Lessons for the Future: Supporting Policy Makers' Choice of Stringency-Index Level While Facing Pandemic Viruses using Machine Learning Techniques

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ABSTRACT
Recently, the Corona pandemic wave has lessened, and most people got vaccinated, but the road to reach this status was rough and had some trials and errors. After going through several challenges with the pandemic during the past two years, a lot of related datasets have been created to help researchers. In these datasets, the choice of stringency level index has played a key role in controlling the spread of the pandemic as well as the associated number of deaths. Machine learning techniques have been deployed to relate policy makers' choices of stringency index level to different related outcomes such as the number of infected cases as well as the number of associated death cases. In this proposed research, the problem is approached from a different angle where the designed machine learning models will predict the stringency index level based on a few attributes such as infected cases and death cases. Different supervised machine learning techniques have been used in the designed models, and the achieved accuracies reached 94.84%. In addition, an important note for policy makers wasrevealedto take into consideration while applying the designed prediction models to make their decision choices more robust. It is believed that the discovered lag noted in public response to the applied stringency measures should be amended to achieve better accurate results and therefore a solution for policy makershave been suggested. Based on the findings of our proposed research, it is believed that policy makers could benefit from the designed prediction models as well as the lag avoidance suggested approach to have more control on similar future pandemics.

Keywords
Corona Pandemic, Stringency Index, Supervised Machine Learning Techniques

1. INTRODUCTION
Various research efforts have focused on the Corona pandemic, and many techniques have been applied to detangle the complexities involved in analyzing the breadth and width involved. It is believed that Corona related research should continue in order to be ready for any other similar pandemics in the future. That could be achieved if we really understand what happened in every challenge that we met as we tried to overcome the pandemic over the past two years. Table 1 shows a list of the Corona virus variants that the world has faced for the past two years [1]. One of the ways that many governments have used to overcome the pandemic is controlling their stringency measures.

Stringency measure is an index that is composed of many parameters, and it ranges from zero to one hundred, where one hundred represents a very strict response measure. It comprises many measured indicators such as canceling a public event or controlling travel domestically and internationally. The application of these measures differs from one country to another. Also, the adherence to these measures by the public is another major challenge that sometimes has to be inspected. However, sometimes, it may end up that the responsibility is on each individual to take care of his or her health by following the applied stringency measure. There is no doubt that these restrictions have great impact on economy, people social life and many other important matters. However, it was necessary to follow these measures to reduce the number of infected individuals for fear of life loss or serious health problems' consequences.

Table 1. WHO Corona Virus Variants Designations for the Years 2020-2021

Variant Name	Location of Earliest Observed Cases	Official Label Recognition
Alpha	United Kingdom, Sep-2020	Dec 18th, 2020
Beta	South Africa, May-2020	Dec 18th, 2020
Gama	Brazil, Nov-2020	Jan 11th, 2021
Delta	India, Oct-2020	April 4th & May 11th, 2021
Lambda	Peru, Dec-2020	June 14th, 2021
Mu	Colombia, Jan-2021	Aug 30th, 2021
Omicron	Multiple countries, Nov-2021	Nov 24th & Nov 26th, 2021

2. LITERATURE REVIEW
There is no doubt that for the past two years the Covid-19 pandemic has greatly affected our societies. There has been a continuous interaction between government legislations trying to curb the spread of the virus and the public response as they try to adhere to these legislations. It is believed that there should be a lot of studies post pandemic to analyze all the incidents that took place. We should learn from this past challenging experience that constituted a huge problem for the whole world by acting proactively and not to wait for another pandemic to start continuing investigation. Preparing these types of studies is crucial least we face another unpredictable situation in the future, and we race time for solutions while casualties take place. Investigating the literature, a few research articles have focused specifically on the stringency

index to control the spread of the virus infections as well as to reduce the number of deaths.

Most of the work found in the literature was done by deploying a variety of machine learning techniques; the thing that was expected as different designed prediction models have proven worthy in different applications. Nevertheless, aside from machine learning techniques, A few researchers have tried some computational statistical approaches that helped to reach useful finding during the pandemic [2-6]. For example, in [2], an interesting statistical approach, latent variable path analysis (LVPA), was used to evaluate the impact of studied attributes towards the predicted class by deploying different causal pathways. This analysis method is close to the feature importance analysis provided in some machine learning models like Random Forests for example. Their findings showed that the number of new daily cases per million and the mortality rate are affected significantly by the length of the lockdown period. However, Since the focus of our proposed research is on using machine learning techniques to analyze the problem at hand, the rest of the literature review will be devoted to the research work that utilized machine learning approaches.

Some researchers have used machine learning techniques to study the relation between the stringency measures provided by government regulations and the total reported Covid-19 daily cases [7-9]. For example, in [7], researchers investigated the relation between the applied stringy index measure and the total time spent outside home, and also with the total reported Covid-19 daily cases. Their finding stated that there is negative correlation between the applied stringency index measures and the Covid-19 outcomes. In addition, they found that spending more time outdoors is positively correlated with the Covid-19 outcomes. It is believed that these results are reasonable given that higher or stricter stringency measure will lead to lower Covid-19 daily cases. As well, spending more time outside will increase interaction among individuals, the thing that may lead to more infections if precautions were not taken properly.

Other researchers have used different techniques such as ElasticNet algorithm, Linear Regression and LASSO in [10-14]. For example, in [10], the main objective of that article was to investigate the influence of stringency measures and socio-economic factors on the new Covid-19 daily cases. That relation was found to be highly dependent on the socioeconomic and the culture of the data of the country being investigated. While building their prediction models, they investigated the most influencing attributes that affected the prediction of the number of new Covid-19 daily cases. They found that the stay-at-home stringency measure is the most influencing attribute, followed by work closure and school closure. The later findings of their proposed research agree with the early mentioned research findings as they complement each other. Both findings agree that spending more time outside will lead to an increase in the new cases, while staying at home reduces the spread of the virus.

