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MACHINE LEARNING-BASED RNN-LSTM FOR PREDICTING COVID-19 CASES IN MALAYSIA

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ABSTRACT

Since January 2020, the world has struggled to cope with the spread of COVID-19, including in Malaysia. Although vaccines have been developed, the coronavirus remains a significant issue, potentially continuing for several years. This study examines the trend of COVID-19 spread in Malaysia two years after the onset of the pandemic, particularly when it transitioned into an endemic phase. A prediction model based on recurrent neural networks (RNNs) with long short-term memory (LSTM) is developed to forecast COVID-19 outbreaks during both pandemic and endemic periods. This study categorises COVID-19 into susceptible, exposed, infectious, and recovered classes. Two models, RNN-LSTM and support vector regression (SVR), are used to predict cases 60 days ahead. Analysis reveals that both models effectively capture underlying trends. Specifically, RNN-LSTM performed better in predicting the susceptible and exposed classes, while SVR is more accurate for forecasting the infected and recovered classes. This study highlights the strengths of each model in predicting future COVID-19 trends.

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Introduction

Coronaviruses are a group of viruses commonly found in the environment that can infect the nose, sinuses, or upper throat. While most coronaviruses are not harmful to humans, one particular type, severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), is highly infectious and causes coronavirus disease 2019 (COVID-19) [1]. This virus was identified by the World Health Organisation (WHO) as a novel strain in 2020, following its emergence in Wuhan, China, in December 2019. Since then, it has spread globally, resulting in a pandemic [1].

The overwhelming number of COVID-19 infections created an emergency-like situation worldwide, where lockdowns were implemented in nearly every country as a measure to reduce and prevent the transmission of the disease. This situation had a profound impact, not only on the global economy, but also in people's ability to lead fulfilling lives.

This study aims to predict the transmission of COVID-19 within the human population, which is divided into four classes: susceptible (S), exposed (infected but not yet infectious) (E), infectious (confirmed and infected) (I), and recovered (R). Two machine learning models, artificial neural networks (ANNs) and support vector regression (SVR), were used to forecast the distribution across these classes.

Machine learning (ML) applications are widely used for forecasting to improve decision-making processes across various fields [2]. While statistical approaches and ML methods share similarities, as both typically aim for forecasting accuracy, ML methods are more complex due to requiring implementation through computer science techniques. Several ML models have been used to predict diseases, such as heart attacks, diabetes, and cancer. ML has also been used by Zoabi *et al*. [3] to forecast COVID-19-related deaths and recoveries. The most effective solutions must account for the influence of various natural factors. The daily trends across all classes are illustrated in Figure 1.

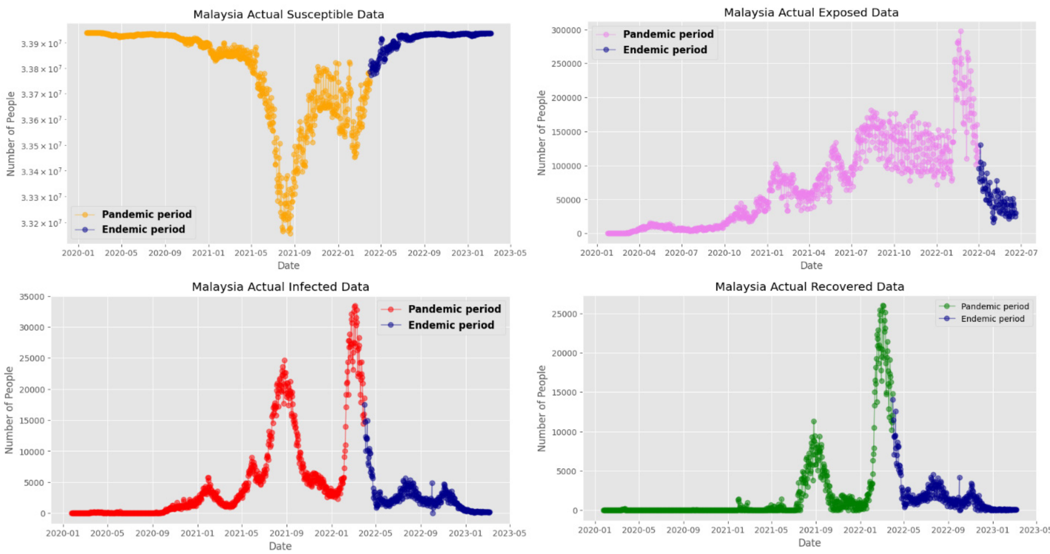


Figure 1: Actual data for susceptible, exposed, infected, and recovered COVID-19 cases in Malaysia

