Advances in Industrial Engineering, Autumn 2021, 55(4): 433-446
DOI: 10.22059/aie.2022.336859.1819
RESEARCH PAPER

Targeted Vaccination for Covid-19 Based on Machine Learning Model: A Case Study of Jobs' Prioritization

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Received: 04 January 2022, Revised: 06 Februaury 2022, Accepted: 08 Februaury 2022

Abstract

Today, the spread of the coronavirus has affected many models of life. Despite making some vaccines such as AstraZeneca, Pfizer-BioNTech, and Moderna, vaccination has not been widely used. Due to the lack of vaccines in sufficient numbers, COVID-19 vaccination is usually performed in several phases. Using machine learning methods can be influential in selecting the nominated groups to achieve an acceptable level of immunity called herd immunity. The approach of this article is to introduce the high-risk occupational groups that are most exposed to the coronavirus to the vaccination phasing is done effectively, to provide the fastest immunity. The Genetic algorithm was employed to feature selection for getting appropriate performance in the predictive model. The machine learning regression algorithms, such as decision tree, random forest, and logistic regression, were utilized to build a predictive model, in which random forest with 88.3 % accuracy is selected by comparison among other algorithms for this purpose. The different jobs' categories priorities were determined due to the feature importance based on coefficients to get the vaccine, which this help to reduce the covid 19 deaths.

Keywords:
Machine Learning;
Vaccine;
Job Priority;
Genetic Algorithm

Introduction

Today, with the spread of coronavirus worldwide, the need for intelligent vaccination is essential since there is no vaccine for the entire population of a community; targeted vaccination can be an effective way to prevent the spread of the epidemic [1]. The idea of using targeted vaccination is a logical method in the event of a global outbreak that aims to increase the efficiency of vaccination in a way that provides maximum immunity in a short time. However, in order to carry out targeted vaccination, it is necessary to evaluate the general conditions of the statistical information, such as population and movement trends in public places. The vaccination operation should be performed with the highest accuracy, not including just that two pieces of information to create the most immunity. In this decision, there are different factors, such as the history of the underlying disease, that cover the biological characteristics of humans. Maybe the most straightforward way of vaccination is vaccinating the elderly and those with underlying diseases. But making this decision may not cover a fully targeted vaccination since many people are ignored, which may have critical jobs and should be

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nominated for the first stage of vaccination. Therefore, it is necessary to consider other characteristics in order to provide a suitable model for targeted vaccination.

Various methods can be considered during the Pandemic, which has a situation close to the coronavirus. Chen showed that if the communication ratio, which is defined as the ratio of communication to the number of people present in public neighborhoods, increased, then there is a unique Nash equilibrium [2]. This equilibrium is unique if the ratio is equal to one, and if this ratio decreases, then many Nashs are not uncommon. Other similar studies in widespread infectious diseases can be used for the corona vaccination model. Wells, Klein examined restrictive policies to prevent the spread of influenza. This article points out that vaccination should be based on past experiences. The experimental results show that the number of daily contacts is directly related to the virus spread model [3]. Stockwell, Fiks referred to the shortage of vaccines required globally and sought to estimate the number of vaccines needed using personal data. This research points out that health information during infancy can help estimate the number of vaccines required for each disease. The method proposed in this article is to send the infancy information in a text to a system to inform the country's health system to provide the number of vaccines required for a particular disease [4]. Dharmawardana, Lokuge has developed an evacuation model using an artificial intelligence network that uses mobile users' information to model the tropical infectious disease spread by mosquitoes. The dataset used in this article consists of information on Sri Lankan countries' contacts to reduce the rate of instantaneous displacement [5].

There are several patterns for vaccination COVID-19, each presenting its patterns from a different perspective. For example, one of the issues that can affect the pattern of virus transmission is the children's role in spreading the virus. On the other hand, phasing methods to classify vaccinations can effectively reduce the spread effect [6]. Experts believe that a minimum of 60% vaccination is required to create immunity to the comprehensiveness of society [7]. Also, governments' implementation of labor policies can be one way to make immunity and prevent the spread of the virus. Holzmann-Littig, Braunisch surveyed a degree of ambiguity in vaccination practice between different age and occupational groups. In these groups, the age groups under 20 years had the lowest acceptance rate, while the German workers' group had the highest vaccination acceptance rate [8].

On psychological factors, although the study of Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2) to increase vaccination efficiency is offered, but some psychological characteristics such as stress, loneliness, and depression can affect how to be vaccinated [9]. In other words, the use of psychological and behavioral characteristics can effectively increase vaccination efficiency. These indicators, which are usually more pronounced in the elderly, can be considered in immunization to reduce the vaccination side effects. Using a plannable roadmap for vaccination can be effective in increasing productivity. According to indicator groups and the risk, UK vaccination models are categorized [10]. In this model, vaccination of treatment centers and hospital service is proposed as a model that can increase productivity. Razai, Osama examined the causes of doubts about using vaccines by different people. In this review, vaccine hesitancy is characterized by uncertainty and ambivalence about vaccination. This article explains why people are skeptical about vaccination and persuade them to use it [11].

