve.

The number of COVID-19 cases in the Kingdom of Saudi Arabia increased as of May 5th, 2020. Additionally, COVID-19 was responsible for a rise in the number of deaths. The recorded death toll in the Kingdom of Saudi Arabia was in the single digits as of the indicated date, although it was anticipated to rise. The Kingdom of Saudi Arabia and other countries are in a difficult position in their efforts to stop the development of COVID-19 due to the unprecedented worldwide spread of the disease and the lack of a vaccine or effective treatment. The majority of these nations have chosen to impose lockdowns and other precautionary measures. According to the present investigation, up to 3 million individuals in the Kingdom of Saudi Arabia might get the disease two months after the first confirmed case, under the precarious assumption that there is no social isolation. However, this is unlikely to occur given the implementation of a proper nighttime curfew and a lockdown strategy in the kingdom's major cities to restrict transmission. The deep learning model and SEIR model were implemented based on the characteristics of the kingdom area and taking into account the population movement. To fit the new model parameters, the real data were used together with the most recent research and publications. The pandemic pattern was then estimated and evaluated using the model.

3. MATERIALS AND METHODS

Many mathematical models are created or used to study the transmission of communicable illnesses throughout the past three decades. Predicting the dispersion within a population in a certain area or nation is the major goal. There are both stochastic and deterministic models among them. According to Nakamura *et al.* [68], a stochastic technique may be utilized as a tool to measure the probability distributions of probable outputs where the usage of random input variation is necessary. It relies on the risk factors for viral exposure and other pathological elements. To calculate the statistical disease spread for small or big populations, a stochastic technique is used. Contrarily, Brauer and Castillo-Chávez [69] said that when dealing with huge populations, such as in the case of COVID-19, deterministic approaches and compartmental mathematical models are applied. A deterministic model divides the population into sections, each of which corresponds to a different stage of the illness. This model is constructed as derivatives from a mathematical statement of transition rates from one class to another using differential equations. These models are constructed based on the differentiability of the population size in a particular compartment, taking time and the deterministic disease process into consideration. Thus, the study will utilize compartmental (i.e., deterministic-based) methods to predict the infection rate for COVID-19 among the Saudi population throughout the next autumn term in 2021.

3.1. SEIR model

Numerous derivative models, including SEIR, SIR, susceptible exposed infectious susceptible (SEIS), and maternally-derived-immunity susceptible infectious recovered (MSIR), have been used to evaluate the transmission of pandemic over 40 years. Please see [55], [70]–[73] for further information. They are founded on many compartments, like in the SEIR case, which is founded on 4 compartments that are explained in the following manner:

$$dS/dt = -\alpha SI \quad (1)$$

$$dE/dt = \alpha SI - \mu E \quad (2)$$

$$dI/dt = \mu E - \beta I \quad (3)$$

$$dR/dt = \beta I \quad (4)$$

S stands for the susceptible groups, E for those who have been exposed to the disease but do not show any symptoms (also known as latent carriers), I for those who have COVID-19 infection, and R for those who have recovered. Included in the list of other factors are the transmission rate $\propto$, incubation rate μ, and recovery rate β (transferring contaminated people into recovered sections). Earlier, Naresh *et al.* [74] projected the spread of AIDS or human immunodeficiency virus (HIV) using the SEIR model and achieved a moderate level of accuracy; more recently, it was used by [6], [75] to estimate the spread of COVID-19 in Italy, Saudi Arabia, and Spain. Therefore, the SEIR model may be used to forecast the spread of COVID-19 among Saudi citizens. A nonlinear ODEs system, the SEIR model operates arbitrarily as follows: i) According to determinism, the COVID-19 infection will ultimately spread to every member of the population; and ii) The spread is assumed to last for a short time while the population remains constant in the model. Include both the number of deaths and births. As a result, it is possible to state that $E + S + R + I = Total\ Populations = Constant$.

The SEIR model may be used to analyze data from a huge population, like Saudi Arabia's 34,813,867 population as of March 1st, 2021 [76]. In our simulations, we start with S equal to the precise population size, initialize I to 12 (the number of affected patients at the commencement of lockdown on March 21st, 2020), and initialize R to 0 (sum of 0 death and recoveries s). The initial $E = 2.399 * 12$ (exposed population) is then estimated using the 2.399* number of affected persons in the last 6 days, as described by Hamzah *et al.* [19]. We also made the assumption that, as suggested in [19], $D = 2.3$ and $Y = 5.2$. The birth and death rates for R, S, and E are not taken into account in our simulation. The forecasts are thus simply estimates and not specific numbers. The likelihood of the virus spreading from an infected to a vulnerable individual ($\propto$) is one of the other anticipated criteria that is considered. This value (2.3), which is between [2, 2.5], is calculated using the predicted reproductive number. We get at $\propto = 1$ by using $R_o = \propto/\beta$. The rate at which those who have been exposed are infectious is another parameter, μ. It is equal to 1/Y, where Y stands for the average incubation time. while D stands for the typical time it takes to recover from an illness, $\beta = 1/D$. Since symptoms may not appear for up to 14 days after exposure, the affected group is the major source of viral transmission [52], [54].

3.2. DNN and SEIR model

The following steps were taken to create the DNN and SEIR model: The systematic observation was used to conduct the data-based time series analysis (pattern prediction). It was designed to predict the order of variables, such as the progression of infection. This prediction model is categorized into different categories based on the analysis techniques used, including market life cycle prediction method, simple sequential average, seasonal trend prediction approach, exponential smoothing approach, moving average, trend prediction approach, weighted sequential average, and weighted moving average. As machine learning, in particular, deep learning theory has gained popularity, DNN has recently been used to anticipate and evaluate a variety of time series difficulties. To produce a basic training data set for this investigation, Saudi infection statistics and the SEIR model were employed. They were adjusted to take into consideration the conventional time series method that was used to suit the progression of the spread of identical pneumonia cases. As a result, the DNN method was used to analyze and forecast the COVID-19 transmission pattern. Like the human nervous system, DNN is made up of highly linked processing and computation units. Although a single neuron has a relatively basic structure, the functioning of the nervous system, which is made up of a vast number of interconnected neurons, is incredibly complex. The DNN is capable of computing and adaptive learning in parallel. Because of its features, the DNN is primarily more effective and accurate than classic prediction techniques like linear regression and decision trees. The characteristics of complex systems that are adaptive, significantly nonlinear, and difficult to predict mathematically well are well described by DNN. The DNN model's parameters were generated and adjusted to account for the impending input after it had been trained on a large dataset to reduce the loss function. The linear connection between the output and the input is represented by (5), where input data is denoted by *xi*, the weight parameter by *wi*, and bias by *b* [77].

$$Y = \sum_{i=1}^{m} wixi + b \tag{5}$$

The DNN model used in this work is made up of a 32-node hidden layer, a 1-node output layer, and a nine-node input layer. The Tanh activation function was used to improve the nonlinear degree of model fitting. Additionally, dropout was used to reduce the model's tendency toward overfitting. The formula for the Tanh activation function is given in (6) [77].

$$f(x) = \frac{1 - e^{-2x}}{1 + e^{2x}} \tag{6}$$

Figure 1 presents the DNN model architecture utilized in this investigation. To select the best model, the loss function can objectively assess the model quality. The (7) serves as an example of how the mean square error loss function was applied in this investigation [77].

$$SE(y_{-}, y) = \frac{\sum_{i=1}^{n}(y-y_{-})^2}{n} \tag{7}$$

The adaptive moment estimation (Adam) optimizer, an adaptive learning rate optimization technique, was used to modify the weight in the minimal loss direction based on the loss function. This was done to produce the best model. The first-moment estimate of the gradient and the second raw moment estimate are computed to construct an independent adaptive learning rate for varying parameters. This formula is given (8) [77].