Literature Review

COVID-19

The research articles reviewed regarding COVID-19 were retrieved from 2019. According to these articles, COVID-19 was anticipated to cause a worldwide emergency, with its rapid spread and high mortality rate resulting in severe disruptions [4]. The disease, a pneumonia of unknown origin, was first reported in Wuhan, Huben Province, China, in December 2019. The Huanan Seafood Wholesale Market was epidemiologically linked to the majority of these cases [5]. Common symptoms of COVID-19 include fever, fatigue, and dry cough. Infected individuals may also experience mild symptoms such as headaches, nasal congestion, runny nose, muscle pain, sore throat, and diarrhoea. About 70% of individuals recover without needing special treatment. However, approximately 15% of cases progress to more severe symptoms, with some patients developing severe pneumonia and acute respiratory tract infections. About 5% may develop acute respiratory distress syndrome, septic shock, or multiple organ failure, potentially leading to death. Additionally, some individuals are asymptomatic carriers, meaning they remain healthy despite being infected [6, 7]. People at high risk of contracting COVID-19 include pregnant women, young children, the elderly, and individuals with chronic conditions, such as hypertension, diabetes, and kidney and heart issues, as well as those who are immunocompromised, including patients with cancer, HIV, and autoimmune disorders, and smokers [6].

According to a United States National Institutes of Health study on the pathophysiology of COVID-19, most cases were observed among the elderly. As the outbreak continued, the number of cases increased among individuals aged 65 years and older, though an increase among children was also observed. In a univariable analysis, the presence of coronary artery disease, diabetes, and hypertension was identified as risk factors. A study of 85 fatal COVID-19 cases, involving patients with a median age of 65 years in Wuhan, found that most deaths were due to multiple organ failure, with respiratory failure, shock, and acute respiratory distress syndrome present in 94%, 81%, and 74% of the cases, respectively [8]. Although the case fatality rate for patients aged 70 years or older was higher in Italy, the rate was similar for those aged between 0 and 69 years in other countries. Since 23% of the Italian population was aged 65 years or older, the high case fatality rate in Italy can be partly explained by demographic factors. The data on country variations is available from the website Our World in Data.

Machine Learning

ML is a field of study that enables computers to learn through data without requiring explicit programming [10]. It is used to teach machines how to process and handle data more efficiently. At times, after examining the data, it may not be possible to immediately interpret the exact information contained within it.

This is supported by [11], who states that ML is at the heart of the "Big Data" era. Initially, it was used in computer centres to store and process. With the advent of personal computers and the widespread use of wireless communication, data production expanded exponentially. Solving problems on computers requires algorithms—sequences of commands that transform inputs to outputs. When knowledge is lacking, data compensates for this gap. The computer (machine) will automatically extract the algorithm needed for a specific task, such as sorting numbers, for which an algorithm has been established. However, many applications lack predefined algorithms, but contain vast amounts of data. In these cases, ML may not fully identify the process, but can build a useful estimate based on the available data. While this estimate may not explain everything, it can still provide valuable insights. This is the core function of ML.

Research suggests ML is not just a database problem, but also a component of artificial intelligence [11]. ML aids in finding solutions to various problems in areas such as vision, speech recognition, and robotics. It also helps optimise performance criteria by using sample data or experience in computer programming. Examples of ML applications include learning associations, classification, regression, unsupervised learning, and reinforcement learning (Figure 2).

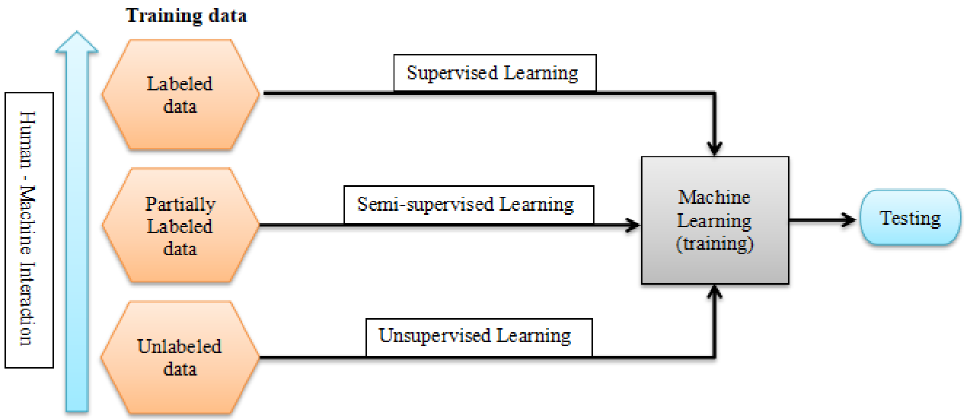


Figure 2: Categories of machine learning algorithms according to the nature of training data

Artificial Neural Networks

Artificial Neural Networks (ANNs) are biologically inspired computer programmes designed to simulate the way the human brain processes information [12]. Unlike standard statistical methods of analysis, ANNs learn by identifying patterns in data and training based on experience, rather than being explicitly programmed. Neural networks aim to acquire knowledge by detecting patterns and relationships in data, much like the human brain, which excels at recognising patterns. ANNs serve as a modelling technique particularly suited for datasets with nonlinear relationships, which are frequently observed in pharmaceutical processes.

