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Weather Conditions and COVID-19 Cases: Insights from the GCC Countries

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ABSTRACT

The prediction of new COVID-19 cases is crucial for decision makers in many countries. Researchers are continually proposing new models to forecast the future tendencies of this pandemic, among which long short-term memory (LSTM) artificial neural networks have exhibited relative superiority compared to other forecasting techniques. Moreover, the correlation between the spread of COVID-19 and exogenous factors, specifically weather features, has been explored to improve forecasting models. However, contradictory results have been reported regarding the incorporation of weather features into COVID-19 forecasting models. Therefore, this study compares uni-variate with bi- and multi-variate LSTM forecasting models for predicting COVID-19 cases, among which the latter models consider weather features. LSTM models were used to forecast COVID-19 cases in the six Gulf Cooperation Council countries. The root mean square error (RMSE) and coefficient of determination (R^2) were employed to measure the accuracy of the LSTM forecasting models. Despite similar weather conditions, the weather features that exhibited the strongest correlation with COVID-19 cases differed among the six countries. Moreover, according to the statistical comparisons that were conducted, the improvements gained by including weather features were insignificant in terms of the RMSE values and marginally significant in terms of the R^2 values. Consequently, it is concluded that the uni-variate LSTM models were as good as the best bi- and multi-variate LSTM models; therefore, weather features need not be included. Furthermore, we could not identify a single weather feature that can consistently improve the forecasting accuracy.

1. Introduction

The World Health Organization (WHO) declared the coronavirus disease (COVID-19) a pandemic on 11 March, 2020 (WHO, 2020). The severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), which is responsible for COVID-19, first appeared in Wuhan, Hubei Province, China, in December 2019 (Bodapati et al., 2020). Since then, COVID-19 has resulted in a significant public health crisis (Wang et al., 2022). As of February 2022, the number of confirmed COVID-19 cases had reached 422 million (Organization et al., 2022).

As with many other respiratory viruses, SARS-CoV-2 spreads via respiratory droplets, human-to-human contact, and aerosol transmission (Yin et al., 2022). According to the Centers for Disease Control and Prevention, physical contact, such as the touching of surfaces that carry viral particles, is another virus-spreading mechanism (Al-Qaness et al., 2020). Several studies have demonstrated that weather features can affect the spread and stability of respiratory infections (Choi et al., 2021; Liu et al., 2020). For example, ambient humidity, is a weather feature that can change the lifetime and size of respiratory droplets. It may reduce the size of droplets to such an extent that they fall to the ground, or maintain them in the air such that they are absorbed into the respiratory tracts of vulnerable individuals (El Hassan et al., 2022; Pica and Bouvier, 2012).

Furthermore, temperature was found to be a significant factor affecting the COVID-19 outbreak in Wuhan, China (Chen et al., 2020). Liu et al. (2020) confirmed this finding by demonstrating that COVID-19 cases were linked to temperature in 17 cities in China. Liu et al. (2020) also found that a 1 °C increase in the ambient temperature led to a decline in the daily reported COVID-19 cases. The effect of temperature on the spread of COVID-19 cases was also reported in India (Sharma et al., 2020) and Indonesia (Tosepu et al., 2020). In addition to temperature, researchers have demonstrated that weather features, such as humidity can affect the spread of COVID-19 (Bhimala et al., 2020; Chen et al., 2020; Gupta et al., 2020; Méndez-Arriaga, 2020; Oliveiros et al., 2020; Wang et al., 2020). This association between weather conditions and the spread of COVID-19 is expected to improve COVID-19 forecasting models. However, other scholars have denied such an association (Briz-Redón and Serrano-Aroca, 2020; Iqbal et al., 2020; Jahangiri

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et al., 2020); consequently, it has been stated that weather conditions must be completely ignored in the development of COVID-19 forecasting models.

The forecasting of COVID-19 cases is important for decision makers who must implement appropriate precautionary measures, such as lockdowns and distance learning, to stop the spread of the virus, while maintaining regular economic activities. Several researchers have studied variants of artificial neural networks (ANNs) for forecasting COVID-19 cases, one of which is the long short-term memory (LSTM) network, which is a special type of ANN network that can deal with time series. Uni-variate LSTM networks (Chatterjee et al., 2020; Direkoglu and Sah, 2020; Elsheikh et al., 2021; Hartono, 2020; Vadyala et al., 2020) have been used to forecast COVID-19 cases and deaths based on previously published COVID-19 data. Certain researchers included meteorological conditions along with COVID-19 data in LSTM forecasting models by using multi-variate LSTM networks to forecast COVID-19 cases (Batool and Tian, 2021; Khennou and Akhloufi, 2021).

As stated previously, conflicting opinions exist regarding the role of weather conditions in the prediction of new COVID-19 cases. Therefore, in this study, we investigate these contradictions by comparing the accuracy of LSTM forecasting models that consider weather conditions with those that ignore weather conditions. We analyze the Gulf Cooperation Council (GCC) countries, which include the United Arab Emirates (UAE), Kingdom of Saudi Arabia (KSA), Bahrain, Kuwait, Qatar, and Oman. The GCC were selected owing to their similarity in terms of weather conditions, high COVID-19 testing rates, and preventive policies that have been adopted to curb the spread of the virus. Moreover, their high testing rates compared to the number of cases make the GCC countries reliable study objects (Al-Shihabi and Abu-Abdoun, 2021).

This study seeks to answer the following research questions (RQs):

1. (**RQ1**): Should the effects of weather on the spread of COVID-19 be the same for countries with similar weather conditions?
2. (**RQ2**): Will the accuracy of LSTM forecasting models that only consider COVID-19 cases be improved by including relevant weather conditions in bi- or multi-variate LSTM forecasting models?

To answer **RQ1**, we (i) studied the correlation between weather conditions and COVID-19 cases and (ii) compared several bi- and multi-variate LSTM models in terms of their accuracy in predicting the number of future COVID-19 cases. Surprisingly, the six countries provided different answers regarding the weather conditions to be included along with the COVID-19 cases for developing the most accurate LSTM forecasting model. To answer **RQ2**, after identifying the best bi- or multi-variate LSTM model for each GCC country, we compared these models with uni-variate LSTM models that consider only COVID-19 cases. Using two accuracy measures, we found that the forecasting accuracy was only improved for three countries, and these improvements were not statistically significant. Therefore, weather features need not be considered as inputs into LSTM models that are used to forecast COVID-19 cases.

The main contributions of this study are as follows: (i) Uni-variate LSTM models for forecasting COVID-19 cases in the GCC countries are investigated. (ii) The correlations between COVID-19 cases and weather conditions in the GCC countries are examined. (iii) Several bi- and multi-variate LSTM models are developed to forecast COVID-19 cases in the GCC countries, which incorporate the most relevant weather features. (iv) The uni-variate LSTM models are compared with the best bi- and multi-variate LSTM models to answer **RQ1** and **RQ2**. Furthermore, the optimization of the configurations of the LSTM models using the Keras tuning algorithm can be considered as a minor contribution of this study. A limitation of this study is that it only considers LSTM forecasting models for the GCC countries.

The remainder of this paper is organized as follows. Section 2 presents the literature review. The dataset sources are outlined in Section 3, and Section 4 describes the experiments that were conducted. Finally, the conclusions and future work are summarized in Section 5.

2. Literature review

Techniques for predicting the spread of COVID-19 can be divided into three major categories: machine-learning models, statistical models, and mathematical models that use compartmental mathematics (Mohamadou et al., 2020). Among the compartmental mathematical models, the susceptible-exposed-infected-removed (SEIR) and susceptible-infected-recovered models are the most popular for forecasting the spread of COVID-19 (Pandey et al., 2020; Ranjan, 2020; RSY, 2020). Examples of statistical techniques for forecasting the spread of COVID-19 include simple techniques such as the moving average, weighted moving average, and single exponential smoothing methods (Elmousalami and Hassanien, 2020) and advanced techniques such as the auto-regressive integrated moving average (ARIMA) method (Roy et al., 2021; Talkhi et al., 2021).

Machine-learning forecasting techniques are more accurate than statistical models, and the superiority of LSTM models has been proven (Assaf et al., 2020). Consequently, in the following subsections, we review the related machine-learning techniques that have been employed to forecast the spread of COVID-19. This review is limited to methods that are relevant to this study; therefore, we focus on LSTM forecasting models and the effects of weather features on improving the forecasting accuracy.