Adherence to health protocols and policies such as social distance can effectively prevent the spread of disease, but in some cases, full compliance with these conditions is not possible. For example, it is not possible to observe social distance or use the mask for the workers. Therefore, workers can play an influential role in spreading the coronavirus. For this reason, vaccination priorities can be changed in specific circumstances. Buckner, Chowell introduced a dynamic model based on epidemiological characteristics that depend on three main features: sensitivity, severity, and contact rate. The model uses three policies: minimize infections, life years, and death, ultimately prioritizing older workers receiving the vaccine [12]. Around the world, lockdown policies have been implemented in the city to mitigate the transmission of SARS-CoV-2. But the implementation of the lockdown policy alone is not enough, and the model will be optimal, dynamic, and depending on changing circumstances. Rachaniotis, Dasaklis presented a dynamic two-phase statistical model for Greece in which the silent policy changes step by step. Using this method can prevent complete blackouts and help the city survive [13].

With the further spread of the coronavirus and in line with movement control policies, many social events, such as college classrooms and conferences, were shut down and replaced with virtual events. At this time, the role of mobile phones has been effective in improving quarantine conditions and has helped people adapt psychologically to these conditions. Therefore, mobile phones can contain important information that their analysis effectively determines vaccination and phasing it for job risk. According to this, Jadidi, Jamshidiha presented a two-phase model for prioritizing vaccination using mobile data. At its first phase, some populations are selected in order to achieve the most Herd immunity. At its second phase, some mobile wireless contact tracing methods are investigated to do targeted vaccination and create the most significant reduction in disease transmission. This method is compared versus random immunization, which has achieved a 30% reduction in infection rate [14]. Another perspective of movement is described by Sun, Lu [15]. In this study, router sensors to analyze displacement are introduced as an effective policy of targeted vaccination in widespread diseases. Using the router sensors attached to the students' bodies, their routes were tracked, the students' communications with each other were collected, and the virus spread was analyzed. The computational results in this paper show that the displacement parameter will significantly affect the spread of the virus. Salvamani, Tan showed that government policies, such as lockdown in the city, can reduce the movement of people. In other words, reducing the amount of displacement as movement control can be effective in SARS-CoV-2 immunity [16]. The use of isolation, quarantine, and social distance methods are other relevant movement control parameters that can effectively prevent coronavirus spread [17]. According to this study, accurate analysis of the clinical spectrum of the disease can estimate the mortality rate and introduce methods to prevent its spread.

With the development of machine learning tools in various sciences [18, 19], the use of these methods can effectively analyze the patterns of movement of people. According to this, a deep analysis of the impact of human mobility and diffusion corona on air is investigated [20]. This study indicated that people's socioeconomic effect on human mobility could be a contradictory parameter for movement control. The use of a comprehensive database from Google mobility reports for machine learning-based analysis seems essential in the COVID-19 analysis since its worldwide spreading. Some supervised learning algorithms such as random forest and K-Nearest Neighbor are investigated to check the impact of social distancing with the help of relativity between lockdown and pandemic severity by a correlation of 0.68 [21]. One of the basic parameters in analyzing the movement rate based on the probability of spreading the virus is public transportation in the city. Since this movement is done several times during the day and usually many people are present on these devices, it won't be easy to follow social protocols, including social distance. It can be one way of spreading the virus. Asad, Dashtipour introduced a machine learning-based approach to intelligently analyzing daily travel between different age groups. In this study, the Support Vector Machine (SVM) method achieved considerable accuracy in classifying different age categories on London Underground and Overground (LUO) dataset [22]. Hosseini and Gittler showed that most people use their phones when moving around, indoors and outdoors. The use of these transfer patterns can be effective in targeted vaccination. So, GPS-enabled smartphones can be effective in routing and analyzing the amount of movement of people. It used the Linear Discriminant Analysis method as a dimension reduction method, followed by multiple regression to estimate the underlying factors in identifying displacement patterns [23].

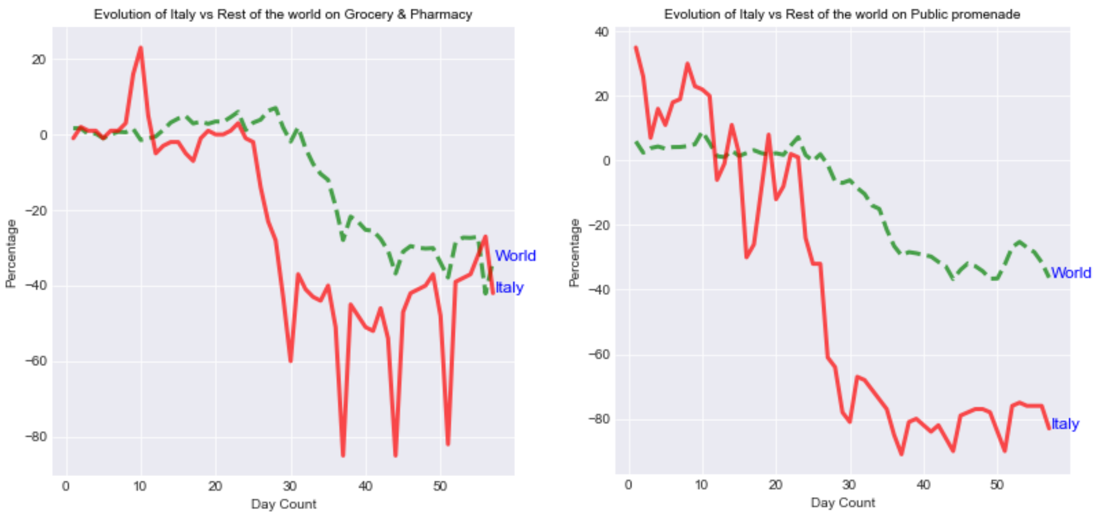
In this paper, despite the age, which is considered in most previous studies, the jobs' category, which is another prominent view and factor in analyzing and prioritizing for vaccination, is investigated with a novel technique such as artificial intelligence. Therefore, according to the necessity of intelligent vaccination and the influence of the movement factor in the spreading of coronavirus, which is investigated in various studies, artificial intelligence techniques are utilized to analyze the movement effect and prioritize the jobs' categories that are most exposed to the virus.

