Forecasting Daily COVID-19 Related Calls in VA Health Care System: Predictive Model Development

Weipeng Zhou¹, BA; Ryan J. Laundry², BA; Paul L. Hebert^{2,3}, PhD; Gang Luo¹, PhD

¹Department of Biomedical Informatics and Medical Education, University of Washington, UW Medicine South Lake Union, 850 Republican Street, Building C, Box 358047, Seattle, WA 98109, USA

² Seattle-Denver Center of Innovation, VA Puget Sound Healthcare System, 1660 South Columbian Way Building 101 Room 4W65, Seattle, WA 98108, USA

³ Department of Health Services, University of Washington School of Public Health, 3980 15th Avenue NE, Seattle, WA, 98195 USA

Abstract

Background: COVID-19 has become a challenge worldwide and properly planning of medical resources is the key to combating COVID-19. In the US Veteran Affairs Health Care System (VA), many of the enrollees are susceptible to COVID-19. Predicting the COVID-19 to allocate medical resources promptly becomes a critical issue. When the VA enrollees have COVID-19 symptoms, it is recommended that their first step should be to call the VA Call Center. For confirmed COVID-19 patients, the median time from the first symptom to hospital admission was seven days. By predicting the number of COVID-19 related calls, we could predict imminent surges in healthcare use and plan medical resources ahead.

Objective: The study aims to develop a method to forecast the daily number of COVID-19 related calls for each of the 110 VA medical centers.

Methods: In the proposed method, we pre-trained a model using a cluster of medical centers and fine-tuned it for individual medical centers. At the cluster level, we performed feature selection to select significant features and automatic hyper-parameter search to select optimal hyper-parameter value combinations for the model.

Results: The proposed method was evaluated for 110 VA medical centers on the test dataset. The prediction error was 2.13±0.23 in mean square error (MSE) when the configurations of the method (medical center clusters, selected features, and optimal hyper-parameter value combinations) were determined on the first prediction day and reused in the rest of the days. We constructed a baseline method where we built one model directly for each medical center. Compared to the baseline method, the MSE mean of the proposed method decreased by 73.07% and the standard deviation decreased by 68.05%. The proposed method also performed well when the amount of training data was further reduced. In a more computational expensive experiment where the configurations were determined daily, the proposed method's MSE standard deviation further decreased with MSE mean remained similar.

Conclusions: This study proposed an accurate method to forecast the daily number of COVID-19 related calls for VA medical centers. The proposed method was able to overcome modeling challenges by grouping similar medical centers into clusters to enlarge the dataset for training models, and using hyper-parameter search to automatically find optimal hyper-parameter value combinations for models. With the proposed method, surges in health care can be predicted ahead. This allows health care practitioners to better plan medical resources and combat COVID-19.

Keywords: COVID-19 forecasting; clustering; hyper-parameter search; model pre-training; model fine-tuning

Introduction

Background

In 2020, the world was hit by the highly contagious COVID-19 disease [1,2]. The spread of COVID-19 could cause severe social and economic crises. Health care practitioners have been working hard to mitigate the crises. To combat COVID-19, it is necessary to plan medical resources in real-time. During the pandemic, COVID-19 outbreaks escalated quickly and the ability to plan medical resources becomes critical. Hospitals need to react to the outbreaks and at the same time maintaining the existing patients well. In circumstances where physicians are affected by COVID-19, hospitals also need to take immediate actions to monitor and reschedule them. Tools that can forecast COVID-19 could help hospitals plan medical resources and handle such events [3–5].

In the US Department of Veterans Affairs Health Care System (VA), COVID-19 needs to be carefully monitored. The US Department of Veterans Affairs Health Care System is the largest integrated health care system in the United States. It consists of over 100 VA medical centers and serves millions of veterans [6,7]. Many veterans in the VA experienced comorbid chronic conditions [6], increasing their vulnerability to COVID-19 and increasing the likelihood of hospitalization. A sudden outbreak of COVID-19 can result in a significant surge of medical needs in the VA.

To help planning medical resources in the VA, it is useful to forecast the daily number of COVID-19 related phone calls in VA. During the pandemic, health care use mainly starts with a phone call that describes the symptoms. For confirmed COVID-19 patients, the median time from the first symptom to dyspnea has been estimated as five days, to hospital admission was seven days, and to acute respiratory distress was eight days [31]. A large number of COVID-19 related calls is likely to indicate a large number of confirmed COVID-19 patients in the future. Thus, by forecasting the daily number of COVID-19 related calls, we could predict imminent surges in healthcare use in VA and plan medical resources promptly.