2.1. Machine learning-related forecasting techniques

Machine-learning algorithms have been applied to forecast and model the spread of COVID-19. Malki et al. (2021) used a hybrid prediction model of decision trees and linear regression to forecast the spread of COVID-19 in 12 countries during the first week of September 2021. Ribeiro et al. (2020) evaluated the efficiency of the random forest and support vector regression models in forecasting the cumulative COVID-19 cases in Brazil. Sultana et al. (2022) employed linear regression, a multi-layer perceptron (MLP), and vector auto regression to predict various COVID-19 outbreaks in India. The random forest, support vector machine (SVM), and other machine-learning algorithms were used in a study by Alali et al. (2022) for predicting the confirmed and recovered COVID-19 cases in India and Brazil. Finally, in a recent study by Dairi et al. (2021a), an unsupervised detector that integrated a variational autoencoder for feature extraction with an SVM algorithm was proposed to detect COVID-19 cases using routine blood tests.

Among the machine-learning techniques, ANN-based methods have exhibited superiority over other methods in forecasting COVID-19 cases (Shetty and Pai, 2021). ANNs were developed based on the mechanisms of biological nerve systems (Maind et al., 2014). Several ANN variants have been proposed for predicting COVID-19 behavior in different regions. Tamang et al. (2020) used an ANN to construct a forecasting model for confirmed and fatal COVID-19 cases in India, the USA, the UK, and France, whereas Lounis et al. (2021) developed an inverse ANN model to estimate COVID-19 cases, deaths, and recoveries in Algeria.

Feed-forward neural networks and the MLP are forms of ANNs that have been used to forecast the spread rate of COVID-19 in India (Chakraborty et al., 2020; Shetty and Pai, 2021) and across the continental USA (Mollalo et al., 2020). Rizk-Allah and Hassanien (2020) presented a hybrid forecasting model that combines a multi-layer feed-forward neural network with an interior search algorithm to forecast the spread of COVID-19 in the USA, Italy, and Spain. Another ANN variant is the convolutional neural network (CNN), which has been used to forecast the number of confirmed COVID-19 cases in China (Huang et al., 2020). Similarly, Mohimont et al. (2021) developed multiple CNN models to forecast cumulative COVID-19 cases, daily cases, deaths, and recoveries in France. Researchers have also employed self-organizing map (SOM) networks, which are a form of ANNs that are considered to be ideal for data clustering (Ghaseminezhad and Karami, 2011). For example, several researchers (Hartono, 2020; Melin and Castillo, 2021) applied SOM networks to cluster countries in terms of COVID-19

Table 1
COVID-19 forecasting models and weather conditions summary.

Reference	Study area	Machine-learning model	Weather features	Findings of weather impact
Abdulkareem et al. (2021)	Korea	CNN, Decision tree, BayesNet	Temperature, humidity, wind speed, precipitation	Temperature, humidity, wind, and precipitation influence predicting COVID-19 cases.
Da Silva et al. (2020)	Brazil, USA	Bayesian regression, cubist regression, k-nearest neighbors, random forest, support vector machine	Temperature and precipitation	Temperature and precipitation increased the accuracy of COVID-19 prediction models.
Karimuzzaman et al. (2020)	9 countries	ARIMA, MLP, extreme learning machine, generalized linear count	Temperature, wind speed, pressure, humidity, precipitation	Temperature and humidity impact COVID-19 cases in all studied countries except Italy and Sri Lanka.
Malki et al. (2020b)	France, UK	Random forest	Temperature, humidity, sunny hours, wind speed	Weather variables influenced the prediction models compared to the other variables.
Ronald Doni et al. (2021)	India	Concurrent ANN, recurrent ANN, bi-directional ANN	Temperature, dew, humidity	Weather features enhanced the prediction of the model.
Pramanik et al. (2020)	Russia	Random forest	Temperature, humidity, wind speed, sunshine	Random forest model provided accurate predictions with weather features.
Khennou and Akhloufi (2021)	Canada	LSTM model	Temperature, humidity	Temperature and humidity increased the accuracy of COVID-19 forecasting model.
Aragão et al. (2022)	Brazil	LSTM model	Temperature, humidity	LSTM model's accuracy increased with the inclusion of weather conditions data.
Batool and Tian (2021)	Pakistan	LSTM model	Temperature, humidity	LSTM model with weather data achieved highest accuracy.
Bhimala et al. (2020)	India	LSTM model	Temperature, humidity	*Specific humidity influences the spread of COVID-19 in west and northwest regions in India. *Temperature impact COVID-19 spread in high humid regions in India.
Rashed and Hirata (2021)	Japan	LSTM model	Temperature, humidity	Merging temperature, humidity data in the LSTM model reported accurate predictions.
Pal et al. (2020)	USA	Shallow LSTM model	UV, temperature, perception, ozone, dew, and humidity	The prediction accuracy of the model was not affected by weather conditions data.
Iloanusi and Ross (2021)	20 countries	LSTM, random forest,	Temperature, rainfall, windspeed, irradiation, humidity	Temperature improved the accuracy of the forecasting models for most of the studied countries.
Gupta et al. (2021)	-	Convolutional neural network	Temperature, wind speed, sunlight, humidity	Only temperature, wind speed, and sunlight enhanced the performance of the CNN model.

transmission and to predict COVID-19 cases.

2.2. LSTM forecasting models

LSTM is an improved version of the recurrent neural network (RNN) that is used to solve the scaling issue in RNNs (Sundermeyer et al., 2012). LSTM networks can easily handle time series because they have a high capacity to learn dependencies and analyze large amounts of data over a long period (Marzouk et al., 2021). Therefore, various LSTM network-based forecasting models have been applied since the beginning of the COVID-19 pandemic. LSTM forecasting models have been used to forecast COVID-19 cases, deaths, and recoveries (Bodapati et al., 2020; Direkoglu and Sah, 2020; Elsheikh et al., 2021; Yudistira, 2020). Ghany et al. (2021) established two uni-variate LSTM models to forecast COVID-19 cases and deaths in the GCC countries.

The bi-directional and encoder-decoder LSTM are improved versions of LSTM. The former enables information to flow from the backward and forward layers (Zeroual et al., 2020), whereas the latter is a popular sequence-to-sequence network that provides a simple and automated approach for sequential data modeling (Du et al., 2020). Chandra et al. (2021) used an encoder-decoder and bi-directional LSTM network for short-term COVID-19 infection forecasting in India. Furthermore, a bi-directional LSTM model was proposed by Aldhyani and Alkahtani (2021) to forecast COVID-19 cases and deaths in the GCC countries based on previous trends in COVID-19 in the Gulf region. Pustokhin et al. (2020) proposed a novel residual network based on the bi-directional LSTM network for COVID-19 detection. The residual

Table 2
Demographic and meteorological information about the GCC countries.

Country	Population (million)	Area (km^2)	Temperature		Humidity		Wind speed		Dew Point	
			Max.	Min	Max.	Min	Max.	Min	Max.	Min
UAE	9.7	83,600	47	13	100	0	32	0	88	0
KSA	34.77	2,150,000	46	17	94	3	32	0	84	9
Kuwait	4.207	17,818	52	3	100	0	46	0	86	0
Oman	4.975	309,501	47	11	100	0	58	0	97	0
Bahrain	1.64	780	45	13	94	7	33	0	90	25
Qatar	2.64	11,521	48	13	100	0	30	0	90	36

bi-directional LSTM network provides more efficient training and validation, with a short path during training, compared to an ordinary LSTM network (Malki et al., 2020a).

Convolutional LSTM (CNN-LSTM) is another extension of the standard LSTM network that can interpret 2D spatio-temporal data (Shastri et al., 2020). A CNN-LSTM network-based forecasting model was proposed by Ketu and Mishra (2021) to forecast the total number of COVID-19 cases across 29 states in India. Zain and Alturki (2021) demonstrated that the CNN-LSTM forecasting model for global COVID-19 patients outperformed other forecasting models such as CNN and LSTM network-based models as well as statistical models such as ARIMA. Similarly, the CNN-LSTM proposed by Dairi et al. (2021b) exhibited improved performance in forecasting COVID-19 cases compared to the SVM, gated RNNs, CNN, and restricted Boltzmann machine. However, Arora et al. (2020) developed a bi-directional LSTM forecasting model that was superior to CNN-LSTM models in terms of accuracy.