– Update the biased first-moment estimate

$$m_{t,i} = \beta_1 \,.\, m_{t-1,i} + (1 - \beta_1) \,.\, g_{t,i} \tag{8}$$

– Update biased second raw moment estimate

$$V_{t,i} = \beta_2 \,.\, V_{t-1,i} + (1 - \beta_2) \,.\, g_{t,i}^2 \tag{9}$$

– Update parameters

$$w_{t+1} = w_t - n_t = w_t - l_r \,.\, \frac{m_{t,i}}{1-\beta_1^t} / \sqrt{\frac{V_{t,i}}{1-\beta_2^t}} \tag{10}$$

We used a DNN model to analyze and forecast time series issues associated with projecting future cases of infection. The transmission likelihood, incubation rate, and death/recovery probabilities associated with COVID-19 are all accounted for. To avoid overfitting, we used a more basic network structure given the limited size of the dataset. Model optimization was performed using Adam with a batch size of 1, using mean square error as the loss function, and performing 500 iterations.

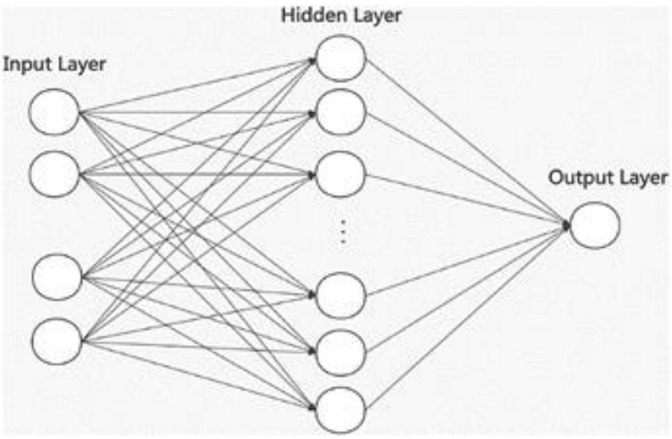


Figure 1. A generic DNN model structure

4. RESULTS AND DISCUSSION

When compared with more conventional approaches to prediction, neural networks perform better. Since the DNN model has more parameters and useful associations between important features from the dataset, it was employed in this research to aid the prediction method of the conventional SEIR model. Based on the labels of the dataset, the following 15 attributes, out of a total of 60 characteristics, were normalized and chosen for the data inputs of the prediction model: the number of instances that have been confirmed; the emergence of new cases daily; the total number of deaths; incidents of death occurring every day; cases overall per million; total deaths/million; new cases/million; reproduction rate; new deaths/million; population density; total population; diabetes occurrence; cardiovascular death rate; total vaccinations per hundred; hospital beds per thousands. Other untapped characteristics, such as the vaccination rate and total immunized individuals (17487842), are either partial or currently unavailable for Saudi Arabia, including ICU patients; weekly ICU admissions; hospital patients; weekly admissions to hospitals; complete vaccinations; total shots administered (16354913); and complete vaccination rates per 100. It is necessary to be selective when taking into account a small number of characteristics that are crucial for the classification to get the correct classification for the prediction model. This may be done by using a filter to find the association between those 15 attributes and the training phase parameters for the neural network. Therefore, after passing 15 inputs through the DNN model's input layer, it only chooses strongly correlated characteristics to support the SEIR model's prediction as it moves on to the output and hidden layers. Further choices are made here utilizing the principal component analysis (PCA) approach for 6 of the 15 factors that had a substantial influence on the prediction. Confirmed total deaths (7789); confirmed total cases (484539); total population (34813867); population density (15.322); reproduction rate (0.78 to 2.37); and confirmed total vaccines per hundred (50.23 between 2/3/2021 and 28/6/2021) are these characteristics. The SEIR model (Exposed, Susceptible, Recovered, Infectious, Death, and Healer) will get 6 outputs from the DNN's output layer depending on the following factors: *beta*: infection rate; *alpha*: healing rate; *delta*: the rate at which person enter in quarantine; *gamma*: inverse of the average latent time; *kappa*: mortality rate; *lambda*: cure rate; *E0*: initial exposed cases; *N*: the total population sample; *t*: vector of time; *Q0*: initial number of quarantine cases; *I0*: initial infectious cases; *D0*: initial death cases; *R0*: initial recovered cases; *kappaFun*: providing the time-dependent death rate anonymously; *lambdaFun*: anonymous function providing the recovery rate that is dependent on time.

First, Min-Max Normalization was used to normalize the data without including the number of epidemic cases. The sample data's lowest value is denoted by X_{min} in (11), while the maximum value sample is denoted by X_{max}. Additionally, a suitable scale was created to scale the number of examples to fit the range of 0 to 1.

$$X = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{11}$$

Following that, the model was fitted using the normalized number of examples X, and the loss using the SE equation was computed. Additionally, the values of b and w were modified. Training for 10,000 epochs usually results in a stable loss. Each day, the network generates an output consisting of the newly scaled-down local examples. By scaling the prior cases, we were able to recover the number of instances. The outcomes are then determined. Over the following three days, the suggested model anticipated that new instances would continually emerge in each location. Following a summary of the earlier data, Riyadh, the capital city of Saudi Arabia, was chosen as the city with the highest representation.

Using John Hopkins University's database, we have extracted the Saudi COVID-19 cases and examined the patterns beginning on March 2, 2020 (the first positive case discovered and verified in Saudi Arabia). We then used a modified SEIR model and predicted the same preventive actions in COVID-19 to account for the impact of social distance. Variations in infection rates and the number of confirmed cases is substantial. These figures are considered to have been disturbed due to precautions and avoiding social connection. Saudi Arabia is particularly susceptible to illnesses caused by international tourists since it is known as a major regional transit and religious tourism center. To reduce the possibility of social encounters, Saudi Arabia has imposed lockdowns and canceled several activities and events. We project the spread of these spread parameters and their impacts on them over the next several days based on previous data up to June 25th, 2021, such as the spreading high in the first quarter of that year. This summer, the nation switched from a rigorous lockdown to a partial lockdown as the number of positive cases number quickly began to decline (mere overnight hours). However, with the peak cases steadily increasing over the last six months, there is concern that the scenario would recur, putting enormous strain on Saudi hospitals from critical cases. Therefore, the third wave of dissemination is anticipated in October 2021.

The only way to improve the situation and stop the spread, in addition to taking social isolation into account, is by immunizing the majority of Saudis and non-Saudis, a task that the Ministry of Health is now doing successfully (approximately 12,762,684 doses have been provided, covering 70% of the adult population) [78]. The forecast is displayed in Figure 2 where the peak is projected 35 days after imposing the lockdown, whereas the number climbed significantly at the start of 2021 owing to this lockdown being implemented at the appropriate moment. We utilized the SEIR model for Saudi Arabia, neglecting social distance. Figure 2 displays the incidence rate for only 4 parameters (R, E, S, and I) over 210 days, where time is expressed in days by the population proportion. The estimate for the incidence rate over 210 days using the SEIR/DNN prediction model is illustrated in Figure 3, in contrast (or rather attributes: E, S, R, I, D, H). When requiring no or partial lockdowns, it demonstrates that the peak would occur during the first 30 days. The mortality rate would be very low throughout 210 days, and by November 13, 2021, everything would be stable.

