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ANALYSIS OF COVID-19 SCOPE IN TUNISIA

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Abstract

Since the year 2019, a new virus called Corona Virus Disease 2019 (Covid-19) has appeared in the world. The spread of this virus has been too fast to affect all continents and have more than 200 countries affected in the world. To fight this pandemic, the most developed countries have put all their efforts in the production of vaccines against Covid-19 and a variety of vaccines with different efficiencies have been created. This study will first visualize the state of the pandemic and the spread of the vaccine in Tunisia. We will test different Machine Learning models that deal with such prediction problems, a comparison of the performance of these models will be made in order to determine the best model to predict the spread of Covid-19 in Tunisia. We will identify the temporal limits of the model prediction and the parameters that influence the prediction. We will eventually prove that the results obtained are promising and of good quality.

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1. Introduction

Towards the end of 2019, specifically on November 16, 2019 in Hubei Province, Wuhan City, China, an emerging infectious disease called Corona Virus Disease 2019 (Covid-19) appeared for the first time [1]. This disease spread rapidly, first throughout the China to record a number of one to five cases of affected people per day. By the end of December 2019, they recorded about 60 cases per day. On February 15, 2020, a report from the World Health Organization (WHO) reported that the 50,000-case mark for Covid-19 had been passed in China. More than 500 cases of infection outside the countries led the WHO to officially declare on March 11, 2020 that Covid-19 is considered a global pandemic.

Since late December 2019 through July 2019, the virus has spread to 212 countries in different continents of the world, with a total of over 3 million confirmed cases [2]. As of July 26, 2021, the number of infected people has reached 4,117,109 and this number continues to grow despite the sanitary measures and vaccination campaigns [3]. Until today, the pandemic has killed more than 4 million people worldwide, according to a balance sheet provided by [4]. Faced with this virus, the countries of the world remain helpless and are still looking for a solution to this pandemic.

Like all countries in the world, Tunisia has also faced this pandemic. Indeed, the first case of infection by Covid-19 was recorded on March 2, 2020. By May 2021, all 24 governorates of the country were affected by this virus and more than 311,000 cases of infection were confirmed. All governorates have experienced active cases since that date and have recorded a total of more than 17,000 deaths and over 7,000 new infections on average daily, according to statistics provided by [5]. To cope with this pandemic, many vaccines have been developed and several vaccination campaigns have begun to make a difference in the world since late 2020

[6, 7]. In March 2021, Tunisia received the first batch of vaccine (93,600 doses), which was a very small quantity that could not fight this virus. Today and following several global donations, the vaccine exists in Tunisia with large quantities and different types [8].

In this article, we will review the status of Covid-19 dissemination, during the second wave, from March 2021 until July 2021, in Tunisia. In fact, studies on the current and future evolution of Covid-19 in Tunisia are very limited. Our work will allow us to review the literature concerning the works that have analyzed the pandemic situation in Tunisia. Some data concerning Covid-19 are present and have allowed us to explore the evolutionary state of the pandemic. However, they are not grouped in the same official source, they are also very aggregated and are in constant evolution. From the official resources, we will collect data to create our own databases that will allow us to analyze the current and future state of Covid-19 spread. Our work will also allow us to study different Machine Learning models that are interested in predicting viral diseases and to identify the one that can give a scenario close to reality.

Our work is mainly organized as follows: In Section 2, we will find a bibliographic study that outlines the research done so far regarding the spread of Covid-19 in Tunisia. In Section 3, we will show the evolution of the pandemic in Tunisia. In Section 4, we will study the different models that can predict the state of evolution of the pandemic in Tunisia in order to identify the most appropriate. Section 5 is devoted to the conclusion and prospects for future work.

2. Existing Work

Much research has been conducted since Covid-19 first appeared in the world to cover its universal impact and spread around the world. Covid-19 has been the subject of work that touches on medical, economic, educational, tourism and other aspects. This section will present the surveys that have touched only the most recent works on the state of the spread of Covid-19 in Tunisia.

Chaari and Golubnitschaja [9] presented a study of the current pandemic situation in Tunisia. They examined the evolution of the infection and considered potential protective and preventive strategies based on pandemic scenarios. Their study covered that, the authors estimated the mortality risks related to Covid-19 from an in-depth analysis of the different factors of the pandemic spread based on statistical studies. They also conducted comparative studies of the status of the pandemic based on data reported by the Ministry of Health in Tunisia compared to the status of Italy and France. The results of their studies proved that reliable and widespread supervision in all regions in real time is based on random tests presenting the optimal predictive strategy to create the most effective preventive measures and its absence led to many incorrect decisions.