The remaining of the paper is organized as follows. Section 2 describes the problem description. Section 3 shows the methodology, Section 4 represents our experimental results, and the paper is finalized by the Conclusion followed by the associated references.

Problem description

One of the problems that arise after discovering the vaccine is the correct way of vaccination. Due to the large population and lack of facilities, it is impossible to vaccinate all community members. Therefore, vaccination will be possible only for a part of society. The goal is to select a part of society with the greatest need for vaccination. By vaccinating a part of society, the immunity of the whole community will be significantly increased. This method of vaccination is called targeted vaccination, which today is done in the form of phasing based on priorities. There are different perspectives on vaccination prioritization, and each focuses on an indicator. In this study, our goal is to focus on the job prioritization based on people mobility trends.

It should be noted; we have omitted specific occupations such as health care providers that are directly associated with the coronavirus because vaccination of this group is the priority and will not require analysis. Instead, it is essential to vaccinate people in other occupations, such as public transport jobs, public promenades, shops, restaurants, or offices. Fig. 1 shows the mobility trends of Italians in each job' category against the average mobility trends of the world.



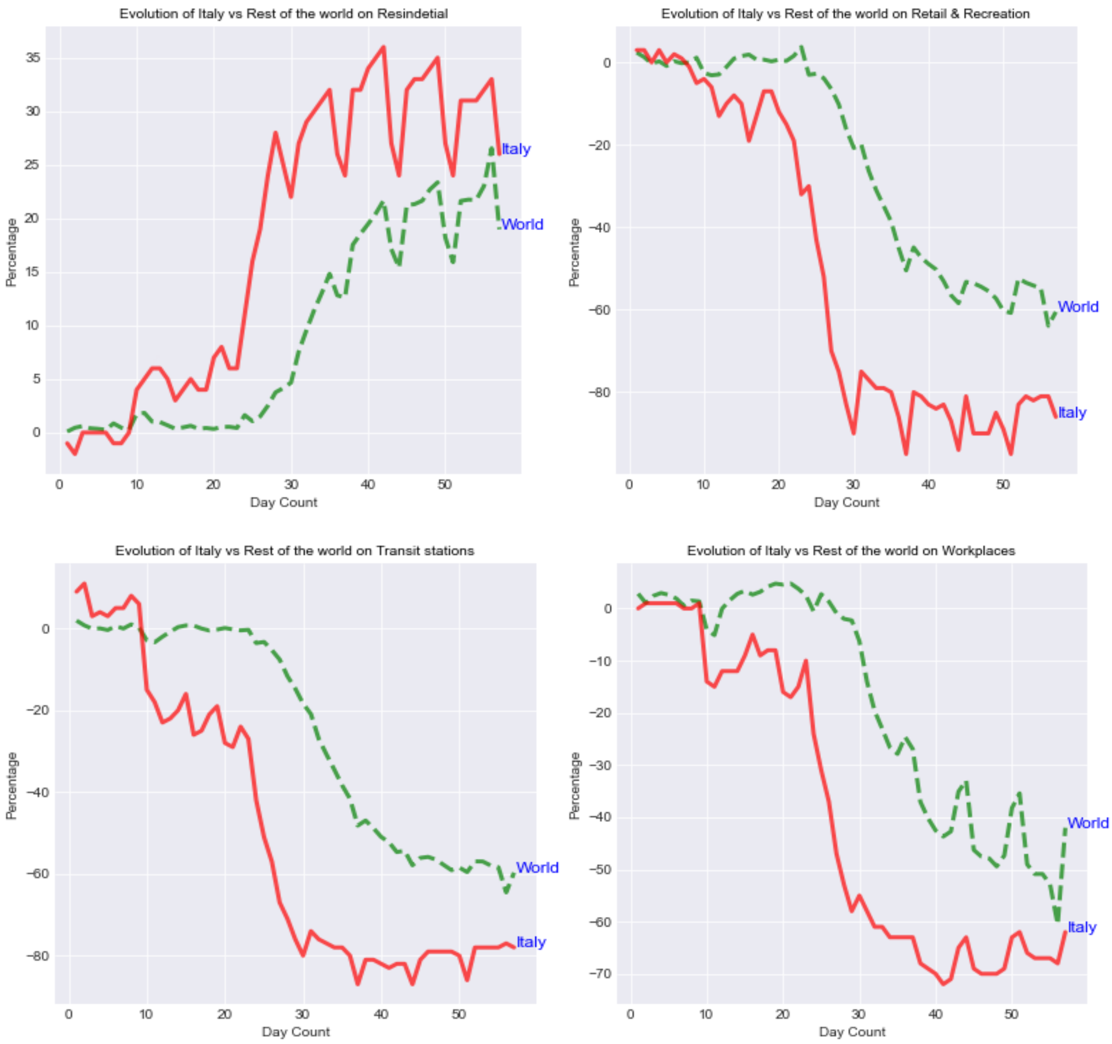


Fig. 1. the mobility trends of Italians in each job' categories against the average mobility trends of the world.