Moreover, hybrid techniques that combine LSTM models with other machine-learning techniques have been developed. A hybrid forecasting model consisting of K-means-LSTM was proposed by Vadyala et al. (2020) to forecast COVID-19 cases in Louisiana, USA, which was more accurate than the SEIR model. Ayoobi et al. (2021) proposed a bi-directional CNN-LSTM forecasting model to predict COVID-19 cases and deaths in Australia and Iran. Furthermore, the hybrid forecasting model developed by Zheng et al. (2020) embedded LSTM into an improved susceptible-infected epidemiological model to predict the cumulative number of COVID-19 cases in China.

2.3. *COVID-19 forecasting and weather conditions*

Table 1 summarizes the COVID-19 forecasting models that include weather features. Column 2 indicates the study area, and column 3 displays the machine-learning algorithm used for forecasting. Column 4 lists the tested weather features, and column 5 summarizes the findings of the study.

Abdulkareem et al. (2021) used principal component analysis for selecting relevant weather features to improve the prediction accuracy of three machine-learning algorithms that were used to predict COVID-19 cases. This improvement was also demonstrated by Da Silva et al. (2020), who included temperature and precipitation data in their machine-learning forecasting algorithms. Karimuzzaman et al. (2020) showed that temperature and humidity had a significant influence on the spread of COVID-19 in several countries, with the exception of Italy and Sri Lanka. Similar to the work of Karimuzzaman et al. (2020), Malki et al. (2020b) confirmed the role of temperature and humidity in forecasting COVID-19 mortality rates in France and the UK. Furthermore, Ronald Doni et al. (2021) claimed that the inclusion of temperature and humidity improved the accuracy of their ANN-based forecasting models. A study by Pramanik et al. (2020) revealed the significant effect of weather variables, such as temperature, humidity, sunshine, and wind speed, on COVID-19 cases and mortality in Russia.

The cited studies used different machine-learning and statistical techniques that did not include LSTM models. The LSTM models that have been used to predict COVID-19-related problems are either bi- or multi-variate, and use weather features as inputs. For example, Khennou and Akhloufi (2021) considered daily temperature, humidity, and precipitation data to forecast the progression of COVID-19 in Canada, whereas Aragão et al. (2022) used temperature, humidity, and air quality index data to forecast COVID-19 deaths in Brazil. Aragão et al. (2022) demonstrated that the inclusion of weather data in the multi-variate LSTM model resulted in higher prediction accuracy compared to that of the uni-variate LSTM model with only COVID-19 deaths as a single input. Batool and Tian (2021) and Bhimala et al. (2020) stated that temperature and humidity were significant parameters in forecasting COVID-19 cases in Pakistan and India, respectively. Rashed and Hirata (2021) merged the maximum temperature, average humidity, and mobility data in an LSTM model developed to forecast COVID-19 cases in Japan. Rashed and Hirata (2021) reported that the predicted COVID-19 cases were consistent with the actual reported COVID-19 cases, and a slight increase in the prediction accuracy was achieved when using meteorological data.

Despite the consensus among the abovementioned researchers regarding the importance of including weather data in forecasting models, several researchers have offered contradicting opinions in this regard. For example, Pal et al. (2020) demonstrated that the prediction accuracy of their LSTM model in forecasting COVID-19 cases, deaths, and recoveries in the USA did not improve when including weather data. Several weather parameters were included as inputs in the multi-variate LSTM model proposed by Iloanusi and Ross (2021) for predicting the COVID-19 cases-to-mortality ratio in 36 countries. According to their study, only temperature was related to an increase in the prediction accuracy, and this increase was only detected in hot countries. The findings of Iloanusi and Ross (2021) do not align with those of previous studies, which indicated that temperature and humidity must be considered together. Moreover, temperature has been shown to improve the forecasting accuracy in cold countries, such as Canada (Khennou and Akhloufi, 2021) and Russia (Pramanik et al., 2020), and these results were rejected by Iloanusi and Ross (2021). Furthermore, Gupta et al. (2021) demonstrated that humidity does not improve the forecasting accuracy, which contradicts the claims of Karimuzzaman et al. (2020), Malki et al. (2020b), and Ronald Doni et al. (2021). Consequently, further research is required to understand the effects of weather on COVID-19 forecasting models.

3. Study context

This section provides important information regarding the countries that were studied, particularly in terms of their weather conditions. Furthermore, the data used in this study are described in detail.

3.1. *Study area*

This study included data from the GCC countries. These countries have similar environmental and weather conditions, such as limited rainfall and long summers with high temperatures. Furthermore, the GCC countries have adopted similar strategies to restrict the spread of the COVID-19 outbreak (Alandijany et al., 2020). Table 2 lists the demographic information and meteorological variables of the GCC

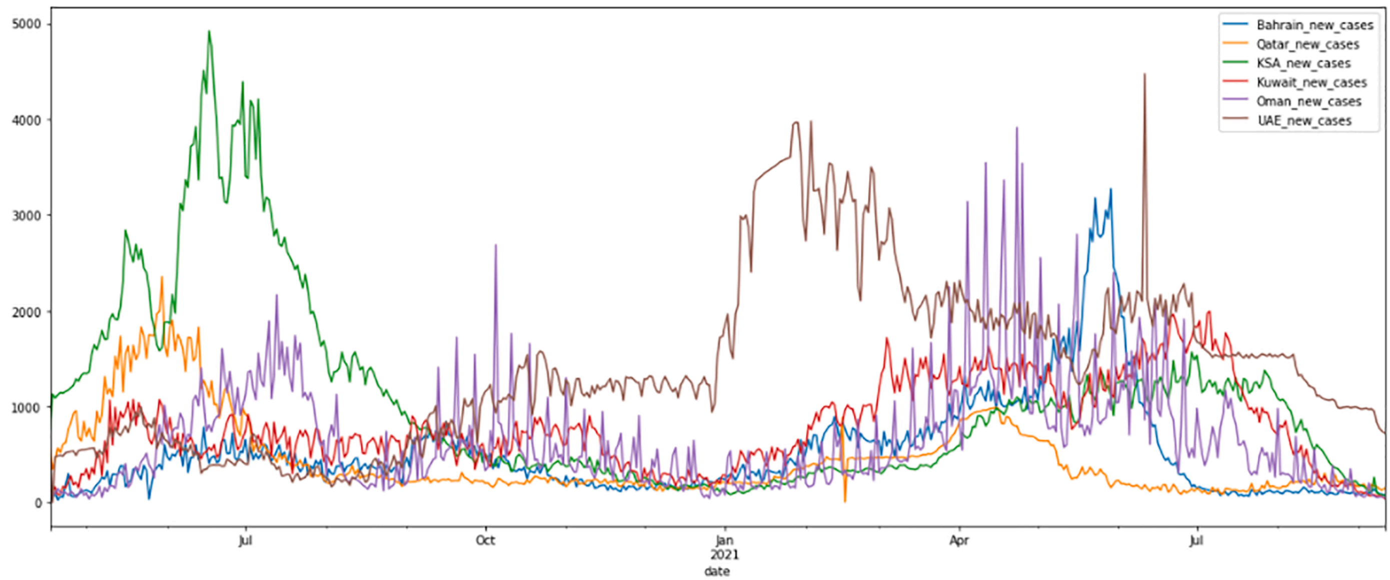

Fig. 1. COVID-19 cases in the GCC countries from April 2020 to September 2021.