Abdeljaoued-Tej and Dhenain [10] presented a study estimating the spread of the virus in Tunisia to determine the number of infected people based on the death rate. They followed a method developed by [11] that uses the number of deaths reported by each country to estimate and compare the actual rate of people affected. They used a data-set reported by the Tunisian Center for Disease Control to model the epidemic in Tunisia. At the end of their study, they deduced that modelling the occurrence of Covid-19 cases and different public health measures is essential to assess the impact of policies to prevent the spread of the virus. Their work raised interesting questions about the relationship between mortality rates and the number of cases of infection. The proposed formula can also be used to assess the impact of policies to prevent the spread of the virus.

Talmoudi et al. [12] presented a study on the progression of the virus in Tunisia. In their research, they described the transmission dynamics of the pandemic and the impact of intervention measures in order to provide timely information to guide policy makers' decisions. This allowed them to estimate the serial interval and the number of temporal replications of Covid-19 in Tunisia. They used different resources to set up their database and used the maximum likelihood approach to test it. They analyzed the data regarding the infectious-infected pairs involved in the reported pre-symptomatic transmission and the correlation between these different data. They also tracked the gamma distribution with a mean per day confidence interval, standard deviation, and estimated large changes in the number of active cases in response to the combined containment interventions.

Ben Fredj et al. [13] presented a study illustrating the main phases of the spread of the pandemic in Tunisia. In their studies, the authors used several methods, such as a dynamic behavioural model of Covid-19 in Tunisia and then studied the qualitative properties of the model considered to establish the stability of the equilibrium point via the basic number of reproductions. The researchers were able to determine theoretically and through numerical simulations the effect of the quarantine strategy on the spread of the disease. They also showed that if the number of reproductions is less than one, the extent of the disease can also decrease.

We have noticed that beyond 2020, no new research in this axis has been done, which, in other words, motivates us to draw up a status of the spread of the pandemic in Tunisia until 2021 and to study the prediction models that can give the best scianios of the future state of the virus. In the next section, we will present a chronological study of the diffusion of Covid-19 and the vaccination campaigns in Tunisia.

3. An Overview of the Spread of Covid-19 in Tunisia

In this section, we will follow the spread of Covid-19 and the defusion of the vaccine in the governorates of Tunisia. We will also study the reactions of the people convened to the vaccination by doses and by age group. We will start by presenting the evolutionary status of Covid-19 in Tunisia since the appearance of the pandemic in the world. The following graph in Figure 1 represents the evolution of the spread of the virus in Tunisia according to the statistics provided by [14]. The diagram shows the number of deaths (the orange curve) and the number of people affected by Covid-19 (the blue bars) per year, considering for 2021 only the months from January to July.

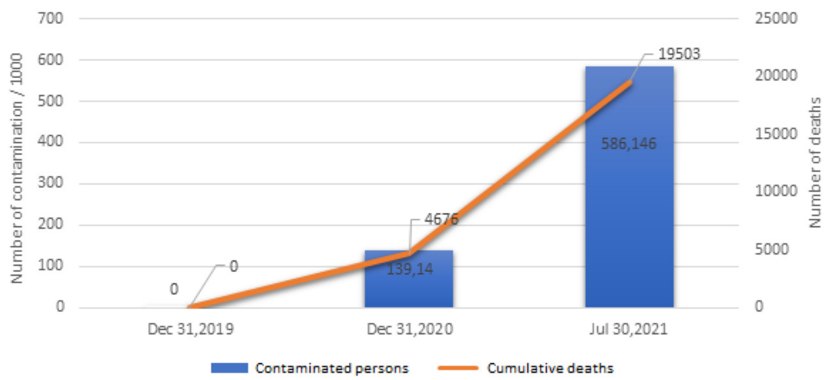

Figure 1. Evolution of the spread of the virus per year.

From the combined graph, we can see that in 2019, Tunisia has not recorded any case of infection or death by the virus (Covid-19), and this is mainly due to the absence of direct traffic between Tunisia and the countries where the virus has appeared. In addition, the virus has not yet recorded a high rate of spread in the world. In 2020, the pandemic has affected Tunisia and the number of confirmed patients has reached 139,140 with 4,676 deaths. However, what has attracted the most attention in the graph is the rapid increase in the number of infected people accumulated.

A peak was observed in July 2021. Indeed, the number of infected persons increased by 4.21 in only 7 months. In other words, 586,146 cases of infection were recorded with a cumulative number of deaths equal to 19,503 (an increase of 4.17 compared to the previous year). In order to better understand the state of evolution of the virus in Tunisia, we will reveal its propagation process by month in order to detect the main peaks and to analyze more precisely its behaviour.

The graph below in Figure 2 represents the evolution of the spread of the virus since its effective appearance in Tunisia from June 2020 to July 2021 in terms of number of infections and cumulative deaths.