If the SEIR/DNN prediction model is utilized, Figure 4 once again shows the prognosis for the estimated incidence over 210 days with seven parameters, like ΔI (for I0-I mode). It demonstrates that when requiring partial or no lockdowns, the peak would occur within the first 30 days. The death rate would be extremely low over 210 days, and everything would be stabilized on March 11th, 2021; one week earlier than if just six factors had been used.

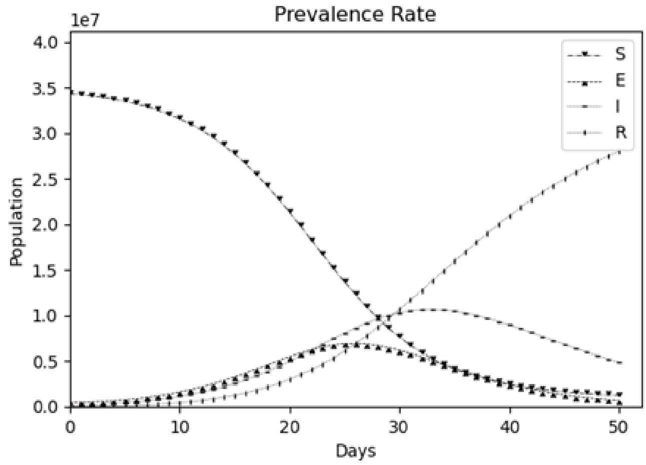


Figure 2. With no social distance, SEIR/DNN forecasts for Saudi Arabia (prevalence rate)

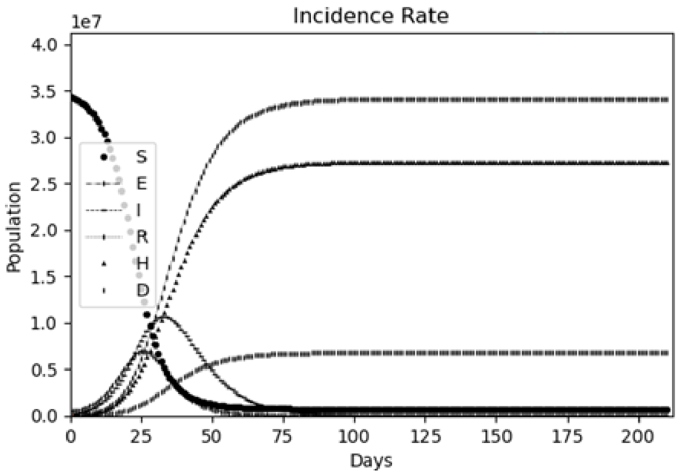


Figure 3. SEIR/DNN predictions for Saudi Arabia with 6 factors (incidence rate)

Figures 4 and 5 show the impact of the DNN model's prediction. It is reported that the machine learning algorithm can accurately anticipate the epidemic scenario in Saudi Arabia using demographic data. Without the lockdown, according to our modeling, the peak would have grown significantly during the identical 22-day period (from June 28 to July 13, 2021), and the health system would have been put under a lot of strain. The spread soon disappears when the reproduction rate is less than one, which has a substantial influence. On contrary, the spread expands rapidly if the rate is greater than one. Regular handwashing reduces the risk of illnesses, and appropriate social distance ensures that the exposed population is kept in check. The SEIR/DNN model demonstrates that if the social distance is correctly implemented in Saudi Arabia, the number of instances may be reduced to below 1 million. However, since COVID-19 is a more complicated disease, a prediction model needs to take into account more important variables like mortality rates and immunization rates to provide more accurate forecasts in [79], [80]. So, these aspects have been taken into account in our model. Due to a lack of information on the vaccination/million or daily vaccination rate in Saudi Arabia, the rate of vaccination is implicitly included in recovered and susceptible people. The specific parameter settings for the SEIR/DNN model that we employed in our simulation are shown in

Table 1. Artificial parameters, Group parameters, and natural propagation parameters are the three categories into which they fall. Figure 5 depicts the forecast for the first half of 2021 without social segregation and after the lockdown measures have been suspended.

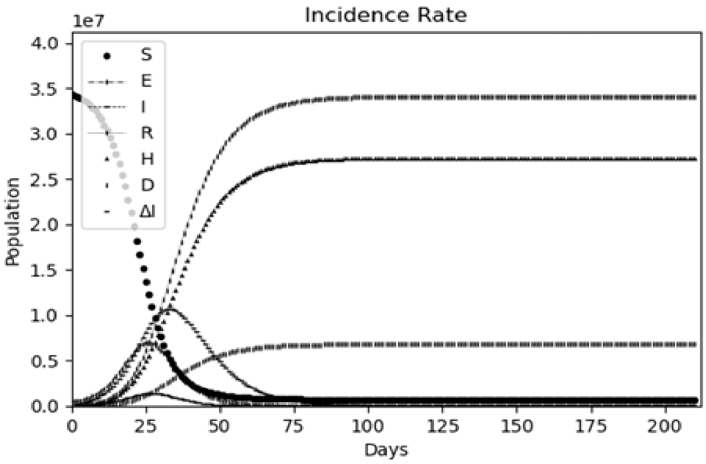


Figure 4. SEIR/DNN predictions for Saudi Arabia with 7 factors (incidence rate)

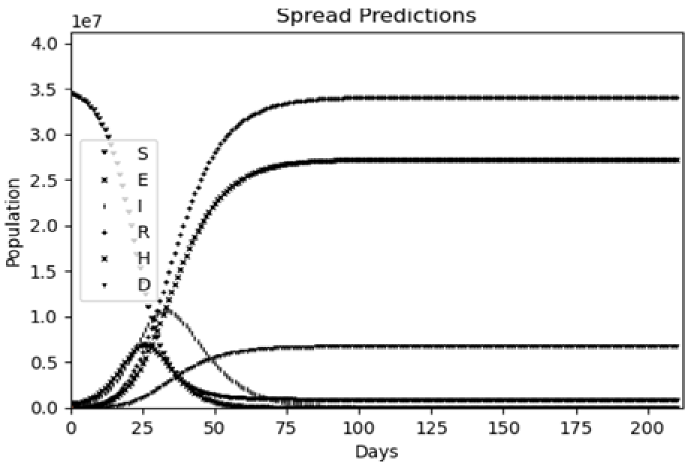


Figure 5. 210-day COVID-19 spread forecasts using a modified SEIR/DNN model

Table 1. Setting the SEIR model's initial settings will begin on June 28th, 2021

Category	Parameter	Value
Group	Total (N)	34813867
	Susceptible (S)	32827872
	Exposed (E)	484539
	Infective (I)	752848
	Healer (H)	739536
	Recovered (R)	739536
	Death (D)	9072
Natural propagation	Infection rate (λ)	0.231
	Incidence rate (σ)	0.2
	Healing/Recover rate (γ)	0.1
	Loss antibody rate (μ)	0
	Latent days (day)	5
	Healing rate (α)	0.8
	Death rate (β)	0.2
Artificial	Quarantine (Q)	0.7
	Medical ability	1.2
	Cure gain	1.250