Based on Fig. 1, the behavioral changes of people in Italy are almost similar to the average behavioral changes of the world. Therefore, by prioritizing jobs in Italy, it is possible to utilize this prioritizing for other countries too.

These jobs are prioritized based on the degree of risk versus the coronavirus, which is evaluated based on mobility trends. Several machine learning techniques are employed to achieve this purpose.

Methods

In this section, the Logistic regression algorithm will be expressed to see how it can build the predictive model, determine the most influential independent variable, and prioritize jobs for vaccination. A genetic algorithm is utilized in this research to select the most influential variables among independent variables for training an appropriate predictive model.

Genetic algorithm

The Genetic algorithm is a population-based search algorithm inspired by the evolution's rules in nature. The Genetic algorithm implements the Darwinian evolution's simplified version [24].

The Genetic algorithm produces appropriate solutions for various optimization problems. This algorithm begins the optimization process by an initial population's generation. Fig. 2 illustrates the Genetic algorithm process.

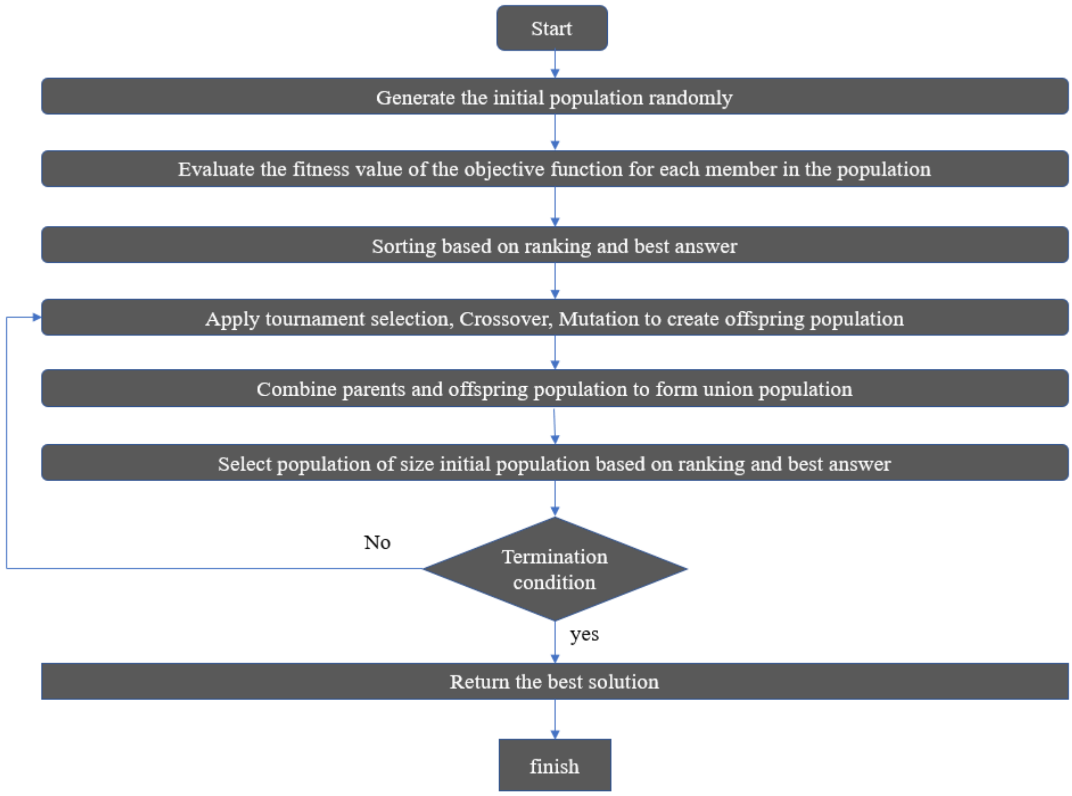


Fig. 2. The Genetic algorithm flow chart

The Genetic algorithm is utilized to make progress in the machine learning model's accuracy and performance by choosing the best subset of independent variables from the input data. The objective is to maximize the machine learning model accuracy by selecting the best input features and dropping redundant components in the feature selection process.

Solution representation

The algorithm's objective is to detect a subset of features with the best performance in the predictive model. Thereupon, a solution's goal is to specify which components are picked and which are dropped. Consequently, a binary value list represents the picked or dropped features. Every member of that list depends on one of the features in the initial input data. The chosen corresponding component is represented by a value of 1, and a 0 value illustrates the feature isn't picked.

Tournament selection

The tournament selection operator is employed to select the parents from the set of individuals. The tournament's winner (i.e., the one with the best fitness) is chosen.

Crossover

The single-point Crossover combines the parents' genetic information to generate new children and solutions to progress in the exploration process in solution space. Fig. 3 shows the single-point crossover process.

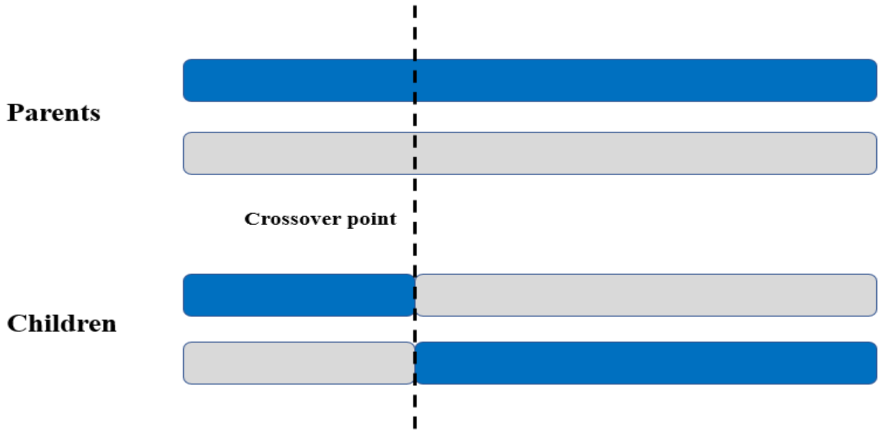


Fig. 3. Single-point crossover process.