The ANN method was first introduced by Warren McCulloch and Walter Pitts in 1943. ANNs have three interconnected layers: the input layer, the hidden layer, and the output layer. The input neurons in the first layer transmit data to the second hidden layer, which processes the information and forwards it to the final output layer. Figure 3 illustrates an ANN structure along with its mathematical model.

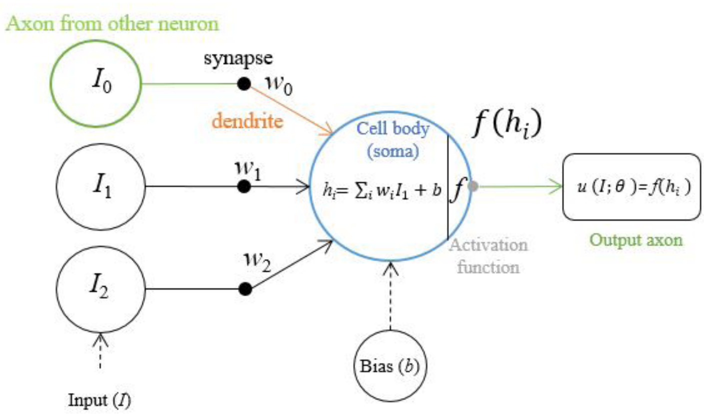


Figure 3: Illustration of an ANN with a mathematical model [13]

ANNs have been applied in various fields, including electricity supply forecasting [14], predicting aeroplane passenger numbers [15], and modelling lockdown strictness during the COVID-19 pandemic [16].

Generally, ANNs can be categorised into two types: feedforward networks and recurrent neural networks (RNNs). A feedforward network is one of the simplest forms of ANN, where data or input travels in a single direction without loops. From the input layer, data flows forward through the network until it reaches the output node. Conversely, RNNs are a type of ANN in which the output of a particular layer is stored and fed back as input.

Qu and Zhao [17] applied long short-term memory (LSTM) and RNN models to forecast foreign exchange financial time series. The models utilised existing foreign exchange prices and technical analysis indices as input parameters. By comparing evaluation metrics, including root mean square error (RMSE) and mean absolute error (MAE), the study determined that the LSTM model outperformed the RNN model, yielding smaller RMSE and MAE values.

Zeroual *et al*. [18] compared five deep learning methods to predict new and recovered COVID-19 cases using time series data. The study evaluated simple RNNs, LSTM, bidirectional LSTM, gated recurrent units and variational autoencoder algorithms. Daily confirmed and recovered case data were collected from six countries—Italy, Spain, France, China, the United States, and Australia. Forecasts for 17 days ahead were generated based on historical data spanning 148 days from January 22, 2020. The models were assessed using RMSE, MAE, mean absolute percentage error, explained variance, and root mean squared logarithmic error. The results indicated that the VAE algorithm outperformed the other models.

Support Vector Regression

SVR leverages kernels, sparse solutions, and Vapnik-Chervonenkis control over the margin and the number of support vectors, which characterise its methodology [19]. While less popular than support vector machines (SVM), SVR has demonstrated its efficacy in real-valued function estimation. As a supervised learning technique, SVR uses a symmetric loss function that equally penalises both high and low false positives. One SVR's main advantages is that its computational complexity is independent of the input space's dimensionality. Furthermore, it exhibits excellent generalisation capability, enabling high predictive accuracy. SVR is formulated as an optimisation problem by minimising convex ε-insensitive loss function and identifying the flattest tube that encompasses the majority of training examples. This establishes an objective manifold derived from the loss function and the tube's geometrical properties.

In a study by [20], the seasonal autoregressive integrated moving average (SARIMA) model and SVR were applied to three different sales time series datasets. The findings revealed that the SVR model produced smaller RMSE values than the SARIMA model. The researchers concluded that SVR has the capability to deal with seasonality and outliers in a dataset. They also suggested considering Fourier transform for future studies involving similar datasets.

Nava *et al*. [21] introduced a multistep-ahead forecasting methodology that combines empirical mode decomposition (EMD) and SVR. Two combinations, univariate EMD-SVR and multivariate EMD-SVR, were proposed and tested on the Standard and Poor's 500 index. The dataset consisted of 128 days of intraday data sampled at 30-second intervals. Forecasting was performed independently for each day using a training sample of 500 prices (approximately 4 hours and 10 minutes) to predict the next hour (50 steps ahead, equivalent to 25 minutes). The results revealed that the multivariate EMD-SVR models significantly outperformed benchmark models (naive, ARIMA, and SVR) in predicting the index from 30 seconds to 25 minutes ahead.

METHODOLOGY

Support Vector Regression

The SVM framework developed by [22] is based on statistical learning theory, where the goal is to minimise the prediction error in testing data [23]. SVR is a crucial application of this methodology. Two primary SVR models exist: the classic ε-SVR and least-squares SVR [24]. Both models minimise a regularised loss function, but differ in the type of the loss function employed [25]. In this study, the classic ε-SVR model is applied to forecast COVID-19 data during both the pandemic and endemic periods. The forecasting process and implementation details are described in the sections below [26].