About 1.1 million people in Saudi Arabia are potentially infected during the peak period, which lasts 3 months from the first lockdown, under no lockdown in Figure 5 (March 21st, 2021). In Figure 5, the mortality rate substantially climbs over 40 days, and the peak of fatalities lasts for around 150 days at the same rate. Therefore, ending lockdowns is not a decision that can be made based on medical expertise, cure, or care for affected individuals. As indicated in Figures 6 and 7, we conducted our tests on infections under various degrees of lockdown, starting with no lockdown and progressing through partial lockdown to severe lockdown, to comprehend the impact of the lockdown in Saudi Arabia better. The drawback of our strategy is that findings might be significantly disrupted by variations in lockdown levels. Peak infections might reach less than 500,000 and occur nine months after the start of the lockdown, which is presently not a possibility. In the event of a partial lockdown, commencing on June 26th, 2021, around 750,000 people might get infected. Figure 6 revealed that the infection rate dropped for approximately a week before increasing again after a month with a million infections altogether. After another two months, the infection rate dropped substantially to only a few hundred infections. Last but not least, Figure 7 demonstrated that under a severe lockdown, the infection rate starts to significantly decline after three months and gradually fades completely. Additionally, under both rigorous and partial lockdowns, the mortality rate is gradually declining.

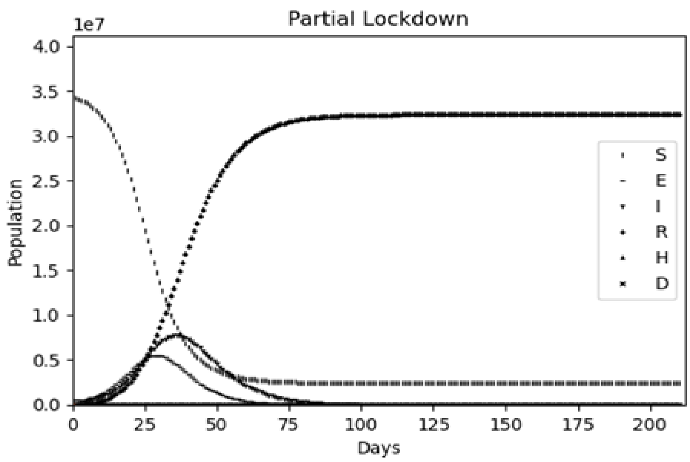


Figure 6. Modified SEIR/DNN model predictions with the partial lockdown

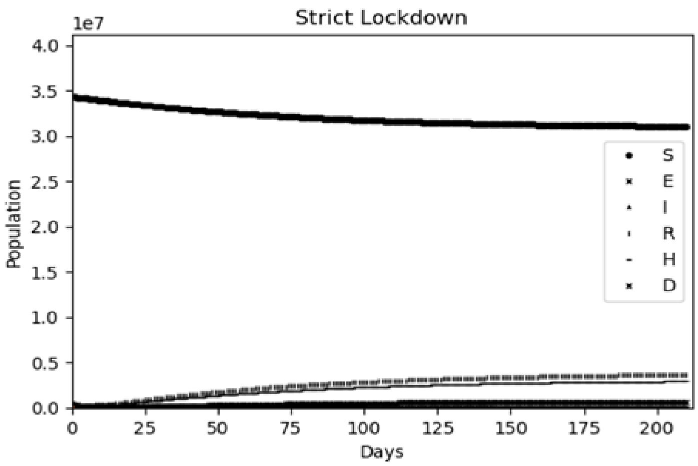


Figure 7. Modified predictions from the SEIR/DNN model with the rigorous lockdown

The exposed population is soon reduced when vaccine recipients are taken into account, and the curve flattens. When infection rates and vaccination rates fall, hospital infrastructure and resources have more time and space to handle serious infection cases, which lowers the COVID-19 mortality rate. The efficacy and efficiency of a partial or strict lockdown over the next 210 days beginning on June 28, 2021, are shown in Figures 6 and 7. To attain the aim of efficiency and efficacy, our simulation took into account quarantine actions, cure gain, and medical prowess. For a complete list of the variables, we used in our simulation, as shown in Table 1. The number of infections has risen by 484539 new instances (before June 27, 2021, to include the total score), which is better than what is shown in Figure 6 when the infections attained their overall score of 4.8 million. In Figure 3, forecasts indicate that at least 1 million instances may be infected, but Figure 7 reveals that the score is only half that high (~750 thousand). A lockdown, on the other hand, would have a significant influence on containment or reducing the incidence of infection. Therefore, if the incidents significantly rise in October when educational institutions are completely open for their students as well as staff in typical classrooms, the Saudi Arabian government may consider implementing a partial lockdown. Nevertheless, until the majority of the population gets immunized, which might happen by the end of September 2021, the government and all Saudi citizens must take precautions. The administration said that the partial lockdown will cease on September 1 unless the situation with the virus was rectified due to the dire economic condition. Figures 6 and 7 further demonstrated that depending on whether tight or partial lockdown is used, the infection curve flattens out after three months or less. Unlike our SEIR-DNN prediction model, Alrashed *et al.* [6] introduced a modified SEIR model, but with only 4 parameters to predict the spread of COVID-19. They additionally considered the social distancing factor. They implemented their model on the initial spread data available for a short period of time (until April 9, 2020) for the Kingdom of Saudi Arabia. Their model also ignored birth rate and death rate; hence the predictions are only estimated values and not accurate (e.g., probability of transmitting the disease, rate of exposed becoming infectious, average duration of recovery). Our model is implemented for a much longer period considering social distancing, lockdown, death rate, and other hyperparameters. Therefore, our SEIR-DNN model outperformed the classical and modified SEIR models in terms of accuracy and other measures.

5. CONCLUSION

The spread of COVID-19 in the Kingdom of Saudi Arabia was predicted by the current research using SEIR, a mathematical spread model. SEIR was modified with the addition of lockdowns before its usage for the research. It was discovered that 310 people were originally affected on the 30th day after the first case was reported in Saudi Arabia. Examining the distribution pattern until April 3rd of 2020, the effects of lockdowns and social distancing were considered. Then, at various degrees of lockdown, the anticipated number of affected instances was calculated. The findings indicate that 3 million subjects would be affected in Saudi Arabia by June 2020 if there were no lockdowns. However, several tactics were being used throughout the Kingdom to stop the spread. Relatively, starting on March 21st, 2020, with a partial lockdown in Saudi Arabia, the number of confirmed incidents was anticipated to be fewer than 500,000, and stronger lockdowns may flatten the COVID-19 curve. This also holds for hypothetical circumstances that are detailed in the results section and begin the simulation on June 27th, 2021, and continue for nine months. A short period of lockdown and vaccination rates were taken into account in the scenario. The results demonstrated that the infection curve will drastically flatten after three months, depending on the vaccination rate, lockdown, and social isolation. The daily number of new instances was calculated using first-order differential analysis of the cumulative number of reported cases, with interpolation employed to take into account outliers. Getting the time series data was done after setting the sequence length time sliding window. The DNN model was utilized as the input for training using the time slice data, and it was looped 500 times before being stored. A nationwide prediction for new cases as well as a pattern chart for cumulative cases over the 210 days after June 26 was obtained by first entering the number of new national COVID-19 cases into the trained DNN model. In terms of predicting the epidemic sizes and peaks, our updated SEIR/DNN model performed well. The forecast has become more accurate and useful in determining whether the lockdown is partial or strict by providing the SEIR model with over 4 characteristics that are closely associated across the layers of DNN. Additionally, the AI-based model (DNN) has promise for the prediction of future epidemics. The scale of the outbreak in Saudi Arabia is expected to decline as a result of the control measures put in place after June 26. However, the strategy of early identification and careful monitoring must continue until the end of 2021.