Mutation

The Mutation by generating a new population establishes the response diversity and avoids falling the discovery process into a local optimum. The Flip-Bit Mutation is employed in this research, get the genome Bit and inverts the Bit; for example, if the genome Bit is 0, it's converted to 1. Fig. 4 illustrates the Flip-Bit mutation process.

Parent	1	0	1	0	0	…	1	0	1
Offspring	1	1	0	1	0	…	0	1	1

Fig. 4. The Flip-Bit mutation process.

Machine Learning

Machine learning is a subset of artificial intelligence that establishes applications that learn from training data to recognize patterns in order to make predictions and decisions based on new data. Machine learning has three branches, namely, supervised learning, unsupervised learning, and reinforcement learning.

Supervised learning has two parts, namely, classification and regression. In regression, the dependent variable is predicted by machine learning algorithms based on independent variables. Based on the statistical view, there are linear and non-linear models; if the model parameters are linear, then the model is counted as linear [25]. Linear regression, Logistic regression, Decision Tree regression, random forest regression are some of the most popular algorithms in supervised learning. Fig. 5 illustrates the supervised learning process.

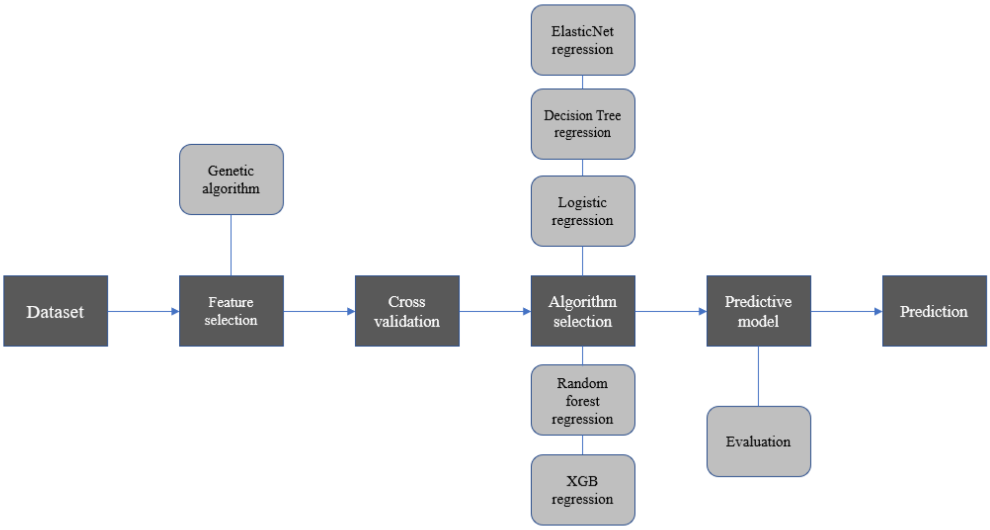


Fig. 5. The supervised learning process.

Based on Fig. 1, the Genetic algorithm is employed to find the best subset of features at the first steps. K-fold cross-validation is utilized to achieve a robust predictive model and avoid overfitting. In the next step, different machine learning algorithms are compared based on the accuracy to find the best algorithm, and the best algorithm is chosen to construct the predictive model.

Regression tree

In Decision Tree regression, the feature space is divided into a set of regions, and in each region, a model is trained. In a regression problem, $X = X_1, X_2, \ldots, X_m$ are assumed as predictor variables, which m is the number of variables. $Y = Y_1, Y_2, \ldots, Y_n$ are assumed as target variables, where n is the number of observations. Eq. 1 shows the left side in the Decision Tree is achieved by splitting the predictor space at the cutpoint.

$$H_l(i, C) = (X, Y) \mid X_i < C \tag{1}$$

C is the cutpoint, and Eq. 2 shows that the right side in the Decision Tree is achieved by splitting the predictor space at the cutpoint.

$$H_r(i, C) = (X, Y) \mid X_i \geq C \tag{2}$$

The goal is to find the best i and C that minimize the mean squares error (MSE), which is formulated as follows:

$$MSE = \frac{1}{n} \sum_{j=1}^{N} (Y_j - \bar{Y}_{H_j})^2 \tag{3}$$

where $\bar{Y}_{H_j}$ is the mean predicted value at nodes, Y_j is actual value, and n is the number of data points. Next, the process is repeated to find the best predictors and cutpoints to divide the data further to minimize the MSE within each of the resulting areas. The process is continued until the stopping criterion is achieved.

Decision tree regression is one of the most useful machine learning algorithms, but in some cases, it has a problem that is overfitting (i.e., the model is trained well but can't predict appropriately based on test data). The random forest regression algorithm can solve this problem [26].

Random forest algorithm

Random forest employs an ensemble learning method for regression. An ensemble method is comprised of multiple machine learning algorithms to make more appropriate predictions than a single algorithm. Ensemble learning has two types, namely, Boosting and Bootstrap Aggregation (bagging).