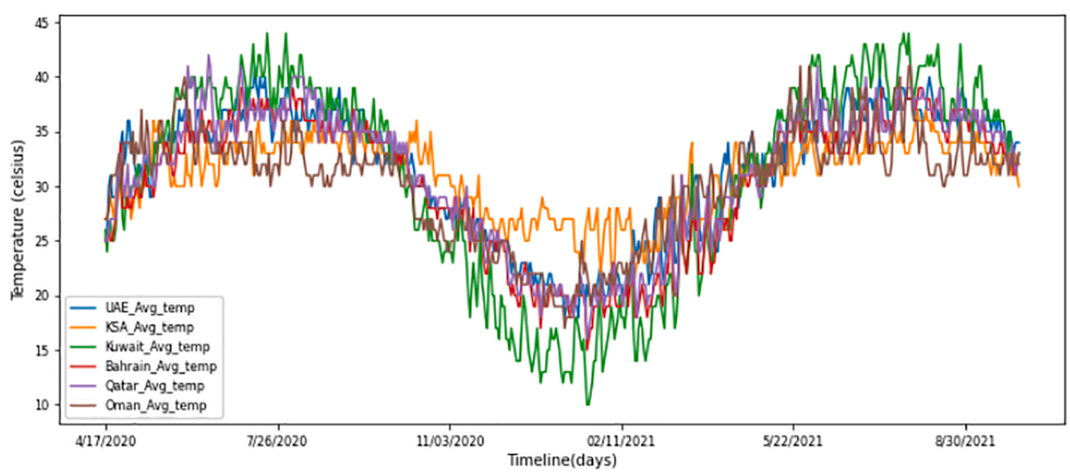

Fig. 2. Average temperature in the GCC countries from April 2020 to September 2021.

countries.

3.2. Dataset description

The daily reported cases of COVID-19 in the GCC countries were obtained from the WHO coronavirus dashboard[1] and compared with the local dataset that was provided by the health ministries in the GCC countries. Fig. 1 depicts the timeline of the COVID-19 cases in the GCC countries that were included in our study (April 2020 to September 2021). The highest numbers of COVID-19 cases detected in the UAE, KSA, Kuwait, Bahrain, Qatar, and Oman were 4471, 4919, 1993, 3273, 2355, and 3910, respectively. We ended the study by September 2021 as vaccination campaigns started in October 2021. Vaccination is expected to decrease COVID-19 transmission by reducing symptomatic and asymptomatic infections, and hindering the person-to-person spread of the virus (Eyre et al., 2022). Moreover, as argued by Iloanusi and Ross (2021), more than one season is required to study the effects of weather on the spread of COVID-19.

Data related to weather conditions for the GCC countries were extracted from the Weather Underground website, in which weather conditions were collected from more than 29,000 weather stations globally[2]. The weather features that were included in this study were the average temperature (°C), average humidity (%), average dew point (°F), and average wind speed (mph). Figs. 2 to 5 present the observed weather conditions in the GCC countries during the study period.

4. Experiment

In this section, we first describe the internal structure and components of the LSTM network. Subsequently, we explain the selection of the weather features that were used to construct the bi- and multivariate LSTM models. Thereafter, we demonstrate the configuration of the LSTM forecasting models. Finally, we present our experimental results and compare them with those of the LSTM forecasting models.

Python, which is a high-level general-purpose programming language, was used to develop all LSTM forecasting models. We used several deep-learning packages, such as NumPy, Pandas, TensorFlow, Keras, Matplotlib, Seaborn, and scikit-learn, to construct our forecasting

[1] WHO COVID-19 Dashboard (https://covid19.who.int/).

[2] Weather Underground (wunderground.com)

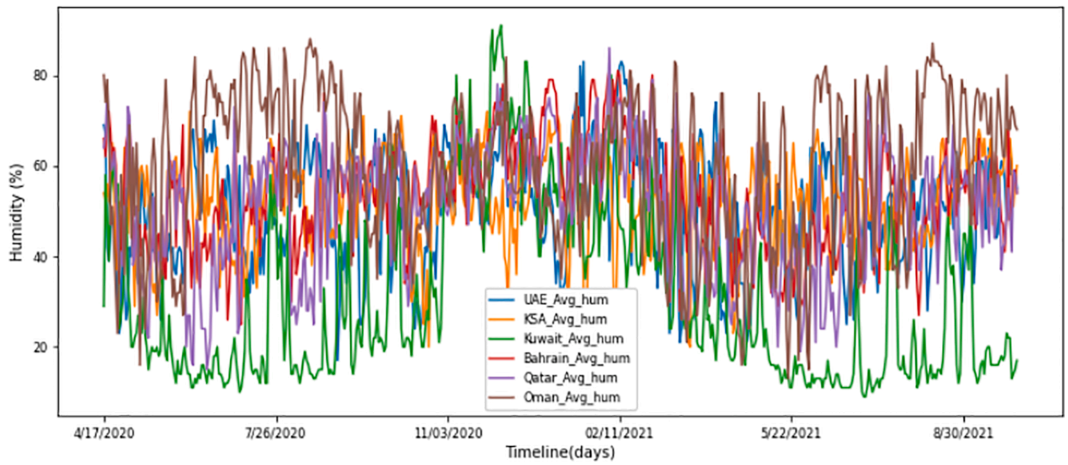

Fig. 3. Average humidity in the GCC countries from April 2020 to September 2021.

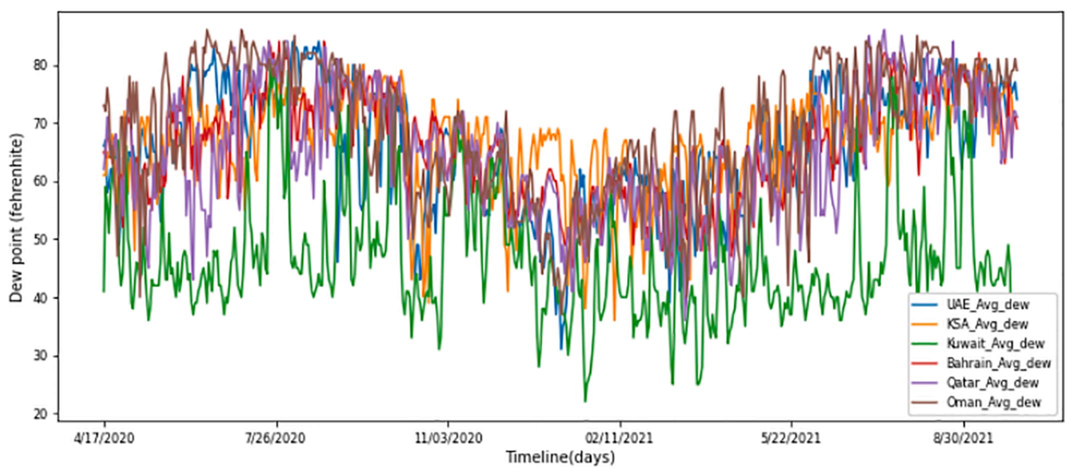

Fig. 4. Average dew point in the GCC countries from April 2020 to September 2021.

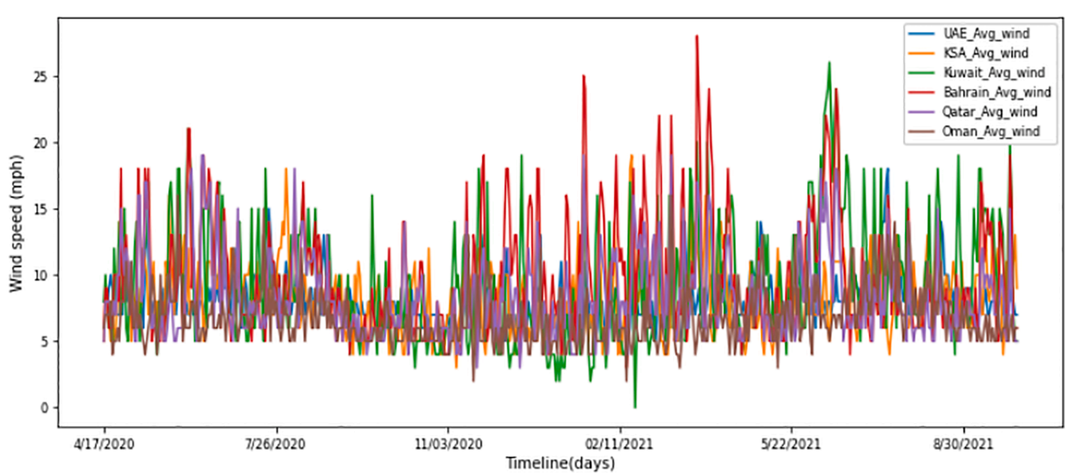

Fig. 5. Average wind speed in the GCC countries from April 2020 to September 2021.

models.