To generate accurate predictions for COVID-19, we employed deep learning models. In the field of COVID-19 forecasting, deep learning models [3,8,9] were particularly effective because of their efficiency in handling multivariate features and long time series. However, applying deep learning models to forecast COVID-19 for VA medical centers has two major challenges. Despite being in the middle of the COVID-19 pandemic, the dataset available for model training is small and deep learning models usually do not perform well with a small dataset. Additionally, even though deep learning models are effective, their performance heavily depends on their hyper-parameter settings. To address them, we proposed a novel method. The method was able to train robust models by enlarging the training dataset. The proposed method grouped similar medical centers into a

cluster, pre-trained a model from the cluster, and fine-tuned the pre-trained model to fit individual medical centers. The method also alleviated the burden of hyper-parameter tuning by employing an automatic hyper-parameter search method. The proposed method could help planning medical resources by providing high quality predictive models.

To forecast the daily number of COVID-19 related calls, this study proposed a data-efficient method. This study demonstrated the proposed method on a VA data set and predicted the daily number of COVID-19 related calls for 110 medical

Methods

Study design and ethics approval

VA's institutional review boards approved this secondary analysis study on clinical data.

In the processed dataset, 110 out of 140 medical centers were selected for modeling (selection criteria were described in the data analysis section). The patient cohort contained VA Health Care System enrollees who called the VA medical centers between January 1st, 2020 and July 27th, 2020.

Prediction target (a.k.a. the dependent variable)

In this study, the prediction target was the daily number of COVID-19 related calls to VA medical centers. On each day and for each medical center, we measured the total number of calls occurred. Based on the call records, we also inferred the daily number of calls related to COVID-19 symptoms for each medical center. According to data from Wuhan, the most common symptoms at the onset of illness were fever (98.6%), fatigue (69.6%), dry cough (59.4%), myalgia (34.8%), and dyspnea (31.2%) [31]. To find calls related to COVID-19, we searched these five keywords in the call records using the Veterans Indexed Search for Analysis tool [30]. A call was considered to be COVID-19 related if a match was found.

Data set

The VA data warehouse supplied textual call data and we processed the data to find the daily number of COVID-19 related calls for each medical enter. After data preparation, the data set contained 110 medical centers and the time period was between January 1st, 2020 and July 27th, 2020.

The training and test set split

The last 30 days of the dataset were used for testing. The test set contained data between June 28th, 2020 and July 27th, 2020. When making forecasting for a prediction day, the training set available for medical center clustering, feature selection, hyper-parameter search and model training consisted of all data prior to the prediction day.

Features (a.k.a. independent variables)

To enhance the model's prediction performance, we also considered features other than the daily number of COVID-19 related calls. When identifying the daily number of COVID-19 related calls, we also recorded the daily number of calls in total and added it to the feature set. We also derived the day of week and week of the year from the call day and used them as features. In the COVID-19 Impact Analysis Platform [11], county-level COVID-19 related features (e.g. daily confirmed COVID-19 cases, daily COVID-19 test positive rate) were available in public and we added them to the feature set. The details of these features were described in Table 1.

Name Description		Sourc
Daily number of	The daily number of calls to VA call centers and related to	VA
COVID-19 related	COVID-19.	

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Name	Description	Source
Daily number of COVID-19 related calls	The daily number of calls to VA call centers and related to COVID-19.	VA
Daily number of calls	The daily number of calls to VA call centers.	VA