Bagging is an algorithm that is proposed to improve the accuracy and stability of machine learning algorithms. This algorithm refers to random sampling with replacement and helps to avoid overfitting by reducing the variance. In bagging, each model runs separately, and then the results are aggregated.

Random forest regression is a bagging technique. A multitude of decision tree algorithms constructs this algorithm. The decision tree algorithms are trained separately, and the final prediction is the average of the outputs of each decision tree. Fig. 6 illustrates the random forest regression structure.

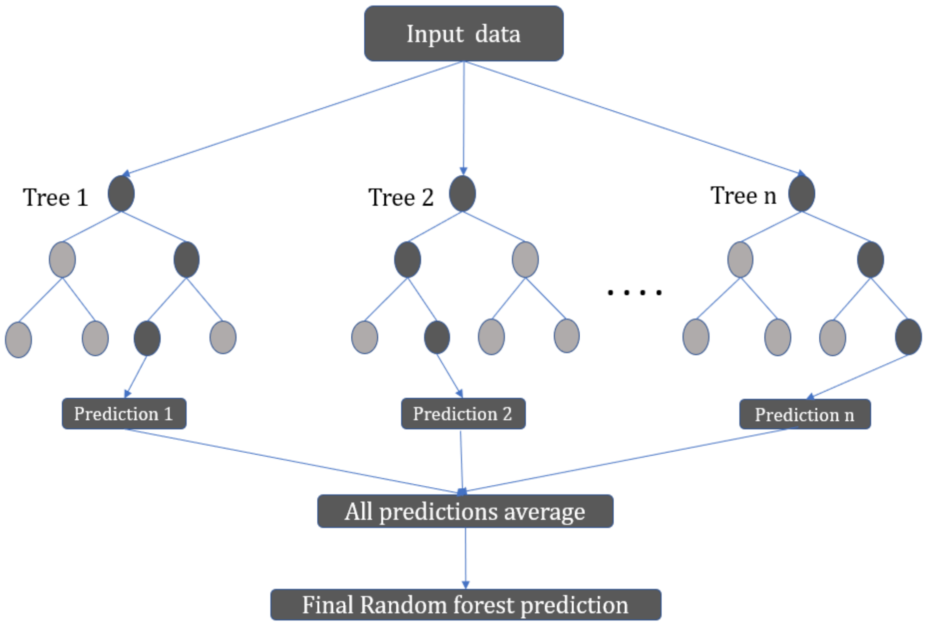


Fig. 6. The random forest regression structure.

K-fold Cross-Validation

The machine learning models are validated by several methods such as Train/test split, k-fold Cross-Validation, Leave-one-out Cross-Validation (LOOCV), Leave-one-group-out Cross-Validation (LOGOCV), Nested Cross-Validation (NCV), Wilcoxon signed-rank test, and Mc Nemar's test. Among these techniques, one of the most applied methods is k-fold Cross-validation, which is employed in this paper too.

K-fold cross-validation is exerted to small datasets to avoid overfitting (i.e., the model has adequately learned but can't predict appropriately). In this technique, the training set is apportioned into K smaller folds, and then the machine learning model is learned by using K-1 of the folds and, the remaining fold is employed for validating. This process repeats, and each time the training folds and validation section changes, and the test part is utilized for the last assessment; consequently, the average of accuracy is calculated. Fig. 7 illustrates the K-fold cross-validation process.

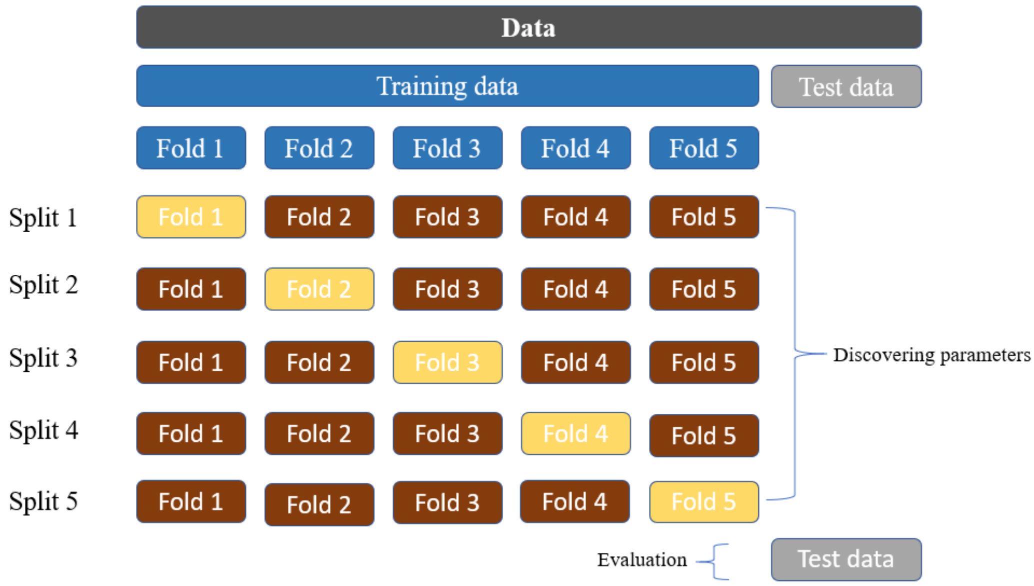


Fig. 7. K-fold cross-validation structure.

Results and discussion

In this section, Random Forest regression will build the predictive model and be evaluated by different metrics. The independent variables will be sorted based on their effectiveness on the number of new patients, the dependent variable; therefore, the jobs prioritizing for vaccination will be determined.