4.1. LSTM ANNs

In a typical RNN model, the gradient vanishes during back-propagation, which prevents the neural networks from learning long-term temporal correlations (Hochreiter and Schmidhuber, 1997). Consequently, in 1997, LSTMs were proposed to overcome the limitations of RNNs. LSTMs are considered to be among the most feasible forecasting tools for prediction tasks (Arora et al., 2020).

Fig. 6 depicts an LSTM network, whereas Fig. 7 shows the internal structure of an LSTM cell. An LSTM unit consists of three inputs: the

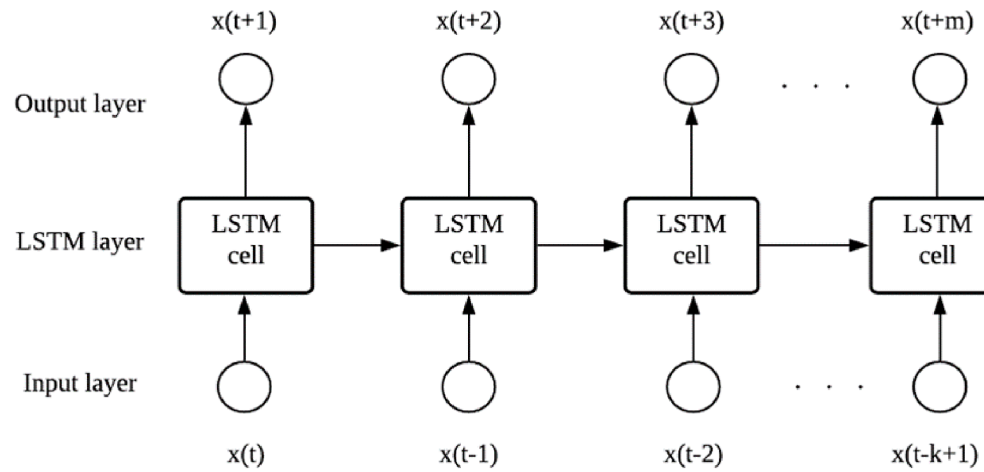

Fig. 6. Example of LSTM structure.

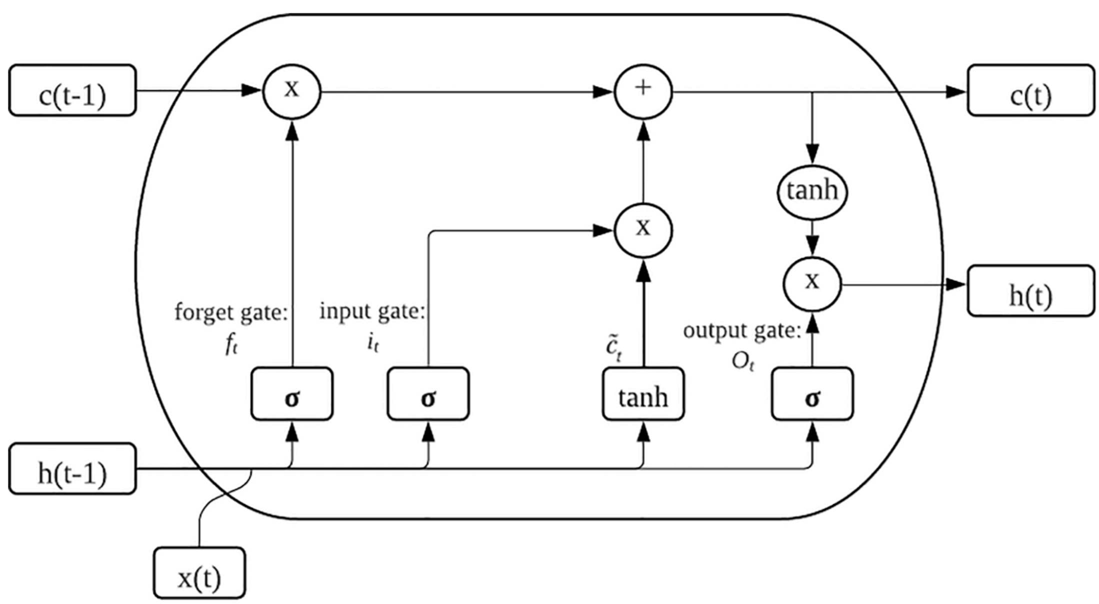

Fig. 7. LSTM cell.

previous cell state c_{t-1}, previous hidden state h_{t-1}, and current input vector x_t. A tanh function is generally used as the nonlinear activation function σ before all gates, as illustrated in Fig. 7. An LSTM cell consists of three gates: input, forget, and output. This arrangement inhibits the memory cells from retaining information across several time steps. The states of the gates are calculated using Eqs. (1)–(3).

$$i_t = \sigma(w_i x_t + u_i h_{t-1} + b_i) \tag{1}$$

$$f_t = \sigma\left(w_f x_t + u_f h_{t-1} + b_f\right) \tag{2}$$

$$o_t = \sigma(w_o x_t + u_o h_{t-1} + b_o) \tag{3}$$

Based on h_{t-1} and x_t, an intermediate state $\widetilde{C}_t$ is generated, as indicated in Eq. (4). Subsequently, the memory cell and hidden state of the LSTM are updated, as shown in Eqs. (5) and (6), respectively. Here, $\odot$ denotes the point-wise multiplication operation for the two vectors. In all of the above equations, the set of weights $\{w_i, w_f, w_o, w_t, w_{ch}, u_i, u_f, u_o, b_i, b_f, b_o, b_c\}$ is determined by optimizing the LSTM forecasting model.

$$\widetilde{C}_t = \tanh(x_t w_t + w_{ch} h_{t-1} + b_c) \tag{4}$$

$$C_{(t)} = \sigma(f_t \odot C_{t-1} + i_t \odot \widetilde{C}_t) \tag{5}$$

$$h_{(t)} = o_t \odot tanh(C_t) \tag{6}$$

The uni-variate forecasting model considers only one data stream. In contrast, the bi- and multi-variate LSTM forecasting networks consider two or more inputs. In this study, COVID-19 cases were used as inputs in all the models. One or more weather features were also included as inputs in the bi- and multi-variate LSTM forecasting models.

4.2. Feature selection

Feature selection refers to selecting the most relevant features for accomplishing the classification task with the smallest error (Pai and Ilango, 2020). We chose the Pearson correlation coefficient ρ as a metric for selecting the appropriate input features. Figs. 8–13 present heat maps that reflect the ρ values between the four selected weather features, namely the temperature (°C), humidity (%), dew point (°F), and wind speed (mph), with the COVID-19 cases in each GCC country. A strong positive correlation of $\rho = 1$ is indicated by dark red, whereas a strong negative correlation $\rho = -1$ is indicated by dark blue in the heat

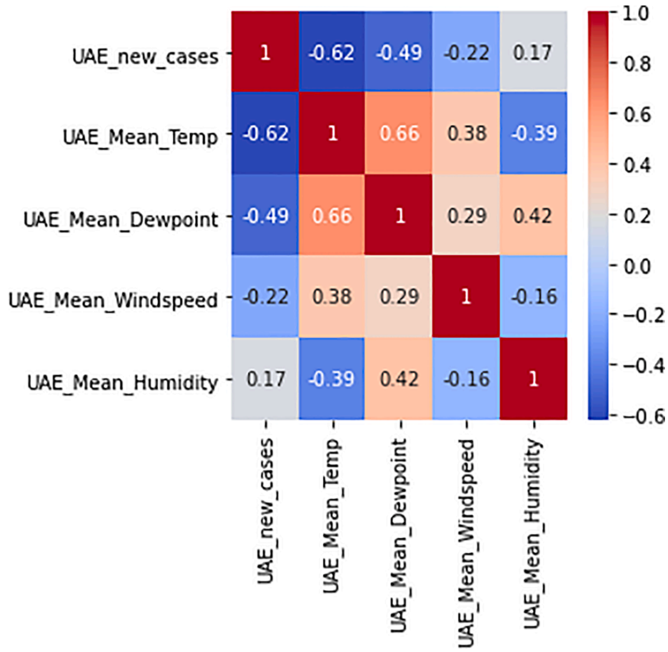

Fig. 8. UAE heat map correlation.