	<u></u>	1
Day of the week	The index of a day in a week (e.g. 1 for Monday, 2 for Tuesday).	Derived from date
Week of the year	The index of a week in a year (e.g. 1 for the first week, 2 for the second week).	Derived from date
Social distancing index	The index measuring the extent the population practicing social distancing in the region served by a VA medical center. Integer value ranging from 0-100.	COVID-19 Impact Analysis Platform
Percentage of people at home	The percentage of people staying at home in the region served by the VA medical center.	COVID-19 Impact Analysis Platform
Trips per person	The average number of trips a person takes per day in the region served by a VA medical center.	COVID-19 Impact Analysis Platform
Percentage of out- of-county trips	The percentage of out-of-county trips in the region served by a VA medical center.	COVID-19 Impact Analysis Platform
Miles traveled per person	The average number of miles a person travels (walk, bike, car, bus, train, plane, etc.) per day in the region served by a VA medical center.	COVID-19 Impact Analysis Platform
Non-work trips per person	The average number of non-work trips (grocery, restaurant, etc.) a person takes per day in the region served by a VA medical center.	COVID-19 Impact Analysis Platform
Number of new COVID-19 cases	The number of new COVID-19 cases found in the region served by a VA medical center.	COVID-19 Impact Analysis Platform
Weighted population	The weighted population in the region served by a VA medical center.	COVID-19 Impact Analysis Platform
Weighted COVID-19 cases per 1000 people	The weighted average of CDC-reported COVID-19 cases per 1000 people in the region served by a VA medical center.	COVID-19 Impact Analysis Platform
Number of COVID-19 tests	The number of COVID-19 tests done in the region served by a VA medical center.	COVID-19 Impact Analysis Platform
Number of COVID-19 tests per 1000 people	The number of COVID-19 tests done per 1000 people in the region served by a VA medical center.	COVID-19 Impact Analysis Platform
COVID-19 test positive rate	The number of positive cases divided by the number of COVID-19 tests in the region served by a VA medical center.	COVID-19 Impact Analysis Platform
Number of COVID-19 hospitalizations	The number of COVID-19 related hospitalizations in the region served by a VA medical center.	COVID-19 Impact Analysis Platform

Data analysis

Data preparation

It is common for a medical center to have missing data for the daily number of COVID-19 related calls. When the missingness is significant, we excluded the medical center from the analysis. For each medical center, we calculated the proportion of days missing a COVID-19 related calls record. We only kept a medical center when the missingness was lower than 5%.

Additionally, we observed that some medical centers had a small number of calls but the number fluctuated highly over time. For example, one medical center received 6.76 COVID-19 related calls per day on average but the standard deviation of the calls per day was 5.45. This indicates that this medical center has a highly fluctuating COVID-19 related call number and it is difficult to predict its future. Moreover, the forecast results for such medical centers could be less meaningful because they could be significantly affected by randomness. As a result, we excluded a medical center from the dataset when it fluctuated significantly. To standardize across medical centers, we measured a medical center's fluctuation by computing the coefficient of variation, which was the mean of the COVID-19 related calls on all days divided by the standard deviation of the COVID-19 calls on all days. We excluded a medical center when its coefficient of variation was less than 1. After filtering by missingness and fluctuation, if a remaining medical center still had missing values, we imputed them using forward fill. This filled a missing value by its nearest backtracked value. A 3-day backward moving average was taken subsequently to smoothen the data and let the data pattern stand out more clearly. After preprocessing, we managed to keep 110 and exclude 30 medical centers. In the processed data set, the mean and standard deviation of the COVID-19 related calls was 7.17±6.47. We see that the COVID-19 related call data was still highly flutuating even after pre-processing and this could be a challenge for forecasting.

Performance metrics

When evaluating the prediction error of a forecast model, we used mean squared error (MSE). Let n be the number of data points to predict, Y_i be the prediction generated by the model and y_i be the prediction target. The mean square error is calculated as

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (Y_i - y_i)^2$$

Model for forecasting the daily COVID-19 related calls

In the field of COVID-19 forecasting, deep learning models [3,8,9] were particularly effective because of their efficiency in handling multivariate features and long time series. In this study, the specific deep learning model to consider was the Long Short-Term Memory network (LSTM) model [27,28]. LSTM is a type of deep learning model that specializes in time series forecasting and can efficiently handle multivariate features and long time series. LSTM has also been shown to perform well in forecasting tasks related to COVID-19 [8,9]. This study employed a simple LSTM for the purpose of demonstration. The simple LSTM contained a recurrent layer followed by a linear layer. The recurrent layer helped to extract significant features from the time series and the linear layer helped to synthesize the extracted features into a forecast. However, applying deep learning models to forecast COVID-19 for VA medical centers has two major challenges. Despite being in the middle of the COVID-19 pandemic, the dataset available for model training is small and deep learning models usually do not perform well with a small dataset. Additionally, even though deep learning models are effective in time series forecasting, their performance heavily depends on their hyper-parameter settings. To figure out an optimal hyper-parameter value combination, manual tuning is usually required by domain experts. In the VA system, there are more than 100 medical centers, each of which serving a unique population of patients. It is almost infeasible to tune a model for each manually. To solve these problems, we proposed a novel method.