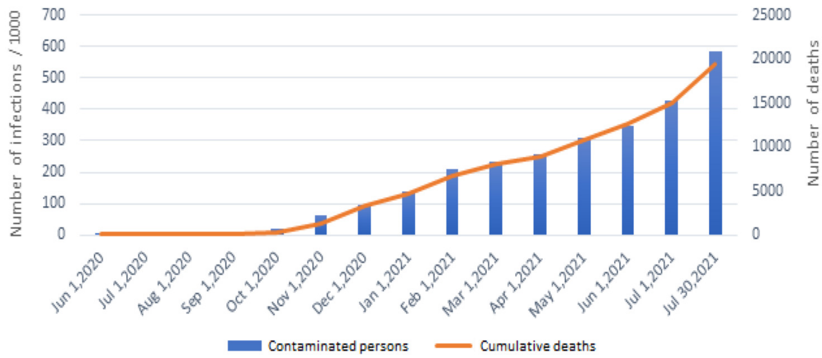

Figure 2. Evolution of Covid-19 propagation by month.

According to the graph above, we can see that the appearance of confirmed cases starts after October 2020. From October 2020, the number of confirmed cases and the number of deaths increases continuously but with a small percentage compared to the beginning of 2021 (January 2021 to July 2021), which represents a period of rapid spread of the virus, contributing to a sharp increase in confirmed patients. Two peaks were observed. The first was in May, when the number of infected people exceeded 300 thousand and the number of deaths reached more than 10 thousand cases. The second peak was observed in July, when the number of cases reached 586,146 and the number of deaths 19,503. A Covid-19 screening campaign has been launched by the state to detect those infected with Covid-19. Figure 3 shows the curve of the number of daily tests during the period from 29/06 to 31/07.

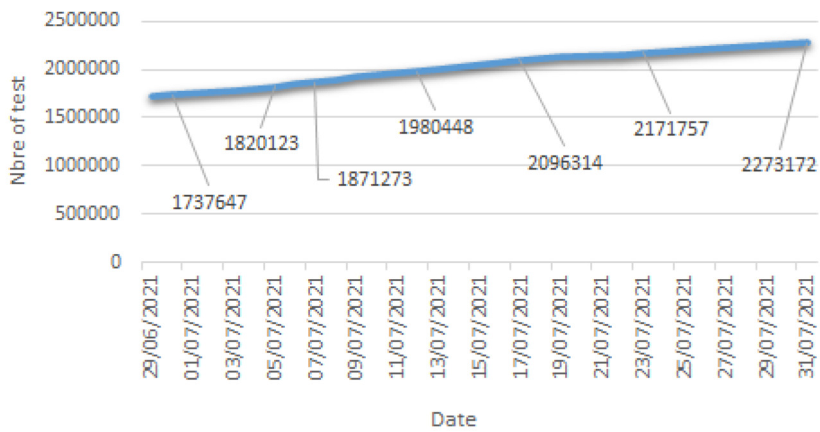

Figure 3. Cumulative number of Covid-19 tests performed per day.

Now, we will study the evolution of the number of confirmed cases in relation to the number of cured from June 2020 to July 2021. To do this, we will use the data presented in Figure 4.

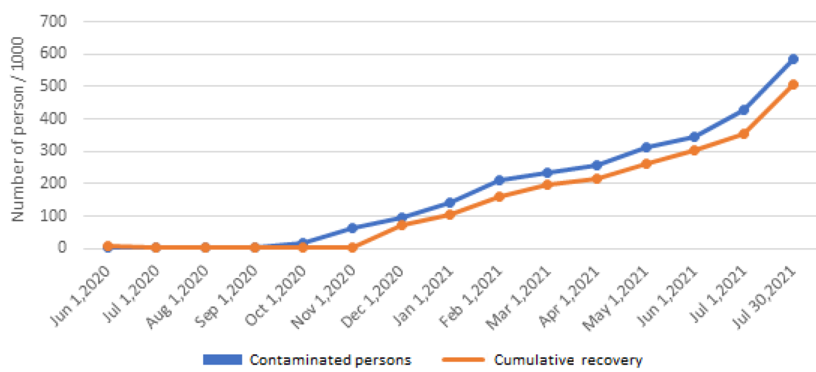

Figure 4. Evolution of confirmed cases and recoveries per month.

According to the research conducted so far, the average incubation, recovery and death periods for Covid-19 are, respectively, 14 days according to [15], 22 days and 9 days according to [16]. From this information, we used the contamination data with the recovery data in order to know the effective recovery rate and we illustrated the results in Figure 5. For the daily recovery data, we considered a 22-day effective recovery rate of 90% per day. This is because the number of people recovered per day also includes those who required more than 22 days to recover and who had persistent symptoms, as well as those who were hospitalized.

We found that the cure rate of individuals between March 10, 2021 and July 8, 2021 increased from 81.94% to 96.73%, see Figure 5. This can be explained by the fact that the existing variant of the virus does not pose a threat to a segment of the population that represents the majority of infected individuals able to recover after 22 days. In addition, the vaccine has begun to show efficacy in the population targeted by the government-led vaccination campaign, and people receiving the Covid-19 vaccine have begun to develop immunity to the virus. Although the cure rate is variable, it remains at least high and increases over time.