Some researchers proposed a hybrid model to predict the active covid-19 cases and the number of deaths based on the type of the stringency measure enforced by the government as well as the duration of its application [15-19]. For example, in [15], according to their design, the designed models were able to recognize the public social habit changes. They found that low stringency measures could cause new daily infections up to 0.94% of the population; however, enforcing milder stringency flattened the curve of the new daily cases which could be an acceptable outcome for some policy makers. They mentioned that using mild stringency measures resulted in approximately five times the number of active new daily cases produced by the stricter stringency index. As well, researchers concluded that lock down durations up to fifty days resulted in a notable reduction in the number new daily cases and deaths; however, they mentioned that increasing the lockdown more than fifty days could result in a negative impact at the social and business levels.

Most of the research found in the literature investigated the effect of stringency index effect on the number of new Covid-19 daily cases as well as the number of related deaths, see Table 2. In our proposed research we will approach the problem from a different angle, where the stringency index will be predicted based on the number of new daily cases and deaths as well as the number of administered vaccinations. Since the data of the past experience with the pandemic is available, it is believed that we can learn a few lessons that can save policy makers a few trial-and-error choices and assist them in deploying informed decision instead. We will start by exploring the related attributes in the dataset under investigation, then build prediction models that can assist in predicting the suitable stringency index in the future in case other pandemics occur. The structure of this proposed article is designed as follows: the related background literature is covered in section two, while the used methods will be described briefly in section three to leave room for more results. Section four covers data pre-processing and data exploration, followed by the results and discussions in section five. Finally, section six covers the conclusion and future works.

3. METHODS

In this section we will have a brief description about the machine learning techniques used in this research. For more details about the math behind the discussed techniques, these articles could be checked [20,21]. As well, more about the methods behind the deployed techniques during our upcoming analysis could be found in [22,23]. The machine learning techniques deployed in this research are supervised machine learning techniques. We chose a few techniques that are

Table 2.Summary of Some Relations Found in the Literature

Stringency Measure	Affected Attributes	Type of Relation
length of the lockdown period	new daily cases per million and the mortality rate	significant
spending more time outdoors	Covid-19 outcomes: new daily cases and deaths	positively correlated
socio-economic factors	Covid-19 outcomes: new daily cases and deaths	highly dependent
stay-at-home stringency measure and school closure	Covid-19 outcomes: new daily cases and deaths	they are the most influencing attributes
stringency measure and its duration	Covid-19 outcomes: new daily cases and deaths	negative relation for a duration up to 50 days

known to be effective during learning and also have a controlled error. The term supervised implies that there is a teacher supervising the learning process. That teacher is controlling the learning process by monitoring the actual output produced by the learning system and compares it with the desired output. Based on the training examples fed to the learning module, the desired output should be produced for a certain input. If there is a difference between the desired and the actual output produced, an error signal occurs, and the teacher recognizes that error. Depending on the machine learning model used, that error should be taken into consideration during the learning process. Next, the following training example in the dataset is fed to the machine learning model and the teachers keeps monitoring for an error, and so forth. When the training examples fed to the learning module finish, the learning system could repeat learning iterations again until an acceptable error level pre-set to the teacher is met. We have used many techniques such as Back Propagation Neural Networks (BPNN), Support Vector Machines (SVM), Random Forests (RF) and other advanced techniques such as ensemble machine learning techniques.

We will briefly shed light on some of these techniques since they have been explained thoroughly in much research works in the literature. One example of such supervised learning systems is the BPNN used in this research, where the error during the learning process is back propagated though the network. The error updates the weights inside the network as a method of adaptation to the error associated with each input example. To decrease the learning error, the supervising teacher mentioned earlier will update the weights of the network using ΔW, see equations (1-4). This update is mostly proportional to the learning rate of the learning network as well as the difference between the actual and the desired output.

$$W_{new} = W_{old} + \Delta W \qquad (1)$$

To be precise, the calculation of ΔWat the output layer differs from its calculation at the hidden layers because of the absence of the comparison with the desired output. Therefore, at the output layer:

$$\Delta W = \alpha \, output_i f'\left(net_j\right)(target_j - output_j)(2)$$

Whereas, at the hidden layers, is calculated based on the previous layer error δ_j calculations:

$$W_{new} = W_{old} + \alpha \, output_i f'\left(net_j\right)(\sum \delta_k W_{kj})(3)$$

$$\text{Where,} \delta_j = f'\left(net_j\right)(\sum \delta_k W_{kj}) \qquad (4)$$

On the other hand, we have a few advanced machine learning techniques considered as meta-algorithms in our research during the analysis process such as Bagging, AdaBoost and LogitBoost. For example, Bagging is trying to get a voted output of a collection of RF tree models. In the BPNN discussed earlier, the training example is used as a one patch during iteration of the learning process. Bagging divides the training examples into N independent base learners, where the sampling process is deployed with replacement. The technique gives same weight to all the designed learners, and the overall model prediction output of the ensembled learners is the average of the output of the individual learner. Therefore, if we assume that there are L_m base learners, then the voted output $V(x)$ could be explained by the following equation:

$$V(x) = argmax_{y \in Y} \sum_{m=1}^{M} I(L_m(x) = y)(5)$$

As for Boosting, a similar process is done in a sequential manner while minimizing an error δ, where the output of each stage is fed to the next stage, and the voted output is given by:

$$V(x) = argmax_{y \in Y} \sum_{m=1}^{M} log \frac{1-\delta_m}{\delta_m} I(L_m(x) = y)(6)$$

4. DATA PRE-PROCESSING and EXPLORATION

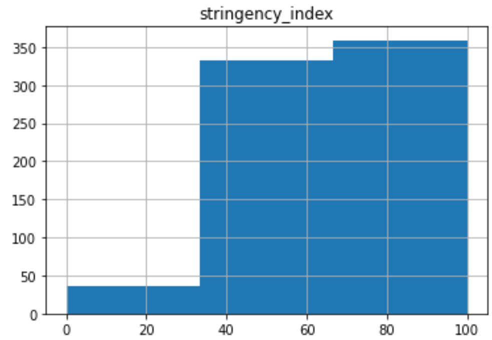
The data set used in our research is maintained by Our World in Data, which collects the data from different trusted sources all over the world. For example, the used new daily case and new deaths are provided by the COVID-19 Data Repository that belongs to the Center for Systems Science and Engineering at Johns Hopkins University. The data file contains more than 165 thousand records with around 70 attributes for records collected from different countries all over the world.