Predictive model

Before the predictive model is created, the Genetic algorithm is utilized for feature selection (i.e., finding the best subset of features to get an appropriate performance). The feature selection result determines the chosen independent variables: the Transit Stations category, Public Promenade category, Grocery and Pharmacy category, Retail and Recreation category, and Workplaces category. The Genetic algorithm parameters are denoted in Table 1.

Table 1. Genetic algorithm parameters

Parameter	Value
* n_{pop}	100
Max iteration	50
*P_c	0.7
* P_m	0.2

*Note: n_{pop} = Population size, P_c = Crossover probability, P_m= Mutation probability

By comparing the machine learning regression algorithms based on the R-squared, the best algorithm is selected among others. The outcome is mentioned in Table 2.

Table 2. The machine learning algorithm comparison

Algorithm	Accuracy (%)
Logistic regression	73.7
Decision Tree	78.1
Random Forest	88.3
ElasticNet	85.2
*XGB regression	82.5

*Note: XGB = Extreme Gradient Boost

Based on Table 2, the Random Forest regression is chosen to create the predictive model. Besides the R-squared, several other metrics such as Mean absolute error (MAE) assess the predictive model performance. The predictive model evaluation result based on R-squared and MAE is 88.3%, 52.6. the MAE metric is calculated by Eq. 4.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|Y_i - \bar{Y}_i| \tag{4}$$

where Y_i is the prediction, and $\bar{Y}_i$ is the actual value.

Prioritizing based on Feature importance

In this section, the Gini importance or Mean Decrease Impurity (MDI) technique is utilized to determine the impact of each independent variable on the objective [27]. This technique is described as the total decrease in node impurity averaged over all of Random Forest's trees. The sorted feature importance result is shown in Fig. 8.

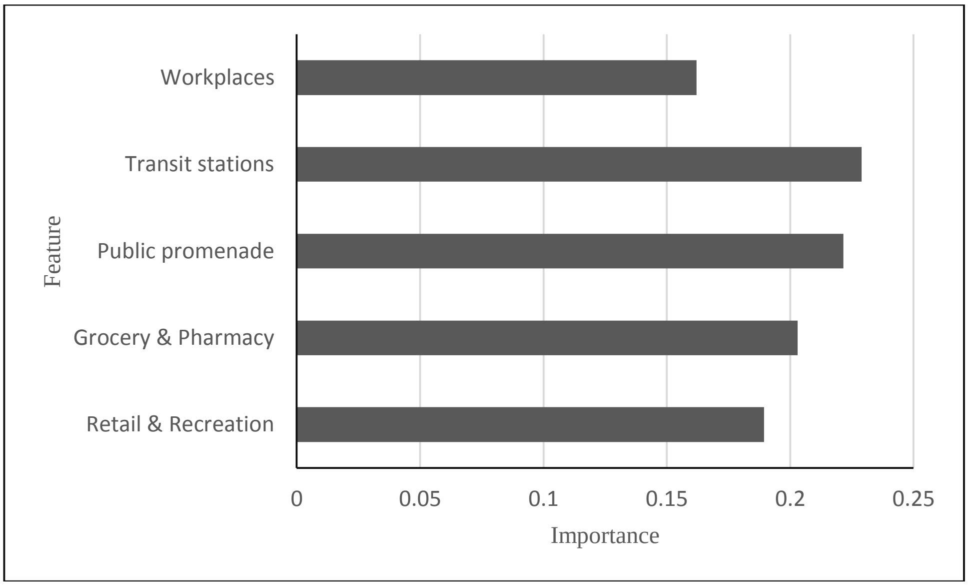


Fig. 8. Feature importance result

Discussion

This research provided a machine learning model and data science techniques to analyze and prioritize the different jobs' categories based on the mobility data for targeted vaccination. The genetic algorithm was utilized to pick the most influential independent variables, leading to an appropriate predictive model. The feature importance technique was applied to the predictive model to evaluate and determine the effect of each independent variable (see Fig. 8).

Based on Fig. 8 and resources' constraints (e.g., lack vaccines, Financial resources, production equipment, and logistics), the different jobs that belong to the Transit Stations category (e.g., the jobs in subways, bus and train stations) are in the first rank for receiving the vaccine. In the second rank, there are the jobs that are members of the Public Promenade category (e.g., the jobs in marinas, plazas, national parks, public beaches). The Grocery and Pharmacy category jobs (e.g., grocery markets, food shops, drug stores, and pharmacies) took the third rank. The Retail and Recreation category jobs (e.g., cafes, shopping centers, museums, libraries, and movie theaters) were placed in the fourth rank, and the last position is appointed to the Workplaces category jobs.

In this analysis, the jobs that are at risk based on mobility are identified and sorted. By considering the resource constraints, this analysis helps decision-makers allocate the vaccines to the most high-risk jobs' categories, leading to reduced covid deaths.

Conclusion

Due to the recourse constraint for vaccine production and decreased death percentage in coronavirus pandemic, it is essential to prioritize a society based on critical factors. The present paper was organized to prioritize the community based on the high-risk jobs. For this purpose, a Random Forest regression algorithm was picked by comparison among other algorithms to build a predictive model based on features selected by the Genetic algorithm. The jobs' categories were prioritized by feature importance technique, and a road map was made for vaccination. For future research, other machine learning algorithms and feature selection techniques can be utilized to improve the predictive model performance. Moreover, other variables such as age and economic variables can be considered.

