

Modelling and Simulation of COVID-19 Outbreak Prediction Using Supervised Machine Learning

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Abstract: Novel Coronavirus-19 (COVID-19) is a newer type of coronavirus that has not been formally detected in humans. It is established that this disease often affects people of different age groups, particularly those with body disorders, blood pressure, diabetes, heart problems, or weakened immune systems. The epidemic of this infection has recently had a huge impact on people around the globe with rising mortality rates. Rising levels of mortality are attributed to their transmitting behavior through physical contact between humans. It is extremely necessary to monitor the transmission of the infection and also to anticipate the early stages of the disease in such a way that the appropriate timing of effective precautionary measures can be taken. The latest global coronavirus epidemic (COVID-19) has brought new challenges to the scientific community. Artificial Intelligence (AI)-motivated methodologies may be useful in predicting the conditions, consequences, and implications of such an outbreak. These forecasts may help to monitor and prevent the spread of these outbreaks. This article proposes a predictive framework incorporating Support Vector Machines (SVM) in the forecasting of a potential outbreak of COVID-19. The findings indicate that the suggested system outperforms cutting-edge approaches. The method could be used to predict the long-term spread of such an outbreak so that we can implement proactive measures in advance. The findings of the analyses indicate that the SVM forecasting framework outperformed the Neural Network methods in terms of accuracy and computational complexity. The proposed SVM system model exhibits 98.88% and 96.79% result in terms of accuracy during training and validation respectively.

Keywords: Coronavirus; outbreak; machine learning; artificial intelligence



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1 Introduction

Coronavirus Disease (COVID-19) is a viral infection that was proclaimed a global epidemic by the World Health Organization (WHO) in March 2020 reflecting the extent of its worldwide transmission. The declaration of the pandemic of the virus also highlighted the growing fear of the alarming spread and severity of COVID-19. It is characterised by its existence as a public health concern that has spread throughout the world. The governing authorities in a variety of counties are implementing prohibitions, restrictions on transport, social gaps, and increasing awareness of hygiene. In addition, the virus continues to transmit very quickly. Most of the people diagnosed with COVID-19 had moderate to severe pulmonary failure, while some had extreme pneumonia. Older people with particular health problems, such as coronary artery disease, asthma, chronic lung cancer, kidney or liver disease, and harmful growth, are likely to cause serious infections. To date, COVID-19 has not provided any specific vaccine or treatment.

COVID-19 was believed to have come from some kind of single wild animal traded on a crowded central marketplace in Wuhan. The number of infected people in the Wuhan region is rising rapidly to many other major areas and will eventually become a pandemic within a few weeks [1]. COVID-19 will be transferred quickly. The infection can spread by sweat particles and can live on the infected surface for about two days [2]. COVID-19 was considered a global disease by the World Health Organization in January 2020.

In Wuhan, at the end of December 2019, some people with histological pneumonia were biochemically associated with the Huanan domestic supermarket, and several products, including birds and rabies, were sold both before and during the outbreak. A new coronavirus is identified using the next-generation sequence [3]. Many people had severe coughing, vomiting, and lung X-rays with abnormal lung spots [4].

Preventive measures have been taken to prevent infected areas from occurring in an attempt to control the widespread and accelerated transmission of infection. This includes the closure of regions until further notice, the termination of policy services and educational institutions, the elimination of national and international travel, etc. The objective is to reduce the possibility of direct communication between humans so as not to spread the novel virus. Both China and other countries face enormous economic losses as a result of the lockdown. The impact of the virus is unknown as it is new, while its infectious activity is very high and its activation period is relatively long compared to other viruses detected. The suspension is lifted too soon; the epidemic could not be fully supported; increased restrictions would lead to greater financial losses. In this sense, lifespan is quite unpredictable, because the disease is novel, but we still have no awareness of its properties.

In addition, the prediction is highly relevant for certain human and social wellness variables, in particular for the slightest indication of different attributes. The most accurate forecast is required in this scenario. This is a complex computing challenge for machine learning [5]. The current research presents four common strategies for building frameworks for predicting a small dataset [6]. One solution is to expand the acquisition of training data by adding additional details to the available details [7,8]. The second method involves collecting the effects of the cumulative estimate, where one of the methods with the smallest error is selected to use the effects of the prediction [9]. The performance of the other nominees would be rejected. The third approach is to focus on a standard predictive method, sometimes with a variety of custom variables. The accuracy of the resulting configuration is very sensitive to variables. In the case of such a method, the standard variable functions sometimes do not have the best efficiency to increase the accuracy of the function values.