The proposed method

Overview

Despite being in the middle of the COVID-19 pandemic, the dataset available for model training is small and deep learning usually does not perform well with a small dataset. To solve this problem, the proposed method applied the idea of model pretraining and fine-tuning [12], a widely used strategy in deep learning for training robust models even with a small dataset. In computer vision, people addressed the insufficient data problem by pre-training models on large datasets such as ImageNet [13,14] and then fine-tuning them on downstream tasks. The rationale behind this idea is that the early layers in the deep learning models are able to learn universal rules appliable across tasks and the fine-tuning step can apply these rules locally to downstream tasks. For example, when building phenotype-specific clinical text encoders, Dligach, Afshar and Miller first pre-trained a universal text encoder using data of multiple phenotypes. They then created an encoder for each phenotype by refining the pre-trained model using data from individual phenotypes [15]. Because pre-trained models learned general feature

representation from a large dataset and used them for the downstream tasks, this model pre-training strategy can also be viewed as a regularization for avoiding overfitting on small datasets.

When building models for forecasting the daily number of COVID-19 related calls, the proposed method applied the idea of pre-training. The proposed method combined multiple medical centers into one dataset, used the dataset to pre-train a general model and fine-tuned the model to fit individual medical centers.

Nevertheless, in order to utilize pre-training models well, the pre-trained model needs to share similar characteristics with the downstream tasks. If not, some of the learned rules in the pre-train model would not be appliable to individual medical centers. This created redundancy in the pre-trained model and made it difficult for fine-tuning the pre-trained model to downstream tasks. Because VA medical centers served different populations, the COVID-19 trend of some medical centers might be more similar than other medical centers'. Our method took advantage of this to make model training more efficient. Instead of creating one pre-trained model using datasets from all medical centers, the proposed method grouped medical centers into clusters and created a pre-trained model for each. When fine-tuning models for individual medical centers, pre-trained models of their corresponding clusters were used. In this way, the proposed method ensured that the rules learned by the pre-trained models were useful for downstream medical centers to the greatest extent. The clustering technique also reduced the burden of hyper-parameter tuning because we only need to tune one pre-trained model for a cluster of medical centers. In a study, researchers grouped Chinese provinces into clusters and used the larger dataset to build a model. They directly used the model to forecast the COVID-19 activity for provinces [16]. Differing from this study, our proposed method took a step further by refining the cluster-level model to create tailored models for individual medical centers.

When training machine learning models, applying feature selection can enhance the learning algorithm by eliminating the redundant information from a dataset [17]. However, applying feature selection on a small dataset is dangerous because feature selection methods themselves are machine learning algorithms and suffer from the curse of dimensionality; in training a machine learning algorithm, the amount of data required for getting a meaningful model often grows exponentially with the number of the dimensions (features) of a dataset [18–20]. To ensure the robustness of feature selection, the proposed method performed feature selection at the cluster-level dataset instead of the medical center-level.

Although deep learning models can usually produce excellent results, their performance is often sensitive to the selection of its hyper-parameter values. Traditionally, expert knowledge was required for tuning and selecting the optimal hyper-parameter value combinations. Recently, automated hyper-parameter search methods were developed for solving this problem. The newly developed methods have been shown to consistently outperform grid search, random search and sometimes even domain experts [21–23]. In major tech companies like Google, hyper-parameter search has also often been the default solution for building machine learning models [24]. This study involved building deep learning models repeatedly for each medical center cluster and each day. To do so with time efficiency and accuracy, we employed hyper-parameter search to automatically find optimal hyper-parameter value combinations.

The proposed method combined clustering, feature selection, hyper-parameter search, model pre-training and fine-tuning into a single workflow to predict the daily number of COVID-19 related calls for 110 VA medical centers. A flow chart illustrating the method's execution order on a prediction day was shown in Figure 1. The proposed method first divided VA medical centers into clusters and performed feature selection at the cluster-level to select significant features; then, hyper-parameter search was performed to find optimal hyper-parameter value combinations and a pre-trained model was built for each cluster; in the end, the pre-trained model was fine-tuned to create models for individual medical centers. The fine-tuned models were used for making forecasts. In a typical scenario, the medical center clusters, selected features and hyper-parameter value combinations could be determined once and reused in the subsequent days. Nevertheless, when computational resources were permitted, they could also be determined daily, and this scenario was explored in a separate experiment. The cluster-level models and fine-tuned models, however, were rebuilt daily as they required neglectable computational resources. The details of the method's components were described in the subsections.