According to both curves of Figure 4, taking into account that an infected person recovers after two to four weeks, the number of infected people is almost equal to the number of recovered people. From the diagram of Figure 4, we can conclude that the evolution of the two curves follows the same rhythm, that the cure and the contamination are proportional even if they are not concordant because of the interval of time which separates the contamination from the cure, remains that the rate of cure is high what leads us to say that the infected persons could develop an immunity to the virus. This period is known by a low rate of vaccination and auto-immunization. In July 2021, there is a peak of infection and recovery, with 586,146 people infected and 505,497 people recovered.

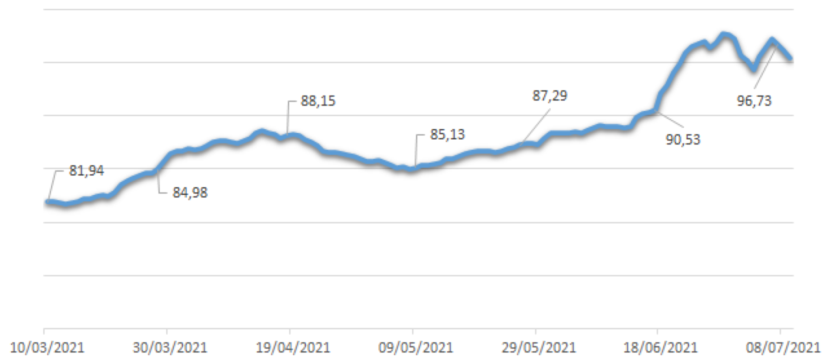

Figure 5. Analysis of the probability of recovery between March 10, 2021 and July 08, 2021.

Vaccination is a very effective parameter to understand the evolution of the pandemic in an environment where it is fought by different types of vaccines. The following Figure 6 defines the distribution of vaccine doses in the governorates of Tunisia, data collected from [17].

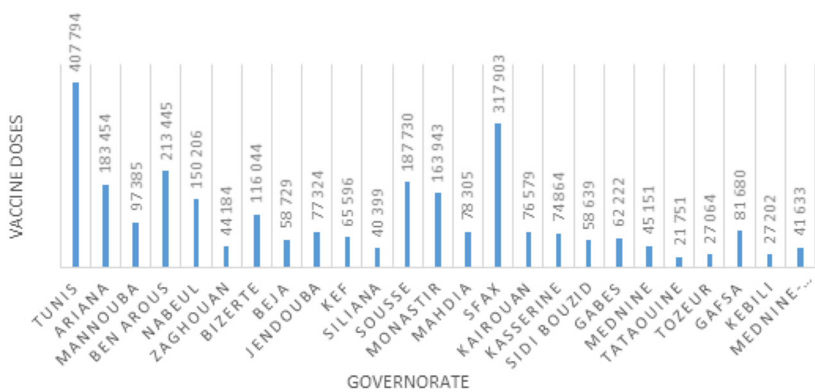

Figure 6. Vaccinated doses by governorate.

According to the bar chart of Figure 6, we can identify three main ranks of governorates according to the number of doses of vaccine distributed. Indeed, the capital Tunis, has the largest number of doses of vaccine distributed with 407,794, followed by Sfax and Ben Arous with a number of doses equal to 317,903 and 213,445. These three governorates represent the first rank. The second rank of distributed doses includes the governorates with a number of doses distributed ranging between 100,000 and 200,000 which are Sousse, Ariana, Monastir, Nabeul and Bizerte. The rest of the governorates have numbers of doses distributed below 100,000 which reach 21,751 doses distributed in Tataouine representing the lowest number of doses of vaccine distributed.

Now, we are going to study the behaviour of the individuals in front of their convocation to be vaccinated. Figure 7 schematize the number of convocations and the number of vaccines distributed. For greater effectiveness, most of the available vaccines are vaccines that require two doses of injection [18]. In the following bar charts, we will present, compare and analyze the number of convocations with the doses of vaccine taken for the 1st and 2nd injection according to a classification established according to the different age groups of the Tunisian population [17]. In the following chart, the blue bars represent the number of people convened and the orange bars define the people vaccinated.