In this research, only a few of the attributes shown in Table 3 have been chosen for analysis as we tried building our prediction models. Based on the literature review, new daily cases and new deaths were the attributes of interest as different researchers have tried to build their models to predict them. Since we are approaching our analysis to that problem at hand from a different angle, it was logical to use these attributes as inputs to our models. We added the number of vaccinated individuals as another attribute in our analysis because many countries were waiting for the number of total vaccinations to reach an acceptable level so they can start lowering their stringency measures. It worth mentioning that the stringency index attribute had numerical values. To start building our classification models, we had to transform this feature into a categorical variable with three categories: low-level, medium-level, and high-level. Figure 1 (a,b), next page, illustrates an example of the original numerical attributes' distributions of Belgium and Egypt.

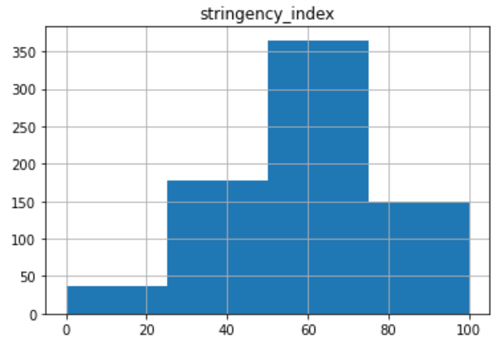
Table 3. Dataset Selected Attributes

Attribute	Description
total_cases	Total reported Covid cases
new_cases	New Covid-19 confirmed cases
total_cases_per_million	Total reported Covid-19 per million people
total_deaths	Total reported deaths due to COVID-19
new_deaths	New Covid-19 confirmed death cases
total_deaths_per_million	Total reported Covid-19 deaths per million people
icu_patients	Daily ICU Covid-19 cases
icu_patients_per_million	Daily ICU Covid-19 cases per million people
hosp_patients	Daily Covid-19 cases at the hospital
hosp_patients_per_million	Daily Covid-19 cases at the hospital per million people
stringency_index	Stringency index for government response
total_tests	Covid-19 total tests
total_tests_per_thousand	Covid-19 total tests per thousand people

total_vaccinations	Covid-19 total administered vaccinations
people_fully_vaccinated	Total number of people who are fully vaccinated
people_fully_vaccinated_per_hundred	Total number of people who are fully vaccinated per 100 people
location	Geographical location
date	Date of data collection

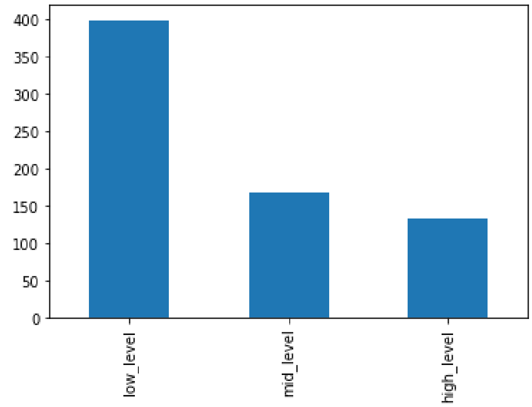


(a)

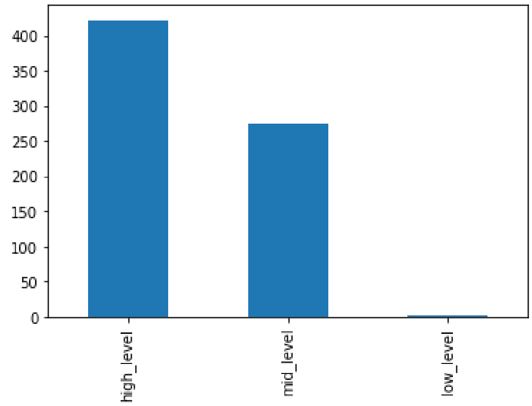


(b)

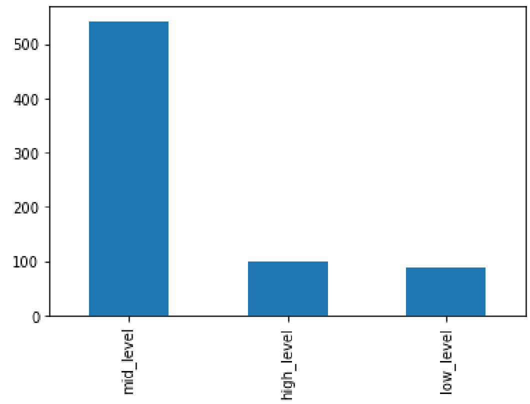
Fig. 1: Stringency Index Histograms for Some Countries: (a) Belgium (b) Egypt