Consider learning a mapping $f(x) : R^p \to R$, given a set of training data

$$(x_1, y_1),\ldots, (x_i, y_i),\ldots, (x_n, y_n), x_i \in R^p, y_i \in R.$$

where, is a p-dimensional input vector, and is a real-valued response variable. Specifically, it is assumed that $f(x)$ is a linear function of the form $f(x) = \boldsymbol{w}'\boldsymbol{x} + b$, where $\boldsymbol{w}$ is a vector of unknown weight, and b is the bias. According to SVM theory, the goal of learning $f(x)$ is to minimise the following regularised loss function:

$$\frac{1}{2}||w||^2 + C\sum_{i=1}^{n} L(e_i)$$

where, $\|w\|^2 = w'w$, represents model complexity, and $e_i = y_i - f(x_i)$ is the error associated with the ith $(i = 1,\ldots, n)$ training data point. L(.) denotes the loss function, and C is the positive regularisation parameter controlling the trade-off between model complexity and training error.

In ε-SVR, the so-called -insensitive loss function [22] is used for L, which is defined as:

$$L_\varepsilon(e) = \begin{cases} 0 & if\ |e| < \varepsilon \\ |e| - \varepsilon & otherwise \end{cases}$$

Thus, the loss function is zero for any absolute error smaller than the predefined value ε. For errors larger than ε, the loss function equals the difference between the absolute error and ε.

RNN-LSTM

An RNN is a type of neural network that contains a feedback loop. LSTM networks are advantageous in retaining information over extended periods. Since prior information can influence the accuracy of the model, LSTMs are often the preferred choice for such tasks [27].

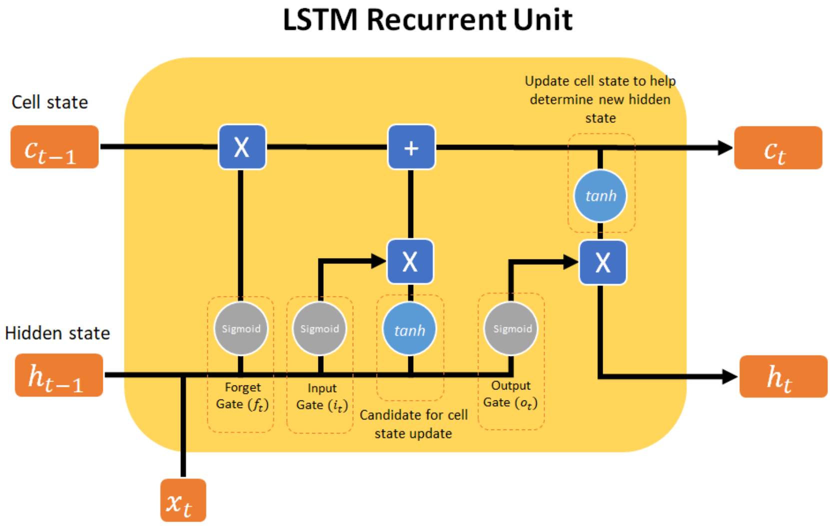


Figure 4: LSTM cell architecture with a forget gate

Figure 4 illustrates the architecture of the LSTM cell state at the current iteration t (c_t). The cell state functions as a memory, carrying information across the entire sequence. Additionally, the current input x_t is combined with the hidden state (h_{t-1}), which is the output from the LSTM cell at the previous iteration $t-1$. This combined information passes through the three main gates that regulate the flow of information into and out of the cell state, as explain below:

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right)$$

The term f_t represents the forget gate, which determines which information should be discarded. Here, and refer to the weights and biases corresponding to the gate. The forget gate is activated using sigmoid activation function, producing a value between zero and one. A value of zero means "completely forget", while a value of one means "retain" the information. Next, the input gate i_t is defined as follows:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$
$$\tilde{c}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c)$$

The input gate i_t consists of two components: a sigmoid function that determines which values to update, and a tanh function that generates the new candidate values to update the cell state $\tilde{c}_t$. The cell state is updated by applying the forget gate's decision to the prior cell state c_{t-1}, and then adding the candidate values $\tilde{c}_t$ scaled by the input gate as follows:

$$c_t = f_t \cdot c_{t-1} + i_t \cdot \tilde{c}_t$$

Finally, the output gate determines h_t as the output for the current iteration, expressed by the following equation:

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$
$$h_t = o_t \cdot \tanh(c_t)$$

RESULTS

The dataset was split into training and testing sets. The pandemic period, January 24, 2020, to March 31, 2022, was used as the training set, comprising 798 data points. The endemic period, from April 1, 2022, to March 7, 2023, served as the testing set, consisting of 341 data points. These periods were selected based on the Malaysian government's declaration that April 1, 2022, marked the transition to the endemic phase. All training and testing were conducted using the same desktop computer configuration. The performance of the RNN-LSTM and RNN models in predicting COVID-19 cases across different classes in Malaysia is shown in Figure 4, covering the period from January 24, 2020, to March 7, 2023, with a total of 1,139 data points. However, data for the "exposed" class is only available from January 24, 2020, to June 12, 2022, as the data from Our World in Data ceased updating after that date. The prediction results for each class for both methods are presented in Figure 5.