Identification of COVID-19 is also a difficult problem, mainly due to the inaccessibility of the test kits, which is confusing everywhere. In particular, due to the lack of availability of the COVID-19 study kits, investigators need to work on a variety of assessment measures. While COVID-19 affects our lungs, X-rays may be used to evaluate the strength of the lungs of the affected patient and any related indications.

Medical experts also assess the signs of a patient's illness. Both clinical professionals are unable to assess the particular indications of the suspected condition and can use these related signs for the COVID-19 test without separate test kits. It is also difficult for medical practitioners to treat a suspected condition in the context of related signs, and it takes a very long time, which is critical because patients around the world are suffering. It is, therefore, necessary to build an integrated prediction system to save time and money for healthcare experts and to diagnose COVID-19 based on realistic data collection.

Jia et al. [10] presented a neural network to anticipate the occurrence of hand-foot-mouth disease. Hamer et al. [11] utilized machine learning methods to predict Spatio-temporal infection pathogenic disease. Artificial intelligence systems for predicting outbreaks of infectious diseases [12,13], influenza, and diarrhea [14] are also projected. A good overview of the artificial intelligence framework for this forecast is published in Philemon et al. [15]. A collaborative learning-based strategy is proposed to classify human risks [16]. Machine-learning modelling has been used in recent years to predict epidemiological features of the Ebola virus epidemic in West Africa [17] and these analyses are also used in Dallatomasina et al. [18] to determine the severity of the Nipah virus. Plowright et al. [19] Suggested Nipah Virus Control System in India. Furthermore, Seetah et al. [20] has suggested a system for forecasting possible outbreaks of Rift Valley disease. Many architectures use a hybrid form of decision-making using computational and machine learning approaches to predict potential developments focused on historical incident information.

The most recent outbreak of COVID-19 disease has attracted the interest of a wide range of researchers in helping and developing methods for coping with the disease. Rao et al. [21] developed a system for the recognition of patients with COVID-19 via a mobile device. Yan et al. [22] developed a modelling system to evaluate high-risk patients in the preliminary phase without moving them from mild to severe conditions. Numerous research papers on the prediction of an outbreak of coronavirus disease have recently been published [23]. Investigators focused on designing a conceptual architecture for artificial intelligence applications, integrating machine learning algorithms with a variety of data approaches [24]. The revised methodology for the Adaptive Neuro-Fuzzy Inference Method (ANFIS) is proposed in Qaness et al. [25]. The Regression Model was developed to predict accelerated development of COVID-19 based on the total number of patients recorded outside of China [26]. Researchers have developed forecasts for the analysis of large-scale weather variability across ten developing machine learning and behavioural forecasting architectures [27].

A number of scholars have recently established a system for the detection of COVID-19 focused on deep learning approaches. Wang et al. [28] utilized ultrasound imaging scanning approaches to screen COVID-19 cases with 89.5% precision and 88% and 87% specificity and sensitivity correspondingly. Linda et al. [29] developed a Deep Convolutional Neural Network with 83.5% accuracy called COVID-Net to classify COVID-19 specific cases via X-ray scanning in the chest. Joaquin [30] used a small data set of 339 samples to train and evaluate using ResNet50-based deep transfer learning techniques and achieved 96.2% accuracy in the study. In this research, we have built the SVM method. This paper proposes an advanced machine learning approach for forecasting the outbreak of COVID-19. Throughout the proposed analysis, more than 98% of the outbreak prediction of the detection was achieved.

The SVM method could also be seen as a substitute for existing solutions for the ideal system for a variety of training modules, taking into account the severity of the pandemic [31]. Epidemic prediction in real-time attracts many scholars because of the increased applicability of the method [32]. In this paper, the SVM-based method for predicting an outbreak of COVID-19 is proposed to achieve optimum accuracy. SVM based COVID-19 outbreak prediction processes a dataset of multiple cases, such that each database contains specific functionality. Quick and reliable theoretical solutions to disease control are urgently needed. Throughout the COVID-19 observations, the objective was to develop an

SVM-based method for predicting outbreaks that could evaluate the COVID-19 epidemic and provide a technical assessment prior to the communicable study, thereby saving critical time to prevent disease.

The SVM solution can be used as an alternative to existing approaches in a way that provides the strongest example of limited training data given the magnitude of the outbreak assessment. In this article, the SVM approach to predicting a novel coronavirus pandemic is being tested to obtain the best possible accuracy. Throughout research and development, dataset instances are used to predict coronavirus outbreaks using SVM, so that each element contains specific and varied attributes. This article combines the benefits of the three approaches in the proposed solution with the following attributes: first, group simulation involves several applicant forecasting methods, and then one with the smallest error. The second, most appropriate parameter values are used in each statistical method, and the third, relevant information on the forecast target is introduced as a nominee for community selection in a number of framework predictive regression methods.