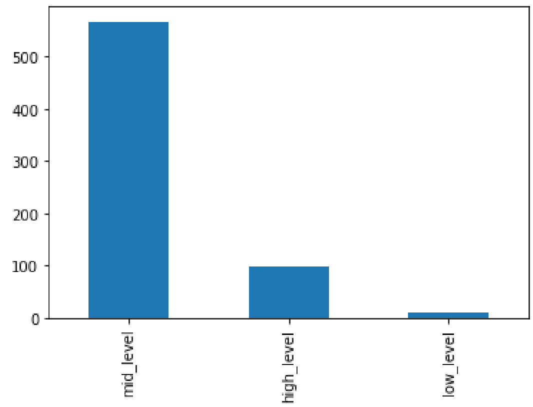
(a) Afghanistan



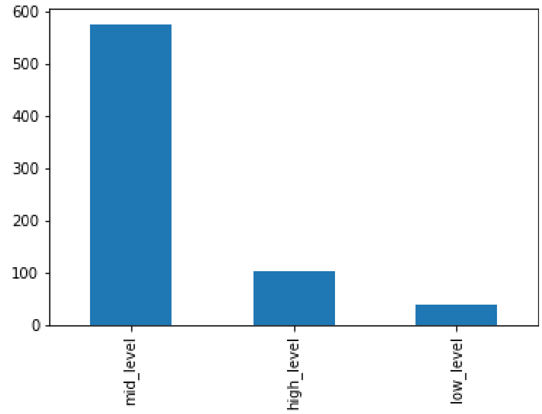
(b) Iraq



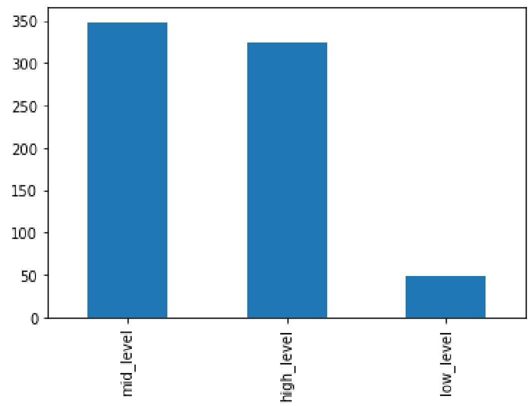
(c) France



(d) Egypt



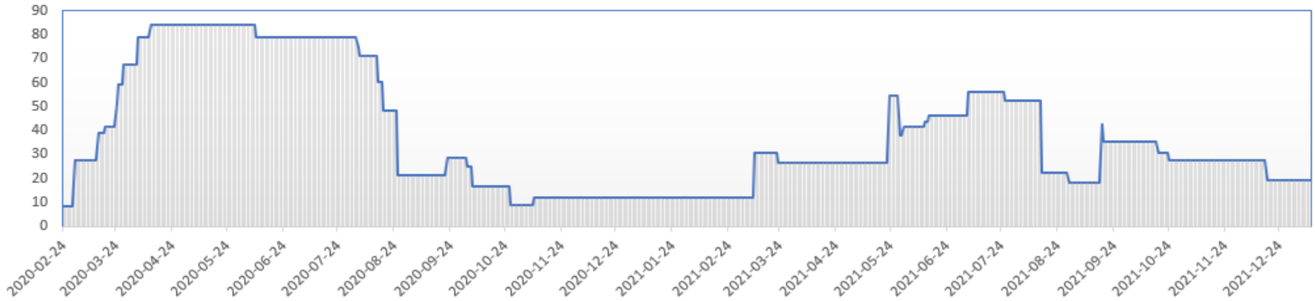
(e) Belgium



(f) United Kingdom

Fig.2: Stringency Index Transformed Categorical Distributions for Different Countries

The transformed categorical values for the investigated countries are illustrated in Fig. 2 (a-f). Based on the shown stringency index levels, we could notice that regardless of the chronological order of the stringency measures applied, Afghanistan applied low levels most of the time, while Iraq applied high level most of the time. It worth mentioning that the analysis showed that United Kingdom have balanced its application of medium and high levels of stringency indices, while France, Belgium and Egypt applied medium level stringencies most of the time. Essentially, one of the methods that we can judge the effectiveness of these stringency measures could be by basically tracking the number of infected individuals or the deaths that occur on a daily basis. The following graphs in Fig. 3 (a) and Fig. 4 (a) show samples of the stringency distribution in different countries over the world such as Afghanistan and France. The common stringency policy applied in these two countries was that both kept their stringency measure high approximately between the month of February up to the month of June; however, after that month their policies varied. In total more periods with higher stringency index were applied in France than in



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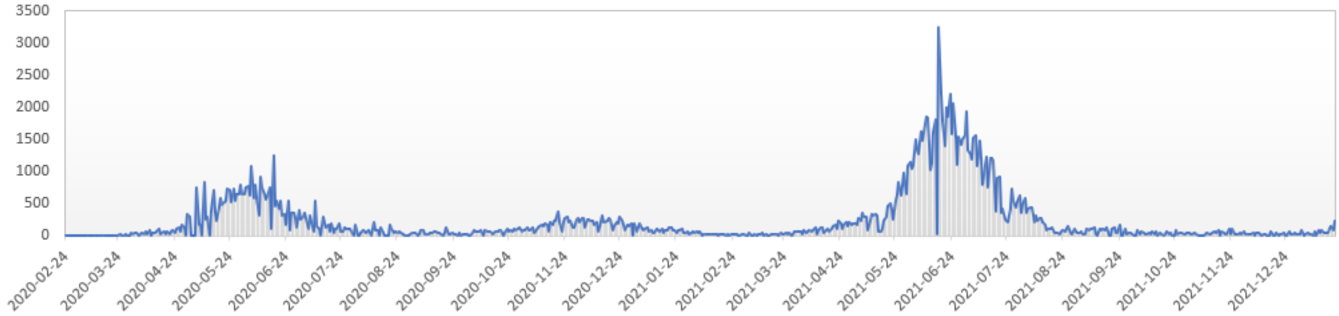

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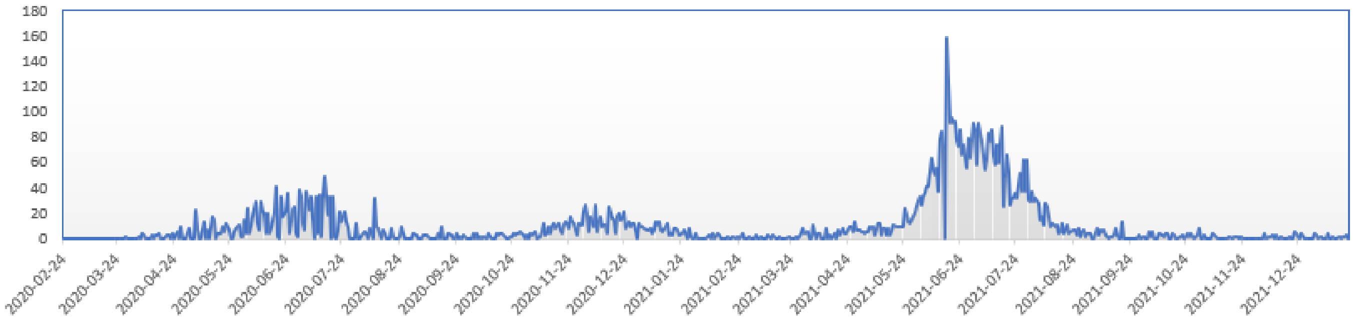