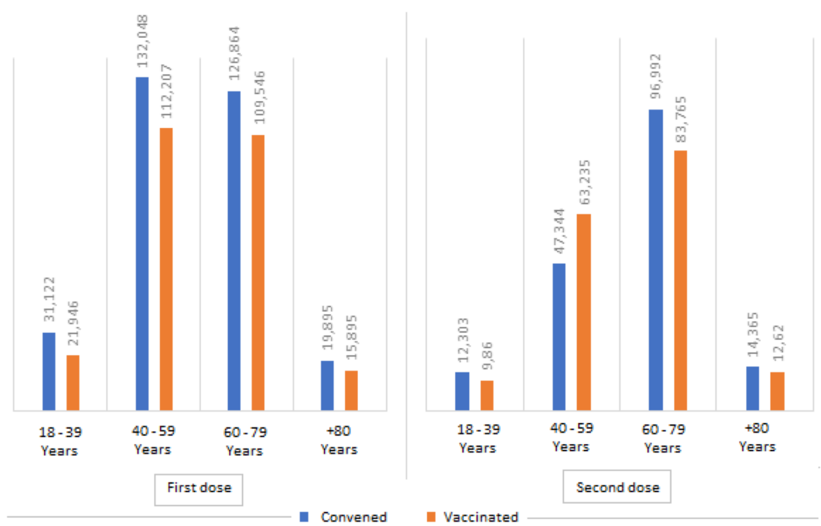

Figure 7. Comparison of convocation and vaccination of the first and second dose of vaccine by age group.

According to the analysis of the data provided by the histograms, it can be seen that the number of convocations varies according to age and that the number of convocations for the first dose is higher than for the second dose. This observation is very legitimate because the number of convocations for the second injection of the vaccine depends on who has already taken their first injection.

Analysis of the first dose histogram shows that the 40-59 age group dominates the number of people called and vaccinated, with over 84% of those called receiving their first dose of vaccine, followed by the 60-79 age group, with over 86% of those called receiving their first dose of vaccine. For the other two age groups, the vaccination rates in relation to the number of convocations were 80.14% and 87.85% for those under 40 and over 80, respectively.

From the two histograms, we can see that the call rate for the second dose is 72% compared to those who had their first dose of vaccine and the vaccination rate for the second dose is 82.17%. For the histogram of the second dose of vaccine, the age group that represents the highest number of convocation and vaccination is the one between 60 and 79 years old followed by the one between 40-59 years old. While the other two age groups of less than 40 years and more than 80 years have the lowest rate of vaccination convocation for the 2nd dose.

Indeed, we note that the number of calls is closer to the number of vaccinations which is explained by the awareness of the importance of vaccination by the Tunisian population, while the difference reported by age group is due to the strategies defined by Tunisia which aims to vaccinate as a priority people of advanced age (+40 years) which have been declared the proportion of the population at risk [19] and more particularly people over 65 years old who have shown according to [20] during the first wave a low resistance to Covid-19.

In the next section, we will study the different models of Machine Learning dedicated to the prediction of diseases in order to find the most appropriate model that can predict the evolution of the pandemic in Tunisia based on the data we have collected from the current pandemic status. The data were collected from [21] and managed in Microsoft Excel spreadsheets.

4. Forecast of the Covid-19 Evolution in Tunisia

Machine Learning is one of the most powerful tools used today for predicting future events. This tool is notably used to make intelligent and fast decisions in uncertain contexts. This technique has been commonly used by researchers to study the extent of Covid-19 in different countries of the world, such as in [22-24]. In our case, we will use it to find a model representing good performances to predict the evolution of this pandemic in Tunisia.

In previous work, Machine Learning models are used to provide future insight into how COVID-19 affects individuals, its confirmation, and death predictions. In our case, a regression model is the most appropriate model to choose for estimating the number of deaths in the near future. We chose Machine Learning models based on regression algorithms, such as the Decision Tree regressor, the Random Forest regressor, the Extra Trees regressor, the Bagging regressor, the Gradient Boosting regressor, and the Ada Boost regressor for the prediction of the number of deaths over a 15-day horizon. This study used a database [25] that we designed from the data we analyzed in the previous section.

The regression score, also known as the Coefficient of Determination (CoD), and accuracy are calculated with a 90/10 ratio between the training and test data-sets. Figures 8 and 9 show respectively, the CoD and the accuracy of the models built on the COVID-19-Tunisia data-set.

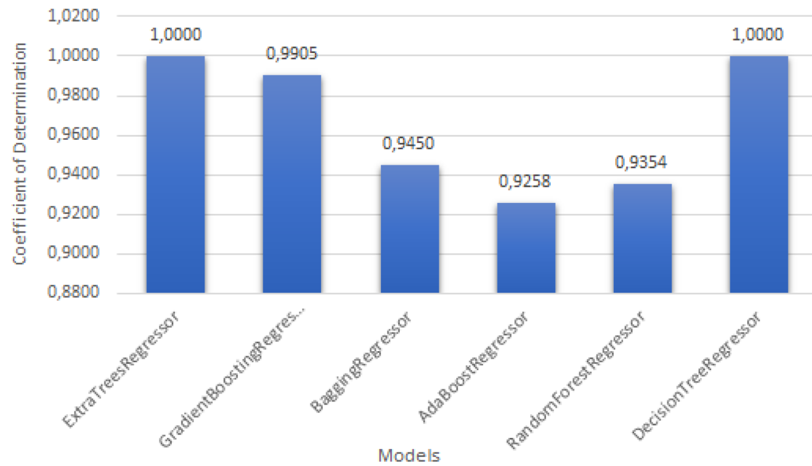

Figure 8. Coefficient of determination for COVID-19-Tunisia.