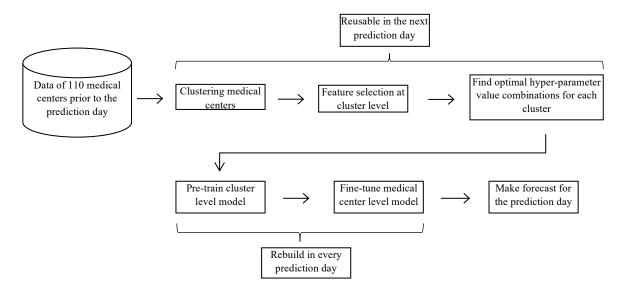


Figure 1. The flow diagram when the proposed method was used to forecast the number of COVID-19 related calls for 110 medical centers on a prediction day.

Medical center clustering

At the beginning of the workflow, the method used a clustering algorithm to divide medical centers into clusters such that medical centers in the same cluster share similar characteristics [16]. In the clustering algorithm, each medical center was characterized by its number of COVID-19 related calls over time. The algorithm computed a pairwise correlation matrix for the medical centers. Each value in the matrix represents the level of similarity between two medical centers. According to the correlation matrix, the clustering algorithm applied hierarchical clustering. It iteratively found medical centers that had high similarity and merged them into clusters. The smaller clusters could also be merged into a larger one. To determine the appropriate number of clusters to generate at last, the algorithm calculated and maximized the Calinski-Harabasz Index [25]. The index measured the difference between inter-cluster dispersion and between-clusters dispersion. Let n be the size of the data set, k be the number clusters generated. The Calinski-Harabasz Index (CH) is calculated as

$$CH = \frac{\operatorname{tr}(B_k)}{\operatorname{tr}(W_k)} \times \frac{n-k}{k-1}$$

where $tr(B_k)$ is the trace of the between group dispersion matrix B_k and $tr(W_k)$ is the trace of the within-cluster dispersion matrix W_k . Let C_q be the data points in cluster q, c_q be the center of cluster q, c_q be the center of the entire data set, and n_q be the number of points in cluster q. The two matrices are calculated as

$$W_{k} = \sum_{q=1}^{k} \sum_{x \in C_{q}} (x - c_{q}) (x - c_{q})^{T}$$

$$B_{k} = \sum_{q=1}^{k} n_{q} (c_{q} - c) (c_{q} - c)^{T}$$

Feature selection

After determining medical center clusters, the method applied feature selection at the cluster level. The method combined medical centers in the same clusters into one dataset and performed feature selection on it. The proposed method used the backward feature selection algorithm [26]. The algorithm started by building a linear regression model using all features and computing the level of significance (p-value) for each feature in the linear regression model; it then dropped a feature if the feature's p-value was greater than 0.05 and the feature had the highest p-value. The algorithm continued building the linear regression model with the remaining features and dropped a feature if the same condition was met. The algorithm terminated when it could no longer find a feature that satisfied the drop condition.

Hyper-parameter search

Feature selection could remove redundancy in the feature set; however, to make the model use the selected features well, an optimal hyper-parameter value combination should also be selected. In the proposed method, the selection of hyper-parameter value combination was carried out by automatic hyper-parameter search. The proposed method used Bayesian Optimization and Hyperband (BOHB), a robust tool for searching hyper-parameters and has been shown to be successful on a wide range of machine learning tasks [29]. The hyper-parameter search space provided to BOHB contained three LSTM hyper-parameters. Their names, value ranges and value distributions were listed in Table 2. For each medical center cluster, BOHB automatically found an optimal hyper-parameter value combination for building a pre-trained model.

Hyperparameter	Value range	Value distribution
Learning rate	0. 00001-0.1	Logarithmic uniform (right-tailed)
Number of hidden dimensions	10-150	Discrete uniform
Dropout rate	0-0.7	Uniform

Table 2. Description of hyper-parameter, value range, and distribution.