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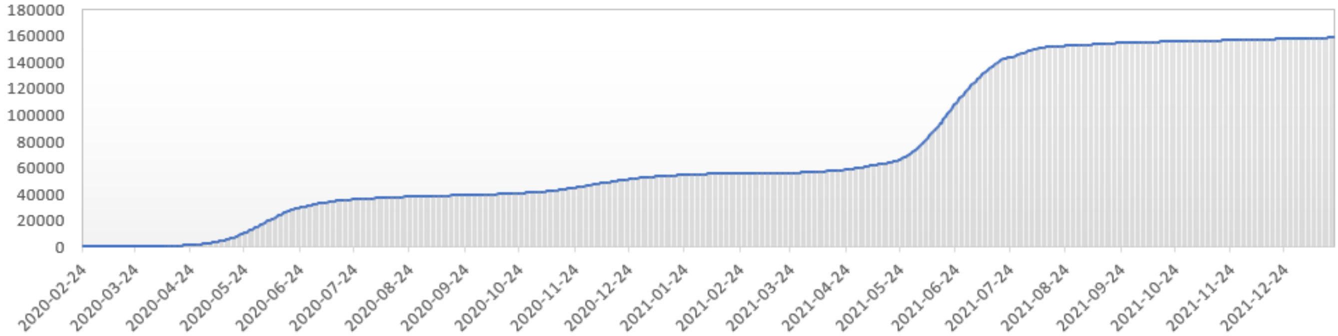
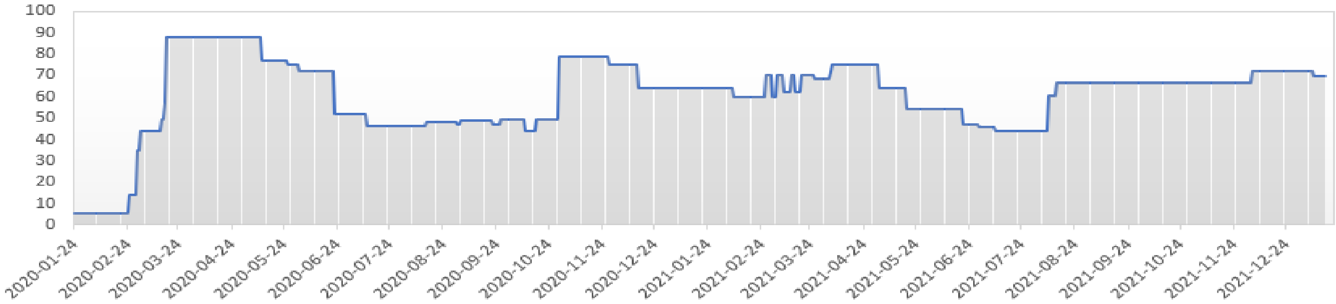


(d)

Fig. 3: Afghanistan Analysis: (a) Stringency Index Distributionbetween February 2020 and December 2022. (b) Associated New Daily Infection Cases for the Applied Stringency Indecies (c) Associated New Daily Death Cases for the Applied Stringency Indecies (d) Associated Total Daily Cases for the Applied Stringency Indecies



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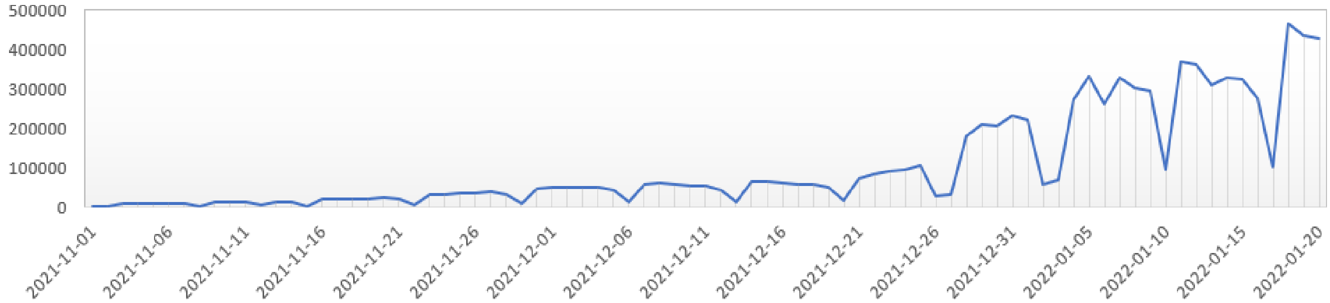

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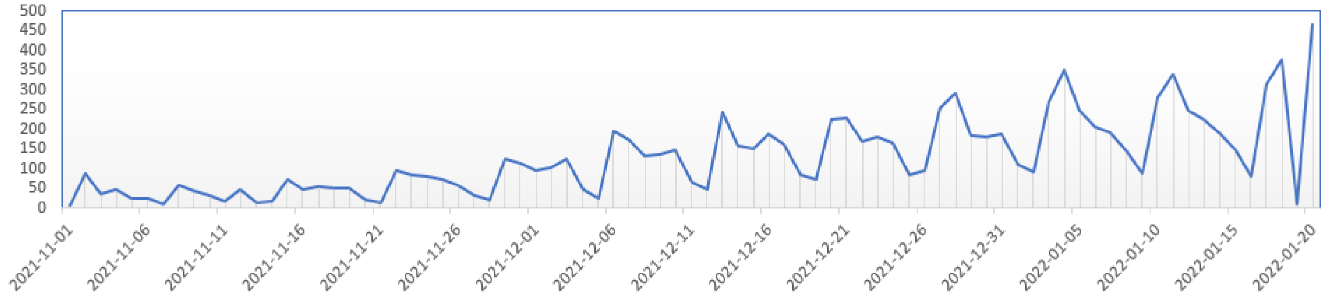

(c)

Fig. 4: France Analysis: (a) Stringency Index Distributionbetween January 2020 and December 2022. (b) Associated New Daily Cases for the Months of October and November 2021 (c) Associated New Death Cases for the Months of October and November 2021

Afghanistan for the past two years.