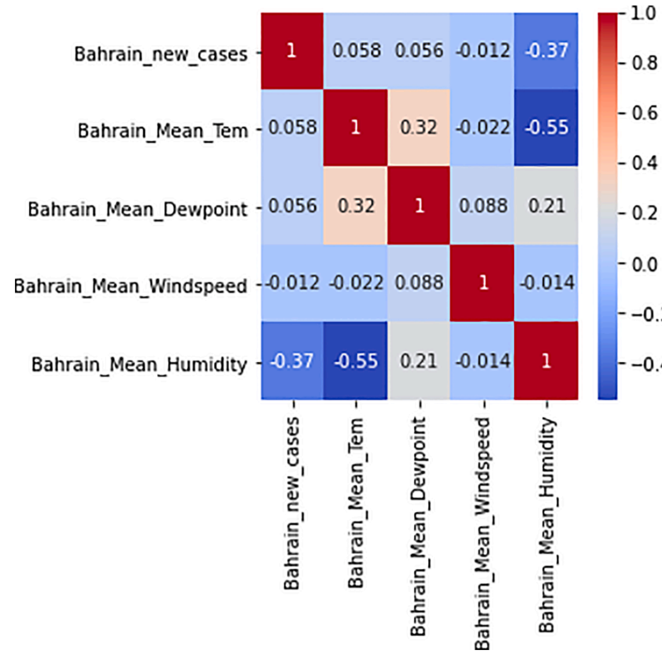

Fig. 10. Bahrain heat map correlation.

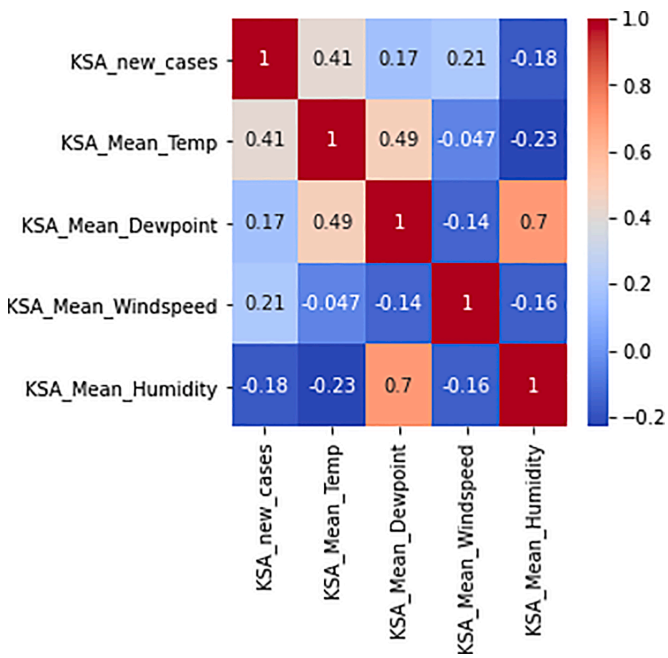

Fig. 9. KSA heat map correlation.

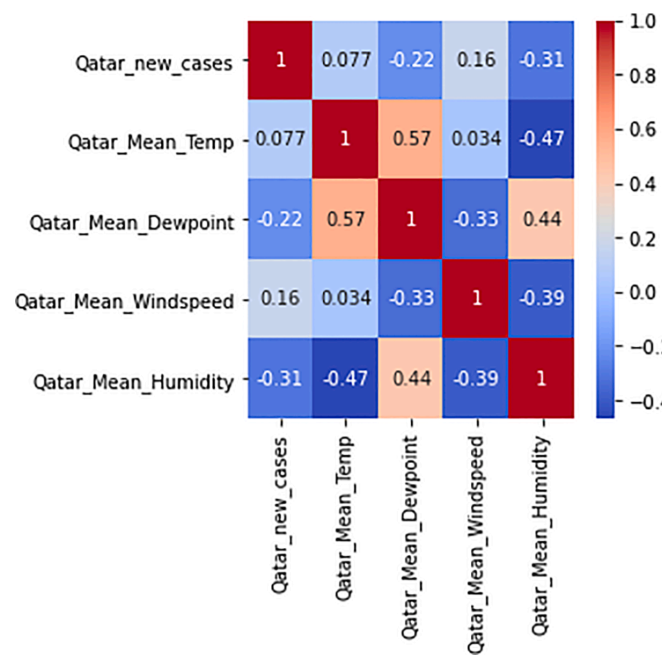

Fig. 11. Qatar heat map correlation.

map. Table 3 lists the weather features for for $\rho \geq 0.2$. We used these features to construct the multi-variate LSTM models.

4.3. LSTM models

We developed the following seven LSTM forecasting models for each GCC country to predict COVID-19 cases:

1. A uni-variate LSTM model that takes COVID-19 cases as input.
2. Four bi-variate LSTM forecasting models. Each bi-variate LSTM model takes one weather feature (i.e., temperature, humidity, dew point, and wind speed) as an input along with the COVID-19 cases.
3. Two multi-variate LSTM forecasting models that use the weather features listed in Table 3 as the input with the COVID-19 cases.

As data scaling improves the performance of forecasting models, the min-max scalar algorithm from the scikit-learn library was used to scale the weather features and COVID-19 case data to values between 0 and 1. Moreover, the datasets of COVID-19 and the weather conditions in each forecasting model were divided into 80% for training and 20% for testing. During the training of the LSTM models, the *Adam* optimizer was used to optimize the mean squared error (MSE) loss. The neural networks of the LSTM forecasting models were trained for 40 epochs, with a batch size of 1. All LSTM models were configured using the Keras tuning

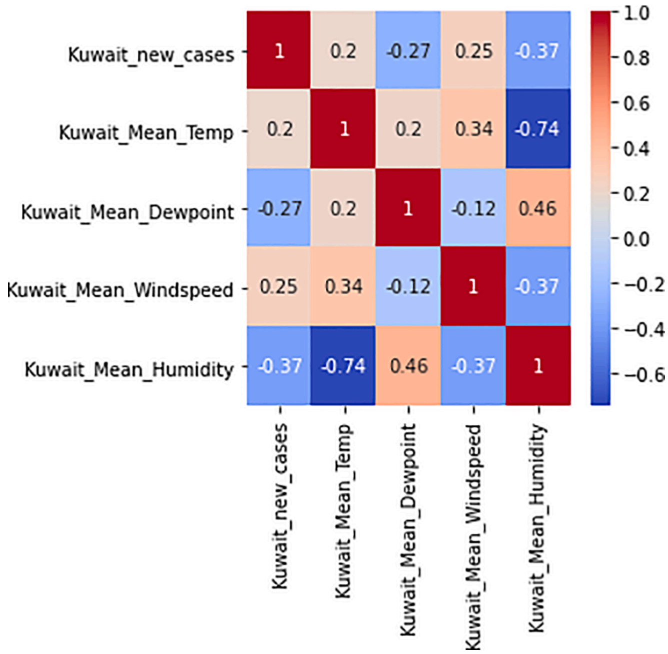

Fig. 12. Kuwait heat map correlation.

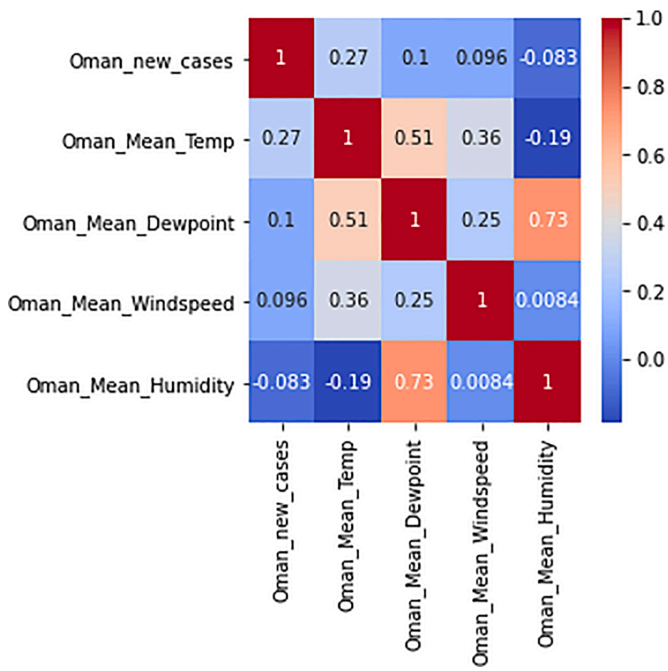

Fig. 13. Oman heat map correlation.