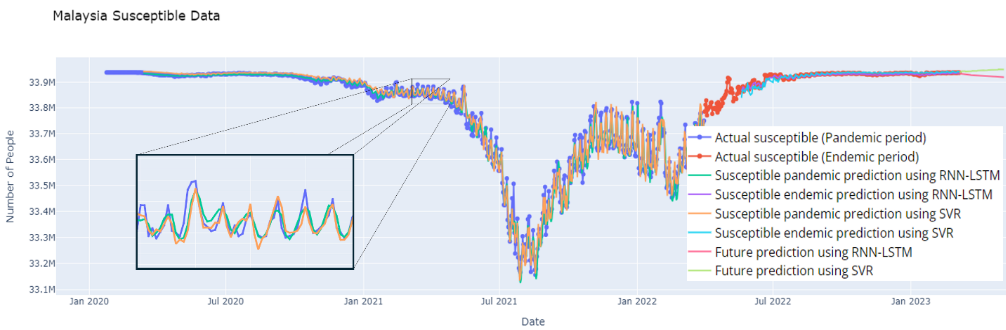


Figure 5: Performance comparison between the RNN-LSTM and SVR models in predicting the susceptible class during the pandemic and endemic periods of COVID-19 in Malaysia

Figure 5 illustrates the prediction results for the susceptible class using the RNN-LSTM and SVR models. Both models align with the observed trends during the pandemic (blue dotted line) and endemic (red dotted line) phases. However, notable differences in their prediction patterns are evident. Specifically, the RNN-LSTM model (red line) forecasts a decrease in susceptibility starting from March 8, 2023, whereas the SVR model (light green line) predicts an increase. A more detailed view of these 60-day predictions is presented in Figure 6.

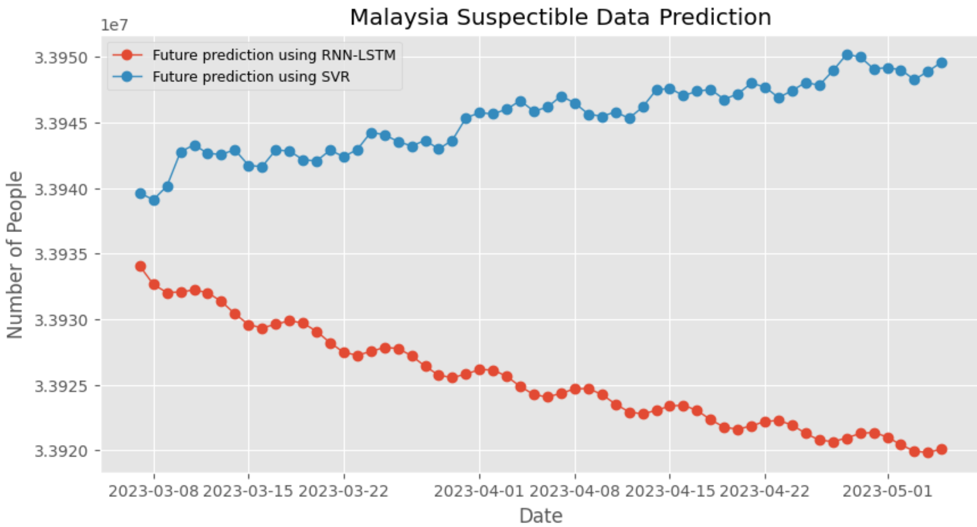


Figure 6: Comparison of predictions for COVID-19 cases in the susceptible class using the RNN-LSTM and SVR models

Figure 7 presents the performance evaluations for both models in predicting COVID-19 cases in the susceptible class.

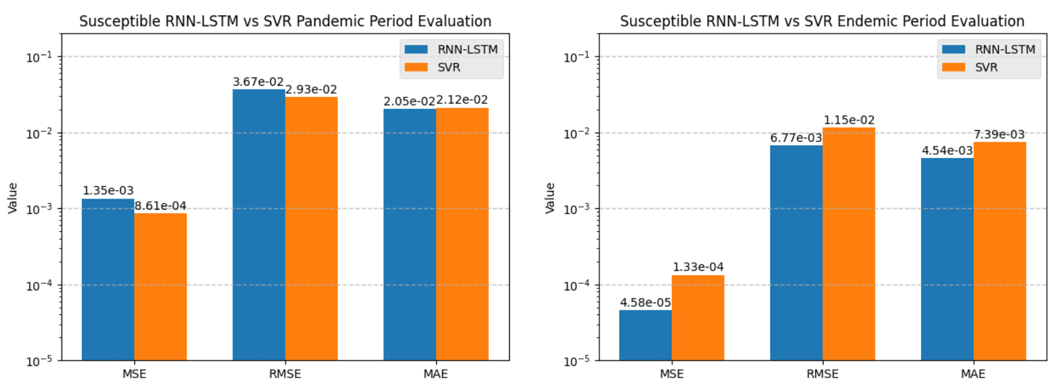


Figure 7: The performances of the RNN-LSTM and SVR models in predicting the pandemic and endemic periods of COVID-19 from susceptible class in Malaysia