Figure 3 (a,b) show the analysis of the expected effect of the stringency index distribution on the new daily cases almost over the period of the past two years in Afghanistan. A note that seems intriguing is that the increase in the number of cases happened within the periods with high stringency index. One possible explanation is the lag that happened between enforcing a certain health prevention measure and the adherence of the people to it, which is expected to differ from one country to another. That note will be revisited later at the results and discussion section. Figure 3 (b,c) shows that the infection cases and the associated death cases are closely related; however, further investigation is needed to ensure what type of relation exists between these two dataset attributes. The graphs also show the government efforts to flatten the curve of the total daily cases; however, the increase in the new daily cases increased the levels of the total daily cases, see Fig. 3 (d).

According to the investigated data, France began applying high restriction measures starting March 2020, and their stringency index kept fluctuating until the end of that year, see Fig. 4 (a). The associated new daily infection was fluctuating with a lag as described earlier, especially during the two major pandemic waves of Delta and Omicron, recall Table 1. Due to the high infection rates that occurred during October and November 2021, we had to draw their distributions in separate graphs, see Fig. 4 (b,c). It was noticed that the new deaths were not high during these two months despite the huge number of infections and the medium stringency index that was applied. One possible explanation could be that the number of immune people has increased because of vaccination, and therefore they could be infected but they are going to survive. It is possible that those individuals were not necessarily following the restriction measures and they were still able to infect others.

5. RESULTS and DISCUSSION

Using ensemble DT methods, feature analysis has been conducted for different countries to see the importance of these chosen attributes to building the desired prediction models. A few countries were chosen for the analysis from different continents such as Europe, Asia, and Africa as we have done earlier. Most of the countries ranked the newly discovered daily cases as the most important factor to predict the right level of the stringency measure, see Fig. 5 and Fig. 6. For these analyzed countries, this finding could mean that if the new cases are under control and more people are

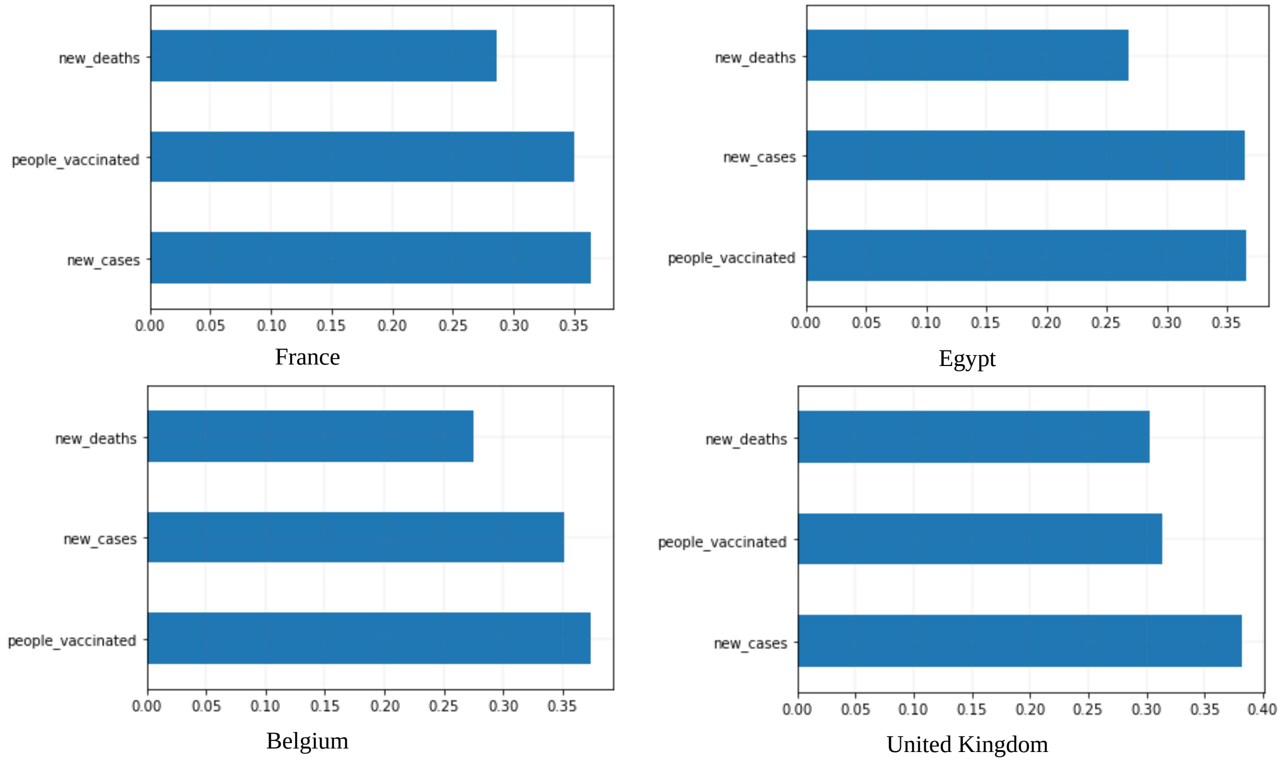

Fig. 5: Most Imortant Features Related to the Prediction of the Stringency Index Levels for different Countries

vaccinated, then they can go ahead and reduce stringency measures. However, how ethically is that action to take without considering the number of new deaths that are taking place is a critical issue, which all policy makers are not ignoring and are carefully addressing. After all, a computer is a machine, and according to algorithms and data calculations, new deaths is the least important factor; however, according to laws of humanity it should be the most important factor even if one person died because of the pandemic.