Model pre-training and fine-tuning

The method proceeded by pre-training a general model for each medical center cluster. Using the optimal hyper-parameter value combinations retrieved from hyper-parameter search, as well as the selected features, the method created a pre-trained LSTM model for each cluster.

Building on the pre-trained model, the method fine-tuned a tailored model for each medical center. In the pre-trained LSTM model, there was one recurrent layer and a linear layer, each containing learned parameters. The proposed method performed fine-tuning by training the pre-trained model again using the specific medical center's features. In model pre-training, the parameters of both the recurrent layer and the linear layer were learnable; however, in model fine-tuning, the parameters of the recurrent layer were fixed to be those of the pre-trained model and only parameters of the linear layer was learnable. Following the pretrain-finetune paradigm [12,15], this ensured that the fine-tuned model inherited characteristics from the pre-trained model but also contained characteristics specific to the medical center it was tailored for.

Evaluating the proposed method

Evaluation procedure

We evaluated the proposed method on 110 VA medical centers. Each medical center contained data between January 1st, 2020 and July 27th, 2020. We used the last 30 days of the data for testing. To simulate typical usage of the method, we determined the medical center clusters, selected features, and optimal hyper-parameter value combinations once on the first testing day and reused them throughout the rest of the days. This reduced the computational resources as the determination of the medical center clusters, selected features, and optimal hyper-parameter value combinations were computationally expensive.

On each testing day, we rebuilt a model for each medical center using the most recent data up to the testing day because the model pre-training and fine-tuning were less computationally expensive. These models were used to forecast the number of COVID-19 related calls for the testing day. The forecast results were compared with their true values.

During the evaluation, we used mean squared error (MSE) to measure the forecast error. To control randomness, we repeated the whole evaluation process 5 times with different random seeds. The mean and standard error of the repetitions were reported.

Baseline method

Aside from the proposed method, a baseline method was also constructed for the purpose of comparison. In the baseline method, hyper-parameter search was used to create one LSTM model for each medical center directly. The hyper-parameter search was performed on the first testing day to determine the optimal hyper-parameter value combination for each medical center and reused on the rest of the days. Other settings of the baseline method were the same as those of the proposed method.

Evaluating the method's performance with limited training data

In the previous experiment, there were 179 days of data available for the proposed method to make forecasts on the first testing day. In reality, we would like a forecasting model to work even when the amount of training data was small. This is especially true at the earlier stage of a pandemic when there were little training data but forecasting was highly beneficial for allocating medical resources.

To further test the proposed method's performance under these cases, we simulated more scenarios. It is possible that a pandemic had an abrupt outburst and only limited disease history was available. Thus, we tested the method's performance with different amounts of training data. To ensure a fair comparison between the experiments, we also fixed the test dataset. We performed the comparable experiments by truncating the earlier portion of the data.

In this session, the available training data no longer started from Jan 1st (179 days of training data) as before. Instead, we performed experiments where the available data for the proposed method started from March 30th, April 29th, and May 29th. These experiments were equivalent to having 90, 60, 30 days of training data for the proposed method to make forecasts on the first testing day. The available data still ended on July 27th and we still used the last 30 days of the data for testing.

Evaluating the impact of the frequency of determining the configurations (medical center clusters, selected features, and optimal hyper-parameter value combinations)

In a more rigorous environment (e.g. sufficient time and abundant energy consumption were permitted), the medical center clusters, selected features, and optimal hyper-parameter value combinations could be updated every few days. We experimented with the circumstances where the configurations were determined every 5, 3 and 1 day(s). We sought to analyze if updating these configurations frequently had an impact on the forecast performance.

Results

Comparison between the proposed method and the baseline method

The MSE of the forecast was 2.13 ± 0.23 for the proposed method and 7.91 ± 0.72 for the baseline method. Compared to the baseline method, the MSE mean of the proposed method decreased by 73.07% (5.78/7.91) and the MSE standard deviation decreased by 68.05% (0.49/0.72). Most of the time, the medical centers were clustered into 3 groups, despite the fact that the maximumly allowable clusters were 10. In rare cases, the medical centers were clustered into 4 groups. This indicated that the VA medical centers had distinctive characteristics in receiving COVID-19 related calls but they were not significantly different.