Ethical approval

No ethical approval from the Committee on Health Research Ethics was needed. The data used in this study was freely available information on Google COVID-19 community Mobility Reports and was completely anonymized.

References

1. Gandon, S. and S. Lion, *Targeted vaccination and the speed of SARS-CoV-2 adaptation.* Proceedings of the National Academy of Sciences, 2022. **119**(3).
2. Chen, F.J.J.o.t.b., *A mathematical analysis of public avoidance behavior during epidemics using game theory.* 2012. **302**: p. 18-28.
3. Wells, C.R., E.Y. Klein, and C.T.J.P.C.B. Bauch, *Policy resistance undermines superspreader vaccination strategies for influenza.* 2013. **9**(3): p. e1002945.
4. Stockwell, M.S., A.G.J.H.v. Fiks, and immunotherapeutics, *Utilizing health information technology to improve vaccine communication and coverage.* 2013. **9**(8): p. 1802-1811.
5. Dharmawardana, K., et al. *Predictive model for the dengue incidences in Sri Lanka using mobile network big data*. in *2017 IEEE International Conference on Industrial and Information Systems (ICIIS)*. 2017. IEEE.
6. Bhopal, S. and M.J.A.o.D.i.C. Nielsen, *Vaccine hesitancy in low-and middle-income countries: potential implications for the COVID-19 response.* 2021. **106**(2): p. 113-114.
7. Altmann, D.M., D.C. Douek, and R.J.J.T.L. Boyton, *What policy makers need to know about COVID-19 protective immunity*. 2020. **395**(10236): p. 1527-1529.
8. Holzmann-Littig, C., et al., *COVID-19 vaccination acceptance among healthcare workers in Germany.* 2021.
9. Madison, A.A., et al., *Psychological and behavioral predictors of vaccine efficacy: Considerations for COVID-19.* 2021. **16**(2): p. 191-203.

10. Cook, T. and J.J.A. Roberts, *Impact of vaccination by priority group on UK deaths, hospital admissions and intensive care admissions from COVID‐ 19.* 2021. **76**(5): p. 608-616.
11. Razai, M.S., et al., *Covid-19 vaccine hesitancy among ethnic minority groups*. 2021, British Medical Journal Publishing Group.
12. Buckner, J.H., G. Chowell, and M.R.J.P.o.t.N.A.o.S. Springborn, *Dynamic prioritization of COVID-19 vaccines when social distancing is limited for essential workers.* 2021. **118**(16).
13. Rachaniotis, N.P., et al., *A two-phase stochastic dynamic model for COVID-19 mid-term policy recommendations in Greece: a pathway towards mass vaccination.* 2021. **18**(5): p. 2497.
14. Jadidi, M., et al., *A two-step vaccination technique to limit COVID-19 spread using mobile data.* 2021. **70**: p. 102886.
15. Sun, X., et al. *Targeted vaccination based on a wireless sensor system*. in *2015 IEEE International Conference on Pervasive Computing and Communications (PerCom)*. 2015. IEEE.
16. Salvamani, S., et al., *Understanding the dynamics of COVID-19; implications for therapeutic intervention, vaccine development and movement control.* 2020. **77**(4): p. 168-184.
17. Wilder-Smith, A. and D.O.J.J.o.t.m. Freedman, *Isolation, quarantine, social distancing and community containment: pivotal role for old-style public health measures in the novel coronavirus (2019-nCoV) outbreak.* 2020.
18. Behdinian, A., et al., *An integrating Machine learning algorithm and simulation method for improving Software Project Management: A real case study.* Journal of Quality Engineering and Production Optimization, 2022.
19. Amani, M.A. and F. Marinello, *A Deep Learning-Based Model to Reduce Costs and Increase Productivity in the Case of Small Datasets: A Case Study in Cotton Cultivation.* Agriculture, 2022. **12**(2): p. 267.
20. Rahman, M., et al., *Machine Learning on the COVID-19 Pandemic, Human Mobility and Air Quality: A Review.* 2021.
21. Al Zobbi, M., et al., *Measurement Method for Evaluating the Lockdown Policies during the COVID-19 Pandemic.* 2020. **17**(15): p. 5574.
22. Asad, S.M., et al. *Travelers-Tracing and Mobility Profiling Using Machine Learning in Railway Systems*. in *2020 International Conference on UK-China Emerging Technologies (UCET)*. 2020. IEEE.
23. Hosseini, M.S. and A.M. Gittler. *Factors Influencing Human Mobility During The COVID-19 Pandemic in Selected Countries of Europe and North America*. in *2020 IEEE International Conference on Big Data (Big Data)*. 2020. IEEE.
24. Ahmadi, M.R. and R.S. Shahabi, *Cutoff grade optimization in open pit mines using genetic algorithm.* Resources Policy, 2018. **55**: p. 184-191.
25. Amani, M.A., et al., *A machine learning-based model for the estimation of the temperature-dependent moduli of graphene oxide reinforced nanocomposites and its application in a thermally affected buckling analysis.* Engineering with Computers, 2021. **37**(3): p. 2245-2255.
26. Lan, T., et al., *A comparative study of decision tree, random forest, and convolutional neural network for spread-F identification.* Advances in Space Research, 2020. **65**(8): p. 2052-2061.
27. Joshi, T., et al., *An improved ant colony optimization with correlation and Gini importance for feature selection*, in *Communication and Intelligent Systems*. 2021, Springer. p. 629-641.