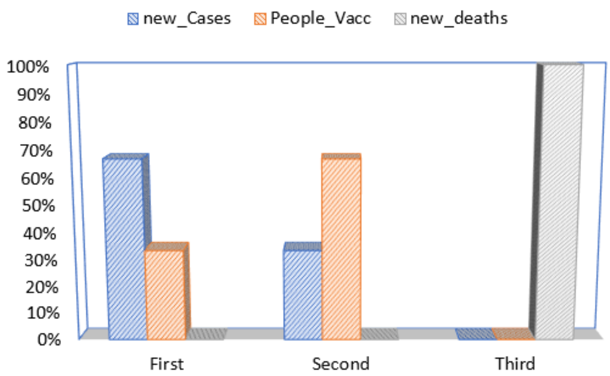

Fig. 6: Summary of Frequency of the Most Important Features for Different Countries

Different machine learning models have been designed, trained, and tested based on the earlier discussed methods with a 10-fold cross validation method. Table 4 shows the accuracy of the designed models for different countries such as Afghanistan, France, and Belgium for example. Egypt and Belgium had the highest average accuracies, while Afghanistan had the lowest. Precisely, Belgium had the highest accuracy of 94.84%, in Red, achieved by the RF and Bagging machine learning techniques. Across the investigated countries, Bagging performed the best in general with an average accuracy of approximately 89% followed by the RF models at 88.89%, while the SVM models performed the lowest at approximately 75%. Given the previous findings, it is believed that policy makers in the studied countries, and in other countries, could benefit from the designed machine learning models as they plan their future health restriction measures. However, as discussed earlier, the application of these models may depend on many other factors such as cultural and socioeconomic factors for example.

We previously mentioned that there was a lag when we analyzed the graph timeline of the applied stringency index and the corresponding new daily cases. In France for example,

Table 4. Stringency Index Prediction Models' Performances Designed for Different Countries

Index	Model Type	Countries Models' Accuracies					
		Afghanistan	Iraq	France	Egypt	Belgium	United Kingdom
1	BPNN	72.17	75.18	77.88	90.52	86.47	85.43
2	SVM	66	66.14	75.41	80.20	80.20	79.47
3	RF	76.33	92.11	90.66	89.25	94.84	90.15
4	AdaBoost	57.10	72.88	74.31	84.58	80.20	85.02
5	Bagging	77.47	92.11	90.66	90.81	94.84	89.46
6	LogitBoost	76.04	86.80	89.97	88.40	93.86	89.74
Average Accuracies		70.85	80.87	83.15	87.29	88.40	86.55

we may notice that there is a lag between the application of the stringency index measures for the periods T1 and T2, and the start of the daily cases reduction response, see Fig. 7. For example, low stringency measures were applied for the period T1 that took place between the end of June 2020 and the end of October 2022 spanning a period of approximately four months. When the government raised the level of the stringency index to a high level by the end of period T1, it took around 50 days lag for the number of daily cases to start dropping. A similar argument could be said about the infection cases' increase in response to the T2 period, but the associated lag appears to be bigger.

Based on the lag that we have mentioned, the use of the predicted stringency index produced by our designed machine learning models should be tuned to ensure better results when applied by policy makers. It is believed that once the proper stringency index is predicted, the previous associated lag based on the previous two years recorded public response has to be taken into consideration by policy makers. One suggested approach to amend that lag is to make the application of the chosen stringency measure longer by a time equal to earlier noticed lag for that particular country. It is believed that adaptation of the stringency index application time could decrease the expected lag or maybe remove it. However, that may require an intensive simulation analysis by some researchers in that direction to find an optimal solution.

Finally, we will briefly compare our findings with the state-of-the-art research found earlier in the literature. There are two approaches for that comparison based on the nature of the input-output mapping of the designed models and based on the relations among variables of these models. First, based on the nature of the input-output mapping of the designed models, most of the early discussed models in the literature had the stringency index fed as an input along with other attributes. These designed models generated a few predicated outputs such as the number of infected cases as well as the number of death cases, see Fig. 8(a). On the other hand, in our designed models, the new daily cases as well as the number of associated death cases along with number on vaccinations were fed as inputs, where the stringency index was generated as a model output, see Fig. 8(b).

Second, based on the relations among variables, our findings agree with some of the state-of-the-art results, see Table 5. For example, in our proposed research, infection cases are highly positively related to the associate death cases, 0.847, which is close to the results found in the state-of-the-art articles, 0.973 in Red [7], and 0.750 in Blue [10]. Social mobility, on the other hand, was investigated by other researchers in [7] and it was found to be negatively related to