Figure 7 reveals a notable contrast between the SVR and RNN-LSTM models in predicting the susceptible class of COVID-19 cases in Malaysia. During the training period (pandemic phase), SVR demonstrates superior performance, with lower MSE, RMSE, and MAE. However, during the testing period (endemic phase), RNN-LSTM consistently outperforms SVR with better metrics. This suggests that RNN-LSTM is more effective for susceptibility predictions. The prediction results for the exposed class are depicted in Figure 8.

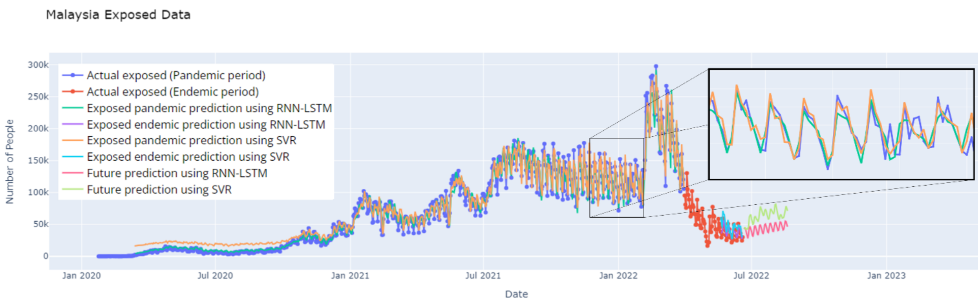


Figure 8: Performance comparison of the RNN-LSTM and SVR models in predicting the COVID-19 pandemic and endemic periods for the exposed class in Malaysia

In contrast to the other classes, the exposed dataset comprises 878 data points, with 798 during the pandemic period, and 80 during the endemic phase. Figure 8 exhibits patterns similar to those observed in the susceptible class. Both the RNN-LSTM and SVR methods align with the actual data trends during both phases. However, the future predictions for the exposed class diverge, with an upward trend observed in both methods. Notably, while RNN-LSTM predicts an increase, its values are not as high as those predicted by SVR. A more detailed visualisation of the future predictions for the exposed class is presented in Figure 9.

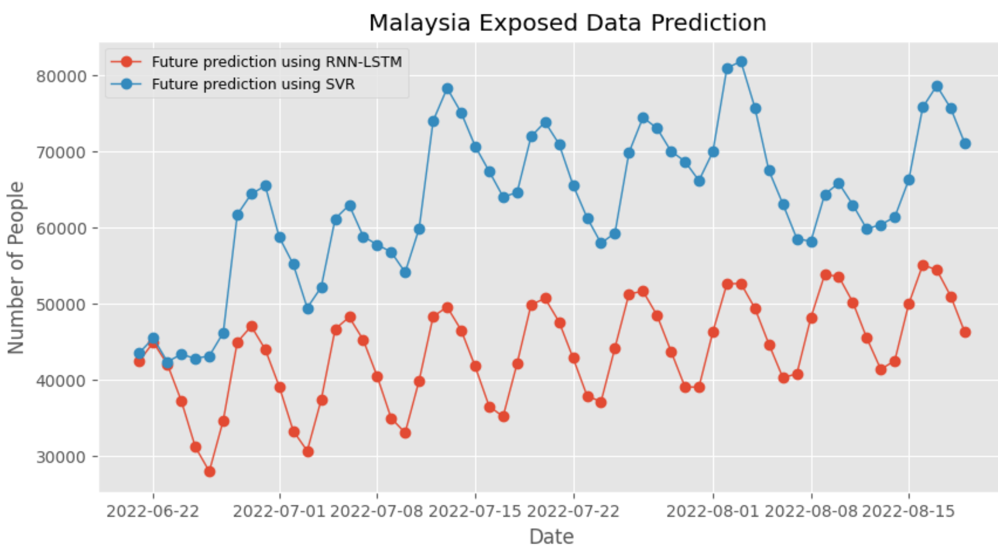


Figure 9: Comparison of the future predictions for COVID-19 cases from the exposed class, as predicted by the RNN-LSTM and SVR models

The performance evaluations for the prediction of the exposed class are shown in Figure 10.