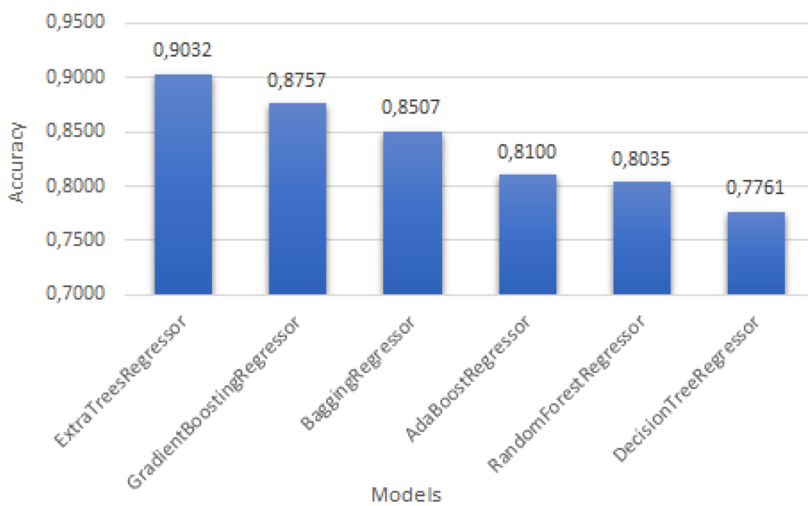

Figure 9. Accuracy for COVID-19-Tunisia.

The results of CoD and Accuracy displayed in both Figures 8 and 9 show that the Extra Trees Regressor model outperforms the other Machine Learning models. A feature analysis was also done to detect which features had the most influence on the result. In fact, the features that influenced the result are: Day, No. Contaminated, Cumulative

Contaminated, No. of Guerisons, Dose 1 and Dose 2. The significance of the features for the best data-set of the Covid-19-Tunisia model is presented in Figure 10.

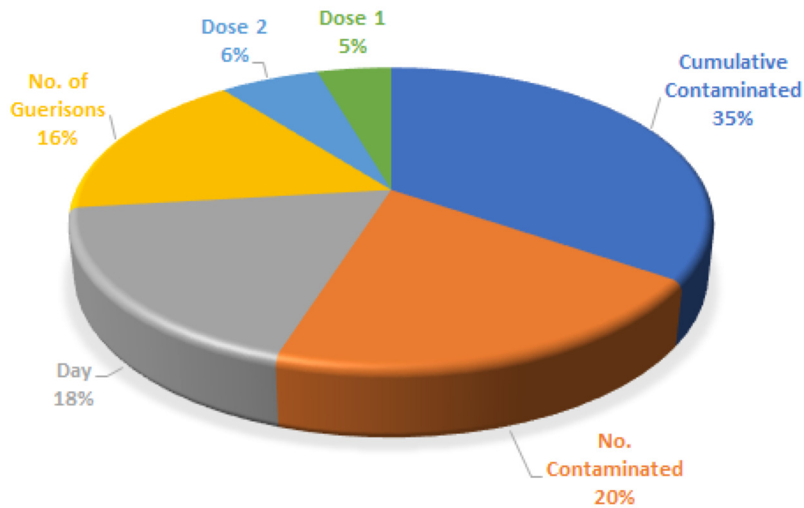

Figure 10. Feature importance using Extra Trees Regressor.

The Extra Trees algorithm works by creating a large number of unpruned decision trees from the training data set. Predictions are made by averaging the predictions of the decision trees in the regression case. To improve the forecasting results of our chosen model, we reduced the ratio between the training and test data-sets from 90/10 to 95/5, in order to reduce the 15-day forecast to 8 days. We noticed that the forecast is improved each time we reduce the number of days of prediction and that at eight days we have a certainty rate equal to 96.02%, so an improvement of 5.7%.

The diagram below shows the evolution of the number of deaths per day from March 10, 2021 to July 31, 2021 as well as the trend curve (red curve) approximated by a polynomial function determined from the Extra Trees model to represent the results of the experiment with an estimated determination coefficient of 96.02%.

From the Extra Trees model, we were able to obtain a trend curve that will be used to predict the evolution of the number of deaths. Indeed, this curve is a representation of the average number of deaths recorded per day until 08/08/21, i.e., it allows prediction on a horizon of 8 days. The prediction scenario presented is feasible with a certainty of 96.02%. The red curve in the Figure 11 indicates a continuation of the trend of the last 8 days, i.e., if nothing changes and the average number of deaths will vary between 150 and 250 cases in the next 8 days. We conclude this section with the fact that Extra Trees model has shown good performance in predicting the evolution of the number of deaths on our data-sets which can exceed 90%.