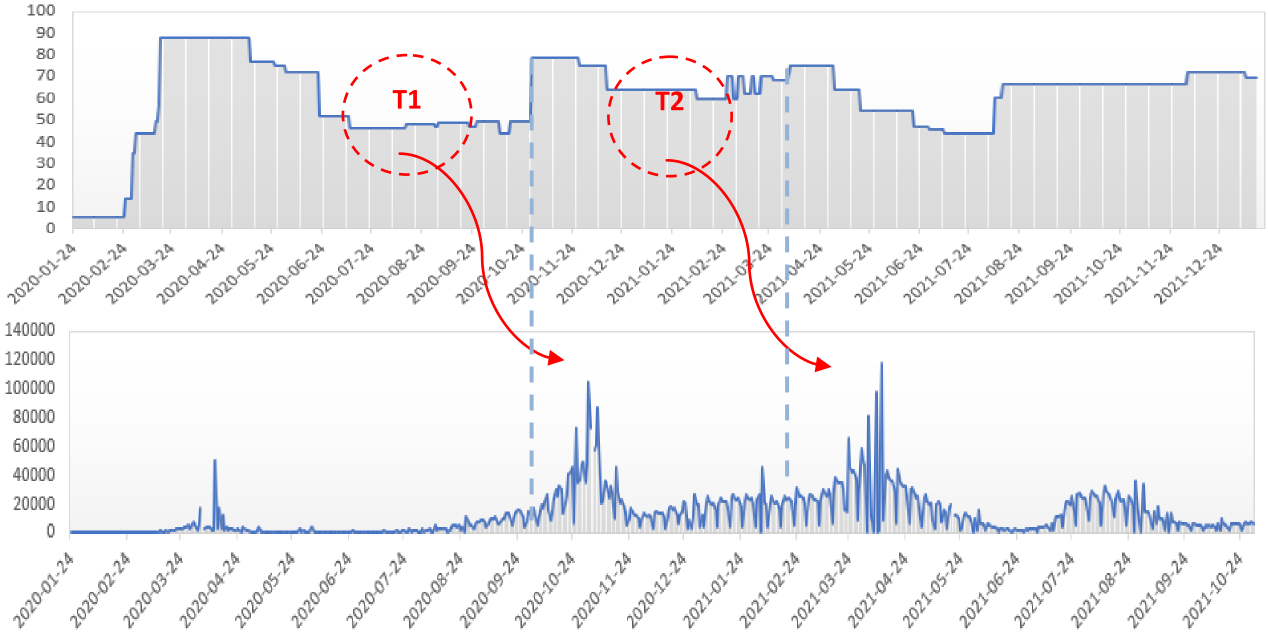

Fig. 7: Stringency Measure Application and its Associated Lag of New Daily Cases in France

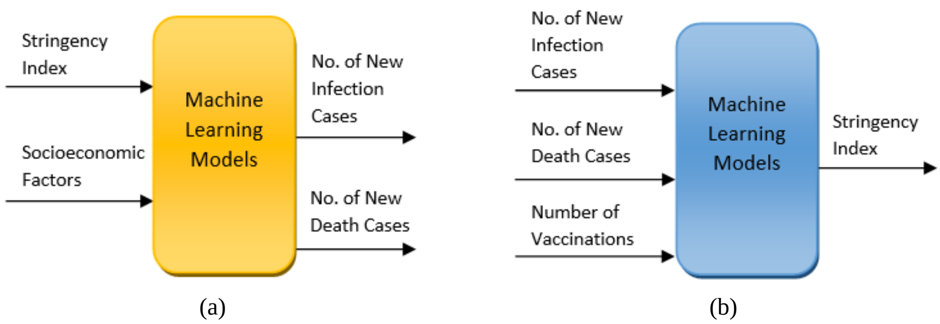

Fig. 8: A Comparison between the state-of-the-art Models' Design and the Models' Design in this Proposed Research

stringency index choices. There were a contradiction and an agreement with the state-of-the-art research regarding the nature of the relation between the infection cases and stringency index choices, see Table 5. For example, in our proposed research and in [10], the relation was found to be positive, 0.183 and 0.220 respectively, while the relation in [7] was negatively related at -0.441. Similar situations occurred between the death cases and the stringency index choices by having positive relations, 0.155 and 0.220, while having -0.363 as a negative relation.

It is believed that there could be evidence that supports our findings as well as the findings generated in [10]. For example, in Afghanistan, recalling early Fig. 3(b,c) showing the distribution of daily cases and death cases, we can notice that there is a direct relation between the number of infection cases and the number of deaths. However, there have been always a lag between the application of a certain stringency index level and decrease in the number of infection cases and consequently the reduction in the death cases. Recalling Fig. 7 in France for example, it is believed that according to the given data at hand, chronologically, a certain positive relation should exist because the lag delayed the infection cases' reduction. This means that when the machine learning algorithms perform computations, the data available showing high stringency level will be compared to high infection cases during the months of October and November 2020 for example, which will lead to a positive relation. However, as the lag diminishes, the situation will change, and it will gradually lead to a negative relation.

Table 5. Pairwise Correlation Matrix among the Variables in our Dataset-Country: Egypt, along with Variables from the state-of-the-art Results (in Red for [7] &Blue for [10])

Indicator	Infection Cases	Deaths Cases	People Vaccinated	Social Mobility	Stringency Index
Infection cases	1	-	-	-	-
Deaths cases	0.847 Vs 0.973 Vs 0.750	1	-	-	-
People vaccinated	0.303	0.152	1	-	-
Social mobility	0.233	0.136	-	1	-
Stringency index	0.183 Vs. -0.441 Vs 0.220	0.155 Vs -0.363 Vs 0.220	-0.305	-0.759	1

6. CONCLUSION and FUTURE WORKS

In this research we have investigated the relation between different factors related to the Corona pandemic and the suitable stringency level chosen by policy makers in different countries. Different machine learning models have been designed to predict the suitable stringency index based on key attributes such as the infection cases and associated death cases as well as the number of vaccinated people. Based on the investigated data which contained our past experience with the pandemic over the past two years, infection cases seemed to influence policy makers' choices the most in different countries, almost 67% of the time. One the other hand, people vaccination level was ranked second in influencing the policy makers decisions, almost 67% of the time as well, while the death cases always came third in place.

The accuracy of the designed models ranged between 57% using the Adaboost machine learning model on Afghanistan data to 94.84% using RF and Bagging machine learning techniques on Belgium data. The designed predication models produced a predicted output that represents the suitable predicted stringency index that should be used in different pandemic situations. As policy makers use the designed models, we proposed a certain adaptation tuning mechanism that should be applied post prediction to consider the lag discovered earlier. Finally, our research findings agreed with some of the state-of-the-art research and conflicted with some, but other researchers are welcome to try different datasets in the future to check on the produced results. As well, more research should be done to investigate the inclusion of the previously experienced lags in policy application for different countries to come up with more robust stringency measure application choices. We wish that these future directions for researchers are tackled as soon as possible to be ready for any future similar pandemic situations.

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