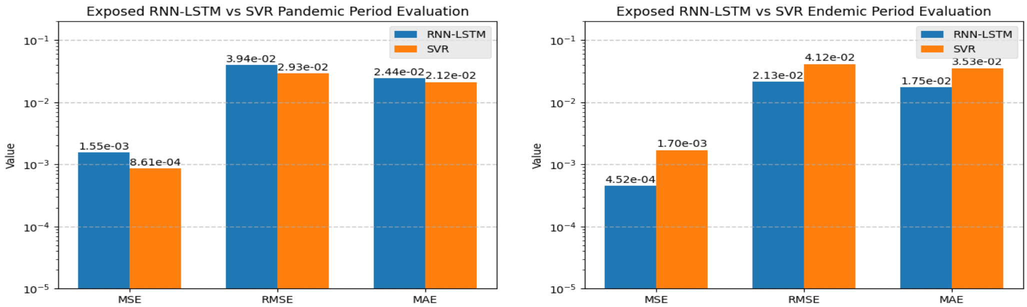
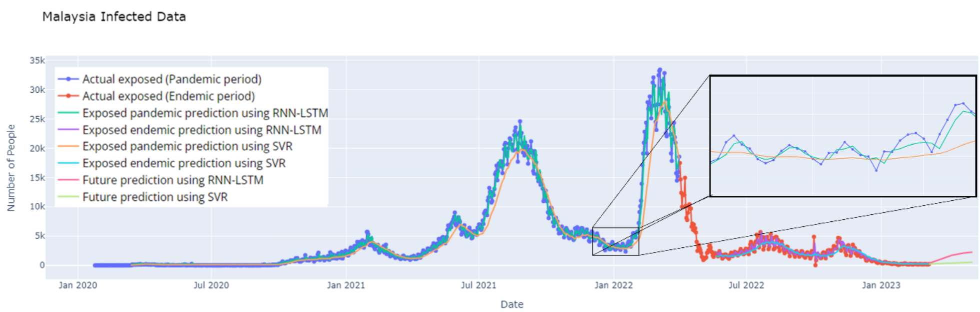
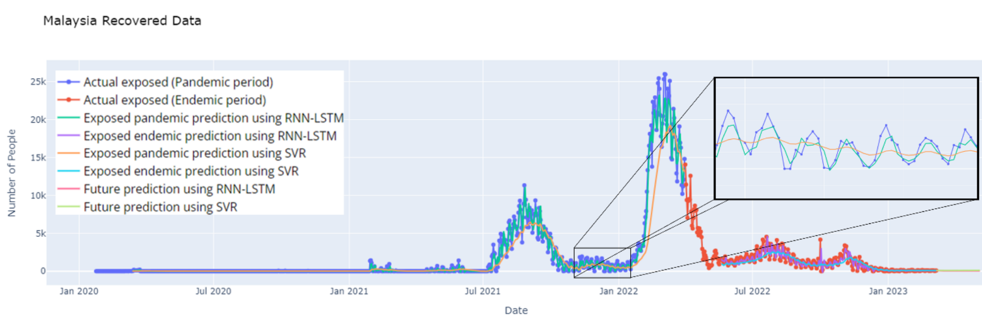


Figure 10: The performances of the RNN-LSTM and SVR models in predicting the pandemic and endemic periods of COVID-19 from the exposed class in Malaysia

Notably, despite having a smaller total dataset, the RNN-LSTM model consistently outperforms SVR for the endemic phase. Specifically, RNN-LSTM achieves lower values for MSE, RMSE, and MAE in the testing data, even though its performance for the training period is comparatively higher. The prediction results for the infected and recovered classes are shown in Figure 11.



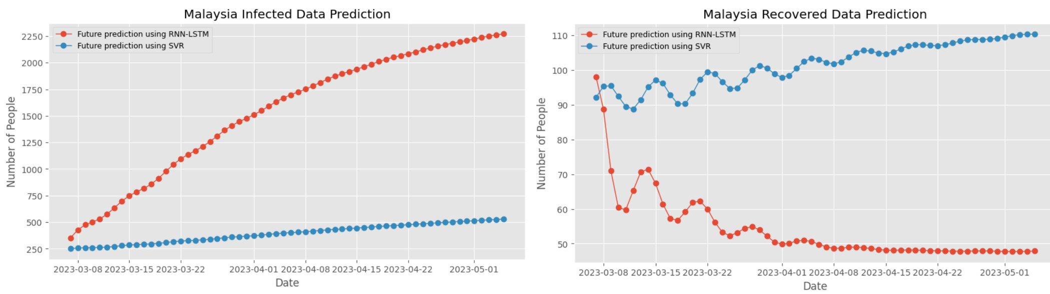
(a) Infected



(b) Recovered

Figure 11: The RNN-LSTM and SVR predictions for the infected and recovered classes during the pandemic and endemic periods in Malaysia