Evaluating the method's performance with limited training data

The forecast MSE for 90, 60, 30 days of training data were 2.32 ± 0.16 , 3.05 ± 0.29 , and 4.66 ± 1.09 respectively. The mean and standard deviation of the MSE consistently increased with the reducing amount of training data. When the number of training days reduced from 90 to 60 to 30, the MSE mean increased by 31.47% (0.73/2.32) and 52.79% (1.61/3.05); the MSE standard deviation increased by 81.25% (0.13/0.16) and 275.86% (0.8/0.29). The performance decrease was the most significant when the number of training days was reduced from 60 to 30.

Compared to the case where the full COVID-19 history (179 days) was available for the method, the MSE mean increased by 8.92% (0.19/2.13), 43.19% (0.92/2.13) and 118.78% (2.53/2.13); the MSE standard increased by -30.43% (-0.07/0.23), 26.09% (0.06/0.23), 373.91% (0.86/0.23). The performance was similar when the amount of training data was nearly halved to 90 days. The method performed worst when the amount of training data was 30 days. It is worth noticing that even when the amount of training data was 30, the proposed method still outperformed the baseline (MSE 7.91 ± 0.72) by a large margin (P<.001). This finding was particularly surprising considering that the baseline method had access to the full COVID-19 history (179 days). We hypothesized that this was because the proposed method's medical center clustering and model pre-training effectively remedied the problem of data insufficiency. This showed that the proposed method performed robustly even when the amount of training data was limited.

Evaluating the impact of the frequency of determining the configurations

When the configurations (medical center clusters, selected features, and optimal hyper-parameter value combinations) of the proposed method were determined every 5, 3 and 1 day(s), the MSE were 2.20±0.15, 2.18±0.15 and 2.19±0.06, respectively. In an earlier experiment, the proposed method's configurations were determined on the first day and reused throughout the rest of the days. We considered this experiment as a circumstance where the configurations were determined every 30 days because the test dataset contained 30 days. With this auxiliary experiment added, we concluded that when the frequency of determining the configurations changed from 30 to 5, 3 and 1, the mean of the MSE remained similar, but the standard deviation of MSE reduced by 34.78% (0.08/0.23), 34.78% (0.08/0.23) and 73.01% (0.17/0.23) respectively.

Discussion

Principal results

In this study, we proposed a method to forecast the daily number of COVID-19 related calls for 110 medical centers; the prediction error was 2.13 ± 0.23 when the configurations of the method (medical center clusters, selected features, and optimal hyper-parameter value combinations) were determined on the first prediction day and reused in the rest of the days. Compared to the baseline method, the MSE mean of the proposed method decreased by 73.07% and the standard deviation decreased by 68.05%. The proposed method also performed well when the amount of training data was limited. In a more computational expensive experiment where the configurations were determined daily, the proposed method's MSE standard deviation further decreased with MSE mean remained similar. The decrease of the MSE standard deviation reached its highest point when the configurations were determined daily. This showed that updating the configurations frequently increased the stability of the forecast.

Limitations

This study has 2 limitations that help guide future research.

- 1) This study demonstrated the proposed method by predicting the number of COVID-19 related calls for VA medical centers. In the future, the proposed method can also be applied to more prediction tasks, such as predicting the daily number of COVID-19 vaccination walk-ins or appointments; the proposed method can also be applied to a broader scope such as predicting the daily number of VA emergency department visits.
- 2) In this study, the proposed method was evaluated using the VA health care system's dataset. In the future, it would be helpful to test the proposed method on datasets from other health care systems.

Conclusions

This study developed a method to forecast the daily number of COVID-19 related calls for 110 VA medical centers. The proposed method overcame modeling challenges by dividing similar medical centers into clusters to enlarge the dataset for model pre-training. It also used hyper-parameter search to automatically find optimal hyper-parameter value combinations for building models. Additionally, the method could also produce more stable predictions when its configurations were updated daily. Besides helping health care practitioners better plan medical resources during the COVID-19 pandemic, the proposed method is also generally applicable for scenarios where prediction tasks are needed to be performed for a large number of entities but individual entities only have limited data.

Authors' contributions

WZ was the main contributor to this study. RL pulled and processed the call data from VA. PH and GL participated in proposing the research, gathering the data and editing the article.

Conflicts of interest

None declared.

Abbreviations:

COVID-19: coronavirus disease 2019 VA: US Veteran Affairs Health Care System LSTM: long short-term memory network

CDC: Centers for Disease Control and Prevention

MSE: mean square error

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