The remainder of this paper is clarified as follows. Section 2 provides the basis for the successful forecasting of the COVID-19 outbreak. Section 3 examines the findings of the SVM process. Section 4 discusses the conclusions of the research.

2 Proposed System Model

Insufficient information is available during the early stages of decision-making on the accelerated growth of the outbreak. This is to be a novel virus and medical experts should be assessed until a theoretical judgement is made comparable to that of Delphi. In the context of three key objectives, the SVM solution using a small data set is required, the accepted prediction model wants to be more effective than its equivalents (with the smallest error), the effective system itself includes optimum output and has the versatility to provide specific, reasonable time intervals for correlation. The proposed solution seeks to achieve optimum statistical accuracy, with limited access to information and knowledge. The study aims at collective forecasting through a set of integrated prediction frameworks, many of which may use different knowledge samples as inputs.

The early predictive pattern of an outbreak of COVID-19 in a human being must be identified. However, accurate evaluation is a difficult challenge. A method for the accurate estimation of the SVM-focused COVID-19 system is suggested in this study. The suggested approach was divided into three main layers: the data collection layer, the pre-processing layer, and the application layer. The level of data acquisition shall comply with the data set necessary for analysis. Standard data analysis techniques are used in the pre-processing layer to remove data irregularities. There are two sub-levels in the application layer, including the level of prediction and the level of evaluation of results, respectively. The suggested SVM approach is discussed in the application layer to enhance the COVID-19 predictive framework.

[Fig. 1](#) illustrates the aspects and descriptions of the proposed method for predicting the outbreak of COVID-19. It reveals that the data processing layer includes data input for the neural network, where the most recent Coronavirus pandemic was predicted using a supervised learning algorithm. The artificial neural network consists of a group of neurons that are the basic unit of processing information that distinguishes the layered structure, primarily the input layer, the output layer, and the hidden layer. The supervised approach to machine learning to predict the outbreak of COVID-19 is being integrated into this study.

The data collected by the data acquisition layer is raw, as it may include some incomplete parameters and inconsistent data. In addition, the information is processed in the pre-processing layer. Predict missing values in this layer using moving average form, mean or mode, and minimise noise with normalisation. Each layer is divided into two sub-layers: the forecasting and the performance layer, as the processing results are further

submitted to the implementation layer. A supervised machine learning model called Support Vector Machine (SVM) is used in the prediction system to train algorithms.

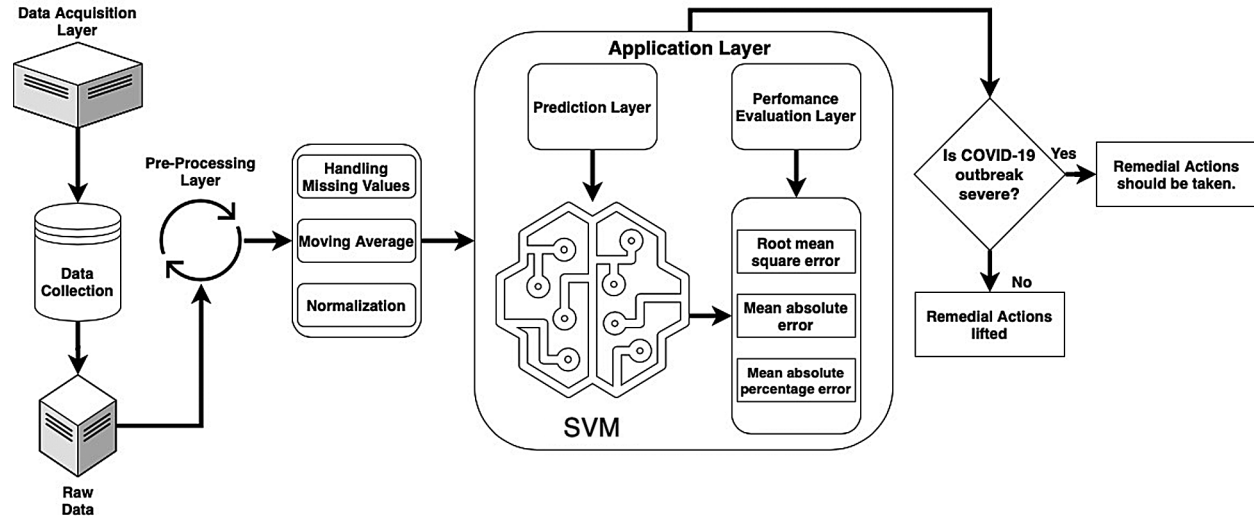


Figure 1: Proposed intelligent COVID-19 outbreak prediction system model architecture

The performance of the estimation system for different statistical measures, such as precision and misrate, was evaluated after the training phase. If the appropriate training requirements are not met, the forecasting layer should be retrained and the output evaluated. Once the appropriate threshold learning requirements or several iterations have been reached, an effective training framework is stored that can be used in different applications.