Table 3
Weather factors selected for multi-variate LSTM models.

Country	High correlated weather factors
UAE	Temperature, Dew point, Wind speed
KSA	Temperature, Wind speed
Bahrain	Humidity
Kuwait	Temperature, Dew point, Wind speed, Humidity
Qatar	Dew point, Humidity
Oman	Temperature

Table 4
Keras-tuning results on models configurations.

Country	Model type	Hyperparameters with keras tuning			
		Input nodes	Hidden layers	Hidden nodes	MSE
UAE	Multi-variate	160	2	300,10	0.0022
	High correlated factors	280	1	0	0.0021
	Uni-variate	20	2	220,220	0.0023
	Bi-variate Windspeed	300	2	280,10	0.0021
	Bi-variate Dewpoint	30	2	80,10	0.0024
	Bi-variate Humidity	140	2	20,60	0.0024
	Bi-variate Temperature	270	2	20,10	0.0026
KSA	Multi-variate	30	1	40,10	0.0011
	High correlated factors	210	3	90,10,10	0.0013
	Uni-variate	100	3	170,10,10	0.0010
	Bi-variate Windspeed	50	3	220,10,10	0.0013
	Bi-variate Dewpoint	20	2	80,10	0.0011
	Bi-variate Humidity	210	2	60,190	0.0012
	Bi-variate Temperature	290	2	30,300	0.0011
Kuwait	Multi-variate	70	2	270,80	0.0044
	High correlated factors	70	2	270,80	0.0044
	Uni-variate	200	3	190,290,240	0.0048
	Bi-variate Windspeed	50	2	280,210	0.0044
	Bi-variate Dewpoint	70	3	260,50,160	0.0044
	Bi-variate Humidity	280	1	170	0.0044
	Bi-variate Temperature	90	2	90,200	0.0045
Bahrain	Multi-variate	160	3	60,10,10	0.0015
	High correlated factors	120	2	210,50	0.0011
	Uni-variate	90	2	20,10	0.0014
	Bi-variate Windspeed	130	2	60,20	0.0013
	Bi-variate Dewpoint	70	3	240,10,10	0.0017
	Bi-variate Humidity	20	2	60,240	0.0013
	Bi-variate Temperature	150	3	10,80,130	0.0014
Qatar	Multi-variate	210	1	180	0.0016
	High correlated factors	210	2	50,120	0.0017
	Uni-variate	160	2	170,160	0.0018
	Bi-variate Windspeed	30	1	70	0.0018
	Bi-variate Dewpoint	270	2	260,40	0.0021
	Bi-variate Humidity	220	2	270,230	0.0018
	Bi-variate Temperature	20	2	70,270	0.0017
Oman	Multi-variate	170	1	20	0.0069
	High correlated factors	200	2	110,190	0.0071
	Uni-variate	220	2	40,10	0.0077
	Bi-variate Windspeed	160	1	70	0.0071
	Bi-variate Dewpoint	210	2	170,70	0.0079
	Bi-variate Humidity	260	1	280	0.0080
	Bi-variate Temperature	110	1	220	0.0073

Table 5
LSTM models accuracy evaluation.

Country	LSTM model	Evaluation metrics		Country	LSTM model	Evaluation metrics	
		RMSE	R^2			RMSE	R^2
7*UAE	Multi-variate	94.7	0.95	Bahrain	Multi-variate	184.76	0.85
	High correlated factors	86.28	0.97		High correlated factors	128.81	0.93
	Uni-variate	148.1	0.98		Uni-variate	110.87	0.94
	Bi-variate Wind speed	137.79	0.96		Bi-variate Wind speed	114.56	0.94
	Bi-variate Dew point	117.34	0.97		Bi-variate Dew point	182.43	0.85
	Bi-variate Humidity	111.89	0.97		Bi-variate Humidity	128.81	0.93
	Bi-variate Temperature	131.02	0.96		Bi-variate Temperature	134.33	0.92
KSA	Multi-variate	178.5	0.97	Qatar	Multi-variate	87.46	0.93
	High correlated factors	186.38	0.97		High correlated factors	77.46	0.95
	Uni-variate	173.73	0.97		Uni-variate	68.23	0.95
	Bi-variate Wind speed	184.05	0.97		Bi-variate Wind speed	80.48	0.94
	Bi-variate Dew point	197.07	0.97		Bi-variate Dew point	75.04	0.95
	Bi-variate Humidity	176.47	0.97		Bi-variate Humidity	74.54	0.95
	Bi-variate Temperature	165.13	0.98		Bi-variate Temperature	93	0.92
Kuwait	Multi-variate	129.43	0.90	Oman	Multi-variate	268.7	0.79
	High correlated factors	129.43	0.90		High correlated factors	273.97	0.78
	Uni-variate	122.05	0.79		Uni-variate	275.41	0.70
	Bi-variate Wind speed	141.94	0.87		Bi-variate Wind speed	280.26	0.77
	Bi-variate Dew point	133.57	0.86		Bi-variate Dew point	271.73	0.78
	Bi-variate Humidity	150.91	0.85		Bi-variate Humidity	255.24	0.80
	Bi-variate Temperature	137.17	0.85		Bi-variate Temperature	273.97	0.78

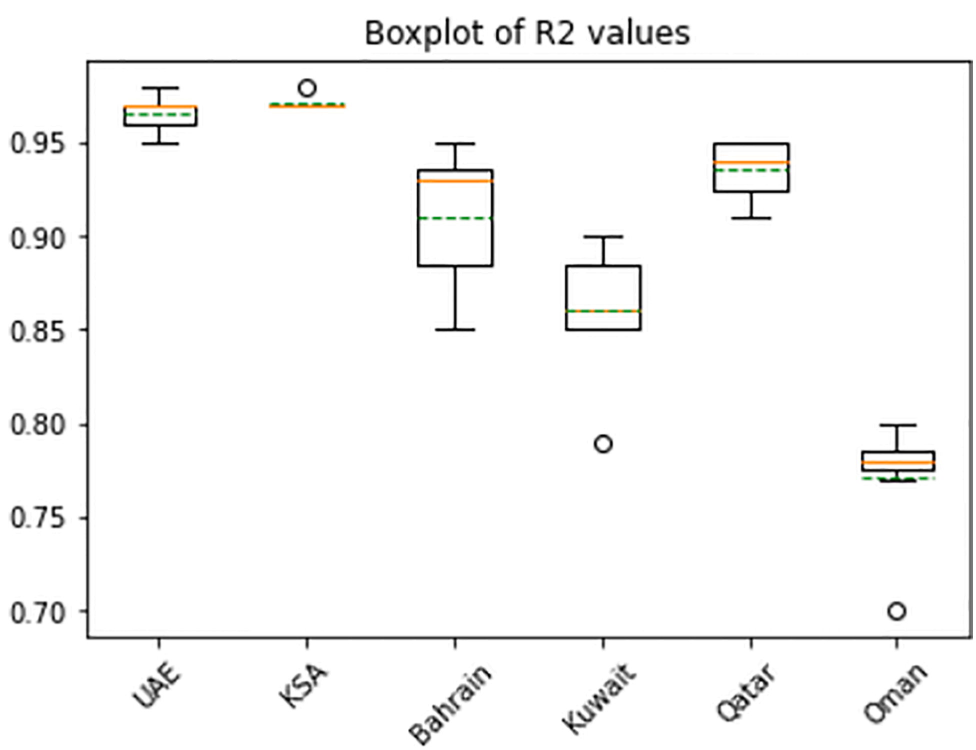

Fig. 14. R^2 box-plot for the GCC countries' models.

algorithm to ensure that the highest possible prediction accuracy was achieved by all forecasting models.

The LSTM model architecture is composed of three layers: an input layer, a hidden layer, and an output layer. The Keras tuning algorithm selects the hyperparameters of the layers, namely the number of hidden layers, number of nodes in each layer, and activation function in each layer.