REFERENCES

[1] Q. Li *et al.*, "Early transmission dynamics in Wuhan, China, of novel coronavirus–infected pneumonia," *New England Journal of Medicine*, vol. 382, no. 13, pp. 1199–1207, Mar. 2020, doi: 10.1056/NEJMoa2001316.

[2] Y. Liu, A. A. Gayle, A. Wilder-Smith, and J. Rocklöv, "The reproductive number of COVID-19 is higher compared to SARS coronavirus," *Journal of Travel Medicine*, vol. 27, no. 2, Mar. 2020, doi: 10.1093/jtm/taaa021.

[3] Q. Gao, Y. Hu, Z. Dai, F. Xiao, J. Wang, and J. Wu, "The epidemiological characteristics of 2019 novel coronavirus diseases (COVID-19) in Jingmen, Hubei, China," *Medicine*, vol. 99, no. 23, p. e20605, Jun. 2020, doi: 10.1097/MD.0000000000020605.

[4] V. Surveillances, "The epidemiological characteristics of an outbreak of 2019 novel coronavirus diseases (COVID-19)—China, 2020," *China CDC weekly*, vol. 2, no. 8, pp. 113–122, 2020.

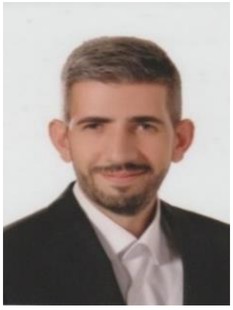
[5] M. K. Alsmadi *et al.*, “Digitalization of learning in Saudi Arabia during the COVID-19 outbreak: A survey,” *Informatics in Medicine Unlocked*, vol. 25, 2021, doi: 10.1016/j.imu.2021.100632.
[6] S. Alrashed, N. Min-Allah, A. Saxena, I. Ali, and R. Mehmood, “Impact of lockdowns on the spread of COVID-19 in Saudi Arabia,” *Informatics in Medicine Unlocked*, vol. 20, 2020, doi: 10.1016/j.imu.2020.100420.
[7] M. K. Alsmadi, “Modified SEIR and machine learning prediction of the trend of the epidemic of COVID-19 in Jordan under lockdowns impact,” *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 12, no. 5, pp. 5455–5466, Oct. 2022, doi: 10.11591/ijece.v12i5.pp5455-5466.
[8] A. Abuhamdah, G. M. Jaradat, and M. Alsmadi, “Deep learning for COVID-19 cases-based XCR and chest CT images,” in *Advances on Smart and Soft Computing*, 2022, pp. 285–299. doi: 10.1007/978-981-16-5559-3_24.
[9] D. Wang *et al.*, “Clinical characteristics of 138 hospitalized patients with 2019 novel coronavirus–infected pneumonia in Wuhan, China,” *JAMA*, vol. 323, no. 11, pp. 1061–1069, Mar. 2020, doi: 10.1001/jama.2020.1585.
[10] J. Li *et al.*, “Epidemiological and clinical characteristics of 17 hospitalized patients with 2019 novel coronavirus infections outside Wuhan, China,” *MedRxiv*, 2020, doi: 10.1101/2020.02.11.20022053.
[11] C. Huang *et al.*, “Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China,” *The Lancet*, vol. 395, no. 10223, pp. 497–506, Feb. 2020, doi: 10.1016/S0140-6736(20)30183-5.
[12] B. E. Young *et al.*, “Epidemiologic features and clinical course of patients infected with SARS-CoV-2 in Singapore,” *JAMA*, vol. 323, no. 15, pp. 1488–1494, Apr. 2020, doi: 10.1001/jama.2020.3204.
[13] J. Cohen, “COVID-19 shot protects monkeys,” *Science*, vol. 368, no. 6490, pp. 456–457, May 2020, doi: 10.1126/science.368.6490.456.
[14] J. Yu *et al.*, “DNA vaccine protection against SARS-CoV-2 in rhesus macaques,” *Science*, vol. 369, no. 6505, pp. 806–811, Aug. 2020, doi: 10.1126/science.abc6284.
[15] T. Thanh Le *et al.*, “The COVID-19 vaccine development landscape,” *Nature Reviews Drug Discovery*, vol. 19, no. 5, pp. 305–306, May 2020, doi: 10.1038/d41573-020-00073-5.
[16] B. Korber *et al.*, “Tracking changes in SARS-CoV-2 spike: evidence that D614G increases infectivity of the COVID-19 virus,” *Cell*, vol. 182, no. 4, pp. 812-827.e19, Aug. 2020, doi: 10.1016/j.cell.2020.06.043.
[17] Y. Wang, Y. Wang, Y. Chen, and Q. Qin, “Unique epidemiological and clinical features of the emerging 2019 novel coronavirus pneumonia (COVID-19) implicate special control measures,” *Journal of Medical Virology*, vol. 92, no. 6, pp. 568–576, Jun. 2020, doi: 10.1002/jmv.25748.
[18] D. S. Hui *et al.*, “The continuing 2019-nCoV epidemic threat of novel coronaviruses to global health — The latest 2019 novel coronavirus outbreak in Wuhan, China,” *International Journal of Infectious Diseases*, vol. 91, pp. 264–266, Feb. 2020, doi: 10.1016/j.ijid.2020.01.009.
[19] F. A. B. Hamzah *et al.*, “CoronaTracker: worldwide COVID-19 outbreak data analysis and prediction,” *Bull World Health Organ*, vol. 1, no. 32, 2020.
[20] S. I. Alzahrani, I. A. Aljamaan, and E. A. Al-Fakih, “Forecasting the spread of the COVID-19 pandemic in Saudi Arabia using ARIMA prediction model under current public health interventions,” *Journal of Infection and Public Health*, vol. 13, no. 7, pp. 914–919, Jul. 2020, doi: 10.1016/j.jiph.2020.06.001.
[21] P. Kumar *et al.*, “Forecasting the dynamics of COVID-19 pandemic in top 15 countries in April 2020: ARIMA model with machine learning approach,” *MedRxiv*, 2020.
[22] Y. Sugishita, J. Kurita, T. Sugawara, and Y. Ohkusa, “Forecast of the COVID-19 outbreak, collapse of medical facilities, and lockdown effects in Tokyo, Japan,” *MedRxiv*, 2020.
[23] N. Hasan, “A methodological approach for predicting COVID-19 epidemic using EEMD-ANN hybrid model,” *Internet of Things*, vol. 11, Sep. 2020, doi: 10.1016/j.iot.2020.100228.
[24] G. Pinter, I. Felde, A. Mosavi, P. Ghamisi, and R. Gloaguen, “COVID-19 pandemic prediction for Hungary; A hybrid machine learning approach,” *Mathematics*, vol. 8, no. 6, Jun. 2020, doi: 10.3390/math8060890.
[25] R. Bhardwaj and A. Bangia, “Data driven estimation of novel COVID-19 transmission risks through hybrid soft-computing techniques,” *Chaos, Solitons & Fractals*, vol. 140, Nov. 2020, doi: 10.1016/j.chaos.2020.110152.
[26] F. Shi *et al.*, “Review of artificial intelligence techniques in imaging data acquisition, segmentation, and diagnosis for COVID-19,” *IEEE Reviews in Biomedical Engineering*, vol. 14, pp. 4–15, 2021, doi: 10.1109/RBME.2020.2987975.
[27] B. A. Aldeeb *et al.*, “Hybrid intelligent water Drops algorithm for examination timetabling problem,” *Journal of King Saud University - Computer and Information Sciences*, vol. 34, no. 8, pp. 4847–4859, Sep. 2022, doi: 10.1016/j.jksuci.2021.06.016.
[28] A. Abuhamdah, W. Boulila, G. M. Jaradat, A. M. Quteishat, M. K. Alsmadi, and I. A. Almarashdeh, “A novel population-based local search for nurse rostering problem,” *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 11, no. 1, pp. 471–480, Feb. 2021, doi: 10.11591/ijece.v11i1.pp471-480.
[29] Y. K. Qawqzeh *et al.*, “Applying the big bang-big crunch metaheuristic to large-sized operational problems,” *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 10, no. 3, pp. 2484–2502, Jun. 2020, doi: 10.11591/ijece.v10i3.pp2484-2502.
[30] M. Alzaqebah, N. Alrefai, E. A. E. Ahmed, S. Jawarneh, and M. K. Alsmadi, “Neighborhood search methods with moth optimization algorithm as a wrapper method for feature selection problems,” *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 10, no. 4, pp. 3672–3684, Aug. 2020, doi: 10.11591/ijece.v10i4.pp3672-3684.
[31] M. Alzaqebah *et al.*, “Hybrid feature selection method based on particle swarm optimization and adaptive local search method,” *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 11, no. 3, pp. 2414–2422, Jun. 2021, doi: 10.11591/ijece.v11i3.pp2414-2422.
[32] M. Alzaqebah, S. Jawarneh, M. Alwohaibi, M. K. Alsmadi, I. Almarashdeh, and R. Mustafa A. Mohammad, “Hybrid brain storm optimization algorithm and Late acceptance hill climbing to solve the flexible job-shop scheduling problem,” *Journal of King Saud University - Computer and Information Sciences*, vol. 34, no. 6, pp. 2926–2937, 2022, doi: 10.1016/j.jksuci.2020.09.004.
[33] M. K. Alsmadi and I. Almarashdeh, “A survey on fish classification techniques,” *Journal of King Saud University - Computer and Information Sciences*, vol. 34, no. 5, pp. 1625–1638, May 2022, doi: 10.1016/j.jksuci.2020.07.005.
[34] M. K. Alsmadi, M. Tayfour, R. A. Alkhasawneh, U. Badawi, I. Almarashdeh, and F. Haddad, “Robust features extraction for general fish classification,” *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 9, no. 6, pp. 5192–5204, Dec. 2019, doi: 10.11591/ijece.v9i6.pp5192-5204.
[35] I. Al-Marashdeh, G. M. Jaradat, M. Ayob, A. Abu-Al-Aish, and M. Alsmadi, “An elite pool-based big bang-big crunch metaheuristic for data clustering,” *Journal of Computer Science*, vol. 14, no. 12, pp. 1611–1626, Dec. 2018, doi: 10.3844/jcssp.2018.1611.1626.
[36] M. K. Alsmadi, “Query-sensitive similarity measure for content-based image retrieval using meta-heuristic algorithm,” *Journal of*