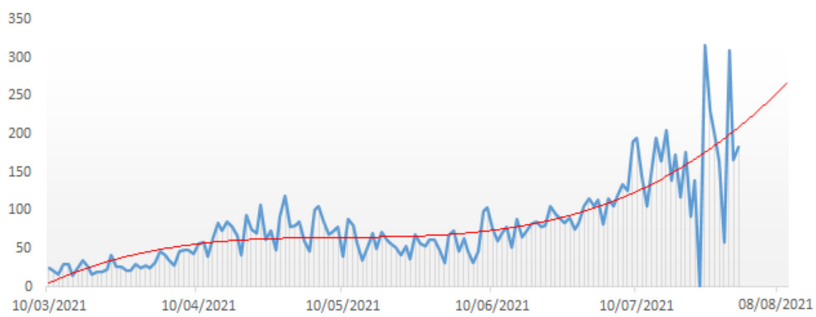

Figure 11. Prevision of death using extra trees regressor.

5. Conclusion

Since its appearance in the world, the Covid-19 has affected a very large number of people. Although the number of cures is important, the number of deaths has been remarkable and frightening especially for people over 40 years old. In this study, we were interested in the status of the evolution of Covid-19 in Tunisia. A literature review of the works that have studied the evolution of the pandemic in Tunisia was carried out. We were interested in the distribution of the vaccine in Tunisia as well as in the Tunisian vaccination campaigns of which we noticed that they targeted the age groups between 40-59 years and 60-79 years whose mortality rate was the highest. We also found that the infection and cure rates are proportional. We exposed different Machine Learning models that are used to predict the state of future viral spread in Tunisia and we finished our work by selecting the model with the highest prediction rate.

This work can be considered as an opening for future investigations at several levels. First, the use of the model selected in this work to predict the rise of Covid-19 in Tunisia. We can identify other new models that have been used in the literature to solve such problems in other countries and try them on our case study. We can also combine different Machine Learning models to reduce the error rate, refine our predictions, find more data and new effective features, have a scenario closer to reality and get a wider prediction horizon. Finally, we can go beyond the local setting and predict the state of the global pandemic on several aspects.

References

[1] T. P. Velavan and C. G. Meyer, The COVID-19 epidemic, Tropical Medicine & International Health 25(3) (2020), 278-280.

DOI: https://doi.org/10.1111/tmi.13383

[2] Countries where COVID-19 has Spread, Worldometer, Accessed March 27, 2020.

https://www.worldometers.info/coronavirus/countries-where-coronavirus-has-spread/

[3] WHO Coronavirus (COVID-19) Dashboard, World Health Organization, Accessed July 26, 2021.

https://covid19.who.int/

[4] R. Hannah, M. Edouard, R. G. Lucas et al., Coronavirus Pandemic (COVID-19), Our World in Data, 2020.

https://ourworldindata.org/coronavirus

[5] National Observatory of New and Emerging Diseases, Weekly operational update on COVID-19: 06 August 2021, Accessed August 06, 2021.

https://www.onmne.tn/?p=12407

[6] K. B. Talha, The Russian vaccine for COVID-19, The Lancet 8(11) (2020), 85-86.

DOI: https://doi.org/10.1016/S2213-2600(20)30402-1

[7] D. K. Maria and W. Chizoba, The Russian vaccine for COVID-19, The Lancet 397(10269) (2020), 72-74.

DOI: https://doi.org/10.1016/S0140-6736(20)32623-4

[8] Brendon Sen-Crowe, Mark McKenney and Adel Elkbuli, Disparities in global COVID-19 vaccination rates & allocation of resources to countries in need, Annals of Medicine and Surgery 68 (2020); Article 102620.

https://doi.org/10.1016/j.amsu.2021.102620

[9] L. Chaari and O. Golubnitschaja, Covid-19 pandemic by the “real-time” monitoring: The Tunisian case and lessons for global epidemics in the context of 3PM strategies, EPMA Journal 11(2) (2020), 133-138.

DOI: https://doi.org/10.1007/s13167-020-00207-0

[10] Ines Abdeljaoued-Tej and Marc Dhenain, Estimation of Tunisia COVID-19 infected cases based on mortality rate, medRxiv (2020), 20065532.

DOI: https://doi.org/10.1101/2020.04.15.20065532

[11] M. Dhenain, Estimation du nombre de cas de COVID-19 en France et dans differents pays: Homogeneisation basée sur la mortalité, Bulletin de l’Academie Vétérinaire de France 173(1) (2020), 35-42.

DOI: https://doi.org/10.4267/2042/70840

[12] K. Talmoudi, M. Safer, H. Letaief, A. Hchaichi, C. Harizi, S. Dhaouadi, S. Derouiche, I. Bouaziz, D. Gharbi, N. Najar, M. Osman, I. Cherif, R. Mlallekh, O. Ben-Ayed, Y. Ayedi, L. Bouabid, S. Bougatef, N. B. Ben-Alaya and M. K. Chahed, Estimating transmission dynamics and serial interval of the first wave of COVID-19 infections under different control measures: A statistical analysis in Tunisia from February 29 to May 5, 2020, BMC Infectious Diseases 20(914) (2020), 102620.