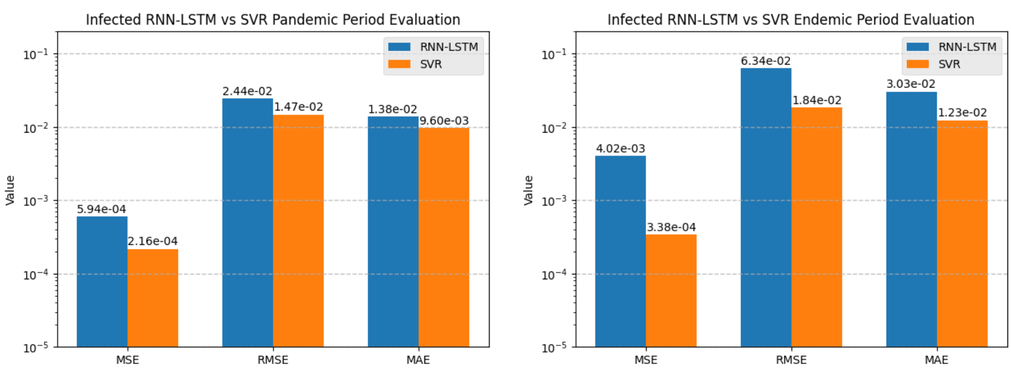
Figure 11 illustrates the contrasting prediction behaviours of the SVR and RNN-LSTM models during both the pandemic and endemic phases. Notably, SVR predictions (orange and light blue lines) exhibit smoother trends, while RNN-LSTM predictions (green and violet lines) show greater fluctuations. Looking specifically at future predictions, a divergence emerges between the infected and recovered classes. Both methods predict an increasing trend in infections after March 8, 2023. However, for recovered cases, SVR forecasts an upward trajectory, whereas RNN-LSTM predicts the opposite. A more detailed visualisation is presented in Figure 12.



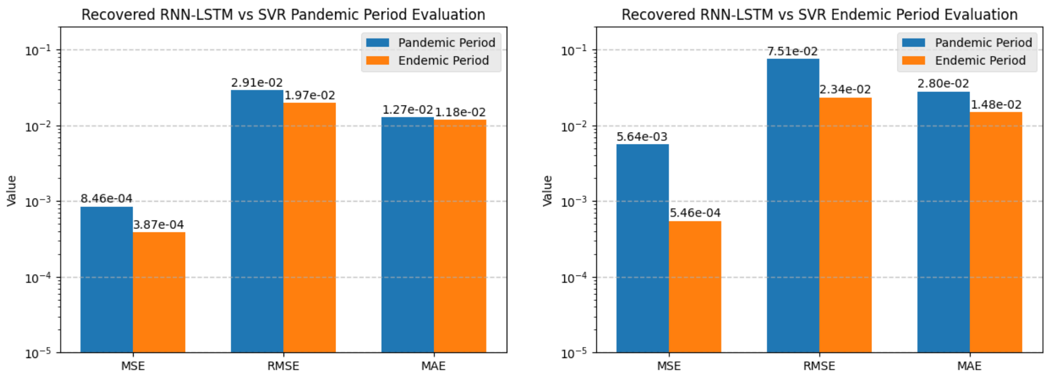
(a) Infected Prediction (b) Recovered Prediction

Figure 12: Comparison of future predictions for COVID-19 cases in the infected and recovered classes using RNN-LSTM and SVR models

An interesting observation arises from the performance evaluations: predictions for both the infected and recovered classes show better performance with SVR compared with RNN-LSTM. The SVR model consistently yields lower MSE, RMSE, and MAE values for both the pandemic and endemic periods for these classes. Figure 13 presents a visual representation of the performance evaluations for both models' predictions of the infected and recovered classes.



(a) Infected performance metrics



(b) Recovered performance metrics

Figure 13: Performance comparison of the RNN-LSTM and SVR models in predicting COVID-19 cases during the pandemic and endemic periods for the infected and recovered classes in Malaysia

Conclusions

This study compares the predictive capabilities of SVR and RNN-LSTM models for forecasting COVID-19 cases in Malaysia during the pandemic (January 24, 2020, to March 31, 2022) and endemic (April 1, 2022, to March 7, 2023) phases across various epidemiological classes: susceptible, exposed, infectious, and recovered. The RNN-LSTM model comprises two hidden layers, each with 50 neurons, and is trained over 100 iterations with the Adam optimiser. In contrast, the SVR model employs the radial basis function kernel with hyperparameters set as follows: C = 10, gamma = 0.5, and epsilon = 0.05.

Analysis reveals that both SVR and RNN-LSTM effectively capture the underlying trends, with minor deviations observed in the infected and recovered classes. Notably, SVR predictions exhibit smoother trajectories in these classes. However, when evaluating performance metrics, RNN-LSTM outperforms SVR in predicting the susceptible and exposed classes. In contrast, SVR demonstrates superior performance in forecasting the recovered and infected classes, as indicated by better performance metrics in both categories.

In summary, this study highlights the strengths of each model, underscoring the importance of selecting the appropriate approach based on the specific class of interest. Further research could explore the optimisation of hyperparameters for both models, such as enhancing the architectural complexity of the RNN-LSTM model by adjusting the number of hidden layers and iterations, or experimenting with different kernel types and hyperparameters within the SVR model. These strategies can leverage the advantages of both models, leading to more accurate predictions.

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Conflicts of Interest Statement

The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

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