King Saud University-Computer and Information Sciences, vol. 30, no. 3, pp. 373–381, 2018, doi: 10.1016/j.jksuci.2017.05.002.
[37] M. Alzaqebah, S. Jawarneh, R. M. Mohammad, M. K. Alsmadi, and I. Al Marashdeh, "Improved multi-verse optimizer feature selection technique with application to phishing, spam, and denial of service attacks," *International Journal of Communication Networks and Information Security (IJCNIS)*, vol. 13, no. 1, pp. 76–81, Apr. 2022, doi: 10.17762/ijcnis.v13i1.4929.
[38] M. Alzaqebah *et al.*, "Memory based cuckoo search algorithm for feature selection of gene expression dataset," *Informatics in Medicine Unlocked*, vol. 24, Jun. 2021, doi: 10.1016/j.imu.2021.100572.
[39] N. Alrefai *et al.*, "An integrated framework based deep learning for cancer classification using microarray datasets," *Journal of Ambient Intelligence and Humanized Computing*, Dec. 2022, doi: 10.1007/s12652-022-04482-9.
[40] K. A. Alissa *et al.*, "Developing a simulated intelligent instrument to measure user behavior toward cybersecurity policies," *International Journal of Communication Networks and Information Security (IJCNIS)*, vol. 13, no. 1, Apr. 2022, doi: 10.17762/ijcnis.v13i1.4923.
[41] M. K. Alsmadi *et al.*, "An enhanced particle swarm optimization for ITC2021 sports timetabling," *Computers, Materials & Continua*, vol. 72, no. 1, pp. 1995–2014, 2022, doi: 10.32604/cmc.2022.025077.
[42] N. Aldhafferi *et al.*, "Learning trends in customer churn with rule-based and kernel methods," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 12, no. 5, pp. 5364–5374, Oct. 2022, doi: 10.11591/ijece.v12i5.pp5364-5374.
[43] R. M. A. Mohammad and M. K. Alsmadi, "Intrusion detection using Highest Wins feature selection algorithm," *Neural Computing and Applications*, vol. 33, no. 16, pp. 9805–9816, Aug. 2021, doi: 10.1007/s00521-021-05745-w.
[44] R. M. A. Mohammad, M. K. Alsmadi, I. Almarashdeh, and M. Alzaqebah, "An improved rule induction based denial of service attacks classification model," *Computers & Security*, vol. 99, Dec. 2020, doi: 10.1016/j.cose.2020.102008.
[45] M. K. Alsmadi, "The students' acceptance of learning management systems in Saudi Arabian Universities," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 10, no. 4, pp. 4155–4161, Aug. 2020, doi: 10.11591/ijece.v10i4.pp4155-4161.
[46] B. Abuhaija *et al.*, "A comprehensive study of machine learning for predicting cardiovascular disease using Weka and Statistical Package for Social Sciences tools," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 13, no. 2, pp. 1891–1902, Apr. 2023, doi: 10.11591/ijece.v13i2.pp1891-1902.
[47] E. Abdulazeem Ahmed *et al.*, "Comparison of specific segmentation methods used for copy move detection," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 13, no. 2, pp. 2363–2374, Apr. 2023, doi: 10.11591/ijece.v13i2.pp2363-2374.
[48] E. H. Alkhammash, H. Algethami, and R. Alshahrani, "Novel prediction model for COVID-19 in Saudi Arabia based on an LSTM algorithm," *Computational Intelligence and Neuroscience*, vol. 2021, pp. 1–12, Dec. 2021, doi: 10.1155/2021/6089677.
[49] A. Muniasamy, R. Bhatnagar, and G. Karunakaran, "Predicting COVID19 spread in Saudi Arabia using artificial intelligence techniques—proposing a shift towards a sustainable healthcare approach," in *Artificial Intelligence for Sustainable Development: Theory, Practice and Future Applications*, 2021, pp. 83–98. doi: 10.1007/978-3-030-51920-9_6.
[50] R. C. Poonia, A. K. J. Saudagar, A. Altameem, M. Alkhathami, M. B. Khan, and M. H. A. Hasanat, "An enhanced SEIR model for prediction of COVID-19 with vaccination effect," *Life*, vol. 12, no. 5, Apr. 2022, doi: 10.3390/life12050647.
[51] S. Sarfraz *et al.*, "Clinical characteristics of patients with COVID-19 in Saudi Arabia - a single center experience," *Research and Reviews of Infectious Diseases*, vol. 3, no. 1, pp. 68–74, Jun. 2020, doi: 10.36959/719/568.
[52] K. J. Locey, T. A. Webb, J. Khan, A. K. Antony, and B. Hota, "An interactive tool to forecast US hospital needs in the coronavirus 2019 pandemic," *JAMIA Open*, vol. 3, no. 4, pp. 506–512, Feb. 2021, doi: 10.1093/jamiaopen/ooaa045.
[53] H. Wang *et al.*, "Phase-adjusted estimation of the number of Coronavirus Disease 2019 cases in Wuhan, China," *Cell Discovery*, vol. 6, no. 1, pp. 10–18, Feb. 2020, doi: 10.1038/s41421-020-0148-0.
[54] I. De Falco, A. Della Cioppa, U. Scafuri, and E. Tarantino, "Coronavirus Covid-19 spreading in Italy: optimizing an epidemiological model with dynamic social distancing through differential evolution," *Prepr. arXiv.2004.00553*, Apr. 2020.
[55] J. T. Wu, K. Leung, and G. M. Leung, "Nowcasting and forecasting the potential domestic and international spread of the 2019-nCoV outbreak originating in Wuhan, China: a modelling study," *The Lancet*, vol. 395, no. 10225, pp. 689–697, Feb. 2020, doi: 10.1016/S0140-6736(20)30260-9.
[56] OECD, "OECD policy responses to Coronavirus (COVID-19). The territorial impact of COVID-19: Managing the crisis across levels of government," OECD. https://www.oecd.org/coronavirus/policy-responses/the-territorial-impact-of-covid-19-managing-the-crisis-across-levels-of-government-d3e314e1/ (accessed Apr. 25, 2021).
[57] W. Ali, "Online and remote learning in higher education institutes: A necessity in light of COVID-19 pandemic," *Higher Education Studies*, vol. 10, no. 3, pp. 16–25, May 2020, doi: 10.5539/hes.v10n3p16.
[58] C. Arndt *et al.*, "Covid-19 lockdowns, income distribution, and food security: An analysis for South Africa," *Global Food Security*, vol. 26, Sep. 2020, doi: 10.1016/j.gfs.2020.100410.
[59] M. Hassounah, H. Raheel, and M. Alhefzi, "Digital response during the COVID-19 pandemic in Saudi Arabia," *Journal of Medical Internet Research*, vol. 22, no. 9, Sep. 2020, doi: 10.2196/19338.
[60] A. Khan *et al.*, "The role of digital technology in responding to COVID-19 pandemic: Saudi Arabia's experience," *Risk Management and Healthcare Policy*, vol. 14, pp. 3923–3934, Sep. 2021, doi: 10.2147/RMHP.S317511.
[61] A. Alammary, M. Alshaikh, and A. Alhogail, "The impact of the COVID-19 pandemic on the adoption of e-learning among academics in Saudi Arabia," *Behaviour & Information Technology*, vol. 41, no. 14, pp. 3138–3160, Oct. 2022, doi: 10.1080/0144929X.2021.1973106.
[62] A. Y. Alqahtani and A. A. Rajkhan, "E-learning critical success factors during the COVID-19 pandemic: A comprehensive analysis of E-learning managerial perspectives," *Education Sciences*, vol. 10, no. 9, Aug. 2020, doi: 10.3390/educsci10090216.
[63] Worldometers, "Total coronavirus cases in Saudi Arabia." https://www.worldometers.info/coronavirus/country/saudi-arabia/ (accessed Nov. 20, 2021).
[64] COVID19 Global Map, "Coronavirus resource center, John Hopkins University & medicine," Johns Hopkins Coronavirus Resource Center (CRC), 2020. https://coronavirus.jhu.edu/map.html (accessed Aug. 22, 2020).
[65] A. Saxena, "The mathematics of lockdown & social distancing: Quantifying the impact of social distancing in containing the spread of COVID-19 using the classical SEIR model," Towards Data Science, 2020. https://towardsdatascience.com/the-mathematics-of-lockdown-social-distancing-1257bc685022 (accessed Apr. 10, 2021).
[66] N. Imai *et al.*, "Report 3: Transmissibility of 2019-nCoV," *Imperial College London COVID-19 Response Team*, 2020, doi: 10.25561/77148.
[67] C. Map, "Coronavirus resource center, John Hopkins University & Medicine," Johns Hopkins Coronavirus Resource Center (CRC), 2022. https://coronavirus.jhu.edu/map.html (accessed Apr. 19, 2022).
[68] G. M. Nakamura, G. C. Cardoso, and A. S. Martinez, "Improved susceptible–infectious–susceptible epidemic equations based on uncertainties and autocorrelation functions," *Royal Society Open Science*, vol. 7, no. 2, Feb. 2020, doi: 10.1098/rsos.191504.