DOI: https://doi.org/10.1186/s12879-020-05577-4

[13] Haifa Ben Fredj and Farouk Chérif, Novel Corona virus disease infection in Tunisia: Mathematical model and the impact of the quarantine strategy, Chaos, Solitons & Fractals 138 (2020), 109969.

DOI: https://doi.org/10.1016/j.chaos.2020.109969

[14] Coronavirus Statistics, Daily operational update on COVID-19: 30 July 2021.

https://www.coronavirus-statistiques.com/open-data/

[15] J. A. Backer, D. Klinkenberg and J. Wallinga, Incubation period of 2019 novel coronavirus (2019-nCoV) infections among travellers from Wuhan, China, 20-28 January, Eurosurveillance 25(5) (2020), 2000062.

DOI: https://doi.org/10.2807/1560-7917.ES.2020.25.5.2000062

[16] Chansik An, Hyunsun Lim, Dong-Wook Kim, Jung Hyun Chang, Yoon Jung Choi and Seong Woo Kim, Machine learning prediction for mortality of patients diagnosed with COVID-19: A nationwide Korean cohort study, Scientific Reports 10 (2020); Article 18716.

DOI: https://doi.org/10.1038/s41598-020-75767-2

[17] Vaccination Platform of the Tunisian Ministry of Health, Accessed July 30, 2021.

https://www.evax.tn/vaccinationOD.html

[18] L. Solforosi, H. Kuipers, M. Jongeneelen, S. K. R. Huber, J. E.M. van der Lubbe, L. Dekking, D. N. Czapska-Casey, A. I. Gil, M. R.M. Baert, J. Drijver, J. Vaneman, E. van Huizen, Y. Choi, J. Vreugdenhil, S. Kroos, A. H. de W., E. Kourkouta, J. Custers, R. van der Vlugt, D. Veldman, J. Huizingh, K. Kaszas, T. J. Dalebout, S. K. Myeni, M. Kikkert, E. J. Snijder, D. H. Barouch, K. P. Böszörményi, M. A. Stammes, I. Kondova, E. J. Verschoor, B. E. Verstrepen, G. Koopman, P. Mooij, W. M. J. M. Bogers, M. van Heerden, L. Muchene, J. T. B. M. Tolboom, R. Roozendaal, B. Brandenburg, H. Schuitemaker, F. Wegmann and R. C. Zahn, Immunogenicity and efficacy of one and two doses of Ad26.COV2.S COVID vaccine in adult and aged NHP, Journal of Experimental Medicine 218(7) (2021); Article 20202756.

DOI: https://doi.org/10.1084/jem.20202756

[19] Michael T. Meehan, Daniel G. Cocks, Jamie M. Caldwell, James M. Trauer, Adeshina I. Adekunle, Romain R. Ragonnet and Emma S. McBryde, Age-targeted dose allocation can halve COVID-19 vaccine requirements, medRxiv (2020), 20208108.

DOI: https://doi.org/10.1101/2020.10.08.20208108

[20] Benjamin K. I. Helfand, Margaret Webb, Sarah L. Gartaganis, Lily Fuller, Churl-Su Kwon and Sharon K. Inouye, The exclusion of older persons from vaccine and treatment trials for Coronavirus disease 2019-missing the target, JAMA Internal Medicine 180(11) (2020), 1546-1549.

DOI: https://doi.org/10.1001/jamainternmed.2020.5084

[21] Coronavirus Statistics, COVID-19 by Country, Number of Cases, Real Time Stats.

https://www.coronavirus-statistiques.com/stats-pays/coronavirusnombre-de-cas-tunisie/

[22] Palash Ghosh, Rik Ghosh and Bibhas Chakraborty, COVID-19 in India: Statewise analysis and prediction, JMIR Public Health and Surveillance 6(3) (2020); Article e20341.

DOI: https://doi.org/10.2196/20341

[23] Ashutosh Mahajan, Ravi Solanki and Namitha Sivadas, Estimation of undetected symptomatic and asymptomatic cases of COVID-19 infection and prediction of its spread in the USA, Journal of Medical Virology 93(5) (2021), 3202-3210.

DOI: https://doi.org/10.1002/jmv.26897

[24] Tahir Mumtaz Awan and Faheem Aslam, Prediction of daily COVID-19 cases in European countries using automatic ARIMA model, Journal Public Health Research 9(3) (2020), 227-233.

DOI: https://doi.org/10.4081/jphr.2020.1765

[25] Dataset of Covid-19 Propagation in Tunisia between March 10, 2021 and July 31, 2021.

http://urlr.me/5zQHP

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