A range for each hyperparameter was selected in the Keras tuning algorithm, and the best parameter values were selected by optimizing the accuracy measure. The objective function of the Keras tuning algorithm was set to the minimum MSE. The configurations of the LSTM models for each GCC country, as determined by the Keras tuning algorithm, are presented in Table 4. Column 1 of Table 4 indicates the country name, column 2 lists the model type, and columns 3 and 4 present the numbers of input and hidden layers, respectively, for each LSTM model. Furthermore, the number of hidden nodes is indicated in column 5. It should be noted that for all models, one output unit was selected to show the expected number of COVID-19 cases. Column 6 lists the MSE values that were obtained for each LSTM model after being optimized by the Keras tuning algorithm. Either sigmoid or tanh activation function was selected for the gates in all models.

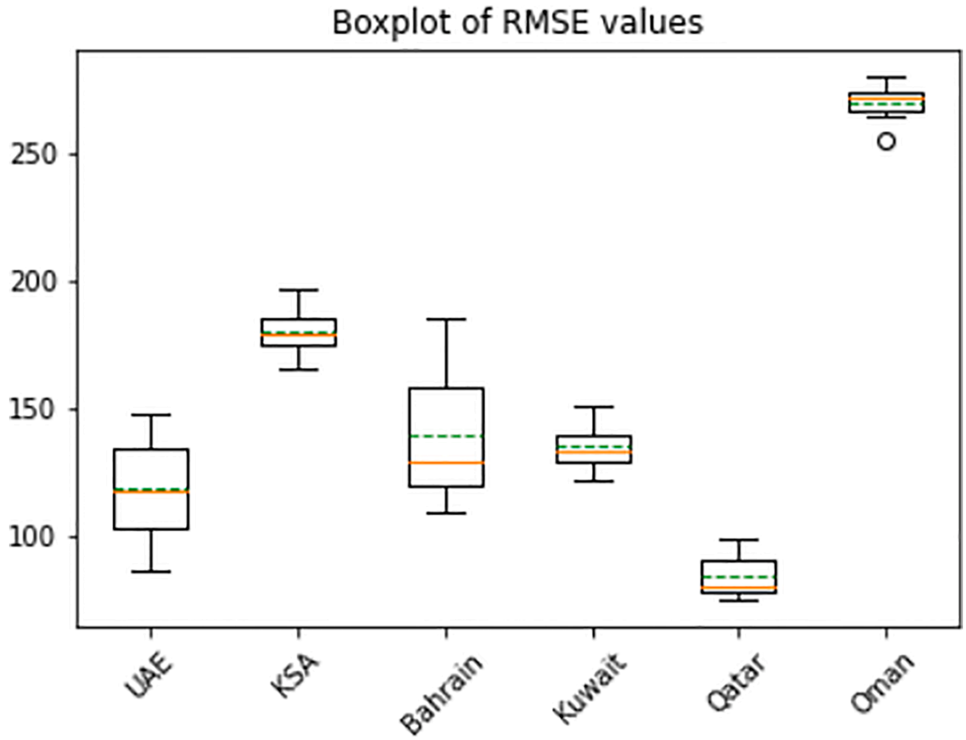

Fig. 15. RMSE box-plot for the GCC countries' models.

Table 6
R^2 comparison between uni-variate LSTM model and bi-,multi-variate LSTM model.

Country	R^2 values		RMSE values	
	Uni-variate	Best bi- or multi-variate	Uni-variate	Best bi- or multi-variate
UAE	0.98	0.97	148.1	86.28
KSA	0.97	0.98	173.73	165.13
Bahrain	0.94	0.94	110.87	128.81
Qatar	0.95	0.95	68.23	74.54
Kuwait	0.80	0.90	122.05	129.43
Oman	0.70	0.79	275.41	255.24

4.4. Model evaluation

A comparison between the actual and predicted values of the COVID-19 cases was performed to evaluate the prediction accuracy of the proposed LSTM forecasting models, as presented in Table 5. We calculated the root mean square error (RMSE) and coefficient of determination (R^2) using Eqs. (7) and (8), respectively. Consequently, we graphically summarized the results in Table 5 using the boxplots depicted in Figs. 14 and 15 for the R^2 and RMSE, respectively. The boxplots present several descriptive measures of the distribution of the R^2 and RMSE values for each country.

$$RMSE = \sqrt{\left(\frac{1}{n}\right)\sum_{i=1}^{n}(\widehat{y_i} - y_i)^2} \tag{7}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \widehat{y_i})^2}{\sum_{i=1}^{n}(y_i - \overline{y})^2} \tag{8}$$

4.5. Main results

The results reported in Table 5 are summarized in Table 6, which compares the results of the best bi- or multi-variate model with those of the uni-variate model, considering both the RMSE and R^2 values as performance measures. Column 1 of Table 6 indicates the country name, whereas columns 2 and 3, and 4 and 5, present comparisons of the best results that were obtained for the R^2 and RMSE, respectively. We used a paired t-test to determine whether a significant difference existed between the uni-variate and best bi- or multi-variate models. The *P*-values for the one-sided test were 0.09 and 0.22 for the R^2 and RMSE, respectively.

As we compared countries that have similar weather conditions, we expected to provide a single answer to **RQ1**. However, we were incorrect in our expectations, as the significant weather features that could affect COVID-19 cases differed for the different countries. This could be observed by considering the following:

1. The correlation coefficients between the COVID-19 cases and weather features: The correlation coefficient between the temperature and COVID-19 cases was high in KSA, Kuwait, Oman, and UAE, but not in Bahrain and Qatar. Moreover, humidity was significantly correlated with COVID-19 cases in Bahrain, Qatar, and Kuwait, but not in the other GCC countries.
2. The best bi- and multi-variate LSTM forecasting models: The best bi-variate model for KSA was the model that considers the temperature as a second input to the model. However, the worst-performing bi-variate model for Qatar also considers temperature as an input.

RQ2 asks whether the accuracy improvement of LSTM models that consider weather conditions is significant. As indicated in Table 6, according to the R^2 values, the inclusion of weather conditions in the bi- and multi-variate LSTM forecasting models resulted in a higher prediction accuracy for KSA, Kuwait, and Oman. However, the uni-variate LSTM, which ignores weather features, was superior to the bi- and multi-variate models for Bahrain and Qatar.

To answer **RQ2** quantitatively, we tested the null hypothesis that there is no difference in accuracy between the uni-variate and bi-variate LSTM forecasting models using the results summarized in Table 6, which shows two accuracy measures. For R^2, we rejected this null hypothesis for a level of significance α equivalent to 0.1. However, we did not reject the hypothesis for RMSE. These contradictory results can be attributed to the relatively large difference between the R^2 values for Kuwait and Oman, as indicated in the final two rows of Table 6.

5. Conclusions and future work

The objective of this study was to determine whether the inclusion of weather data to predict COVID-19 cases using an LSTM forecasting model would improve the forecasting accuracy of the model. This study was conducted on COVID-19 cases in the GCC countries for over one year. To achieve the objective, we compared a uni-variate LSTM model that considered only COVID-19 cases with other bi- and multi-variate models that considered COVID-19 cases and weather features. We evaluated the performance of the LSTM forecasting models using two performance measures, namely the R^2 and RMSE, after optimizing the LSTM configuration using the Keras tuning algorithm.

The experiments that were conducted demonstrated that the inclusion of weather features did not significantly improve the precision of the LSTM models. This conclusion was based on statistical tests in which the uni-variate model was compared with the best bi- and multi-variate LSTM models. Moreover, we expected that the best bi-variate LSTM models would use the same weather features because the GCC countries experienced similar weather conditions; however, this was an incorrect supposition. The best bi-variate LSTM models included different features for different countries.

This study was limited to the GCC countries and the period between April 2020 and September 2021. Furthermore, we could not extend our conclusions to other forecasting models, such as auto-regressive moving average exogenous and other ANN-based models. Finally, we only considered two performance measures, namely the R^2 and RMSE, in our comparisons, and we obtained differences in the accuracy improvement and statistical testing results. Consequently, these observations cannot be extended to other performance metrics.

This study can be extended in two directions. First, the experiment that uses LSTM to forecast COVID-19 cases can be repeated using other time series and machine-learning forecasting algorithms. Second, the experiment can be extended to include countries that experience cold weather conditions. The merits of this research are not limited to COVID-19, but are also relevant to the spread of other viruses, such as influenza.

CRediT authorship contribution statement

Dana I. Abu-Abdoun: Data curation, Formal analysis, Writing – original draft. **Sameh Al-Shihabi:** Data curation, Formal analysis, Writing – original draft.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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