[69] F. Brauer and C. Castillo-Chavez, *Mathematical models in population biology and epidemiology*, vol. 40. New York, NY: Springer New York, 2012. doi: 10.1007/978-1-4614-1686-9.
[70] C. Nunn and S. Altizer, *Infectious diseases in primates*, Oxford University Press, 2006. doi: 10.1093/acprof:oso/9780198565857.001.0001.
[71] T. Harko, F. S. N. Lobo, and M. K. Mak, “Exact analytical solutions of the susceptible-infected-recovered (SIR) epidemic model and of the SIR model with equal death and birth rates,” *Applied Mathematics and Computation*, vol. 236, pp. 184–194, Jun. 2014, doi: 10.1016/j.amc.2014.03.030.
[72] J. C. Miller, “Mathematical models of SIR disease spread with combined non-sexual and sexual transmission routes,” *Infectious Disease Modelling*, vol. 2, no. 1, pp. 35–55, Feb. 2017, doi: 10.1016/j.idm.2016.12.003.
[73] D. E. Bloom, D. Cadarette, and J. Sevilla, “New & resurgent infectious diseases can have far-reaching economic repercussions,” *Finance & Development*, vol. 55, no. 2, pp. 46–49, 2018.
[74] R. Naresh, A. Tripathi, and D. Sharma, “Modelling and analysis of the spread of AIDS epidemic with immigration of HIV infectives,” *Mathematical and Computer Modelling*, vol. 49, no. 5–6, pp. 880–892, Mar. 2009, doi: 10.1016/j.mcm.2008.09.013.
[75] L. López and X. Rodó, “A modified SEIR model to predict the COVID-19 outbreak in Spain and Italy: Simulating control scenarios and multi-scale epidemics,” *Results in Physics*, vol. 21, Feb. 2021, doi: 10.1016/j.rinp.2020.103746.
[76] GASTAT, “The General Authority for Statistics - Kingdom of Saudi Arabia.” https://www.stats.gov.sa/en (accessed Apr. 19, 2022).
[77] S. Feng, Z. Feng, C. Ling, C. Chang, and Z. Feng, “Prediction of the COVID-19 epidemic trends based on SEIR and AI models,” *PLOS ONE*, vol. 16, no. 1, Jan. 2021, doi: 10.1371/journal.pone.0245101.
[78] MOH, “COVID-19 dashboard: Saudi Arabia,” Ministry of Health, Saudi Arabia, https://covid19.moh.gov.sa/ (accessed Apr. 18, 2022).
[79] K. Misha, “How to model a pandemic.” The Conversation, https://theconversation.com/how-to-model-a-pandemic-134187 (accessed Jun. 29, 2021).
[80] T. Singhal, “A Review of Coronavirus Disease-2019 (COVID-19),” *The Indian Journal of Pediatrics*, vol. 87, no. 4, pp. 281–286, Apr. 2020, doi: 10.1007/s12098-020-03263-6.