In the validation process when feedback is obtained, the COVID-19 outbreak was predicted using a genetic qualified model as performance. The dataset was obtained from the WHO in this study.

Since we realize the line equation is

$$c_2 = rc_1 + \check{s} \tag{1}$$

where ‘r’ is a slope of a line and ‘s̃’ is the intersect, therefore

$$rc_1 - c_2 + \check{s} = 0$$

Let $\bar{c} = (c_1, c_2)^T$ and $\bar{u} = (r - 1)$ so you might compose the following equation as

$$\bar{u} \cdot \bar{c} + \check{s} = 0 \tag{2}$$

This equation originates from two-dimensional vectors. In addition, it operates for a variety of dimensions as well, Eq. (2) often recognized as hyperlane equation.

The path of a vector $\bar{c} = (c_1, c_2)^T$ is composed as \bar{w} and is expressed as

$$u = \frac{c_1}{\|c\|} + \frac{c_2}{\|c\|} \tag{3}$$

where

$$||c|| = \sqrt{c_1^2 + c_2^2 + c_3^2 + \dots + c_n^2}$$

As we already understand

$$\cos(g) = \frac{c_1}{||c||} \text{ and } \cos(a) = \frac{c_2}{||c||}$$

Eq. (3) can similarly \check{s}_e composed as

$$\hat{w} = (\cos(g), \cos(a))$$

$$\vec{u} \cdot \vec{c} = ||u|| ||c|| \cos(g)$$

$$g = \beta - a$$

$$\cos(g) = \cos(\beta - a)$$

$$= \cos(\beta) \cos(a) + \sin(\beta) \sin(a)$$

$$= \frac{u_1}{||u||} \frac{c_1}{||c||} + \frac{u_2}{||u||} \frac{c_2}{||c||}$$

$$= \frac{u_1 c_1 + u_2 c_2}{||u|| ||c||}$$

$$u \cdot c = ||u|| ||c|| \left[\frac{u_1 c_1 + u_2 c_2}{||u|| ||c||} \right]$$

$$\vec{u} \cdot \vec{c} = \sum_{i=1}^n u_i c_i \tag{4}$$

The dot product for n-dimensional vectors can be determined as the latter equation where,

$$f = y(u \cdot c + \check{s})$$

If $\text{sign}(f) > 0$ then appropriately organized and if $\text{sign}(f) < 0$ then inaccurately organized. Certain a dataset D, we calculate f on a training dataset

$$f_i = y_i(u \cdot c + \check{s})$$

F is then defined as the practical data set range.

$$F = \min_{i=1, \dots, m} f_i$$

The Lagrangian function is

$$\mathcal{L}(u, \check{s}, a) = \frac{1}{2} u \cdot u - \sum_{i=1}^m a_i [y : (u \cdot c + \check{s}) - 1]$$

$$\nabla_u \mathcal{L}(u, \check{s}, a) = u - \sum_{i=1}^m a_i y_i c_i = 0 \tag{5}$$

$$\nabla_{\check{s}} \mathcal{L} (u, \check{s}, a) = - \sum_{i=1}^m a_i y_i = 0 \tag{6}$$

From the above two Eqs. (5) and (6) we get

$$u = \sum_{i=1}^m a_i y_i c_i \text{ and } \sum_{i=1}^m a_i y_i = 0 \tag{7}$$

After replacement the Lagrangian function \mathcal{L} we get

$$u(a, \check{s}) = \sum_{i=1}^m a_i - \frac{1}{2} \sum_{i=1}^m \sum_{j=1}^m a_i a_j y_i y_j c_i c_j$$

thus

$$\max_a \sum_{i=1}^m a_i - \frac{1}{2} \sum_{i=1}^m \sum_{j=1}^m a_i a_j y_i y_j c_i c_j \tag{8}$$

Subject to

$$a_i \geq 0, i = 1 \dots m, \sum_{i=1}^m a_i y_i = 0$$

Since the limitations of the Karush-Kuhn-Tucker (KKT) requirements are unequal, we expand the Lagrangian principle to multiplier methods. The additional provision of KKT is

$$a_i [y_i (u_i \cdot c^* + \check{s}) - 1] = 0 \tag{9}$$

c^* is the optimal level, a is the positive parameter and o' for the further level are ≈ 0