BIOGRAPHIES OF AUTHORS

Mutasem K. Alsmadi is currently an associate professor at the Faculty of Applied Studies and Community Service, Department of Management of Information Systems, Imam Abdurrahman Bin Faisal University. He received his BS degree in Software engineering in 2006 from Philadelphia University, Jordan, his MSc degree in intelligent systems in 2007 from University Utara Malaysia, Malaysia, and his Ph.D. in Computer Science from The National University of Malaysia. He has published more than one hundred papers in the image processing and Algorithm optimization areas. His research interests include Artificial intelligence, Pattern recognition, Algorithms optimization and Computer vision. He can be contacted at mksalsmadi@gmail.com.



Ghaith M. Jaradat received the B.Sc. degree in Computer Science from Jerash University, Jordan, in 2004, and his M.Sc. degree in Intelligent Systems from Utara University, Malaysia, in 2007, and the Ph.D. degree in Computer Science from the National University of Malaysia, Malaysia, in 2012. He is currently an Associate Professor at Amman Arab University, Jordan, since 2020. His research interests are mainly directed to Metaheuristics and Combinatorial Optimization Problems. He can be contacted at email: g.jaradat@aau.edu.jo.

Sami Abdullah Albahussain is currently a professor at the Department of Business Administration, College of Business Administration, Imam Abdurrahman Bin Faisal University, Dammam, Saudi Arabia. He holds a BA in Project Management from King Faisal University in 1989, Saudi Arabia, and MSc in Management and Organization from the University of Colorado at Denver, Colorado, USA in 1994, and a doctorate from the University of Bradford, UK in HRM in 2000. He has published more than twenty-five papers in the HRM areas. He can be contacted at saalbahussain@iau.edu.sa.

Mohammed Fahed Tayfour is currently Lecturer at the Faculty of Applied Studies and Community Service, Department of Management of Information Systems, Imam Abdurrahman Bin Faisal University. He received his BS degree in Applied Computer Science in 2004 from Philadelphia University, Jordan, his MSc degree in Information Technology in 2008 from University Utara Malaysia, Malaysia. His research interests include Artificial intelligence, Database System, Data Science, Software Engineering and Distance Learning Issues. He can be contacted at mftayfour@iau.edu.sa.

Usama A. Badawi An Assistant Professor of computer Science. His Ph.D. degree in the field of object-oriented distributed systems that is practically performed in the Technical University of Darmstadt-Germany. Has attended many scientific activities such as CIMPA school in Nice-France. Has published many scientific researches in different computer application areas (RG-Score 10.62). Dr. Badawi Research Interests are Computer applications in Business, Artificial Intelligence, Distributed Systems, Image Processing, and Blockchain applications. He can be contacted at ubadawi@gmail.com.

Hayat Alfagham received her BS degree in Computer Information Systems from King Faisal University, Saudi Arabia, her MSc degree in intelligent systems in 2015 from Kings College London, United Kingdom, and her Ph.D. in Computer Science in 2020 from Queen Mary University of London. She is currently an associate professor at the Faculty of Applied Studies and Community Service, Department of Management of Information Systems, Imam Abdurrahman Bin Faisal University. Her research interests include Link prediction, big data, pattern recognition, machine learning, and network evolution. She can be contacted at hmalfagham@iau.edu.sa.

Muneerah Ebrahem Alshabanah is currently a lecturer at the Faculty of Applied Studies and Community Service, Department of Management of Information Systems, Imam Abdurrahman Bin Faisal University. She received her BS degree in Management Information Systems in 2012 from Dammam University, Saudi Arabia, her MSc degree in Business Information Systems Management in 2016 from Middlesex University in London, the United Kingdom. She has published several papers. She can be contacted at email: m.i.alshabanah@gmail.com.

Daniah Abdulrahman Alrajhi is currently a lecturer at the Faculty of Applied Studies and Community Service, Department of Management of Information Systems, Imam Abdurrahman Bin Faisal University. She received her BS degree in Management Information Systems in 2012 from Dammam University, Saudi Arabia, her MSc degree in Business Information Systems Management in 2016 from Middlesex University in London, the United Kingdom. She has published several papers. She can be contacted at email: daniah.alrajhi@gmail.com.

Hanouf Naif ALkhaldi is currently a lecturer at the Faculty of Applied Studies and Community Service, Department of Management of Information Systems, Imam Abdurrahman Bin Faisal University. She received her BS degree in Management Information Systems in 2012 from Dammam University, Saudi Arabia, her MSc degree in Information System in 2017 from University of Brighton, the United Kingdom. She has published several papers. She can be contacted at email: mis.hanouf@gmail.com.

Njoud Ahmad Altuwaijri is currently a teaching assistant at the faculty of Applied studies and community service., Department of Management Information Systems, Imam Abdulrahman Bin Faisal University. Graduated in 2018 with a degree in Management information systems from Imam Abdulrahman Bin Faisal University, Saudi Arabia. She has published two papers since graduation. She can be contacted at naialtuwaijri@iau.edu.sa.

Hany Answer ShoShan He is currently working as an Assistant Professor at the Faculty of Applied Studies and Community Service, Department of General Courses. He obtained a Bachelor's degree in Law, Mansoura University, Egypt in 2006, and obtained a Master's degree in Economic and Financial Sciences, Mansoura University in 2010. He obtained a PhD in Economic and Financial Sciences in 2014, and he has Many published scientific researches, and his interests include all global economic matters. He can be contacted at email: dr_hany_shoshan@hmail.com.

Hayah Mohamed Abouelnaga She holds a Bachelor of Laws, a Master's degree in Public and Private Law, and a PhD in Commercial Law entitled (Commitment to Negotiation in International Trade Contracts), and has many published scientific papers. She can be contacted at hnaja@iau.edu.sa.

Ahmed Baz Mohamed Metwally He holds a Bachelor of Law, a Master's degree in Public and Private Law, and a PhD in Commercial Law entitled (Commitment to Transparency and Disclosure of Information in the Stock Exchange), and has many published scientific papers. He can be contacted at abmetwally@iau.edu.sa.