So,

$$y_i ((u_i \cdot c^* + \check{s}) - 1) = 0 \tag{10}$$

Those are referred to as support vectors, which are the hyperplanes nearest. Conferring to the aforementioned Eq. (10)

$$u - \sum_{i=1}^m a_i y_i c_i = 0$$

$$u = \sum_{i=1}^m a_i y_i c_i \tag{11}$$

To calculate the value of \check{s} we develop

$$y_i ((u_i \cdot c^* + \check{s}) - 1) = 0 \tag{12}$$

Multiply by equally sides \check{s}_y in Eq. (12) then we get

$$y_i^2 ((u_i \cdot c^* + \check{s}) - y_i) = 0, \text{ where } y_i^2 = 1$$

$$((u_i \cdot c^* + \check{s}) - y_i) = 0 \tag{13}$$

Then

$$\frac{1}{S} \sum_{i=1}^s (y_i - u \cdot c) \quad (14)$$

S is the range of vectors to sustain it. For one point we'll get the hyperplane, and then we will create projections with the hyperplane. Where feature of the hypothesis is

$$h(u_i) = \begin{cases} +1 & \text{if } u \cdot c + \check{s} \geq 0 \\ -1 & \text{if } u \cdot c + \check{s} < 0 \end{cases} \quad (15)$$

The aim of the proposed intelligent COVID-19 outbreak prediction method, enhanced by a supervised machine learning algorithm, is to locate a hyperplane that can correctly distinguish the information and we should identify the right one, also referred to as the ideal hyperplane.

3 Results and Discussion

MATLAB 2019 is employed for the goal of the simulation. The suggest intelligent COVID-19 outbreak prediction system empowered with supervised machine learning has been implemented on the dataset that was collected from WHO. 243 samples (80%) are utilized for training, while 60 samples (20%) are utilized for validation. Several statistical measures are employed for the assessment of the suggested framework predicted outcome.

SVM has sought to explore the best software pattern for a novel coronavirus pandemic. In this research, we employed the proposed SVM for forecasting to better check the efficacy of this methodology. We employed various statistical methods written in Eqs. (16) and (17) to calculate the efficiency of this SVM algorithm along with the corresponding methodologies. In Eq. (16), P signifies the prognostic outcome of the COVID-19 pandemic, and Q signifies the real outcome. P₀ and Q₀ signifies that there is no variation in projected output in the COVID-19 outbreak correspondingly from the preceding sequence. P_K and Q_K signifies the variation in prediction from the preceding sequence of the projected and real forecast correspondingly. P_k/Q_k signifies projected and the real outcome is similar. Likewise, P_k/Q_{j≠k} signifies an inaccuracy, in which the prognostic and real outcome of the COVID-19 outbreak is different.

$$\text{Miss rate} = \frac{\sum_{k=0}^2 (P_k / Q_{j \neq k})}{\sum_{k=0}^2 (Q_k)} \quad (16)$$

where j = 1, 2, 3... n

$$\text{Accuracy} = \frac{\sum_{k=0}^2 (P_k / Q_{j \neq k})}{\sum_{k=0}^2 (Q_k)} \quad (17)$$

Tab. 1 displays the efficiency of the suggested SVM system model in terms of accuracy and miss rate during the training and validation process. This demonstrated that the suggested SVM system provides 98.88% and 1.12% accuracy and miss rate simultaneously during training and 96.79% and 3.21% accuracy and miss rate during validation respectively.

Tab. 2 illustrates the performance evaluation with a previous publish approach empowered with DELM [32]. As shown in Tab. 2, our proposed model outperforms the other algorithm in terms of accuracy and miss rate.

Table 1: Performance evaluation of the proposed system model during validation and training

	Training	Validation
Accuracy	98.88%	96.79%
Miss Rate	1.12%	3.21%

Table 2: Performance evaluation of the proposed system model with literature

	DELM [32]		Proposed SVM system model	
	Training	Validation	Training	Validation
Accuracy	97.59%	95.53%	98.88%	96.79%
Miss Rate	2.41%	4.47%	1.12%	3.21%

4 Conclusion

This article proposes an intelligent framework for predicting an outbreak of COVID-19 that has been enabled by supervised machine learning. The simulation findings have shown that the efficiency of the proposed model achieves an improved result. It also concluded that the proposed intelligent COVID-19 outbreak prediction method with a supervised machine learning framework model provides 98.88% and 96.79% accuracy during training and validation. This may be useful in an outbreak of disease where the likelihood of infection and the need for preventive action does not match the resources available. More appropriate, more structured and finer data sets would further improve the learning rate of the system.

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